UNIVERSITI TEKNOLOGI MARA

THE IMPACT OF MULTIDIMENSIONAL SOCIAL MEDIA USE ON ACADEMICIANS' PERFORMANCE IN UNIVERSITI TEKNOLOGI MARA: A MEDIATING ROLE OF SOCIAL CAPITAL

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PhD

May 2026

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Thesis submitted in fulfilment
of the requirements for the degree of
Doctor of Philosophy
(Information Management)

Faculty of Information Science

May 2026

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ABSTRACT

The widespread adoption of social media in higher education has reshaped how academicians communicate, collaborate, and perform their professional roles. However, existing studies often treat Social Media Use (SMU) as a unidimensional construct, typically measured by frequency, duration, and intensity, resulting in a limited understanding of how different forms of use influence Academician's Performance (AP). Addressing this gap, the present study aims to develop and empirically validate a multidimensional model of SMU and examine its effects on AP in Malaysian public higher education institutions, with Social Capital (SC) examined as a mediating mechanism. Guided by Uses and Gratifications Theory (UGT), Social Capital Theory (SCT), and Information Systems (IS) perspectives, SMU is conceptualised across four dimensions: System Use (SyU), Social Use (SU), Content Use (CU), and Hedonic Use (HU), while AP is treated as a multifaceted construct encompassing teaching, research and publication, supervision, and consultation. Data were collected through an online survey of 206 academicians from Universiti Teknologi MARA (UiTM) using a stratified sampling method. The measurement and structural models were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings confirm the reliability and validity of the proposed constructs. SyU, SU, and CU were reported to have significant positive effects on AP, whereas HU exhibited a significant negative effect. SC significantly predicted AP and partially mediated the relationship between SU and performance. The results highlight social and content-oriented uses of social media as the most influential dimensions in enhancing AP. This study contributes theoretically by advancing a multidimensional understanding of SMU and empirically confirming the mediating role of SC in academic contexts. Methodologically, it refines measurement by modelling SC and AP as Higher-Order Constructs (HOCs). In practice, the findings inform institutional strategies to promote purposeful, performance-oriented social media engagement among academicians. Conversely, limitations related to the cross-sectional design and single-institution focus suggest avenues for future longitudinal and multi-institutional research.

ACKNOWLEDGEMENT

بِسۡمِ ٱللَّهِ ٱلرَّحۡمَٰنِ ٱلرَّحِيمِ

Firstly, in Praise to ﷲ and His beloved ﷺ. I wish to thank ﷲ for allowing me to embark on my PhD and for completing this long and challenging journey successfully. Part of the journey was realising that the time I spent for ﷲ and His beloved is the source of tranquillity.

My gratitude and thanks go to my supervisors, Assoc. Prof. Ts. Dr. Abd Latif Abdul Rahman and Prof. Ts. Dr. Norhayati Hussin. They shared knowledge, time, and endless support until the end. Their positive attitudes encouraged me to finish the thesis. My gratitude to my supervisors is beyond words.

My appreciation goes to the Universiti Teknologi MARA, which provided the facilities and assistance during my study. Special thanks to my colleagues, friends, and siblings for helping me with this PhD.

Finally, this thesis is dedicated to my beloved father and mother for their vision and determination in educating me since I was young. They always want their children to be educated, not to endure the same struggles they did. If the PhD is full of struggle, it was nothing compared to them. Thank you, and I love you. This thesis is dedicated to both of you ٱلۡحَمۡدُ لِلَّٰهِ.

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LIST OF SYMBOLS

Symbols

A	Number of PLS or PCA Components in the Model; Number of Selected Latent Variables
a	Index or Count of Pls or PCA Components
b	PLS Regression Coefficient
b	Number Of Blocks in the Model (B = 1, 2, 3, ..., K)
β	Path Coefficient
λ	Outer (Factor) Loading of an Indicator on Its Latent Variable
t	T-Value
p	P-Value
R^2	Coefficient of Determination
f^2	Effect Size
Q^2	Predictive Relevance
n	Sample Size
K	Total Number of Latent Constructs in the Model
Σ	Summation Symbol
X	Matrix of Observed Indicator Variables
Y	Dependent Variable or Outcome Matrix
Z	Standardized Values or Z-Scores
ε	Error Term or Residual in Regression Equations

LIST OF ABBREVIATIONS

Abbreviations

AP	Academician Performance
AVE	Average Variance Extracted
CCA	Confirmatory Composite Analysis
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
CSC	Cognitive Social Capital
CU	Content Use
EFA	Exploratory Factor Analysis
HOC	Higher-Order Construct
HTMT	Heterotrait-Monotrait Ratio
HU	Hedonic Use
IPMA	Importance-Performance Map Analysis
LOC	Lower Order Construct
PCA	Principal Component Analysis
PLS-SEM	Partial Least Squares Structural Equation Modelling
RO	Research Objective
RQ	Research Question
RSC	Relational Social Capital
SC	Social Capital

SCT	Social Capital Theory
SEM	Structural Equation Modelling
SMU	Social Media Use
SPSS	Statistical Package for the Social Sciences
SSC	Structural Social Capital
SU	Social Use
SyU	System Use

LIST OF NOMENCLATURES

Nomenclatures

AVE	Average Variance Extracted (Measure of Convergent Validity)
CR	Composite Reliability (Internal Consistency Measure)
f^2	Effect Size (Impact of Exogenous Construct on Endogenous Construct)
p	Significance Level (Probability Value)
Q^2	Predictive Relevance (Stone–Geisser's Q^2)
R^2	Coefficient Of Determination (Explained Variance of Endogenous Construct)
RMSEA	Root Mean Square Error of Approximation (Model Fit Index)
SRMR	Standardised Root Mean Square Residual (Model Fit Index)
t	T-Statistic for Testing Significance in Bootstrapping
VAF	Variance Accounted For (Used to Assess the Strength of Mediation)
VIF	Variance Inflation Factor (Multicollinearity Indicator)
α	Cronbach's Alpha (Internal Consistency Reliability)
β	Path Coefficient (Standardised Regression Weight)
λ	Outer Loading (Indicator Loading on Construct)
ρ_a	Dijkstra–Henseler's Rho (Composite Construct Reliability)

CHAPTER 1
INTRODUCTION

1.1 Introduction

This chapter provides the foundational framework for the study, beginning with a comprehensive research background and a detailed problem statement that addresses critical theoretical gaps and the need to develop new dimensions in the field. The chapter outlines the study's purpose, specifically defining the Research Objectives (ROs) and Research Questions (RQs) that guide the investigation toward a refined theoretical framework. Furthermore, it discusses the significance of the research through its intended theoretical contributions and practical implications. Finally, the chapter establishes the scope and limitations of the study and provides operational definitions for the key constructs to ensure conceptual clarity.

1.2 Research Background

Social media has emerged as a dynamic digital platform characterised by user-generated content, interactive engagement, and network-driven communication, distinguishing it from traditional Information Technologies (IT) such as e-commerce, digital libraries, and mass media. Its participatory design enables users to shape their experience according to their personal and professional goals, making it particularly relevant for academicians engaged in knowledge creation, teaching, and collaborative research.

In higher education, social media supports diverse academic activities, including instructional delivery, student interaction, research collaboration, professional networking, and knowledge dissemination. Studies have shown that social media can enhance learning environments and foster academic engagement through platforms such as Facebook, LinkedIn, and Twitter (Ansari & Khan, 2020; Jena, 2015; Ambika et al., 2016). Key adoption drivers include Perceived Ease of Use (PEU), usefulness, and the desire for networking and resource sharing (Arshad & Akram, 2018; Al Kurdi, 2024). Additionally, social media promotes trust and collaborative networks among

scholars, even if it does not always align with institutional strategies or unified visions (Sidhu et al., 2023).

Within this study, these collaborative and relational benefits are conceptualised through the lens of Social Capital (SC). SC is defined as the network of social relationships embedded within individuals that can be leveraged for academic or professional purposes (Nahapiet & Ghoshal, 1998). In academic settings, SC manifests through professional connections, trust-based relationships, and shared understanding that enable knowledge exchange, collaboration, and performance enhancement. This study adopts SC as a key explanatory mechanism linking Social Media Use (SMU) to Academicians' Performance (AP), with its specific dimensions elaborated later in this chapter.

Despite its growing presence in academia, most studies treat SMU as a unidimensional construct, often measured by frequency, duration, or intensity. However, recent empirical findings suggest that not all types of use yield equal benefits. Therefore, this study distinguishes between four key dimensions of SMU (i.e., System Use (SyU), Social Use (SU), Content Use (CU), and Hedonic Use (HU)). SyU is related to Frequency, duration, and intensity of general usage; meanwhile, SU is Engagement in interpersonal and professional networking. On the other hand, CU relates to the creation, sharing, and consumption of academic and professional content, and HU is entertainment-based or leisure-oriented.

Therefore, the central focus of this research is to examine how these diverse types of SMU impact AP, a Higher-Order Construct (HOC) encompassing four performance domains: Teaching, Research & Publication, Supervision, and Consultation. Moreover, the study integrates SC, which is also modelled as an HOC with structural, relational, and cognitive dimensions, as a potential mediator. Drawing on Social Capital Theory (SCT) (Nahapiet & Ghoshal, 1998) and informed by the Technology Acceptance Model (TAM) and Uses and Gratification Theory (UGT), the research investigates how network embeddedness, interpersonal trust, and shared understanding fostered through social media may enhance or constrain AP.

The impact of these dimensions on AP was assessed using a quantitative approach, focusing on whether SC, including Structural Social Capital (SSC), Relational Social Capital (RSC), and Cognitive Social Capital (CSC), mediates these effects. These constructs were tested using data collected from Universiti Teknologi

MARA (UiTM), one of Malaysia's largest public universities, offering insights into how social media shapes academic work in a local institutional setting.

1.3 Problem Statement

In Malaysian higher education, social media has become widely embedded in academicians' daily academic activities, including teaching communication, research dissemination, networking, and professional visibility. However, informal observations and institutional reports suggest that academicians often engage with social media without clear awareness of how different forms of use may support or hinder their academic and career performance. While some academicians leverage social media strategically for collaboration and scholarly visibility, others experience distraction, technostress, and blurred work-life boundaries. This practical inconsistency highlights a lack of structured guidance and an evidence-based understanding of effective SMU in academic contexts, underscoring the need for a systematic investigation.

1.3.1 Theoretical Gap

In traditional Information Systems (IS) research, SyU is frequently conceptualised as a unidimensional construct, measured in terms of frequency, duration, or intensity, emphasising a task-oriented, instrumental view of technology adoption (Venkatesh et al., 2003). However, this approach is insufficient for capturing the complexities of SMU, which differ significantly from those of conventional systems in purpose, interaction patterns, and user motivations. Social media platforms are inherently multifunctional, enabling communication, collaboration, content creation, and knowledge dissemination, beyond mere task completion (Hinojosa & Cleveland, 2017; Murthy & Lewis, 2015; Kotsenas et al., 2018).

Recent research highlights the limitations of existing IS models, such as the TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT), in fully capturing the dynamics of social media engagement. While these models effectively assess factors such as perceived usefulness, ease of use, and behavioural intention (Davis, 1989; Venkatesh et al., 2003), they often neglect the nuanced ways digital tools are integrated into professional contexts and fail to reflect evolving user behaviour. For instance, Gil-Fernández and Calderón-Garrido (2023) argued that TAM and UTAUT

overlook the influence of digital competencies in professional settings, limiting their applicability in educational environments. Likewise, Pillai and Mukherjee (2011) demonstrated that TAM's utilitarian assumptions inadequately explain platform-specific motivations, such as enjoyment on hedonic platforms, such as Facebook. This is comparable to the usefulness of utilitarian platforms like LinkedIn, thus failing to address the full spectrum of user engagement.

Further extending these concerns, Dang et al. (2020) emphasised the importance of task-technology fit, suggesting that user engagement depends on how well technologies align with specific work needs, rather than on general intentions. Similarly, Abu Sa'a and Asplund (2025) differentiated between types of collaborative structures, highlighting that the context of collaboration, formal research versus informal networking, produces different usage patterns. These studies underscore that SMU is best understood as a multidimensional and context-dependent phenomenon that current IS models inadequately capture.

In contrast, media and communication studies grounded in UGT provide a more comprehensive framework. UGT positions media use as a purposive behaviour shaped by individual psychological, social, and functional needs (Katz, Blumler, & Gurevitch, 1973; Whiting & Williams, 2013). From this perspective, SMU comprises diverse patterns, such as content consumption, creation, social interaction, and entertainment, each driven by distinct motivations and producing different outcomes. This multidimensional conceptualisation is particularly relevant in academic contexts, where platforms are used not only for information access and dissemination but also for research collaboration, professional development, and pedagogical innovation.

Despite increasing social media integration into academic environments, most empirical studies treat SMU as a generalised behaviour. This oversimplification obscures how distinct usage patterns influence specific academic functions. AP is multidimensional, encompassing research and publication, teaching, student supervision, and consultation. Measuring SMU solely through frequency or intensity fails to reveal which academic roles are most impacted by which types of engagement. For instance, content-focused use may enrich teaching quality through multimedia integration; SU may enhance research collaboration; HU may indirectly support creativity or reduce burnout; and SyU may foster long-term professional growth through sustained engagement.

Moreover, SC, a key theoretical mechanism linking SMU to performance, remains underexplored. While TAM and UTAUT account for individual cognitive factors, they often overlook the relational benefits of SMU, such as trust-building, shared norms, and network development (Nahapiet & Ghoshal, 1998; Putnam, 2000). These elements are central to academic collaboration and knowledge exchange. Although emerging studies acknowledge the role of SC in academic SMU (Alajmi & Alasousi, 2023; Filipovic & Arslanagic-Kalajdzic, 2023), few have empirically tested its mediating role between SMU and performance, particularly in the Malaysian higher education context. This omission may contribute to the inconsistent empirical findings on the relationship between social media and AP (Brooks, 2015; Tandon et al., 2021). Several critical issues persist in the literature, (1) the lack of validated dimensions of SMU specifically tailored to the diverse roles of academicians; (2) a limited understanding of which dimensions of use are most strongly associated with improved AP; (3) insufficient empirical testing of SC as a mediating variable; and (4) the absence of practical frameworks or policy guidance for institutions aiming to integrate social media into academic workflows strategically. These gaps highlight the need for a more integrated, theory-driven, and empirically validated model that captures the complex interplay between SMU, SC, and performance in the academic context.

1.3.2 The Requirement to Create New Dimensions

The exponential growth of social media has transformed how individuals communicate, collaborate, and consume information across various sectors, including education, healthcare, and business. Unlike traditional IS or IT, which are typically transactional, task-specific, and functionally isolated (e.g., banking systems, digital libraries, e-commerce platforms), social media platforms are inherently dynamic, participatory, and socially interactive (Kietzmann et al., 2011; Kaplan & Haenlein, 2010). These platforms enable users to access information and create, modify, and share content in real time, thereby fostering complex patterns of social engagement and facilitating emergent forms of SC, knowledge sharing, and professional networking.

Despite this paradigm shift, many existing studies on SMU continue to rely on measurement constructs rooted in classical IS/IT frameworks, most notably SyU indicators such as frequency, duration, and intensity of use (Venkatesh et al., 2003; Junco, 2012). While these traditional metrics offer a degree of insight into user activity,

they fall short in capturing the socially embedded and behaviorally diverse nature of contemporary social media engagement, particularly within professional and academic environments where the platforms are employed for a spectrum of purposes, ranging from work coordination and consultation to entertainment and personal interaction. The continued reliance on such limited and often unidimensional metrics significantly constrains the explanatory power of theoretical models like the TAM, the Theory of Reasoned Action (TRA), and the Theory of Planned Behaviour (TPB), which were initially developed within the context of structured, task-oriented systems (Ajzen, 1991; Davis, 1989).

A critical review of recent literature further highlights the inconsistency in findings regarding the impact of SMU on performance, with some studies reporting beneficial outcomes while others reporting adverse effects (Brooks, 2015; Cao & Yu, 2019; Dantas et al., 2022; Masood et al., 2022). For example, the use of social media for professional collaboration, academic communication, or knowledge sharing has been shown to enhance productivity and task efficiency (Permana et al., 2023; Sendurur et al., 2015). In contrast, excessive or non-purposeful use, especially for leisure or social browsing during work or study hours, has been linked to technostress, distraction, and reduced performance (Brooks, 2015; Khan & Mahapatra, 2017; Yu et al., 2019). These contradictory findings underscore a critical methodological gap: the lack of a standardised, context-sensitive measurement framework capable of distinguishing among different types of social media engagement.

Thus, there is an increasing scholarly consensus that the current approach to measuring SMU is inadequate. Simply quantifying use by time or frequency fails to differentiate between intent, content, and usage context. For instance, two users may spend the same amount of time on a platform like Facebook, but one may use it to share research materials and collaborate with colleagues. At the same time, the other engages in passive scrolling or entertainment consumption. Treating these behaviours as equivalent in quantitative models distorts the relationship between SMU and performance outcomes (Masood et al., 2022; Yu et al., 2019).

Accordingly, a strong imperative is to develop multidimensional measurement models that reflect social media's complex, user-driven affordances. These models should integrate multiple usage dimensions that reflect instrumental (e.g., SyU, content sharing, collaboration) and gratification-based (e.g., social bonding, entertainment, emotional support) motivations. Such an approach aligns closely with the assumptions

of UGT, which posits that individuals actively select media based on specific psychological and social needs (Blumler & Katz, 1974; Katz et al., 1973). Incorporating dimensions such as SyU, SU, CU, and HU, as validated in emerging studies, offers a more theoretically grounded and empirically sensitive framework for understanding the differential impacts of social media across various domains (Guo et al., 2025; Dantas et al., 2022).

Furthermore, multidimensional models would allow researchers to examine how specific types of use influence outcomes differently. For example, SU may foster relational capital and collaboration, whereas HU may increase technostress if overused during task-intensive periods. In this way, the effects of SMU on academic or professional performance can be more precisely captured and explained, accounting for both positive and negative impacts depending on the use purpose, setting, and user role.

Thus, the development of new dimensions for measuring SMU is not only methodologically necessary but also theoretically justified. By embracing a nuanced, multidimensional approach to SMU measurement, future research can better reconcile the inconsistent findings in the literature, enhance theoretical model validity, and provide more actionable insights for managing SMU in academic and organisational contexts.

1.3.3 Toward a Refined Theoretical Framework

In light of the methodological and conceptual limitations identified in prior research, particularly the reliance on narrow, unidimensional measures of SMU, this study proposes a more comprehensive and theoretically grounded framework. The need to move beyond traditional metrics such as frequency, intensity, and duration of use is underscored by social media platforms' increasingly complex and multifaceted roles in academic environments (Brooks, 2015; Cao & Yu, 2019; Dantas et al., 2022). Drawing on the theoretical underpinnings of UGT and SCT, this study seeks to capture how academicians use social media, why it is used, and with what outcomes.

Specifically, the present study proposes and empirically validates four key dimensions of SMU, SyU, SU, CU, and HU to more accurately represent the scope of social media engagement in academic settings. These dimensions were conceptualised in alignment with UGT, which posits that media use is driven by a diverse range of cognitive, affective, and social gratifications (Blumler & Katz, 1974; Katz et al., 1973).

SyU reflects functional interactions with social media platforms, including system navigation and technical capabilities; SU refers to relational interactions and network building; CU involves the creation, sharing, or consumption of academic and professional content; while HU captures the leisure and emotional gratification derived from social media.

The model further incorporates SC as a mediating variable, operationalised through its structural, relational, and cognitive dimensions (Nahapiet & Ghoshal, 1998). SCT posits that digital interactions can foster access to resources, knowledge exchange, trust, and shared values, particularly relevant elements in academic environments where collaboration and networking are integral to success. In this model, SC is theorised to mediate the relationship between SMU and AP, thereby capturing the transformation of online engagement into professional outcomes.

Unlike traditional IS models such as the TAM or the TRA, which primarily focus on PEU and behavioral intention (Davis, 1989; Ajzen, 1991), the refined framework adopted in this study reflects both the motivational (via UGT) and relational (via SCT) drivers of SMU. This integration allows for a more nuanced understanding of how different types of social media engagement contribute to or hinder key academic functions.

Given the limitations of traditional IS models in capturing the socially embedded and motivationally diverse nature of SMU, and the tendency to treat AP as a unidimensional outcome, there is a pressing need for a refined theoretical framework. Such a framework should integrate motivational theories like UGT and relational theories such as SCT to better explain how and why academicians engage with social media, and what implications the engagement has.

Besides that, SMU in academia presents opportunities and challenges. On the positive side, it can enhance scholarly communication, knowledge sharing, and professional networking (Chan et al., 2021). However, excessive use may result in adverse outcomes, such as information, communication, and social overload, three stressors that contribute to technostress, cognitive exhaustion, and diminished AP (Shi et al., 2020; Yu et al., 2019). These challenges are further compounded by barriers, including instructors' limited proficiency with Web 2.0 technologies, privacy concerns, and data overload (Feng et al., 2024; Piotrowski, 2015). While such issues have been documented among students, general social media users, and educators, the specific implications for academicians remain underexplored. Existing studies point to cognitive

fragmentation caused by “clip thinking” (Bushuyev et al., 2024, 2023), digital literacy gaps (Kang et al., 2024), and technophobia (Willekens et al., 2022) as related phenomena, yet empirical investigations into how these barriers influence academicians’ professional productivity, scholarly communication, and collaborative work are scarce. Addressing this gap is essential for developing targeted strategies that maximise the benefits of social media while mitigating its adverse effects in academic contexts.

The central problem addressed in this study is the limited awareness and empirical understanding of how different forms of SMU affect AP. Therefore, this study proposes a multidimensional model of SMU, incorporating four distinct usage dimensions, SyU, SU, CU, and HU, and conceptualises AP as a multifaceted construct encompassing teaching, supervision, research and publication, and consultation. The framework also considers the mediating role of SC in translating digital engagement into professional outcomes. This integrated theoretical lens offers a more holistic approach to understanding social media’s role in AP and addresses the critical gaps found in previous literature.

1.4 Purpose of Study

The primary purpose of this study is to develop and empirically validate a comprehensive theoretical model that examines the influence of SMU on AP in Malaysian Higher Education Institutions (HEIs), with particular emphasis on the mediating role of SC. In contrast to prior research that often treats SMU as a singular or unidimensional construct, typically measured in terms of usage frequency, duration, or general intensity, this study adopts a multidimensional approach. It identifies and evaluates four distinct dimensions of SMU: SyU, SU, CU, and HU. Each dimension reflects specific user behaviours and affordances associated with social media engagement in academic contexts.

The study begins by conducting an in-depth literature review to establish the theoretical foundations of the model, drawing from established frameworks such as the TAM, UGT, and SCT. These frameworks inform the conceptualisation of the independent variables (SMU dimensions) and the mediating construct (SC), which is operationalised through three interrelated components: Structural, Relational, and CSC.

Using a quantitative research design, data were collected through a structured survey instrument distributed to academicians at UiTM, a leading public university in Malaysia. The survey instrument was designed to move beyond simplistic usage metrics by incorporating indicators that capture the nuanced, goal-oriented, and socially embedded nature of SMU in academic work.

Data analysis was performed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to test the direct and indirect relationships among the constructs. In doing so, the study evaluates the individual and collective impact of the dimensions of SMU on AP. It is treated as an HOC comprising four sub-dimensions: Teaching, Research and Publication, Supervision, and Consultation. In addition, the study applies Importance-Performance Map Analysis (IPMA) to identify priority areas where SMU is high but yields low performance outcomes, as well as underutilised areas with high potential impact. These findings offer evidence-based recommendations for institutional strategies and personal academic development.

Ultimately, this research seeks to contribute to the existing body of knowledge by:

- Advancing a validated multidimensional model of SMU specific to academic settings,
- Clarifying the mechanism through which SC mediates the relationship between SMU and AP, and
- Offering practical insights and strategic directions for optimising SMU in Malaysian HEIs.

By doing so, the study enhances theoretical understanding of digital engagement among academicians and supports informed decision-making at both the policy and operational levels within universities.

1.5 Research Objectives

This study investigates the effect of SMU on AP and their consideration of SMU from the perspective of their professional work and practice. This study aims to answer how and why SMU benefits AP. The RQs and ROs are discussed below:

The ROs are as follows:

1. To identify the key dimensions of SMU in AP.
2. To examine how each dimension of SMU influences AP.
3. To determine the level of each dimension of SMU and its impact on AP.
4. To analyse the challenges academicians face in different dimensions of SMU.
5. To examine the mediating role of SC in the relationship between SMU and AP.
6. To recommend effective strategies for optimising SMU in academia.

Although the study articulates six specific ROs, these objectives collectively address three core elements of the research framework. Objectives 1 to 4 focus on SMU, including its dimensional structure, effects, levels, and associated challenges. Objective 5 addresses the role of SC as a mediating mechanism linking SMU to AP. Objective 6 synthesises the empirical findings to inform the proposed model and practical strategies. This grouping enhances conceptual clarity while preserving the study's analytical depth.

1.6 Research Questions

The RQs are as follows:

1. *What are the dimensions of SMU among academicians?* This RQ seeks to identify and define the multi-dimensional nature of social media usage among academicians, moving beyond simplistic measures such as frequency or duration of use. While early IS research often treated SMU as a unidimensional construct, recent studies have emphasised its interactive, user-generated, and socially embedded characteristics (Kietzmann et al., 2011; Hinojosa & Cleveland, 2017).

2. *How does each dimension of SMU affect AP?* This question explores the direct impact of each identified dimension of SMU on AP. It builds upon previous research that linked digital behaviour to job outcomes, but introduces a rougher view by examining whether all forms of social media yield equal benefits.

3. *What is the level of engagement in each dimension of SMU, and how does it correlate with AP?* This question investigates the intensity of SMU across various dimensions and how that usage translates into measurable performance outcomes.

Engagement levels are typically assessed using metrics such as time spent online, number of interactions, and frequency of posts or shares.

4. *What challenges do academicians face when integrating different dimensions of social media into their professional roles?* This RQ addresses the barriers and limitations that hinder the effective integration of social media into academic work. Despite its growing adoption in higher education, many academicians report challenges related to time management, institutional support, privacy concerns, and role ambiguity when using social media for professional purposes. This question is crucial for understanding why some use dimensions are underutilised or show minimal impact on performance. It will be explored through open-ended responses, qualitative coding, and thematic analysis, providing rich insights into the lived experiences of academicians as they navigate digital tools in their professional lives. The findings from this question will inform recommendations for institutional policy development and training programs to overcome common barriers to productive SMU.

5. *Does SC mediate the relationship between SMU and AP?* This RQ investigates whether SC is an intermediary mechanism through which SMU influences AP. While prior research has examined the direct effects of social media on professional outcomes, fewer studies have explored the indirect pathways through which digital engagement translates into measurable performance improvements.

6. *How can these problems be addressed to improve SMU among academicians?* This RQ focuses on identifying practical strategies and interventions that can help overcome the challenges associated with SMU in academic settings. While the previous questions explored the dimensions of use, their impact on performance, and the mediating role of SC, this question shifts toward a solution-oriented thinking approach, aiming to provide actionable insights for academicians and institutional policymakers.

Table 1.1 presents the alignment between the research problem, ROs, and RQs, ensuring consistency and coherence between the study's aims and its empirical investigation.

Table 1.1
Alignment Between Research Problem, Objectives, and Questions.

Research Problem	Research Objectives (RO)	Research Questions (RQ)
Traditional IS models (such as TAM, UTAUT, ISSM) conceptualise "use" in a unidimensional, task-oriented way, overlooking diverse motivations such as entertainment, self-expression, identity construction, and social belonging.	**RO1:** To identify dimensions of social media use among academicians	**RQ1:** What are the key dimensions of social media use among academicians in Malaysian higher education institutions?
Social media use produces mixed performance outcomes: purposeful use can enhance productivity and collaboration, while excessive/non-purposeful use can cause technostress, distraction, and reduced performance.	**RO2:** To examine which dimensions of social media use influence academician performance	**RQ2:** Which dimensions of social media use significantly influence academician performance?
There is a lack of empirical measurement capturing the extent of social media engagement and its impact on performance levels in higher education contexts.	**RO3:** To determine the level of social media use and academician performance	**RQ3:** What is the current level of social media use and academicians' performance among UiTM academicians?
Underexplored issues and barriers in using social media effectively in academic work (e.g., distraction, overload, technostress).	**RO4:** To identify the challenges of social media use in academic settings	**RQ4:** What challenges do academicians face when integrating social media into their academic work?
Social capital as a mediating mechanism is overlooked in traditional IS models, despite being integral to social media's impact on performance.	**RO5:** To examine the mediating role of social capital between social media use and academician performance.	**RQ5:** Does social capital mediate the relationship between social media use and academician performance?
Need for actionable guidelines to improve positive, performance-enhancing social media use in academia, based on findings.	**RO6:** To recommend improvements to enhance effective social media use among academicians	**RQ6:** What practical strategies can enhance the positive use of social media for academic productivity?

1.7 Significance of the Study

1.7.1 Theoretical Contribution

The outcome of this research is predicted to improve the understanding of the measurement of SMU in the context of AP. The findings refine current TAMs (e.g., TAM, UTAUT) by introducing a multi-dimensional view of SMU, moving beyond simplistic adoption measures. It also strengthens the application of SCT in explaining how digital engagement translates into professional outcomes. This study presents the reality of SMU and its relationship with AP. Understand how SMU can highly impact AP through the dimensions involved and how these dimensions interplay with each other. Problems regarding SMU in academic institutions could be addressed by understanding the performance that academicians need to fulfill.

By developing and empirically testing a conceptual model of SMU, this study advances understanding of how social media influences AP. This contribution will help fill a gap in existing research, where previous studies often rely on simplistic measures of SMU and lack depth in understanding how it affects professional outcomes in academia.

The study offers valuable insights into academicians' real-world use of social media, highlighting how it is reshaping teaching, research, and professional networking. The study can provide practical recommendations for academicians seeking to harness the benefits of social media while addressing potential challenges, such as information overload or time management. This focus on practical outcomes aligns the study with the needs of academicians in navigating the digital shift in their professional roles.

1.7.2 Practical Implications

This study is expected to offer practical value to HEIs, academicians, and university administrators by enhancing understanding of how different forms of SMU may influence academic work and professional outcomes. By examining SMU as a multidimensional construct, the study seeks to inform institutional decision-making related to digital engagement, professional development, and academic productivity. The findings of this research are anticipated to assist universities in developing evidence-based guidelines and policies for the effective and responsible use of social

media in academic contexts. These may include considerations related to academic content sharing, professional networking, digital well-being, privacy protection, and the maintenance of appropriate professional boundaries. In addition, the study aims to provide academicians with insights into how strategic use of social media platforms can support scholarly communication, collaboration, and performance, while also raising awareness of potential challenges associated with non-academic or excessive use. A detailed discussion of the practical implications derived from the empirical findings is presented in Chapter 5.

1.8 Scope and Limitation of the Study

This study focuses on academicians employed at comprehensive public universities in Malaysia, with UiTM serving as the primary research context. As one of the largest public universities in the country, UiTM provides a suitable and representative setting for examining the relationships between SMU, SC, and AP across diverse faculties, disciplines, and academic ranks.

The scope of the study encompasses academicians' professional use of social media in relation to their academic roles, including teaching, research, professional networking, and knowledge sharing. Specifically, the study investigates multiple dimensions of SMU, namely SyU, SU, CU, and HU, and examines how these dimensions influence AP outcomes. In addition, the study considers SC as a mediating construct, focusing on its structural, relational, and cognitive dimensions.

Data are collected from academicians across multiple UiTM campuses and disciplinary backgrounds to capture variation in social media practices within a comprehensive university environment.

The limitation of the study includes the contextual specificity. The findings are drawn from a single institution (UiTM), which may limit generalisability to other types of universities in Malaysia or abroad. On the other hand, the limitation of the study is the cross-sectional Design, which captures only the current state of SMU and cannot establish causality or long-term trends. Therefore, the study acknowledges certain limitations that may impact the generalisability of its findings. Although UiTM represents an extensive and comprehensive institution, the results may not fully generalise to other types of universities, such as private or specialised institutions, which might have different social media practices and institutional cultures.

Consequently, while UiTM provides a valuable case study, further research would be needed to confirm if similar patterns apply in other academic contexts or institutions with different structures and resources.

Another limitation of this study is the reliance on self-reported data to measure SMU and its effects. Self-reported surveys are subject to biases, such as the tendency to over- or under-report actual behaviour, which may impact the accuracy of the findings. Although the study will use validated instruments and encourage honest responses, these biases may still affect the conclusions drawn about social media's influence on AP. Furthermore, the study's findings capture only a specific moment in time, while social media technology and usage patterns continue to evolve. This limitation means that new platforms, features, and usage trends might emerge, potentially affecting how future academicians engage with social media.

Finally, the study limits its focus to general patterns and dimensions of SMU, rather than examining the specific content shared or accessed by academicians. While understanding how frequently and intensively academicians engage with social media is valuable, the nature and quality of the content they interact with can also play a significant role in influencing AP. Despite these limitations, this study contributes essential insights into how social media supports or challenges academic roles, potentially guiding future research, practical strategies, and policy recommendations for universities in Malaysia and beyond.

1.9 Operational Definitions of Key Constructs

The following definitions represent the operationalisation of constructs as measured in the questionnaire instruments used in this study:

1.9.1 Social Media Use (SMU)

SMU is defined as the use of social media platforms across four dimensions: SyU, SU, CU, and HU (Miller, 2019; Högberg, 2018; Kaplan & Haenlein, 2010; Boyd & Ellison, 2007; Kietzmann et al., 2011; Gruzd, Staves, and Wilk, 2011; Aldahdouh, Nokelainen, and Korhonen, 2020).

1.9.2 System Use (SyU)

SyU refers to the behavioural aspects of social media usage in terms of frequency, duration, and intensity of use (Al-Rahmi et al., 2020; Nah & Saxton, 2013).

1.9.3 Social Use (SU)

SU refers to the use of social media for social interaction and communication. It includes connecting with individuals or groups, as well as using social media for collaborative research or academic work (Gruzd et al., 2012; Lapoe et al., 2017; Kietzmann et al., 2011).

1.9.4 Content Use (CU)

CU refers to the use of social media for information-seeking, content consumption, and sharing of information and knowledge (Vásquez et al., 2015; Lim et al., 2020).

1.9.5 Hedonic Use (HU)

HU refers to the use of social media for entertainment, enjoyment, and relaxation purposes (Peña-Acuña & Jaramillo, 2024; Raja, 2024; Zhou et al., 2020).

1.9.6 Social Capital (SC)

SC is defined as the network of social relationships embedded within individuals that can be leveraged for academic or professional purposes (Nahapiet & Ghoshal, 1998)

1.9.7 Structural Social Capital (SSC)

SSC refers to the network of relationships between individuals or groups from different backgrounds, facilitating access to diverse perspectives and resources (Nahapiet & Ghoshal, 1998; Inkpen & Tsang, 2005).

1.9.8 Relational Social Capital (RSC)

RSC refers to social ties among individuals or groups with shared backgrounds, typically built upon trust and prior interactions, such as among co-workers, classmates, or colleagues (Nahapiet & Ghoshal, 1998; Inkpen & Tsang, 2005).

1.9.9 Cognitive Social Capital (CSC)

CSC refers to an individual's ability to understand and interpret information shared by others and express shared meanings and values within an academic or professional community (Nahapiet & Ghoshal, 1998; Inkpen & Tsang, 2005; Adler & Kwon, 2002).

1.9.10 Academician Performance (AP)

AP is defined as AP across core areas such as teaching, supervision, research, publication, consultation, administrative duties, and community service. This study is operationalised into four dimensions: Teaching, Supervision, Research & Publication, and Consultation (Comm & Mathaisel, 1998; Masron, Ahmad, & Rahim, 2012; Che Omar et al, 2017; SETARA Rating, 2020; Lim et al., 2024).

1.10 Thesis Outline

This thesis consists of five chapters. Chapter 1 introduces the background, problem statement, ROs, RQs, significance, and scope of the study. Chapter 2 reviews relevant literature, focusing on theoretical frameworks, the role of social media in academia, and job performance appraisal. Chapter 3 outlines the research methodology, detailing the design, population, sampling, data collection, and analysis techniques. Chapter 4 presents the results, including descriptive statistics, quantitative findings on social media's impact on performance, mediating factors, and qualitative insights. Finally, Chapter 5 concludes with empirical findings and interpretations, theoretical and practical implications, recommendations for academicians and policymakers, study limitations, and suggestions for future research.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

This chapter reviews the relevant literature underpinning the study on Social Media Use (SMU) and its impact on Academicians' Performance (AP) in Malaysian higher education. It begins by defining social media and examining its core elements, categories, and academic relevance. The chapter then distinguishes SMU from general Information Technology (IT) use, highlighting its unique applications in academic contexts. It proceeds to explore the concept of AP, particularly within Malaysian public universities, including a case focus on Universiti Teknologi MARA (UiTM). The chapter also investigates the role of Social Capital (SC) and its mediating influence on the relationship between SMU and AP. To provide a strong theoretical foundation, the chapter reviews key models, including the Uses and Gratifications Theory (UGT), the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT). The application of these models in social media research is discussed to support the study's conceptual development. Finally, the chapter identifies key variables and dimensions, dependent, independent, and mediating, and presents the study's conceptual model and hypotheses, establishing the framework for the research.

2.2 Conceptual Foundation of Social Media

Although social media is a widely understood concept, its application in academic contexts remains conceptually fragmented across platforms, functions, and use cases. This section, therefore, does not aim to reintroduce social media at a general level but to delineate the specific elements, categories, and characteristics of social media relevant to academic use, which are later operationalised in this study.

2.2.1 What is Social Media

In the academic study of social media, various definitions highlight its multifaceted nature and influence on social communication and interaction. Daniel Miller (2019) introduced the concept of "scalable sociality," describing social media as a series of platforms operating across various scales and parameters of social interaction, thereby providing a framework for understanding the diverse ways in which social media can connect individuals and communities. Miller's concept emphasised the flexibility and adaptability of social media platforms in facilitating communication across different social contexts (Miller, 2019). Social media is also defined as online tools that enable users to create, publish, share, and communicate content online, as discussed by Högberg (2018). This definition underscores the role of social media as a facilitator of user-generated content and interactive communication (Högberg, 2018).

Furthermore, Turner (2016) adopted Kaplan's definition, describing social media as "a group of internet-based applications that build on the ideological and technological foundations of Web 2.0," allowing user-generated content to be created and exchanged. This perspective highlights the technological and ideological foundations of social media, grounded in the principles of Web 2.0, which prioritise user participation and content sharing (Kaplan & Haenlein, 2010; Turner, 2016). Boyd and Ellison (2007) defined social media as "web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system." This definition highlights the structured nature of social media platforms, which facilitate social connections and networking within defined digital spaces (Boyd & Ellison, 2007). Similarly, Kietzmann et al. (2011) described social media as "a form of online communication that combines technology and social interaction, allowing users to share information, ideas, and interests with others." This definition emphasises the interplay between technology and social interaction, which is central to the functioning of social media (Kietzmann et al., 2011).

Gruzd, Staves, and Wilk (2011) offered a broad definition of Online Social Media (OSM) tools, describing them as "web-based websites that include Web 2.0 characteristics and contain some aspect of user-generated content." Their definition encompassed a wide range of technologies, from video conferencing tools such as

Skype to social networking sites like Facebook and Academia.edu, illustrating the diverse applications of social media in academic contexts (Gruzd, Staves, & Wilk, 2011). Lastly, Aldahdouh, Nokelainen, and Korhonen (2020) defined social media as platforms intended to "foster communication and collaboration on a large scale," highlighting its collaborative potential in both academic and broader social contexts.

The definitions of social media presented across academic studies illustrate the platforms' complex and multifaceted nature. Social media is not merely a collection of digital tools; it represents a convergence of technology, social interaction, and user-generated content, all of which play crucial roles in shaping how individuals and organisations communicate and collaborate. From Miller's (2019) concept of "scalable sociality," which emphasises the adaptability of social media across different social contexts, to the structured and network-focused perspective offered by Boyd and Ellison (2007), it is evident that social media serves as a dynamic space where social relationships are formed, maintained, and expanded. The emphasis on Web 2.0 technologies in Kaplan and Haenlein's (2010) definition further highlighted how social media has revolutionised traditional modes of communication by empowering users to create and share content, thus democratising the flow of information. Moreover, the broad definitions provided by researchers such as Gruzd, Staves, and Wilk (2011) and Aldahdouh, Nokelainen, and Korhonen (2020) underscore the versatility of social media platforms across contexts, including academic environments, where they facilitate large-scale communication and collaboration. This versatility is crucial for understanding the impact of social media on different spheres, including education, where these platforms can enhance AP by fostering greater engagement, knowledge sharing, and collaboration among scholars.

2.2.2 Elements of Social Media

Various elements are fundamental in understanding how these platforms operate and influence user behaviour. Bayer, Triệu, and Ellison (2020) provided a comprehensive framework for analysing social media through four key elements: Profile, Network, Stream, and Message. These elements are critical in shaping the user experience and the dynamics of interaction on social media platforms.

The "Profile" element is central to identity formation on social media. It enables users to maintain a unique collection of personal attributes, which may be created by the user, their network, and/or the platform itself (Bayer et al., 2020). Profiles are digital representations of individuals that include names, photos, interests, and other personal data. This curated self-presentation allows users to control how they are perceived by others online, thus influencing social interactions and relationships within the platform. The significance of the profile in social media is also highlighted by Ellison and Boyd (2013), who discuss its role in defining Social Network Sites (SNSs), where the profile serves as the foundation for user identity and interaction within these digital environments.

The "Network" element represents the web of social connections on social media platforms. This includes a collection of contacts that are created through mutual “friending” or one-way “following” (Bayer et al., 2020). The network element is crucial, as it defines the scope and reach of an individual's social connections and determines the flow of information and SC. The structure and size of one’s network can significantly impact one’s influence and the type of content they are exposed to. Networks facilitate the exchange of social support, information, and resources, which are essential for community building and sustaining relationships on social media (Ellison & Boyd, 2013).

The "Stream" element is a key feature of social media that allows users to consume and engage with feeds of user-generated content from their networks (Bayer et al., 2020). Streams, often seen as timelines or newsfeeds, are dynamic and constantly updated with content shared by users within the network. This continuous flow of information is integral to the real-time engagement and interaction that characterise social media. Streams keep users connected to their network's activities, thoughts, and interests, fostering immediacy and presence. Ellison and Boyd (2013) also emphasised the importance of the stream in SNSs, noting that it is through these streams that users participate in sociality, stay informed, and engage in ongoing conversations.

The "Message" element facilitates directed social interaction through various media, including text, video, photos, and other digital content (Bayer et al., 2020). Messaging is a fundamental mode of communication on social media, allowing users to engage in private or public conversations, share information, and build relationships. This element underscores the interactive nature of social media, where users are not merely passive consumers of content but active participants in dialogue and exchange.

Messages can be synchronous, such as instant messaging, or asynchronous, such as email, enabling flexible and diverse modes of communication that cater to different social needs.

Cheung et al. (2021) expanded on the role of social media elements in driving co-creation and engagement, particularly in marketing contexts. They identify how elements such as profiles and networks contribute to brand engagement and consumer interaction, highlighting their importance in commercial SMU. Similarly, Godey et al. (2016) discussed how Social Media Marketing (SMM) elements such as entertainment, customisation, interactivity, Electronic Word-of-Mouth (eWOM), and trendiness influence consumer behaviour and brand equity. These insights demonstrate that the foundational elements of social media, profiles, networks, streams, and messages are crucial for individual social interactions, strategic marketing, and brand management. Kietzmann et al. (2011) further elaborated on the functional building blocks of social media, identifying elements such as identity, conversations, sharing, presence, relationships, reputation, and groups. These elements provide a more granular understanding of how social media platforms function, offering a comprehensive view of the diverse mechanisms that underpin social media interactions. Each element contributes to the social media ecosystem, creating a complex environment where users interact, share content, build relationships, and establish reputations.

Social media profiles, networks, streams, and messages are integral to understanding how these platforms facilitate interaction, communication, and content creation. They provide a framework for analysing the user experience and the complex social dynamics in digital environments. As these elements evolve, they will likely play an increasingly important role in shaping individual behaviours and broader social trends.

Table 2.1
Social Media Element

Element	Description	Study
Profile	Acts as the digital representation of an individual, allowing users to maintain unique personal attributes (e.g., name, photo, interests). Enables self-presentation and influences social interactions and relationships within the platform.	Bayer, Triệu, & Ellison (2020); Ellison & boyd (2013)
Network	Represents the web of social connections, including mutual "friending" or one-way "following." Defines the scope and	Bayer, Triệu, & Ellison (2020);

Element	Description	Study
	reach of social connections, facilitating the flow of information and resources.	Ellison & boyd (2013)
Stream	Allows users to consume and engage with user-generated content feeds (e.g., timelines or newsfeeds). It provides real-time engagement, keeps users connected to network activities, and fosters immediacy and presence.	Bayer, Triệu, & Ellison (2020); Ellison & boyd (2013)
Message	Facilitates directed social interaction through text, video, photo, or other digital content, supporting private and public conversations.	Bayer, Triệu, & Ellison (2020)
Co-creation and Engagement	Drives user and brand engagement in marketing contexts through elements like profiles and networks, impacting consumer interaction and brand equity.	Cheung et al. (2021); Godey et al. (2016)
Functional Building Blocks	Comprises identity, conversations, sharing, presence, relationships, reputation, and groups, providing a detailed view of social media dynamics.	Kietzmann et al. (2011)

2.2.3 Categories of Social Media

Social networking platforms are primarily designed to connect individuals and communities, enabling them to share and exchange information across networks. These platforms allow users to create profiles, establish connections through "friending" or "following," and interact through status updates, comments, and messages. The primary function of social networking sites is to foster relationships and facilitate communication among users, making them pivotal in both personal and professional contexts. Examples include Facebook, Google+, and LinkedIn (Bajracharya, 2016). These platforms serve as digital hubs for personal expression, community building, and professional networking, allowing users to maintain and expand their social circles online.

Media-sharing platforms focus on distributing and consuming multimedia content, including videos, photos, and audio files. These platforms enable users to upload, share, and interact with media content, often fostering communities around specific media types. Media-sharing sites are particularly significant in educational settings, where visual and auditory materials can enhance learning experiences. Examples include YouTube, Picasa, Pinterest, and Flickr (Bajracharya, 2016). These

platforms have become essential for content creators and consumers alike, offering vast libraries of user-generated content and facilitating the viral spread of media.

Document-sharing platforms facilitate the exchange and collaboration on text-based content, allowing users to upload, share, and edit documents in various formats. These platforms are instrumental in academic and professional environments, where collaborative work on documents, presentations, and spreadsheets is everyday. Examples include SlideShare, Prezi, Dropbox, and Google Drive (Bajracharya, 2016). Document-sharing tools have revolutionised how individuals and teams work together, providing cloud-based solutions that enable remote collaboration and real-time updates.

Live communication platforms enable synchronous, real-time communication between users, supporting text and multimedia exchanges. These platforms are essential for maintaining immediate, dynamic interactions via video calls, instant messaging, or live chats. They are widely used in personal and professional contexts, from casual conversations to formal meetings and webinars. Examples include Hangouts, Skype, and Viber (Bajracharya, 2016). These tools have become increasingly important in the era of remote work and online education, offering seamless communication channels across distances.

Collaboration platforms are designed to support group work and collective content creation, often providing tools for joint editing, task management, and project coordination. These platforms are indispensable in educational and corporate settings, where teamwork and collaborative problem-solving are essential. Examples include Wikis and Google Drive (Bajracharya, 2016). Collaborative tools enable users to contribute to shared projects, track changes, and ensure that all team members are aligned, thus enhancing productivity and the quality of group outputs.

Blogging platforms allow users to publish journal-like entries, often combining text with multimedia content, arranged in reverse chronological order. Individuals or communities can maintain blogs and focus on specific topics or interests. Microblogging, a subset of blogging, restricts content length, encouraging short, frequent updates. These platforms are key for content creation, self-expression, and niche community engagement. Examples of blogging platforms include WordPress and Blogger, while Twitter and Tumblr are popular microblogging sites (Bajracharya, 2016). Blogging and microblogging have democratised content creation, allowing users to share ideas, opinions, and information with a global audience.

Social news platforms allow users to share, discuss, and vote on news stories and articles, often fostering communities around shared interests in current events or specific topics. These platforms rely heavily on user-generated content and the collective curation of news, offering an alternative to traditional media outlets. Examples include Digg, Slashdot, Reddit, and Quora (Gundecha & Liu, 2012). Social news sites influence public discourse by amplifying stories that resonate with large user bases and allow diverse perspectives.

Social bookmarking platforms enable users to bookmark, organise, and share web content, making it easier to store and access useful information. These platforms often include features that allow users to comment on and categorise content, fostering knowledge sharing and discovery within communities. Examples include Delicious and StumbleUpon (Gundecha & Liu, 2012). Social bookmarking tools are valuable for research, education, and personal knowledge management, as they provide users with efficient ways to collect and disseminate information.

Platforms focused on opinions, reviews, and ratings allow users to submit subjective commentary on products, services, entertainment, businesses, and places. These sites serve as valuable resources for consumer decision-making, offering insights based on real-world experiences. Examples include Yelp, TripAdvisor, and Cnet (Gundecha & Liu, 2012). These platforms are critical in consumer behaviour, influencing perceptions and choices through collective user feedback.

Virtual worlds are immersive digital environments where users can create avatars, interact with others, and engage in a variety of activities, from gaming to socialising. These platforms blur the lines between social media and online gaming, offering rich, interactive experiences that simulate real-world or fantasy environments. Virtual worlds have applications in entertainment, education, and even virtual workspaces. Examples include Second Life and World of Warcraft (Wang et al., 2017).

Enterprise-owned social media refers to platforms created and managed by businesses for internal communication, collaboration, and knowledge sharing. These platforms often include features similar to public social media but are tailored to meet the specific needs of organisations. Examples include enterprise social networks like Yammer and Jive (Wang et al., 2017). These platforms enhance corporate communication and collaboration, fostering a connected and informed workforce.

Entertainment and profiling networks are a newer category of social media that focuses on providing entertainment content and detailed user profiling for targeted advertising and content delivery. These platforms often blend social networking with streaming services, gaming, or personalised content recommendations. Examples include platforms like TikTok and Snapchat, which offer highly engaging, personalised content experiences (Koukaras et al., 2020). These platforms are particularly popular among younger audiences, driving trends and shaping popular culture through viral content. The categorisation of social media highlights the diverse functions and tools these platforms offer, each catering to specific user needs and interactions. From social networking and media sharing to live communication and collaboration, these categories illustrate the multifaceted nature of social media and its pervasive influence across education, business, and entertainment.

Table 2.2
Social Media Categories

Category	Description	Example	Study
Social Networking	Connects individuals and communities, enabling profile creation, connections, and interactions (e.g., "friending," status updates). Fosters personal and professional relationships.	Facebook, Google+, LinkedIn	Bajracharya (2016)
Media Sharing	Focuses on distributing and consuming multimedia content (videos, photos, audio). Often builds communities around shared interests and is significant in educational settings.	YouTube, Picasa, Pinterest, Flickr	Bajracharya (2016)
Document Sharing	It supports text-based content exchange and collaboration and is helpful for academic and professional settings with real-time updates and collaborative work on documents.	SlideShare, Prezi, Dropbox, Google Drive	Bajracharya (2016)
Live Communication	Facilitates synchronous, real-time text and multimedia communication, essential for immediate interactions, such as video calls, messaging, and live chats.	Hangouts, Skype, Viber	Bajracharya (2016)
Collaboration Platforms	Designed for group work and content creation, offering tools for joint editing, task management, and project coordination, enhancing productivity.	Wikis, Google Drive	Bajracharya (2016)
Blogging & Microblogging	Allows users to publish journal-like entries or short updates (microblogging), combining text	WordPress, Blogger,	Bajracharya (2016)

Category	Description	Example	Study
	with multimedia to create niche content and foster community engagement.	Twitter, Tumblr	
Social News	Enables users to share, discuss, and vote on news stories, emphasising user-generated content and collective curation as alternatives to traditional news sources.	Digg, Slashdot, Reddit, Quora	Gundecha & Liu (2012)
Social Bookmarking	Allows bookmarking, organising, and sharing web content, facilitating information storage and community-based discovery.	Delicious, StumbleUpon	Gundecha & Liu (2012)
Opinions, Reviews, and Ratings	Users submit commentary on products, services, entertainment, etc., influencing consumer decisions based on real-world experiences and user feedback.	Yelp, TripAdvisor, Cnet	Gundecha & Liu (2012)
Virtual Worlds	Immersive digital environments where users interact through avatars, often blending gaming with socialising. Used in entertainment and virtual workspaces.	Second Life, World of Warcraft	Wang et al. (2017)
Enterprise-Owned Social Media	Internal corporate communication, collaboration, and knowledge sharing platforms are similar to public social media but tailored for organisational use.	Yammer, Jive	Wang et al. (2017)
Entertainment & Profiling Networks	Focuses on entertainment and user profiling, often combining social networking with streaming or gaming, and personalised recommendations for targeted advertising.	TikTok, Snapchat	Koukaras et al. (2020)

2.2.4 Characteristics of Social Media

Social media, as a communication tool, has several characteristics that support its function. First, users as content creators create posts, express opinions, or update their activities. Second, instant communication: the latest or current news can be delivered to social media users through these platforms, and lastly, interactivity characteristics (Roberts, 2016). In terms of interactivity, social media has a character that enables it. Technological advancements and convergence have made media more diverse, mobile, present, and connected (Jenkins, 2004, 2006, cited in Ariel & Avidar, 2015).

Therefore, social media as new media is characterised by interactivity, user-generated content, and multi-directional communication flows (Schein, Msc, & Keelan, 2010). DeNardis (2014), as cited in Ariel and Avidar (2015), suggested that social media is characterised by user-generated content and by users' ability to select and articulate network connections with other users. Consequently, social media allows users to create their own content, and its use depends on the context. In understanding the context of SMU, the user gratification approach is appropriate.

The user experience and gratification focus on the user sector and its context of use. The UGT view, developed in the literature on communication theory, defines and highlights the motivations of the public to use radio and early television media (Stafford, Stafford, & Schkade, 2004). Thus, Uses and Gratifications (U&G) is appropriate for studying new media, such as social media, given the data features of these platforms. Three data features associated with new media are interactivity, demassification, and asynchronicity. Williams, Rice, and Rogers (1988) stated interactivity as the degree to which the participants have control and can change roles in their communication or mutual discourse. Meanwhile, demassification is the user's ability to control the medium (media) (Williams et al., 1988). Asynchronicity refers to the flexibility of media that allows users to send, receive, save, or retrieve messages (Ruggiero, 2000). Being asynchronous implies that, based on user preferences, the material is accessible in time-shifted and place-shifted forms. YouTube, for instance, enables consumers to save their favourite videos, making repeated viewing simple (Shao, 2009). Valentini and Kruckeberg (2012) provided a detailed description of social media (Table 2.3). The nature of social media requires user-generated content, supports communication, is highly interactive, and demands high user participation.

Table 2.3
Main Characteristics of Social Media

Characteristics	Description
Content production	Anyone
Content control	Shared control among community members and organisations, content is continuously modified by all users in a participatory and collaborative manner.
Type of communication	Conversational /Interpersonal communication (among community members)
Direction of communication	Two-way asymmetrical or two-way symmetrical
Interactions between people	High

Characteristics	Description
Public participation	High (it is necessary)
Power relations	Higher for community members
Capacity for building relationships	High
Capacity for transmitting content	Medium content can directly reach specific audiences but may not be processed and shared if it is not considered relevant for community interactions.
Role of the public	An active role in the co-creation of content and meanings. Publics receive content and engage in creating content, participating in content collaborations, and sharing content with community members.
Entertaining function	High
Possibility for viral effects, publicity tactics	High
Capacity for endorsements	High, if the content is perceived as relevant by community members. Community members trust each other more than organisations.
Market analyses	High organisations can obtain information by monitoring community members' activities, posts, comments, and interactions.
Organisational purposes	Organisation-public relationships, community relations, employee relations, relationship marketing, stakeholder engagement, reputation management, political participation (i.e., e-democracy, e-governance tools)

Source: Valentini & Kruckeberg 2012

Rogers and Shoemaker's (1971) diffusion of innovation theory provides valuable insight into understanding SMU by identifying five key characteristics (i.e., relative advantage, compatibility, complexity, trialability, and observability) that influence its use rate. Relative advantage refers to the degree to which an innovation improves upon its predecessors, such as how social media enables instant communication compared to traditional media. Compatibility highlights the ease with which an innovation integrates into users' lives, exemplified by the accessibility of social platforms on mobile devices. Complexity addresses the difficulty of using the innovation; for social media, user-friendly interfaces reduce this barrier. Trialability underscores the ease of experimenting with the innovation, as social media platforms often provide free trials or open access for new users. Finally, observability emphasises

the visibility of the innovation's impact, as seen in viral trends demonstrating social media platforms' value and influence.

This study aims to build on these characteristics by developing and empirically testing a theoretical model that links SMU to AP. The study will provide insights into how social media can enhance productivity and impact for academicians by examining how interactivity, immediacy, and content creation contribute to professional outcomes.

2.2.5 Social Media in Academic

The role of social media in academic settings is multi-dimensional, supporting professional growth, scholarly networking, and research dissemination. Donelan (2016) highlighted how SMU is linked to career development, with academics reporting greater engagement and success in career-related outcomes as their activity levels increase. These platforms facilitate the exchange of expertise and expand networks, creating new opportunities for professional visibility and advancement. Similarly, Dumpit and Fernandez (2017) established that Social Media Adoption (SMA) in higher education, particularly in the Philippines, is influenced by various factors, such as perceived enjoyment and internet reliability, thereby enhancing both educational engagement and accessibility.

Social media also proves essential for science communication and public engagement, enabling researchers to reach a broader audience more effectively than traditional media. Keng and Cheng (2023) observed that academics regularly use platforms like Facebook and YouTube to communicate scientific insights, driven by a sense of duty to make science accessible to the public. During the COVID-19 pandemic, Zimba et al. (2021) revealed that social media became crucial for maintaining scholarly connections in Eastern Europe, where platforms such as ResearchGate and LinkedIn facilitated continuous research sharing and post-publication interactions. This underscores the adaptability of social media in meeting the evolving needs of academia, particularly in regions with limited access to traditional scientific communities.

Despite its extensive use for professional networking and science outreach, SMA for teaching remains limited, as Manca and Ranieri (2016) highlighted. Academics often prefer using social media to connect with peers rather than integrating it into formal education due to age, seniority, and academic discipline. However, social media has become embedded in other aspects of the scholarly workflow, as noted by

Veletsianos et al. (2018) and Rowlands et al. (2011), who observed its integration across research planning, collaboration, and dissemination. This demonstrated that while social media is indispensable for networking and research, its role in teaching remains cautious, indicating a selective approach to incorporating digital tools into academic practices.

2.3 Social Media Use in Academic Context

Building on the conceptual foundations of social media discussed in Section 2.2, this section shifts the focus from social media as a technological and communicative phenomenon to SMU as an academic work behaviour. While social media platforms and features provide the structural environment, it is the ways academicians engage with these platforms, for professional communication, collaboration, knowledge sharing, and networking, that are more directly associated with academic outcomes. Accordingly, this section reviews the literature on how SMU has been defined, categorised, and operationalised in academic contexts, with particular attention to components of use relevant to AP and relational outcomes, such as SC.

2.3.1 Definition of Social Media Use

The academic conceptualisation of SMU reflects the evolution of digital technologies from static platforms to highly interactive, user-driven environments. Various scholars have defined SMU through different lenses, focusing on its technological infrastructure, communicative affordances, social utility, and contextual adaptability, each offering distinct yet complementary insights.

Miller's (2019) concept of "scalable sociality" is particularly significant in understanding the dynamic nature of social media platforms. The study asserted that social media enables communication across a range of social scales, from intimate, private exchanges to large-scale public interactions. This definition emphasises the contextual elasticity of social media, highlighting its role as a flexible conduit for both personal and institutional engagement. This adaptability supports various scholarly activities in academic settings, such as mentoring, collaborative publishing, and outreach.

In contrast, Högberg (2018) offered a functionalist perspective, defining social media as a suite of online tools that allow users to create, publish, and communicate content. The research emphasis lies in social media's capacity for content generation and dissemination, aligning well with the academic need to publish, comment on research, and curate scholarly dialogue. Unlike Miller, who focused on the breadth of interaction, Högberg zeroed in on the interactive and participatory nature of social media platforms.

Kaplan and Haenlein's (2010) widely cited definition, adopted by Turner (2016), describes social media as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0." This viewpoint emphasises user participation and peer production, positioning social media as a democratising force in the dissemination of information. It is particularly relevant to academia, where the flattening of hierarchical barriers enables early-career researchers and students to engage with senior scholars and global audiences through open forums and platforms such as Twitter, LinkedIn, and ResearchGate.

Boyd and Ellison (2007) provided a more network-centric definition, describing social media as web-based services that allow users to: (1) construct a profile, (2) articulate connections, and (3) navigate those connections. This definition emphasises the social networking infrastructure that underpins many platforms. While it shares Kaplan and Haenlein's concern for user interaction, it highlights the relational architecture that facilitates SC formation, an important variable in this study's conceptual model.

Kietzmann et al. (2011) enriched the discourse by positioning social media as the product of an interplay between technology and social interaction, whereby users engage in the mutual exchange of information, ideas, and values. This definition is more holistic, offering a socio-technical perspective that captures both technological affordances and users' behavioural patterns. It underscores the utility of social media as a strategic tool for disseminating knowledge, facilitating informal learning, and enabling peer-to-peer interaction among academics.

Other scholars offer broader, more application-based definitions, especially in academic contexts. Gruzd, Staves, and Wilk (2011) defined social media as "web-based platforms with Web 2.0 features and user-generated content," including sites such as Academia.edu and Skype. Their framework acknowledges academic-specific tools, emphasising how SMU supports scholarly collaboration and visibility. Similarly,

Aldahdouh, Nokelainen, and Korhonen (2020) viewed social media as platforms designed to "foster communication and collaboration on a large scale." This definition reflects the collaborative potential of social media, particularly in multi-institutional or interdisciplinary research efforts.

Table 2.4
Summarisation of Social Media Use Definitions

Scholar(s)	Core Concept	Focus Area	Academic Relevance
Miller (2019)	Scalable sociality	Social scale and adaptability	Highlights the use across micro (peer) to macro (public) academic interactions.
Högberg (2018)	Tool-based communication	Content creation and sharing	Aligns with academic publishing and knowledge exchange
Kaplan & Haenlein (2010); Turner (2016)	Web 2.0-based applications	Ideological and technical infrastructure	Emphasises participatory culture in academic discourse
Boyd & Ellison (2007).	Social networking structure	Profile-building and connections	Directly relates to academic networking and social capital
Kietzmann et al. (2011).	Socio-technical integration	Technology + interaction	Supports knowledge sharing and community engagement in research
Gruzd et al. (2011).	Academic application of Web 2.0 tools	Educational and research tools	Recognises academia-specific platforms like Academia.edu
Aldahdouh et al. (2020)	Mass-scale collaboration	Communication and teamwork	Reflects large-scale academic collaboration and e-learning

Table 2.4 summarises what SMU is. These definitions illustrate that SMU is not uniform. Instead, it is a multi-dimensional phenomenon encompassing social interaction, technological facilitation, content production, and collaborative potential. This multifaceted understanding is crucial for academic environments as it allows researchers and institutions to appreciate how different aspects of social media, from user profiles to collaborative tools, can impact performance metrics such as teaching, research, and community service. Recognising this complexity, the present study operationalises SMU through four core dimensions: System Use (SyU), Social Use

(SU), Content Use (CU), and Hedonic Use (HU), offering a more granular analysis aligned with contemporary definitions and scholarly practices.

2.3.2 Component of Social Media Use

Social media platforms share core features that enable user-generated content and facilitate interactive user exchanges. These platforms include social networking sites (e.g., Facebook, Twitter, Google+), blogs, forums, bookmarking sites, community sites, Q&A platforms, and messaging apps. Taprial and Kanwar (2017) identified key characteristics of social media, including web-based applications, profile creation, independence of user existence, and interactive functionalities that allow users to build online communities. Obar and Wildman (2015) expanded on this by defining social media as characterised by four main attributes: reliance on Web 2.0 applications, user-generated content, profile creation, and the formation of online social networks, which collectively facilitate extensive user interactions.

Further expanding on social media's features, Zhao et al. (2020) emphasised that social media enables analysis, tracking, and communication, each of which is critical to knowledge sharing. Analysis involves generating user usage summaries and tailored recommendations; tracking involves continuous monitoring of specific topics or individuals; and communication encompasses the exchange of diverse media, including text, sound, and video. These functionalities support interaction, content customisation, and contextual engagement, making social media versatile for professional and personal knowledge sharing.

A broader view is offered by Howard and Parks (2012), who described social media as involving three core elements: the technical infrastructure for distributing content, the digital content itself (e.g., messages, information, and cultural materials), and the individuals and industries that produce and consume this content. This definition underscores social media as a multifaceted channel that enables self-presentation and interaction, providing a dynamic space for professional engagement. Building on these foundational definitions, this study aims to develop and empirically test a theoretical model linking SMU to AP. The study aims to pinpoint how specific social media features, such as knowledge sharing, networking, and tracking, can support professional outcomes for academicians, contributing to career development and academic productivity.

2.3.3 Categories of Social Media from the Perspective of Social Media Use

SU of social media encompasses platforms designed for building and sustaining professional and academic networks. According to Kietzmann et al. (2011), as displayed in Figure 2.1, social media platforms serve functions such as identity, conversations, presence, relationships, and groups, which support networking and relationship-building. Examples of platforms primarily focusing on SU include LinkedIn and academic blogs. LinkedIn is a professional social networking platform that enables academicians to connect locally and globally, fostering collaboration, sharing achievements, and promoting research outputs (Lapoe et al., 2017). These platforms function as virtual meeting spaces where individuals with shared professional goals can interact, exchange ideas, and form scholarly communities (Madhusudhan, 2012; Gruzd et al., 2012; Rowlands et al., 2011; Al-Aufi & Fulton, 2014). Similarly, blogs provide a medium for sharing academic insights, promoting scholarly discourse, and building a community of peers and followers (Herring et al., 2005). Schlagwein and Hu (2016) categorised SMU into broadcast, dialogue, and sociability, all of which support the SU of these platforms in academic contexts. Social media serves as a broadcast channel for disseminating information and a forum for dialogue, enabling multi-directional communication with peers and experts.

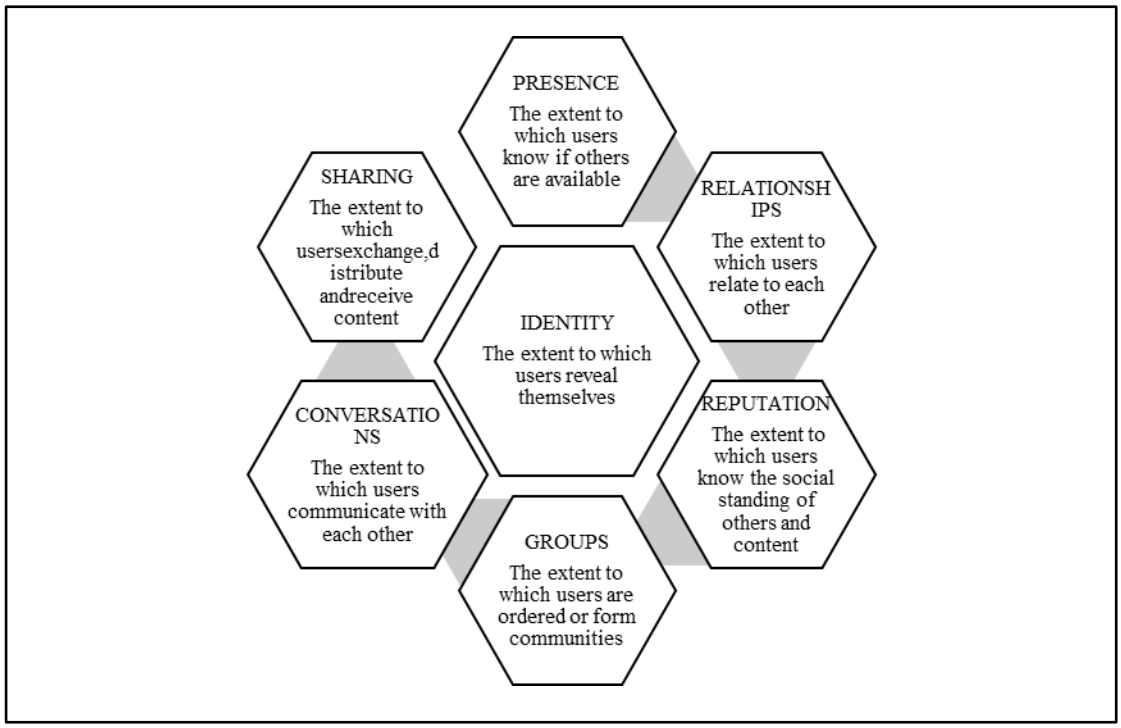


Figure 2.1 Honeycomb Framework of Social Media Functionality

The CU of social media involves platforms and tools that aid in knowledge acquisition, management, and information dissemination. This use aligns with the functionality blocks in the honeycomb framework, especially identity, sharing, and reputation, which support the management and sharing of knowledge resources critical to academic work. Academic-focused social media platforms such as Mendeley and ResearchGate are examples of CU, as they allow users to manage bibliographic data, store research articles, and access resources for learning and research (Vásquez et al., 2015). Mendeley, in particular, enables users to upload, organise, and share documents, making it a collaborative information-management tool (Bullinger, Hallerstede, Renken, Soeldner, & Möslein, 2010, cited in Meishar-Tal & Pieterse, 2017). These platforms support Veletsianos's (2013) assertion that academic social networks facilitate the collection and organisation of personal academic information, including references, articles, and draft ideas. Lim et al. (2020) classified social media into platforms that support microblogging, content communities, and networking. Each type contributes differently to cognitive engagement, while microblogs like Twitter may facilitate rapid information sharing and networking, platforms such as Mendeley or ResearchGate focus on more in-depth scholarly communication and resource management.

HU of social media focuses on platforms that serve entertainment, relaxation, or personal fulfilment, supporting activities such as sharing, presence, and interactions that do not necessarily have a direct academic purpose. Social media's entertainment or HU aligns with Kietzmann et al.'s (2011) functions of presence and reputation and Schlagwein and Hu's (2016) notion of sociability. Video-sharing platforms such as YouTube serve as cognitive and hedonic tools for academicians. While users can engage with educational content, these platforms also allow for recreational browsing, entertainment, and engagement with non-academic content (Hong et al., 2016; Lee & Lehto, 2013, cited in Zhou et al., 2020). Instagram and similar platforms also cater to HU by allowing users to share visual content, express creativity, and engage with broader communities on interests outside academia. Valentini and Kruckeberg (2012) further categorised social media into entertainment and personal use. Entertainment social media targets hobbies and interests, such as music, movies, or sports. In contrast, individual social media platforms allow users to connect with friends and family, fulfilling social and personal needs beyond their academic roles. This dimension

underscores how social media meets not only the professional but also the individual and recreational needs of users in academia.

The integration of SMU within the context of SyU is informed by theoretical models such as the TAM and the Information Systems Success Model (ISSM), which collectively highlight factors influencing adoption and effectiveness. Social media platforms are increasingly utilised in educational settings for their Perceived Ease of Use (PEU), usefulness, and high-quality information, positively impacting AP and student satisfaction (Al-Rahmi et al., 2021). However, nuanced studies, such as Junco's (2018), revealed that while information-sharing activities on platforms like Facebook can enhance academic outcomes, excessive socialising or misuse may inversely affect GPA. Furthermore, models such as UTAUT explore how user perceptions and organisational factors shape adoption in professional and scholarly contexts, emphasising the strategic alignment and governance necessary for effective utilisation (Gruzd et al., 2012; Nah & Saxton, 2013). The mediating role of social media's entertainment value, perceived usefulness, and content quality further underscores its dual role in both engagement and performance enhancement, suggesting targeted approaches for educational and organisational stakeholders to maximise its potential (Badr et al., 2024; McGowan et al., 2012). These findings collectively inform the strategic adoption of social media as a tool for academic and professional advancement.

2.3.4 Platform as Context of Academic Use

Social media platforms in academia can be broadly categorised into profile-based platforms and social networks, each serving distinct yet complementary roles in the academic landscape. Profile-based platforms are essential for managing a researcher’s academic identity by assigning a unique researcher ID and ensuring consistent work attribution across platforms. These platforms, such as Open Researcher and Contributor ID (ORCID) and Scopus Author Identifier, allow researchers to compile their publications, track citation metrics, and measure the impact of their work. They provide a centralised profile that showcases a researcher’s contributions and helps distinguish authors with familiar names or those who have undergone name changes (Adhikari et al., 2020; Aldahdouh et al., 2020).

On the other hand, social networks in academia are designed to facilitate collaboration and knowledge sharing among researchers. Platforms such as ResearchGate and Academia.edu are widely used for connecting with peers, sharing articles, and participating in academic discussions. ResearchGate, for example, has a significant user base in the Natural Sciences, allowing researchers to upload their work, engage in Q&A sessions, and track their academic influence through platform-specific metrics. Academia.edu, with its focus on the Humanities and Social Sciences, offers additional features like grants and job searches, making it a versatile tool for academics (Lumivero, 2023). In addition to these two broad categories, academicians utilise a wide array of social media platforms tailored to specific needs. Table 2.5 below summarises some social media platforms and their academic uses.

Both profile-based platforms and social networks are integral to contemporary academia, each serving distinct yet complementary purposes. Profile-based platforms prioritise the management of organised research and the evaluation of scholarly impact, while social networks foster academic collaboration and interaction. Together, they create a robust academic ecosystem that supports knowledge sharing and enhances scholarly communication. Additionally, Malaysian researchers have widely recognised platforms such as WhatsApp, Facebook, YouTube, Google Scholar, and ResearchGate for their utility, showcasing the versatility of social media in supporting academic activities (Keng & Cheng, 2023).

Table 2.5
Summarises Key Platforms of Social Media and Their Academic Uses

No	Social Media Platform	Descriptions	References
1	Academia.edu	Academia.edu is an academic social networking platform enabling researchers to share their work, monitor its impact through analytics and alternative metrics, and collaborate with other academics.	Adhikari et al., 2020; Masenya, 2021; Stephen & Pramanathan, 202; Knipp, 2024; Villela et al., 2015; Thelwall & Kousha, 2014
2	Blog/Weblog	Blogs, also called weblogs, serve as versatile academic tools that facilitate knowledge dissemination, professional development, public engagement, and personal reflection, while fostering	Abdo et al., 2011; Becker & Freberg, 2014; Brown, 2021; Giarre & Jaccheri, 2008; Heap & Minocha, 2012; Minocha & Kerawalla, 2010; Pinilla et al.,

No	Social Media Platform	Descriptions	References
		collaboration and providing emotional support within scholarly communities.	2013; Powell et al., 2012; Saunders et al., 2017; Smidt et al., 2018; Zhao, 2008
3	Facebook	Facebook supports professional development by enabling teachers and researchers to share information, engage with groups, and communicate scientific knowledge to broader audiences.	Abidin, 2019; Keng & Cheng, 2023); Yildirim, 2019
4	Google Scholar	Google Scholar enables researchers to create profiles, track citations, enhance visibility through academic indexing and search engine optimisation, and connect with peers via shared research interests.	Badke, 2009; Lohia & Prakash, 2022; López-Hermoso et al., 2020; Orduña-Malea et al., 2017; Keng & Cheng, 2023
5	Instagram	Instagram leverages multimedia to enhance informal digital learning, such as language acquisition, and provides engaging educational content.	Almohesh & Altamimi, 2024; Gonulal, 2019; Lee, 2023; Khasawneh, 2024; Martínez-Domingo et al., 2025
6	LinkedIn	LinkedIn is a widely used professional networking platform that enables users to showcase expertise, share professional content, and connect with industry peers.	Adhikari et al. (2020); Keng & Cheng (2023)
7	Mendeley	Mendeley serves as a reference manager and academic social network, helping researchers organise their work, collaborate, and discover new studies.	Adhikari et al., 2020; Chen et al., 2018; Jeng et al., 2014, Oh & Jeng, 2011, Khwaja & Eddy; Zahedi & Nees, 2015
8	ORCID	ORCID provides a unique identifier for researchers to manage their academic profiles and increase visibility across digital platforms.	Adhikari et al., 2020; Yevhenii et al., 2024; Reimer, 2015; Zhang, 2024; Haak, 2013; Zhang, Y., 2024
9	Publons	Publons connects researchers with their published work by recognising and verifying peer review contributions, tracking citation impact through bibliometric indicators, and facilitating	Gruzd et al., 2011; Teixeira da Silva & Nazarovets, 2022; Ortega, 2017; Huang & Zong, 2023

No	Social Media Platform	Descriptions	References
		interdisciplinary collaborations, thereby enhancing academic credibility.	
10	ResearchGate	ResearchGate combines features of social networking and research databases, allowing users to share publications, collaborate, and find research opportunities.	Adhikari et al. (2020); Keng & Cheng (2023)
11	Scopus	Scopus author profiles provide automatic linking of publications, facilitate citation tracking through integrated bibliometric tools, and increase researcher visibility by enhancing discoverability and accurate attribution of scholarly work.	Aldahdouh et al., 2020; Gasparyan et al., 2017; Munshi et al., 2025; Harris et al., 2015
12	Telegram	Telegram enables flexible education through online discussions and teamwork analytics, serving as an effective medium for teaching and collaboration.	Andrayani et al., 2024; Isidori et al., 2023; Swartz et al., 2022; Conde et al., 2020; Firdaus & Shahid, 2023
13	TikTok	TikTok offers significant potential for observational video analysis research by enabling the examination of authentic social behaviours in naturalistic settings across diverse contexts, as demonstrated in studies spanning urban tourism, health, education, and cultural discourse.	Klug et al., 2021; Lau et al., 2025; Mandzufas et al., 2023; Moreno-Albarracín & Blanco-Sánchez, 2024; Nair et al., 2023; Nicely, 2024
14	Twitter	Twitter, as a prominent microblogging platform, is widely utilised by researchers to share timely updates, engage in scholarly discussions, and disseminate research findings to academic and public audiences.	Buettmann et al., 2023; Burns et al., 2020; Daneshjou et al., 2021; Gomez-Vasquez, 2021; Hadgu & Jäschke, 2014; Mansutti & Caruzzo, 2022; Na, 2015; Power, 2022; Shah & Cox, 2017
15	WhatsApp	WhatsApp facilitates academic engagement and collaboration through instant messaging, media sharing, and	Lee et al., 2023; Gomez-Jaramillo & Moreno-Cadavid, 2023; Nyasulu & Chawinga,

No	Social Media Platform	Descriptions	References
		virtual discussions, enhancing postgraduate education.	2019; Venter, 2021; Romero-Saritama et al., 2025; Van Staden & Nel, 2023; Keng & Cheng, 2023
16	YouTube	YouTube supports academic learning by hosting educational videos catering to various disciplines, including medicine and language education.	Alver et al., 2023; Jaffar, 2012; Pilitsi & Steiropoulos, 2018; Trang, 2022; Athreh & Obeidat, 2022;

2.3.4.1 Comparison of Social Media Types and Their Academic Uses

Social media in academia can be broadly classified into two main types: profile-based platforms and academic social networks, each fulfilling distinct roles within the scholarly ecosystem. Profile-based platforms, such as ORCID, Scopus Author ID, and Google Scholar, are primarily designed to manage academic identity, ensure accurate publication attribution, and track scholarly metrics (Adhikari et al., 2020; Aldahdouh et al., 2020; López-Hermoso et al., 2020). These platforms enable researchers to build structured profiles, track citation counts, and consolidate their research outputs in a consistent and verifiable manner. For example, ORCID provides a persistent digital identifier that links a researcher's contributions across platforms and institutions. At the same time, Google Scholar offers a widely used citation tracking feature that enhances discoverability in academic searches.

Conversely, academic social networks such as ResearchGate, Academia.edu, and Mendeley facilitate knowledge dissemination, scholarly collaboration, and informal peer engagement. These platforms allow academics to share publications, receive feedback, and participate in discipline-specific discussions, offering a more interactive and community-driven model of engagement (Adhikari et al., 2020; Keng & Cheng, 2023). For example, ResearchGate is particularly popular in the natural sciences, enabling users to upload research articles, connect with peers, and monitor platform-specific metrics such as reads and recommendations. Similarly, Academia.edu offers profile creation, visibility analytics, and job listings, making it especially appealing to researchers in the humanities and social sciences.

These two categories are supplemented by general-purpose social media platforms, including Facebook, WhatsApp, YouTube, Twitter, Instagram, and TikTok, which are repurposed for academic activities. These platforms support teaching, learning, student engagement, and public scholarship. Research shows that Facebook supports academic group discussions by fostering collaborative learning and peer engagement while also serving as an effective platform for science communication through outreach, public engagement, and the dissemination of accurate scientific information (Davidovitch & Belichenko, 2018; McClain, 2017; Rauchfleisch et al., 2023), while Studies indicate that WhatsApp enhances instant academic communication and collaboration by enabling real-time interaction, resource sharing, and teamwork, making it particularly valuable in postgraduate and remote learning contexts (Lee et al., 2023; Romero-Saritama et al., 2025; Van Staden & Nel, 2023; Keng & Cheng, 2023). YouTube and Instagram are increasingly used for visual learning and digital storytelling (Alver et al., 2023; Almohesh & Altamimi, 2024). Even platforms like TikTok, initially designed for entertainment, are now being explored for research on human behaviour through observational video analysis (Nicely, 2024).

While profile-based platforms focus on academic credibility and research management, academic social networks and general social platforms emphasise interaction, collaboration, and outreach. When integrated strategically, these platforms collectively support various facets of AP, including research dissemination, networking, teaching innovation, and scholarly identity management. Their differentiated yet complementary roles reflect the evolving demands of digital scholarship in higher education.

Table 2.6
Comparison of Social Media Types, Platforms, and Their Academic Uses

Type	Platforms	Primary Function	Academic Applications	References
Profile-Based Platforms	ORCID, Scopus Author ID, Google Scholar, Publons	Academic identity management, citation tracking, and author attribution	Tracking impact, consolidating publications, resolving author ambiguity	Adhikari et al. (2020); Aldahdouh et al. (2020); López-Hermoso et al. (2020); Gruzd et al. (2011)
Academic	ResearchGate,	Scholarly	Sharing	Adhikari et al.

Type	Platforms	Primary Function	Academic Applications	References
Social Networks	Academia.edu, Mendeley	collaboration, content sharing, Q&A forums, and peer feedback	publications, collaboration, analytics, and peer interaction	(2020); Keng & Cheng (2023)
General Social Platforms	Facebook, WhatsApp, YouTube, Twitter, Instagram, TikTok, Telegram	Communication, outreach, informal learning, digital storytelling	Teaching, community building, engagement, observational research, and informal learning	Keng & Cheng (2023); Khan et al. (2024); Nicely (2024); Almohesh & Altamimi (2024); Alver et al. (2023)
Hybrid Platforms	LinkedIn, Google Scholar, YouTube	Professional branding, content visibility, open-access dissemination	Profile visibility, network building, and educational content creation	Adhikari et al. (2020); Keng & Cheng (2023); Alver et al. (2023)

The academic landscape has embraced various social media platforms, as shown in Table 2.6, each fulfilling specific roles supporting scholarly activities such as research dissemination, teaching, collaboration, and professional identity management. Profile-based platforms like ORCID and Scopus provide structured mechanisms for tracking scholarly outputs and ensuring author attribution, while academic social networks such as ResearchGate and Academia.edu foster collaboration and knowledge exchange among peers. Meanwhile, general-purpose platforms like Facebook, WhatsApp, YouTube, and Instagram have been creatively repurposed to enhance communication, engagement, and informal learning. Despite their different functionalities, these platforms collectively contribute to a more connected, responsive, and dynamic academic environment. Their integration into daily academic practice reflects the growing importance of digital tools in shaping how knowledge is produced, shared, and consumed in higher education.

While the previous section outlined the various types and academic applications of social media platforms, it is essential to narrow the focus of this study by conceptualising what constitutes academic SMU in a more precise, context-specific manner. The following section introduces the meaning and operational definition of scholarly SMU adopted in this study.

2.3.5 Meaning and Definitions of Academic Social Media Use in this Study

SMU refers to the use of social media from the perspectives of social, cognitive, hedonic, and SyU. In this study, academic SMU refers to the purposeful engagement with social media platforms for educational purposes, characterised by its social, cognitive, hedonic, and SyU dimensions. SU focuses on building and maintaining professional and academic networks. Platforms like LinkedIn, ResearchGate, and educational blogs are integral to fostering collaboration, sharing research, and forming scholarly communities (Gruzd et al., 2012; Lapoe et al., 2017). These platforms facilitate professional interactions, allowing academicians to connect locally and globally while supporting the exchange of ideas and the development of shared goals (Kietzmann et al., 2011).

The cognitive dimension highlights the role of social media in knowledge acquisition, management, and dissemination. Academic platforms such as Mendeley and Google Scholar enable researchers to organise bibliographic data, store and share research articles, and access valuable resources for scholarly communication (Vásquez et al., 2015). This dimension underscores the potential of social media to enhance productivity, support learning, and provide a structured approach to managing academic information (Lim et al., 2020). In this study, the term “cognitive” has been relabelled as “Content” to better reflect the nature of interactions centred on platform-based content consumption and sharing. This adjustment also helps to reduce potential confusion with the construct of Cognitive Social Capital (CSC), which is separately conceptualised and analysed in this study. Meanwhile, the HU aspect acknowledges social media's ability to meet entertainment and relaxation needs. Platforms like YouTube and Instagram effectively merge entertainment with educational functions by offering visually engaging, interactive content that fosters both personal enjoyment and academic learning, enabling users to maintain a balanced engagement between leisure and scholarly pursuits (Peña-Acuña & Jaramillo, 2024; Raja, 2024; Zhou et al., 2020).

Finally, SyU focuses on social media's technical and functional characteristics, emphasising ease of use, usefulness, and content quality in academic settings. Guided by theoretical models such as the TAM and UTAUT, this dimension explores the factors influencing adoption and engagement (Al-Rahmi et al., 2020; Nah & Saxton, 2013). By integrating these four dimensions (i.e., social, cognitive, hedonic, and system), the study

reflects a comprehensive understanding of how social media platforms support academic activities, foster professional growth, and enhance scholarly communication.

2.3.6 Social Media Use Versus Information Technology Use

An IT transmits, processes, or stores information, while an Information System (IS), by contrast, is an integrated and cooperative set of software-driven IT that support human objectives (Berthon et al., 2010, as cited in DesAutels, 2011). Burton-Jones, A., and Straub (2006) defined IT use as the interplay between users, IT artefacts, and work activities. IT use commonly refers to an activity involving three key elements: users as subjects utilising the IT system, IT features as building blocks or components of IT artefacts, and tasks as functions performed (Nan, 2011).

Increasing capacity and declining costs have made technology simpler to use and have placed more individuals around the globe in its hands. They now have access to the basic parts and abilities required to construct their own data systems, and they are also effectively building and using them, creating UGIS (DesAutels, 2011). Therefore, social media is considered a User-Generated Information System (UGIS) as it requires people to provide content. The social media platform will enable people to connect and communicate. As mentioned by Cann, Dimitriou, and Hooley (2011), 'social media' refers to Internet services in which users generate online content; similarly, Gruzd et al. (2012) and Kaplan & Haenlein (2010) highlighted that social media is a form of user-generated content.

Based on this user-generated information, the system contains a service component that integrates into new configurations. The integration result creates an information service that is (1) qualitatively different from its components and (2) offers the user distinctive value above and beyond the value of their inputs (DesAutels, 2011). Three parts of UGIS include services, platforms, and aggregators. Firstly, services are the UGIS basic construction block; they are the integrating elementary element. The services used in UGIS may be based on technology or people. Content is a vital part of all services. Secondly, platforms allow internal and external connectivity and communication. Lastly, aggregators are the instruments that enable UGIS to be constructed. Aggregators encapsulate the technical aspects of composing services in abstract forms that are easy to use, allowing the masses to build mashups of services (Yu, Benatallah, Casati, & Daniel, 2008). All aggregators give input, output, and

processing capacities. A fundamental characteristic of aggregators is their capacity to encapsulate technical complexity into easy abstract forms readily accessible to users. Aggregators may be physical equipment like mobile phones, iPads, or notebook computers, or from internet services like Facebook or Blogger. Two dominant examples are Facebook (with assistance for application and content aggregation) and the iPhone (with its App Store) (DesAutels, 2011).

Increasing capacity and declining costs have made technology simpler to use and have placed more individuals around the globe in its hands. They now have access to the basic parts and abilities required to build their data systems and to construct and use them effectively, creating UGIS (DesAutels, 2011). Therefore, social media is considered a UGIS as it requires people to provide content. The social media platform will allow connectivity and communication between people. As mentioned by Cann, A., Dimitriou, K., and Hooley (2011), 'social media' refers to Internet services where the users of the service generate the online content, and (Gruzd et al., 2012; Kaplan & Haenlein, 2010a) highlight that social media is an aspect of user-generated content.

Social media is generally a portable, web-enabled tool or technology accessible through platform-independent web browsers that emphasise social activities such as collaboration, communication, community, and creativity (Joosten, 2012; Dabbagh & Kitsantas, 2011). As an internet-based application that strongly supports user-generated content, social media technology enables the sharing of collaborative activities not only in social contexts but also in educational and, increasingly, in business contexts (Lim et al., 2014).

Social media technology focuses on social activities, entertainment, and information sharing. User and gratification theory focuses on how users use media. Katz, Blumler, and Gurevitch (1973) identified that people use media to fulfil social needs, for instance, to communicate with family. In addition, the media is used to relax and find content. Manca and Ranieri (2016) studied Italian scholars' use of social media for scholarly communication and discovered that ResearchGate, Academia.edu, and LinkedIn were the most frequently used platforms. Oh and Syn (2015) reported that social media users who love sharing information and social support are highly motivated to learn, expecting to gain new or updated facts through sharing with others. Collaborative authoring, scheduling, meeting tools, and conferencing are popular social media types in research. Social media is widely used at all stages of the research

lifecycle, from identifying research opportunities to disseminating findings at the end (Rowlands et al., 2011). Table 2.7 shows the summarisation between SMU and IT use.

Table 2.7
Summarised Table of Differences Between Social Media Use (SMU) and Information Technology (IT) Use

Criteria	Social Media Use (SMU)	Information Technology (IT) Use
Purpose	• Focuses on fostering social interaction, collaboration, and entertainment.	• Designed to improve organisational efficiency, productivity, and structured information management.
	• Enables user-generated content creation and sharing.	• Supports predefined workflows and operational tasks.
Structure	• Based on User-Generated Information Systems (UGIS):	• Built as integrated systems combining hardware, software, and IT artefacts (Berthon et al., 2010, cited in DesAutels, 2011).
	• Services: Core components enabling interactions and content creation (DesAutels, 2011).	• Includes technical modules and features customised for specific tasks (Nan, 2011).
	• Platforms: Tools enabling connectivity and communication between users (e.g., Facebook, LinkedIn) (Joosten, 2012).	
	• Aggregators: Interfaces that simplify user interaction (e.g., mobile apps) (DesAutels, 2011).	
Functions	• Facilitates multi-directional communication and social engagement (Rowlands et al., 2011).	• Supports data processing, storage, and task execution (Burton-Jones & Straub, 2006).
	• Encourages community building, collaboration, and knowledge sharing (Oh & Syn, 2015; Kaplan & Haenlein, 2010a).	• Focuses on optimising workflows and providing structured outputs (Nan, 2011).

Social media services are the foundational building blocks enabling real-time interaction and content creation (Kietzmann et al., 2011). Unlike static systems like banking or digital libraries, these services are dynamic and socially interactive. They

support knowledge sharing, professional networking, and collaboration, directly influencing academic productivity and innovation (Murthy & Lewis, 2015; Hinojosa & Cleveland, 2017). This aligns with the study's aim to explore social media's impact on performance metrics beyond frequency and intensity of use. Platforms such as ResearchGate, LinkedIn, and Academia.edu facilitate connectivity and collaboration among academicians. In Malaysia, where little is known about the effects of social media on AP, these platforms enable activities such as teaching, research dissemination, and networking (Kotsenas et al., 2018). Their role in fostering academic connections and enhancing productivity is critical to understanding how social media can be leveraged to achieve academic success, thereby addressing the gap identified in the problem statement. Aggregators simplify the technical complexity of integrating various social media services, making them accessible for academic purposes. For instance, platforms like Facebook and WhatsApp aggregate communication and sharing capabilities, supporting multifaceted academic tasks such as coordinating research teams and engaging with students. Aggregators also enhance social media's usability, enabling broader adoption and application in academia (DesAutels, 2011). This factor is crucial in examining how Malaysian academicians use social media tools and how these tools impact their professional performance.

The discussion in Sections 2.2 and 2.3 establishes SMU as a multi-dimensional construct rather than a generic technological tool. By distinguishing social, system, and content-oriented uses, this review provides the conceptual basis for examining how different patterns of SMU may differentially contribute to AP, directly or indirectly through mediating mechanisms such as SC.

2.4 Social Capital

SC has emerged as a central theoretical construct for explaining how social relationships and networks generate value for individuals and organisations. This section reviews the conceptual foundations and core dimensions of SC. It discusses its relevance to academic work, thereby establishing a theoretical basis for examining its mediating role between SMU and AP.

2.4.1 Conceptualisation of Social Capital

The conceptual foundation of SC is most prominently articulated by Nahapiet and Ghoshal (1998), who define it as the sum of actual and potential resources embedded within, available through, and derived from networks of relationships. They argue that SC facilitates the creation of intellectual capital through social interaction, trust, and shared understanding. To capture this mechanism, SC is conceptualised as comprising three interrelated dimensions, structural, relational, and cognitive, which collectively enable knowledge exchange, coordination, and value creation within organisations. Empirical support for this framework is provided by Tsai and Ghoshal (1998), who demonstrate that social interaction and trust significantly influence patterns of resource exchange, which in turn enhance innovation outcomes. These foundational works establish SC not merely as a social attribute but as a critical mechanism through which collaborative relationships translate into performance-related outcomes.

More broadly, SC is understood as the resources embedded within social relationships that facilitate cooperation, coordination, and the achievement of individual and collective goals (Ferragina, 2016; Kawachi, 2007). Unlike physical or human capital, SC resides in social structures, networks, and shared norms that enable actors to access information, develop trust, and mobilise mutual support (Watson & Mathew, 2021). Prior literature conceptualises SC as a multi-level construct operating at individual, organisational, and societal levels, influencing outcomes such as knowledge sharing, well-being, organisational effectiveness, and social participation (Ferragina, 2016; Kawachi, 2007).

In organisational and professional contexts, SC has been shown to enhance collaboration, problem-solving, innovation, and the integration of knowledge across functional and disciplinary boundaries (Lehtimäki & Karintaus, 2013; Ortiz et al., 2016). Within educational and academic environments, SC is increasingly recognised as a critical mechanism that strengthens relational ties, trust, and cooperative norms among scholars, thereby supporting research collaboration, knowledge dissemination, and academic productivity (Xu et al., 2014; Wojciechowska, 2021a). Collectively, these perspectives position SC as an enabling mechanism that shapes performance-related behaviours, providing a strong theoretical basis for examining its mediating role in the relationship between SMU and AP.

2.4.2 Dimensions of Social Capital

The literature consistently conceptualises SC as a SC construct comprising structural, relational, and cognitive dimensions (Hong, 2025; Shaqrah et al., 2013; Zhang et al., 2025).

Structural Social Capital (SSC) refers to the overall pattern of connections among individuals, including network ties, density, and frequency of interaction (Lehtimäki & Karintaus, 2013; Xu et al., 2014). Empirical studies demonstrate that SSC facilitates access to information, resources, and collaborative opportunities, particularly in professional and academic networks (Filieri et al., 2014; Xu et al., 2014). However, excessive centralisation may constrain innovation and limit knowledge flow (Lehtimäki & Karintaus, 2013). Relational Social Capital (RSC) emphasises the quality of relationships developed through repeated interactions, particularly trust, reciprocity, and mutual respect (Hong, 2025; Ortiz et al., 2016). Trust has been consistently identified as a core relational element that strengthens cooperation, knowledge sharing, and relationship sustainability across organisational and educational settings (Wojciechowska, 2021a; Zhang et al., 2025). CSC refers to shared understandings, common values, and shared goals that enable collective action (Yip et al., 2007; Hong, 2025). Cognitive alignment has been found to enhance coordination, collective engagement, and performance-related outcomes, particularly when individuals share common professional or institutional identities (Yip et al., 2007; Ngoc Ton et al., 2023). Importantly, empirical evidence suggests that these dimensions do not contribute equally across contexts; cognitive and relational dimensions often demonstrate stronger associations with performance-related outcomes than structural connections alone (Yip et al., 2007; Hong, 2025).

2.4.3 Social Capital and Performance-Related Outcomes

A substantial body of literature links SC to various performance-related outcomes, including organisational effectiveness, knowledge sharing, learning performance, and professional engagement (Hong, 2025; Shaqrah et al., 2013; Ngoc Ton et al., 2023). Studies in organisational contexts indicate that SC enhances employee performance by facilitating access to knowledge resources, improving coordination, and fostering trust-based collaboration (Hong, 2025; Ortiz et al., 2016).

In educational and academic settings, SC has been associated with improved learning performance, knowledge-sharing behaviour, and academic collaboration (Ngoc Ton et al., 2023; Wojciechowska, 2021b). Xu et al. (2014) further demonstrated that academic fields accumulate SC over time through co-authorship and collaboration networks, reinforcing the importance of social connections in scholarly productivity.

However, despite growing evidence of positive associations, much of the literature treats SC as a direct predictor, with limited empirical examination of its mediating role between antecedent factors and performance outcomes (Zhang et al., 2025; Ngoc Ton et al., 2023). This limitation is particularly evident in studies related to academic professionals, where complex social and technological interactions influence performance.

2.4.4 Research Gaps Related to Social Capital

Table 2.8 summarises prior empirical and conceptual studies on SC across organisational, educational, and community contexts. While existing research demonstrates the importance of structural, relational, and CSC in facilitating knowledge sharing, collaboration, and well-being, the review reveals limited empirical investigation of SC as a mediating mechanism linking SMU to AP, particularly within Higher Education Institutions (HEIs). Although SC has been extensively studied across organisational, community, and educational contexts, several gaps remain evident. First, empirical studies focusing specifically on academicians as a professional group are limited, with most educational research concentrating on students rather than academic staff (Ngoc Ton et al., 2023; Wojciechowska, 2021b). Second, few studies empirically examine SC as a mediating mechanism linking behavioural or technological factors to performance outcomes (Zhang et al., 2025). Furthermore, while structural, relational, and cognitive dimensions are well established, their integrated role within technology-enabled environments, such as SMU in academic work, remains underexplored. Existing studies tend to examine SC independently of the mechanisms that develop it, leaving a conceptual gap regarding how professional interactions translate into performance outcomes through SC formation. These gaps justify the inclusion of SC as a core mediating construct in the present study, linking SMU to AP and aligning directly with the study's problem statement and conceptual framework.

Table 2.8
Summary of Prior Studies on Social Capital

Authors	Context / Sample	Social Capital Dimension(s)	Method / Design	Key Findings	Relevance & Identified Gap
Duani et al. (2025).	Female university students (UAE)	Structural, Relational, Cognitive	Survey, moderation	All dimensions enhance knowledge sharing; culture is not a moderator	Educational context: performance treated indirectly
Ferragina (2016)	Conceptual	General social capital	Conceptual	Social capital explains cooperation, democracy, cohesion, and performance	Provides a foundational definition; no empirical testing or contextual application
Filieri et al. (2014).	Industry–academia pharmaceutical network	Structural	Longitudinal network analysis	Network evolution from bridging to bonding enhances knowledge transfer	Structural focus only; social capital is not linked to individual academic performance
Gadaire et al. (2025).	Latina immigrant mothers	Structural, Relational	Social network analysis, survey	Social capital improves navigational support and educational involvement	Community-based context; not focused on institutional performance
Hernández-Medina et al. (2025).	Artisan association, Ecuador	Structural, Relational (bonding/bridging)	Mixed methods	Bonding capital is strong; bridging capital is underdeveloped	Highlights the imbalance of dimensions; no technology or mediation focus
Hong (2025)	Tax administration organisations	Structural, Relational, Cognitive	Survey, moderation analysis	All dimensions positively affect performance; trust moderates relational and cognitive effects.	Organisational setting; mediation not tested, academic context absent
Kawachi (2007)	Conceptual	General social capital	Conceptual	Social capital is linked to positive and negative health outcomes	Foundational theory lacks operationalisation for performance
Kilpatrick et al. (2009).	Educational institutions	General social capital	Conceptual	Educational leadership builds social capital through partnerships	Conceptual; lacks empirical testing and social media context
Lehtimäki & Karintaus (2013)	Multinational enterprises	Structural (with trust, sociability)	Case study, interviews, network surveys	High social capital supports problem-solving, innovation, and knowledge integration; centralised structures hinder these outcomes.	Focuses on organisational advantage; lacks individual performance and academic context.
Lu et al. (2020).	Older adults, urban China	Cognitive	Survey, moderation	Cognitive social capital predicts volunteering; gender moderates the effect.	Social participation outcome: limited applicability to professional performance

Authors	Context / Sample	Social Capital Dimension(s)	Method / Design	Key Findings	Relevance & Identified Gap
Ngoc Ton et al. (2023).	University students (Vietnam & Bangladesh)	Relational, Cognitive	PLS-SEM	Social capital → knowledge sharing → learning performance	Closest mediation logic; student focus, not academicians
Ortiz et al. (2016).	Biotechnology & pharma firms	Relational, Cognitive	Survey	Trust influences external knowledge acquisition strategies	Focus on firms; no social media or academic performance outcomes
Shaqrah et al. (2013).	Knowledge stations employees	Structural, Relational, Cognitive	SEM survey	Social capital dimensions improve knowledge sharing quality	Knowledge sharing emphasised; performance outcomes not explicitly tested
Watson & Mathew (2021).	Organisations (general)	General social capital	Conceptual	Social capital supports cohesion, trust, and teamwork	Conceptual overview; no empirical validation
Wojciechowska (2021a)	Library workers & users (20 countries)	Structural, Cognitive (trust)	Survey	Trust strengthens relationships, cooperation, and individual social capital.	Highlights trust importance; does not link to measurable performance outcomes
Wojciechowska (2021b)	Librarians (20 countries)	Individual social capital	Survey	High trust is linked to broader networks and civic engagement	Individual-level focus; no mediation or technology-related mechanisms
Xu et al. (2014)	IS scholars (1980–2012)	Structural	Longitudinal co-authorship network analysis	The IS field has accumulated significant social capital over time	Strong academic relevance; does not test performance or mediating mechanisms
Yip et al. (2007)	Rural China population	Structural, Cognitive	Multilevel quantitative analysis	Cognitive social capital (trust) is positively associated with health and well-being; structural capital showed weak or inconsistent effects.	Demonstrates differential effects of social capital dimensions; limited to health outcomes, not performance contexts.
Zhang et al. (2025).	Disabled veterans in China	Structural, Relational	Survey, mediation & moderation	Social support networks enhance well-being via institutional support and trust.	Strong mediation logic; outcome limited to well-being, not productivity or academic performance

2.5 Academician Performance

AP appraisal systems vary globally, reflecting institutional priorities and national contexts. For example, Curtin University in Australia employs the Curtin Expectations for Academic Performance (CEAP) to promote continual improvement and career development among its academic staff. This framework focuses on five core areas: effective teaching and learning; supervision of honours and Higher-Degree Research (HDR) students; impactful research outputs; strategic leadership; and service aligned with Curtin's mission. These expectations guide the development of individualised annual work plans that include quantitative objectives, such as publication targets and grant acquisitions, as well as qualitative goals, such as forming strategic partnerships or initiating new projects (Curtin University, 2020). Similarly, the University of Queensland outlines its AP principles within four main categories: teaching, research, service and engagement, and the scholarship of teaching and learning. AP evaluation is divided into four staff profiles, each with distinct criteria. These profiles include:

1. Teaching and research academics, who contribute mainly to teaching, research, and engagement.
2. Teaching-focused academics, who emphasise teaching and the scholarship of teaching and learning.
3. Research-focused academics, who prioritise research, including HDR supervision, while also contributing to teaching and service.
4. Clinical academics, who focus on clinical teaching and research within professional and educational settings (The University of Queensland, 2019a; 2019b).

The University of Southampton's academic promotion pathways are tailored to reflect expectations in education, research, enterprise, leadership, and engagement. These career pathways provide a structured framework to support the professional growth of academic staff while aligning their contributions with institutional strategic priorities. This approach aims to enhance staff morale, retention, and overall performance (University of Southampton, 2014). In Vietnam, a study at Vietnam National University, Hanoi (VNU-Hanoi) assessed the role of work motivation in

influencing lecturers' job performance, measured by teaching outcomes, research outputs, and community contributions. This evaluation highlights the interplay between motivational factors and performance in academic settings, offering insights for appraisal systems aimed at improving productivity (Bui et al, 2024). On a broader scale, a global review of academic promotion policies identifies three primary domains of evaluation: research, teaching, and service. These domains are often further categorised into 18 criteria: research outputs, career development, recognition, and service contributions. This mapping underscores the emphasis on productivity and holistic development in AP appraisals (Lim et al., 2023). In Chinese higher education, AP is often assessed using Key Performance Indicators (KPIs). These KPIs are applied to classify and rank staff performance, linking individual achievements to broader institutional goals. Such quantitative metrics drive performance-based assessments and outcomes (Lei et al., 2024).

2.5.1 Academician's Performance in Malaysian Higher Education Institutions (MoHE)

In Malaysia, public HEIs are divided into three categories: research universities, comprehensive universities, and universities focused and regulated by the MoHE (Ministry of Higher Education Malaysia, 2017). In the "University Transformation Programme, Silver Book", public universities have been analysed in three groups:

1. Malaysian Research Universities (MRU) have a high population of postgraduate Students, a High priority on R&D, and extensive research activities across multiple faculties and multi-disciplinary areas.
2. Malaysian Technical University Network (MTUN), Specialisation in technical programmes, including technical vocational education and training (TVET), Strong focus on employer linkages in technical and professional fields, and
3. Malaysian Comprehensive Universities (MCU), with a Primary focus on undergraduate and postgraduate instruction across various subjects. High priority on quality education and training, innovations in programme design.

AP in Malaysia is systematically evaluated to ensure alignment with national higher education objectives and institutional missions. The MoHE emphasises that AP must be linked to three overarching domains of knowledge management: generation, dissemination, and facilitation. These domains are assessed through indicators such as research productivity (e.g., indexed journal publications, patents, and grants), teaching and graduate employability, and the commercialisation or extension of knowledge to industry and community (Ministry of Higher Education Malaysia, 2016). Complementary instruments such as the Malaysian Research Assessment (MyRA), the Rating System for HEIs (SETARA), and the Headline KPI further provide standardised measures to evaluate the quality and competitiveness of public universities, thereby indirectly shaping the criteria used for assessing academicians.

Traditionally, the performance of academic staff in Malaysian HEIs has been measured based on three primary dimensions: teaching, research, and service (Comm & Mathaisel, 1998). Over time, this scope expanded to include supervision of postgraduate students and consultancy, reflecting the evolving roles of universities in knowledge production and application (Masron, Ahmad, & Rahim, 2012). According to Wang and Tete (2017), contemporary performance evaluation frameworks in universities typically account for teaching responsibilities, supervision, research outputs, administrative duties, and contributions to social service. In the Malaysian context, MoHE's promotion guidelines further highlight teaching, supervision, research, publication, consultation, academic leadership, and professional or community service as central performance indicators (Che Omar et al., 2017; Tajul et al., 2018).

Universities operationalise these performance dimensions at the institutional level into detailed evaluation systems. For example, Universiti Teknologi Malaysia (UTM) and Universiti Putra Malaysia (UPM) assess academicians based on KPIs covering teaching, research, publication, professional practice, and leadership, while also embedding broader values such as integrity, innovation, and community engagement (Universiti Teknologi Malaysia, 2018; Universiti Putra Malaysia, 2018a, 2018b). Universiti Kebangsaan Malaysia (UKM) emphasises teaching, research, and service as its three pillars of performance appraisal (Universiti Kebangsaan Malaysia, 2015). In contrast, Universiti Sains Malaysia (USM) and Universiti Malaya (UM) adopt similar dimensions but further include recognition, networking, and institutional contribution to reflect their strategic priorities as research-intensive universities (Universiti Malaya, n.d.).

Taken together, the performance of academicians in Malaysia is measured across multiple but interrelated dimensions. The common elements include teaching, supervision, research, publications, consultation, academic leadership, and service, which are reinforced through national instruments like MyRA and SETARA and adapted to institutional contexts. This multidimensional approach ensures that academicians are not only evaluated on scholarly output but also on their contributions to student development, institutional governance, and societal engagement (Che Omar et al., 2017; Ministry of Higher Education Malaysia, 2016; Wang & Tete, 2017). The MoHE's, Malaysia, periodically evaluates and rates all public universities using the following instruments:

a) Malaysia Research Assessment (MyRA)
b) Rating System for HEIs (SETARA)
c) Headline KPI

The SETARA rating is an assessment methodology used to rate educational institutions. Therefore, the rating also influences the factors used in assessing university academic staff. Table 2.9 below shows the segregation of the SETARA weight of performance area by type of university.

Table 2.9
The SETARA Weight of Performance Area by Type of University

Performance Area	Mature University	Emerging University	University College
General	40%	40%	40%
Teaching & learning	30%	40%	50%
Research	20%	15%	5%
Services	10%	5%	5%

In the SETARA rating, a mature university over 15 years old must fulfil the general (institutional profile) at 40 per cent, teaching and learning at 30 per cent, research at 20 per cent, and services at 10 per cent. Table 2.10 below presents the criteria for the SETARA rating by performance area. In conclusion, this study highlights the dimensions of AP in research universities, including supervision, teaching, consultation, administrative and management work, and social services.

Table 2.10
Detailed Criteria Employed for the SETARA Rating for Each Performance Area

General: Institutional Profile	Teaching & Learning
Student quality and diversity	Capacity of academic staff
Lecturer capability	Student satisfaction with teaching and facilities
Academic staff recognition	Quality of graduates
Quality management system	Internationalisation of Academic programmes
Financial sustainability	Program recognition
Institutional reputation	
Research Capacity	Services and Income Generation
Critical mass of researchers	Income from the commercialisation of intellectual
Research income	property
Quantity of publications	The university's social responsibility and knowledge
Quality management system	transfer programme
Quality of publications	Education and training programmes
	Other sources of income

Source: SETARA Rating (2020)

Thus, AP can be broadly defined as the extent to which staff fulfill their assigned duties. It encompasses measurable outputs and qualitative contributions, reflecting the multifaceted nature of academic responsibilities (Lim et al., 2024). In brief, AP appraisal frameworks emphasise a balanced evaluation of teaching, research, and service contributions, tailored to institutional priorities and contexts. The following discussion will be on the contextual study of UiTM and its performance evaluation criteria for promotional academic staff. Since the requirements for an academician's promotion will be linked to the university's performance, it is necessary to consider the following:

2.5.2 Academicians' Performance in Universiti Teknologi MARA (UiTM)

In the evolving landscape of higher education, technology and social media have become increasingly important in shaping academic practices and performance. UiTM, one of Malaysia's leading comprehensive universities, provides a particularly relevant setting for examining the relationship between SMU and AP. This suitability is underpinned by UiTM's structured performance evaluation system, its size and diversity, and its growing recognition in national and international rankings.

UiTM is Malaysia's largest HEI, with campuses in every state, including Sabah and Sarawak. With 34 campuses, 13 faculties, and over 9,000 academic staff (UiTM, 2023). UiTM is pivotal in fostering future leaders while striving for global recognition by 2025. The institution aligns its academic programs with industry demands, offering more than 500 courses across various levels and hosting over 160,000 students as of mid-2024. UiTM's alumni network of over 900,000 reflects its significant contributions to Malaysia's socio-economic development (Universiti Teknologi MARA, 2020a). Its extensive reach and academic offerings at multiple levels, from foundation to doctoral programmes, make it an influential institution in democratising access to quality education and contributing to Malaysia's socio-economic development agenda. The breadth of UiTM's academic staff, encompassing diverse disciplines and specialisations, provides an ideal population for investigating variations in social media usage and their implications for AP across contexts.

A further reason for UiTM's suitability is its robust performance evaluation framework aligned with the national higher education agenda. UiTM employs KPIs that span critical dimensions of academic work, including teaching, supervision, research, publication, consultancy, community engagement, and administrative responsibilities. According to *Pekeliling Timbalan Naib Canselor (Penyelidikan dan Inovasi) Bilangan 01 Tahun 2020*, faculties are required to clearly define academic staff responsibilities to ensure a balanced workload between teaching, research, consultancy, and service (Universiti Teknologi MARA, 2020b; Universiti Teknologi MARA, 2022). Academicians must also meet a minimum Academic Teaching Period (ATP) performance threshold of 85% annually, with opportunities to enhance performance by exceeding expectations in designated areas. This system ensures fairness and accountability and provides a clear framework for assessing how SMU might influence different performance dimensions.

UiTM's growing visibility in global rankings further underscores its suitability as a sampling site. UiTM demonstrated remarkable improvement in the QS World University Rankings, rising from the 651–700 band in 2023 to 555 in 2024, before being ranked 587 in 2025 (QS World University Rankings, 2020). This achievement is noteworthy, as UiTM is not classified as a research-intensive university like UM, USM, UKM, UPM, or UTM, yet it has advanced significantly in international rankings. Its 2025 Strategic Plan reinforces UiTM's commitment to becoming a world-class research

platform through impactful research, high-quality publications, and strong stakeholder collaborations (Universiti Teknologi MARA. Bahagian Transformasi Universiti, 2020).

The UiTM Strategic Plan 2025 reinforces the institution's emphasis on multidimensional AP. Under Strategic Thrust 1 (Quality Education), academic staff are expected to align with Education 5.0@UiTM and Society 5.0 by innovating in teaching, engaging with technology, and preparing graduates for Industry 4.0. Strategic Thrust 2 (Global Excellence) highlights performance expectations in research productivity, high-impact publications, and international collaboration, while Strategic Thrust 3 (Value-Driven Performance) emphasises governance, integrity, agility, and community engagement (Universiti Teknologi MARA. Bahagian Transformasi Universiti, 2020). These thrusts demonstrate that UiTM's academicians are committed not only to traditional KPIs such as teaching, research, and service but also to their ability to adapt to global challenges, uphold institutional values, and contribute to societal transformation.

This makes UiTM an appropriate and relevant sampling site for investigating the relationship between SMU and AP. Its large and diverse academic staff population enables comprehensive analysis, its nationwide reach ensures representativeness across regions, and its structured performance evaluation system provides measurable dimensions of AP. Furthermore, UiTM's growing global recognition strengthens the credibility of insights from this context. Investigating the relationship between social media usage and AP within UiTM is therefore highly appropriate, offering institutionally relevant and nationally significant findings.

2.6 Social Media and Academicians' Performance

Job performance refers to the degree to which individuals effectively fulfil work-related responsibilities and contribute to organisational goals (Williams & Anderson, 1991). It encompasses formally prescribed duties that are coordinated and evaluated to ensure alignment with institutional objectives (Janssen & Van Yperen, 2004). June and Mahmood (2011) further describe performance as an individual's capacity to understand assigned roles, meet expectations, and produce measurable outcomes. From both qualitative and quantitative perspectives, job performance reflects the attainment of work targets within a specified timeframe (Lawler, 1976; Schermerhorn, 1984, as cited in Kalia & Bhardwaj, 2019). Consequently, performance

evaluation serves as a critical basis for organisational decisions related to promotion, rewards, training, and career advancement (Kalia & Bhardwaj, 2019).

With the increasing integration of social media into organisational practices, a growing body of research has examined its implications for employee performance. Empirical evidence suggests that SMU enhances job performance by facilitating communication, knowledge sharing, and collaboration. In IT and knowledge-intensive sectors, Enterprise Social Media (ESM) has been shown to empower employees, strengthen collaboration, and foster psychological trust, thereby improving task efficiency and work outcomes (Huang & Zulkifli, 2023; Dittes & Smolnik, 2019). From a UGT perspective, individuals actively select media platforms to satisfy specific cognitive, social, and professional needs (Katz et al., 1973; Ruggiero, 2000). In academic settings, social media is commonly used for information seeking, professional networking, scholarly visibility, and collaboration, activities that are closely associated with performance-related outcomes. These uses have been linked to improved internal communication (Cao et al., 2012; Song et al., 2019), strengthened professional networks (Wang & Beh, 2025), and enhanced visibility of work-related interactions (Huang & Zulkifli, 2023), all of which support innovation, coordination, and team cohesion (Dittes & Smolnik, 2019).

Nevertheless, the relationship between SMU and performance is not uniformly positive. Studies indicate that factors such as technostress (Yin et al., 2018), timing and intensity of use (Lu & Pan, 2019), and cultural norms surrounding communication practices (Wang & Beh, 2025) can moderate performance outcomes. Excessive or unmanaged SMU may lead to distraction, information overload, or reduced job satisfaction (Permana et al., 2023; Yin et al., 2018). Despite these risks, evidence consistently suggests that when guided by appropriate organisational policies, norms, and training, SMU remains a valuable enabler of employee performance (Moyo & Nkhahle, 2024).

The relevance of SMU to job performance extends beyond corporate environments to educational and academic contexts. Research indicates that teachers' effective use of social media for professional communication, collaboration, and resource sharing contributes to enhanced job fulfilment and role effectiveness (Chen et al., 2024). Similarly, Jafar et al. (2019) reported that SMU supports productivity by improving connectivity and collaborative capacity among employees. Kumar et al. (2024) further demonstrated that SU, HU, and CU of social media positively influence

both routine and innovative job performance. These findings reinforce UGT's assertion that performance outcomes depend not merely on the frequency of use but also on the alignment between users' motivations and the gratifications they obtain. Complementing this view, Fu (2024), drawing on Media Richness Theory, found that social media enhances workplace outcomes by offering rich communication channels suitable for complex and ambiguous tasks. Lee and Lee (2020) similarly showed that instant messaging platforms such as Facebook and KakaoTalk improve task performance by supporting synchronous and interactive communication under conditions of uncertainty. Although some studies caution that excessive engagement may reduce productivity (Yu et al., 2019; Sendurur et al., 2015), recent syntheses confirm that purpose-driven and professionally aligned SMU enhances performance, whereas entertainment-dominated or excessive use may undermine work outcomes (Zhang, 2024).

Beyond motivational explanations, technology-oriented models provide further insight into how SMU translates into performance outcomes. The TAM and its extensions, including the UTAUT, emphasise the roles of perceived usefulness, ease of use, and facilitating conditions in shaping productive technology use (Davis, 1989; Venkatesh et al., 2012). In higher education contexts, social media platforms perceived as useful for teaching, research collaboration, and academic communication are more likely to be embedded in daily work practices, thereby supporting AP. Empirical studies applying TAM in universities have shown that perceived usefulness and ease of use significantly enhance collaborative authoring, knowledge sharing, and academic productivity (Alenazy et al., 2019; Al-Qeisi & Eletter, 2022).

Relational and engagement-based mechanisms further strengthen the link between SMU and performance. Ellison et al. (2007) provided early evidence that social media facilitates the development of online connections that enhance information access and interaction. Although their study did not directly examine performance outcomes, it established an important theoretical foundation for subsequent research linking social media-enabled engagement to work-related benefits. In educational settings, Alshuaibi et al. (2018) demonstrated that cognitive engagement mediates the relationship between SMU and AP, highlighting the importance of active participation and knowledge processing as pathways through which SMU can enhance performance.

Extending these insights to the academic profession, recent studies have increasingly examined the role of social media in shaping AP. In Malaysia, AP is systematically evaluated across key dimensions, including teaching, research and publication, supervision, and consultation (UiTM, 2025). These dimensions closely align with established conceptualisations of job performance, in which teaching and supervision reflect task performance, research and publication represent innovative and knowledge-creation outputs, and consultation captures service-oriented and contextual contributions to the institution and society (Williams & Anderson, 1991; Janssen & Van Yperen, 2004). Within this framework, social media can support performance by facilitating innovative teaching practices, expanding research collaboration and publication visibility, strengthening professional networks for consultation, and enhancing communication with postgraduate students for supervision.

Faculty-focused studies provide further empirical support for these relationships. Kumar et al. (2024) found that SMU positively influences both routine academic tasks and innovative outputs, particularly when supported by effective internal communication and teamwork. From an IS perspective, these findings align with the DeLone and McLean ISSM, which posits that SyU contributes to individual performance by enhancing task completion and work effectiveness (Petter et al., 2008).

Overall, although much of the foundational evidence on SMU and performance originates from corporate and technology-intensive settings, the underlying mechanisms, knowledge sharing, collaboration, communication visibility, and network building are equally relevant in academic environments. For academicians in institutions such as UiTM, strategic and purposeful use of social media holds significant potential to enhance performance across teaching, research, publication, supervision, and consultation, thereby aligning individual contributions with broader institutional objectives.

Table 2.11
Summary of Empirical Studies on Social Media Use and Performance

Authors	Context	Social Media Use Focus	Mediator	Performance Outcome	Key Findings	Limitations	Relevance to the Present Study
Jafar et al. (2019)	Public & private sector employees, Pakistan	Personal & work-related SM use	Knowledge exchange; SM rules (moderator)	Job performance	SM use enhances performance through knowledge exchange; organisational rules weaken the relationship.	Non-academic context	Establishes knowledge exchange as a key performance mechanism
Kumar et al. (2024)	Faculty members, India	Social, cognitive & hedonic SM use	Internal communication; teamwork	Routine & innovative job performance	All SMU dimensions positively affect faculty performance via communication and teamwork.	Single-country context	Directly supports the SMU–performance link among academicians
Moyo & Nkhahle (2024)	Conceptual review (organisations)	Organisational SM communication	Organisational culture & regulation	Productivity; job satisfaction	SMU offers benefits, but risks productivity loss if unmanaged	Conceptual; no empirical testing	Supports the need for structured, purposeful SMU
Yu et al. (2019)	University students, China	Excessive SM use	Technostress; exhaustion	Academic performance	SM overload negatively affects performance via stress mechanisms	Student-focused	Justifies examining the boundary conditions of SMU
Ellison et al. (2007)	College students	Facebook use	Bonding & bridging social capital	Social capital (not performance)	SM use is strongly linked to social capital	No performance outcome	Foundational link for mediation via social capital
Alshuaibi et al. (2018)	Higher Education students from Malaysia	Educational SM use	Cognitive engagement	Academic performance	Engagement mediates SMU the performance relationship	Student population	Shows mediated effect, but a different population
Zhang (2024)	Systematic review	Mixed SM use	Engagement & distraction	Academic performance	Purposeful use benefits performance; excessive use harms	Review-level	Supports mixed findings in the literature

Taken together, these findings reinforce critiques of unidimensional measures of SyU in traditional IS research. The performance effects of social media are contingent not only on the extent of use, but on the specific purposes, interaction patterns, and relational outcomes it enables. This underscores the need for a multidimensional conceptualisation of SMU that reflects academicians' diverse professional roles, as well as for theoretical mechanisms that explain how use is translated into performance outcomes. Overall, existing literature suggests that SMU can enhance AP when it is motivated by professional gratifications, perceived as useful for academic tasks, and embedded within meaningful engagement processes. Table 2.11 presents a literature review matrix summarising prior studies that examine the relationship between SMU and job or AP.

2.7 Social Capital and Academicians' Performance

The relationship between SC and job performance has attracted increasing scholarly attention, particularly in knowledge-intensive, networked work environments such as HEIs. SC, broadly defined as the resources embedded within, available through, and derived from the social networks of individuals or groups (Nahapiet & Ghoshal, 1998), is recognised as a critical enabler of job performance due to its capacity to facilitate access to information, collaboration, and emotional support. SC can catalyse enhanced outcomes in academic settings, where performance is often evaluated through multidimensional criteria such as research productivity, teaching effectiveness, supervision quality, and service engagement.

Building on the multidimensional view of SMU discussed previously, this section positions SC as a key explanatory mechanism through which specific forms of digital engagement are translated into AP outcomes. SC is commonly conceptualised across three interrelated dimensions: structural, relational, and cognitive (Nahapiet & Ghoshal, 1998; Inkpen & Tsang, 2005). SSC refers to the overall pattern of connections between individuals, who they reach, and how they are linked. RSC encompasses the quality of these relationships, including trust, norms, and obligations. CSC includes shared language, interpretations, and systems of meaning. Each of these dimensions can influence job performance differently. For example, strong structural ties may provide access to critical resources or collaboration opportunities, while high relational capital may foster trust and reduce coordination costs in team-based academic projects.

Cognitive alignment, on the other hand, can improve communication clarity, reduce misunderstandings, and align goals across interdisciplinary teams (Adler & Kwon, 2002).

A growing body of empirical research supports the positive link between SC and job performance. For instance, Negoro et al. (2025) found that SC significantly mediated the relationship between job crafting and work performance among Indonesian law enforcement personnel, indicating that relational and network factors enhance the utility of individual effort. Similarly, Mondal, Sharma, and Panackal (2025) revealed that social trust and academic leadership mediate and moderate the influence of SC on job satisfaction and performance among university staff. Their findings suggest that SC is a direct performance enhancer and interacts with contextual leadership factors to shape work outcomes. These insights are especially relevant in higher education settings, where performance depends on individual competencies and collegial collaboration, peer support, and institutional alignment.

SC plays a further critical role within digital and hybrid work environments. As shown by Majhi, Mukherjee, and Anand (2025), multiple social media platforms enhance managerial performance not through direct use but via their influence on managerial SC and absorptive capacity. This suggests that the benefits of technology use in professional settings depend on users' ability to translate digital interactions into meaningful relational resources. Their findings align with the premise that SC is a mechanism through which digital engagement is transformed into actionable knowledge and collaborative output. In academia, this means that performance gains from social media are likely to be mediated by network quality, trust, and shared norms developed through sustained interactions.

The relevance of SC in AP has also been explored through the lens of knowledge management and the Society 5.0 paradigm. Ancillai et al. (2025) demonstrated that online communities foster multidimensional SC that supports knowledge exchange at individual (micro), organisational (meso), and societal (macro) levels. This resonates with the structure of HEIs, where academics operate within local departments, interdisciplinary networks, and global scholarly communities. Facilitating knowledge sharing, trust-building, and peer mentoring across these layers can significantly influence AP, including research, teaching, and community engagement, and the quality of output.

Furthermore, the theoretical underpinnings of the relationship between SC and job performance are grounded in Social Capital Theory (SCT) (Coleman, 1988; Putnam, 2000) and the Resource-Based View (RBV) of the firm (Barney, 1991). SC is considered a strategic resource that enhances the organisation's and individual's capability to mobilise knowledge, adapt to environmental changes, and innovate. For academic staff whose performance relies heavily on intangible inputs such as ideas, feedback, and co-authorship opportunities, the strategic advantage of a rich social network cannot be overstated. SC can facilitate grant collaborations (Al-Tabbaa & Ankrah, 2016), research productivity (Salaran, 2010; Pan, Zhao, & Ding, 2023), publication opportunities (Katerndahl, 2012; Santen, 2022), and teaching innovations (Yoon & Baker-Doyle, 2021), all of which are fundamental components of AP metrics in universities.

However, the influence of SC on performance is not uniformly positive. Excessively dense networks may lead to groupthink, over-reliance on strong ties, and exclusion of novel perspectives (Portes, 1998). In academic contexts, where interdisciplinary innovation and critical inquiry are valued, the over-embeddedness of SC can constrain diversity of thought. Hence, balanced network configurations that allow both bonding (close ties) and bridging (diverse connections) SC are more desirable for sustainable performance outcomes (Burt, 2005). Future research must continue to investigate the quantity, quality, and diversity of SC to fully understand its impact on academic job performance.

Overall, SC is an essential determinant of job performance in academia. Through structural ties, relational quality, and cognitive alignment, it enhances access to resources, facilitates collaboration, and fosters trust, vital for delivering high-quality teaching, impactful research, adequate supervision, and professional service. In the context of increasing digitalisation and reliance on social media for academic engagement, SC serves as the mediating infrastructure that links technological affordances to real-world academic productivity. The continued exploration of this relationship, particularly through multi-dimensional and platform-sensitive lenses, will be instrumental in shaping institutional strategies and theoretical developments in higher education performance research. Accordingly, SC is not treated as a direct outcome of SMU, but as a relational mechanism that selectively mediates the effects of social and interaction-oriented use on AP.

2.8 Social Capital Mediating Social Media Use and Academicians' Performance

Responding to calls for stronger relational explanations in social media research, SC has increasingly been positioned as a critical mechanism through which SMU translates into AP. While early studies often assumed direct effects of SMU on performance, accumulating evidence suggests that such effects are contingent on intervening social processes, particularly the formation and mobilisation of relational resources. SCT conceptualises value as embedded within social networks, enabling access to information, trust, opportunities for collaboration, and professional support that enhance work outcomes (Ali-Hassan et al., 2015; Reagans & Zuckerman, 2001). Within academic settings, these resources are directly aligned with key performance domains, including teaching effectiveness, research productivity, postgraduate supervision, and consultation.

Importantly, the mediating role of SC is not associated with all dimensions of SMU, but is primarily linked to socially oriented use. As established in Sections 2.2 and 2.3, SMU is a multidimensional construct encompassing social, cognitive, and work-related purposes. However, empirical studies consistently show that these dimensions do not exert uniform effects on performance. Research adopting purpose-based approaches demonstrates that socially oriented interactions, such as informal networking, peer engagement, and relational maintenance, play a distinct role in building SC, whereas cognitive or system-related uses tend to influence outcomes through alternative mechanisms such as engagement or knowledge processing (Chen et al., 2022; Ma et al., 2024; Sada, 2025).

Foundational work by Ellison et al. (2007) established a strong association between SMU and the formation of bonding and bridging SC, providing the theoretical basis for later mediation models. Building on this logic, Sun and Shang (2014) empirically demonstrated that social-related use of social media strengthens SC, which subsequently enhances work-related use and performance, highlighting an indirect pathway rather than a direct effect. Similar patterns are evident in organisational studies, where SMU improves performance only when mediated by SC or related relational mechanisms (Ali-Hassan et al., 2015; Cao et al., 2016; Majhi et al., 2025).

Within academic contexts, although fewer studies formally test mediation models, substantial evidence supports the SC pathway. Ahmad Kharman Shah and Cox (2017) showed that academics' scholarly use of Twitter fosters informal networks and relational ties that enhance collaboration and scholarly visibility, key precursors to AP. Jordan and Weller (2018) similarly found that professional online networking supports peer interaction, professional identity development, and research visibility, despite tensions in platform use. Pieterse (2016) further demonstrated how academic social networking sites facilitate the transformation of social connections into professional capital, such as publication visibility and citation potential.

Empirical evidence for SC as a mediator is provided by Alajmi and Alasousi (2023), who found that SMU enhances SC dimensions (trust and shared vision), which, in turn, drive innovative job performance among academics. Although conducted within a single institutional context, this study offers direct support for the mediating logic central to the present research. Complementary studies that identify alternative mediators such as engagement (Alshuaibi et al., 2018; Su & Huang, 2021), knowledge sharing (Agrawal & Bhatia, 2025), or fatigue (Singh et al., 2023) reinforce the broader conclusion that direct-effect models are insufficient to explain social media–performance relationships.

Crucially, studies distinguishing between social and non-SUs of social media consistently show that performance benefits emerge through relational accumulation rather than mere frequency or intensity of use. Shami et al. (2014) and Ma et al. (2024) illustrated that excessive or undifferentiated use may even undermine performance, further underscoring the importance of theoretically grounded mediators. Saxton and Guo's (2020) conceptualisation of social media capital extends this argument by framing SC as the key resource that enables social media engagement to yield tangible outcomes.

Taken together, the literature supports a mediation framework in which SU of social media fosters SC, which subsequently enhances AP across teaching, research, publication, supervision, and consultation. This synthesis clarifies that SC does not mediate all forms of SMU, but specifically operates within socially oriented interactions that foster trust, reciprocity, and network embeddedness. By explicitly modelling this pathway, the present study addresses theoretical gaps identified in prior research and responds to calls for more nuanced, mechanism-driven explanations of SMU in higher education.

Table 2.12
Summary of Studies on Social Media Use, Mediating Mechanism, and Performance

Authors	Context / Sample	Social Media Use Conceptualisation	Mediating / Mechanism Variable	Performance Outcome	Key Findings	Identified Gaps	Implications for the Present Study
Agrawal & Bhatia (2025)	Employees (WFA)	General SMU	Networking; knowledge sharing	Work performance	SMU improves performance through networking mechanisms	No formal social capital model	Conceptually aligned with social capital mediation
Ahmad Kharman Shah & Cox (2017)	Academics, British university (qualitative interviews, n=28)	Scholarly Twitter use (information seeking, networking, collaboration)	Informal networking; relational ties (implicit social capital)	Scholarly communicati on; collaboration potential	Twitter supports networking, collaboration, and scholarly visibility	No direct performance measurement; qualitative	Demonstrates how SMU fosters relational resources that underpin academic performance
Alajmi & Alasousi (2023)	Academics, Kuwait (n=290)	Professional SM use for knowledge sharing	Social capital (trust, shared vision) → knowledge sharing	Innovative job performance	SMU enhances social capital; knowledge sharing mediates the effect on performance	Single institution; limited generalisability	Direct empirical support for social capital as a mediator between SMU and performance
Ali-Hassan et al. (2015)	IT firm employees	Social, hedonic, cognitive use	Social capital (structural, relational)	Routine & innovative performance	Social and cognitive SMU indirectly enhance performance via social capital	Non-academic context	Core empirical evidence supporting social capital as a mediator
Alshuaibi et al. (2018)	Business students, Malaysia	Educational SMU	Cognitive engagement	Academic performance	Engagement mediates the SMU-performance relationship	Student-focused; not social capital	Shows mediation exists, but the mechanism differs
Cao et al. (2016)	Employees, China (N=379)	Work-related SMU	Social capital; knowledge transfer	Work performance	SMU enhances social capital, which improves performance indirectly	Single-country, non-academic	Strong mediation logic applicable to academic work
Chen et al. (2022)	Employees	Social vs work-related SMU	None tested	Job performance	Performance effects vary by SMU type	No mediator examined	Demonstrates the limits of direct-effect models
Ellison et al. (2007)	College students	Facebook use	Bonding & bridging social capital	Not tested	SMU is strongly associated with social capital formation	No performance outcome	Foundational link: SMU → social capital

Authors	Context / Sample	Social Media Use Conceptualisation	Mediating / Mechanism Variable	Performance Outcome	Key Findings	Identified Gaps	Implications for the Present Study
Esteve Del Valle et al. (2017)	Faculty, multiple HE contexts (n=333)	SM use in teaching (UTAUT2-based)	Performance expectancy, social influence, and facilitating conditions	Teaching effectiveness (implicit)	SM adoption in teaching is driven by performance expectancy and social influence	Focus on adoption, not outcomes	Shows conditions under which SMU becomes performance-relevant in academia
Jordan & Weller (2018)	Academics, large-scale survey dataset	Professional online networking	Peer interaction; professional identity (implicit social capital)	Research visibility; teaching innovation (implicit)	SM provides benefits, but also tensions in professional engagement	No formal mediation testing	Highlights relational mechanisms linking SMU to academic outcomes
Ma et al. (2024)	Employees, China	Purpose-based SMU	None tested	Job performance	U-shaped SMU–performance relationship	No social capital or engagement	Shows complexity beyond frequency
Majhi et al. (2025)	Managers, multi-platform use	Multi-platform SM engagement	Social capital; absorptive capacity	Managerial performance	Performance gains occur through social capital, not direct SMU	Not higher education	Reinforces the indirect pathway via relational resources
Pieterse (2016)	Academics, Israel (survey across 3 institutions)	Academic Social Networking Sites (ResearchGate, Academia.edu)	Self-promotion; belonging; peer community (social capital creation)	Publication visibility; citation potential	ASNS is used primarily for professional information and self-promotion	Low interaction levels; small sample	Shows SMU as a tool for transforming social capital into professional capital
Sada (2025)	HE students	Platform-based SMU	None tested	Study efficiency	Educational use positive; entertainment negative	No mediator	Reinforces use-type differentiation
Saxton & Guo (2020)	Conceptual (organisational focus)	Organisational social media engagement	Social media capital (a form of social capital)	Organisational and individual performance	Social media capital is key to translating SM engagement into outcomes	Conceptual; not HE-specific	Provides a theoretical foundation for mediation logic in Section 2.8
Shami et al. (2014)	Employees (longitudinal)	Participation intensity	None tested	Performance ratings	Moderate SMU linked to better performance	No explanatory mechanism	Justifies the need for mediation testing
Singh et al. (2023)	Students	Compulsive SMU	Social media fatigue	Performance decline	Overuse harms performance via fatigue	Focus on the negative pathway	Reinforces the importance of social vs excessive use

Authors	Context / Sample	Social Media Use Conceptualisation	Mediating / Mechanism Variable	Performance Outcome	Key Findings	Identified Gaps	Implications for the Present Study
Su & Huang (2021)	College students, China	General SMU	Student engagement	Academic performance	Indirect-only effect via engagement	No relational mechanism	Highlights the need for a stronger theoretical mediator
Sun & Shang (2014)	Employees, China (survey)	Social-related vs work-related SM use	Social capital dimensions	Work performance (indirect)	Social use strengthens social capital, which enhances work-related use	Non-academic context	Foundational mediation pathway adapted in this study (social use → social capital → performance)
Zhang (2024)	Systematic review	Mixed-use SMU	Engagement; distraction	Academic performance	Purposeful use is beneficial; excessive use is harmful	Review-level; no causal testing	Supports differentiation of SMU dimensions

Table 2.12 synthesises prior empirical studies examining SMU, mediating mechanisms, and performance outcomes across organisational and educational contexts. The matrix reveals that while numerous studies report associations between SMU and performance, relatively few explicitly theorise or test SC as a mediating mechanism. Instead, many rely on direct-effect models or alternative mediators such as engagement or knowledge sharing. Importantly, studies that distinguish social-oriented uses of social media consistently demonstrate their role in fostering relational resources that indirectly enhance performance. This pattern underscores the need for a focused examination of SC as a mediating mechanism between SU of social media and AP, particularly within higher education contexts.

2.9 Theories and Models in Academic Social Media Use and Job Performance

Building on the theoretical gap identified in Section 1.3.1, this section reviews the key underpinning theories used to explain SMU and performance outcomes in academic and IS research. These include UGT, which accounts for the purposive and multidimensional nature of SMU, and major IS theories and models, such as the TAM, UTAUT, and the DeLone and McLean ISSM, which provide foundations for understanding SyU and net performance benefits. Collectively, these theories inform the conceptual grounding of the present study while also revealing limitations in explaining the relational mechanisms through which SMU translates into AP, thereby motivating the mediating role of SC discussed in Section 2.8.

2.9.1 Uses and Gratifications Theory (UGT)

Uses and gratification focuses on what individuals do with the media rather than the media's influence or effect on the person (Katz et al., 1973). The desire of the individual for media information is the primary variable in explaining why media messages have cognitive, affective, or variable impacts (Ruggiero, 2000). In U&G, cognitive orientation is when the user primarily looks for data on social features and the broader world around them. Other than that, individuals want diversions of many types, including relief from boredom and the limitations of daily routines. Uses and gratification research has often identified a distinct personal identity function, which

refers to ways of using media products to make something significant in the lives or condition of the audience member (Blumler, 1979).

In the uses and gratification theory, people actively choose the media they want to use. It illustrates that the person was mindful of the media that they chose. Therefore, the uses and gratification theory studies the function of the media from the user's perspective. Thus, we will be able to understand the application of certain media (McQuail, 1996), as cited in Ma et al. 2019). In the early study of uses and gratification by Blumer and Katz (1974), which studied the perspective of broadcast media, there are five main reasons for a person using a particular medium (i.e., cognitive, affective, self-affirmation, social, and escapism). Table 2.13 demonstrates that media consumption is not random or passive but is motivated by specific, goal-oriented needs. Understanding these needs helps explain why users select particular media channels or content types, and why different platforms (e.g., YouTube vs. LinkedIn) appeal to various segments of users.

Table 2.13
Needs Gratified by the Media

Need Type	Description	Media Examples
Cognitive	Acquiring information, knowledge, comprehension	Television (news), video ("How to Install Ceramic Tile"), movies (documentaries or films based on history.
Affective	Emotional, pleasant, or aesthetic experience	Movies, television
Personal integrative	Enhancing credibility, confidence, and status	Video
Social integrative	Enhancing connections with family, friends, and so forth	Internet (email, Facebook, Instagram)
Tension release	Escape and diversion	Television, movies, video, radio, Internet

Source: Adapted from Katz, Gurevitch, & Haas (1973); West, & Turner (2019)

As supported by the study on how information professionals use social media to fulfil work-related and personal needs, and self-gratification. The study in the context of uses and gratification emphasises what a person does with media. Based on the results, it confirms that the information professional gained gratifications related to their cognitive needs, which involve information and knowledge searching, comprehension (Hussain, Shabir, & Taimoor-Ul-Hassan, 2020).

2.9.2 Theory of Reasoned Action (TRA) and the Technology Acceptance Model (TAM)

TAM, as shown in Figure 2.2, predicts individual adoption and voluntary use of technology. Use refers to the direct usage of the given system in personal work. Perceived usefulness is what a user believes that using a particular system would increase work performance. Meanwhile, PEU is what a user believes that using a specific system would free them from physical and mental work (Davis, 1989). On the other hand, a study examines the individual adoption behaviour of the social networking site Facebook. The study argues that TAM emphasises system design and initially expected that IS would be used in organisational settings to improve the efficiency of the workers (Rauniar, Rawski, Yang, & Johnson, 2014).

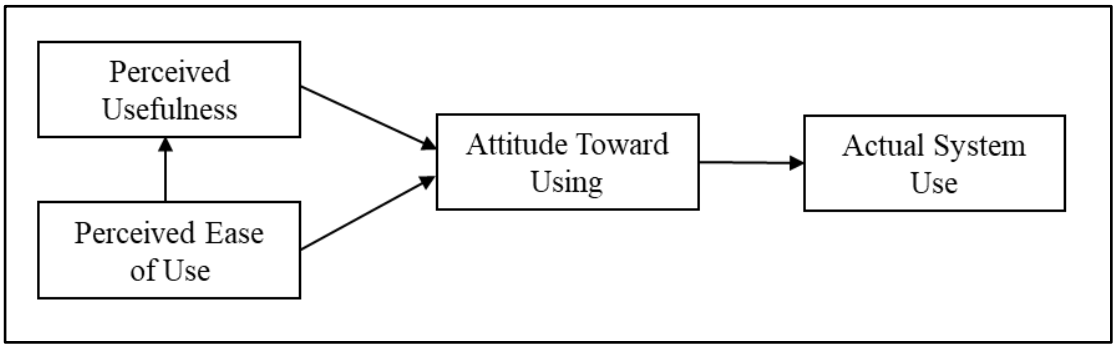


Figure 2.2 Technology Acceptance Model

Meanwhile, the Theory of Reasoned Action (TRA) (Figure 2.3) and the TAM were used to evaluate people's acceptance and use of technology. The outcome demonstrates the positive impact of SMA on Perceived Utility (PU) and PEU of social media. However, variable control has no important effect on the implementation of social media. On the other hand, the social media experience has significant and beneficial impacts. This indicates that people with more social media utilisation experience may exhibit a more favourable attitude toward SMA than those with less experience. The findings create an essential role of collaboration, communication, and sharing of resources in determining the choice to adopt social media for a user. Furthermore, the usefulness and ease of use of social media play a mediating role in the connection between the characteristics of social media and the adoption of social media. Overall, the research offers substantial assistance for the scholarly use of social media platforms. The study supports the role of media environment characteristics in social

learning, including communication, cooperation, and resource sharing, as predictors of adoption of social learning. This demonstrates that the scholarly community believes that a collaborative learning atmosphere on a social media platform helps establish better communication relationships between peers and colleagues (Arshad & Akram, 2018).

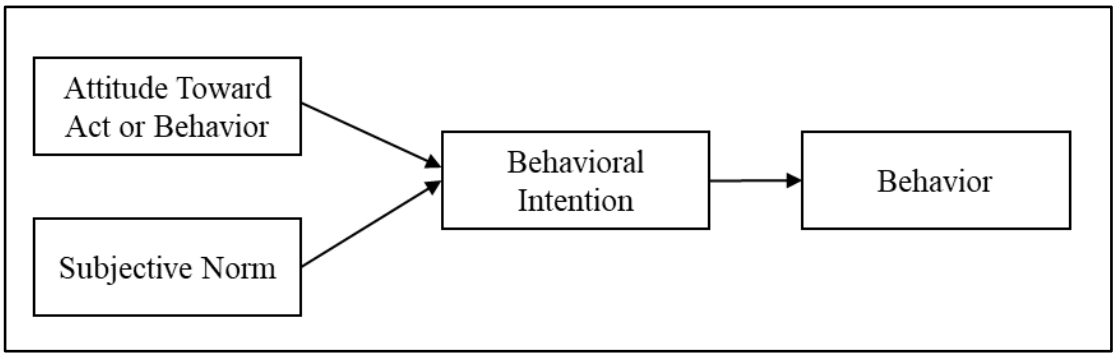


Figure 2.3 Theory of Reasoned Action

2.9.3 Theory of Planned Behaviour (TPB)

TPB, as shown in Figure 2.4, explains the behavioural performance. TPB consists of three dimensions: attitudes ("refers to the degree to which a person has a favourable or unfavourable evaluation"), subjective norms ("perceived social pressure to perform or not to perform the behaviour"), and perceived behavioural control ("people's behaviour is strongly influenced by their confidence in their ability to perform it"). Based on TPB, intentions are influenced by these dimensions. "Intentions are assumed to capture the motivational factors that influence a behaviour; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, to perform the behaviour" (Ajzen, 1991). TPB is used to understand the behaviour of work-related SMU (van Zoonen, Ward, Verhoeven, Joost W. M., &. TPB is also useful for studying IS continuance and discontinuance behaviour, as Turel studied the discontinuance of the SNS's as a hedonic system.

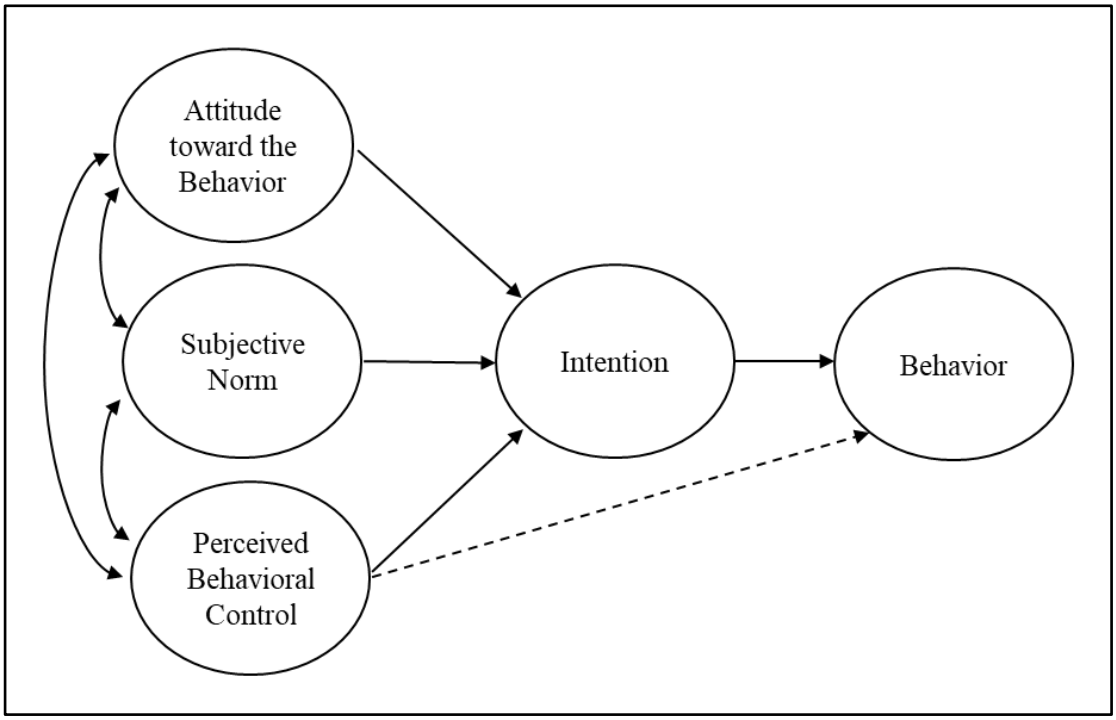


Figure 2.4 Theory of Planned Behaviour

2.9.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

Social media technology offers its users an interactive way to connect with people. Making new connections, collaborating, and disseminating research are the uses of social media among academicians (Gruzd et al., 2012). Rigorous studies have measured technology use mainly using frequency, duration, and intensity. The intention to use technology based on UTAUT theory (Figure 2.5) is chiefly measured by utilisation duration, frequency, and intensity or separation, on a self-report basis (Venkatesh, Thong, & Xu, 2012). UTAUT is a theory based on acceptance of technology. It has four dimensions (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions).

UTAUT is a theory that measures acceptance of technology. It has been used widely in research. The first dimension, performance expectancy, is the degree to which technology will benefit the user. Second, effort expectancy is perceived as the ease related to technology use. Third, social influence extends the importance of technology to others, and lastly, the facilitating condition is the user's perception of the support system in using the technology. UTAUT claims that all performance expectancy, effort expectancy, and social influence influence the intention to use a particular technology.

To determine the technology used using behavioural intention and facilitating conditions.

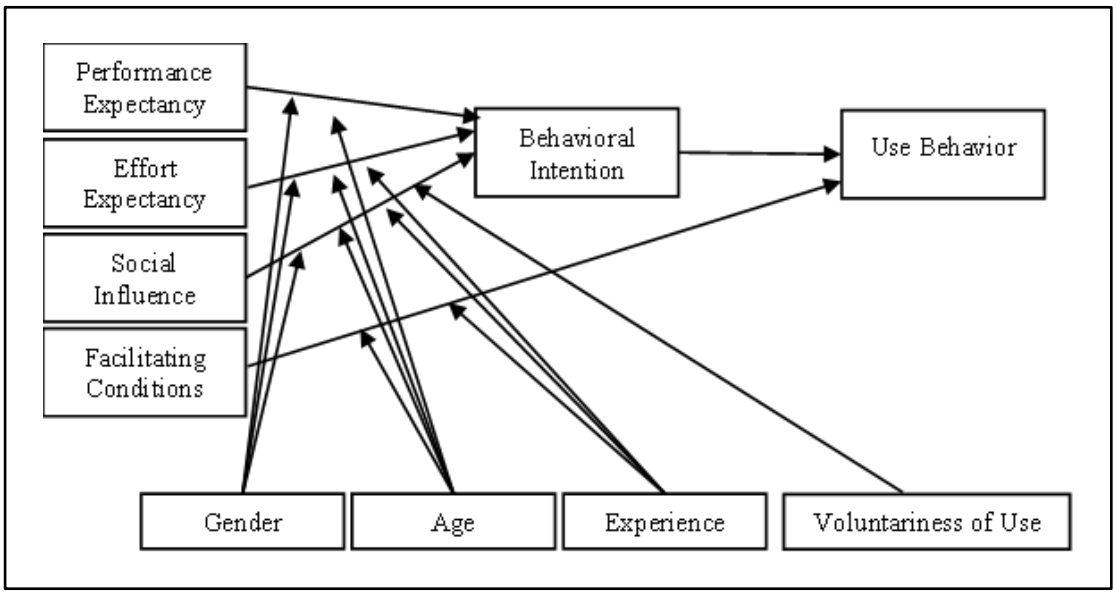


Figure 2.5 Unified Theory of Acceptance and Use of Technology (UTAUT)

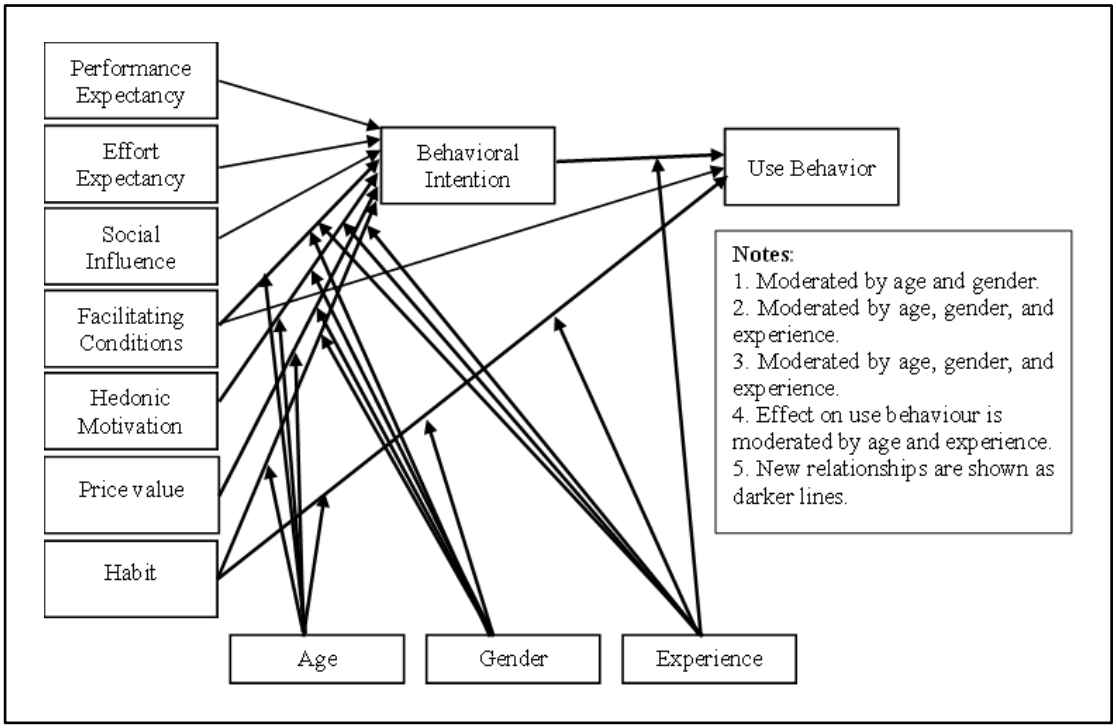


Figure 2.6 Unified Theory of Acceptance and Use of Technology (UTAUT) 2

Then, in UTAUT 2 (Figure 2.6), three dimensions (i.e., hedonic, price value, and habit) are added as predictors to provide more insight into the user's use context. Firstly, hedonic is the pleasure gained by using technology. Second, price value is the

cost that may impact the user's use of technology. Lastly, habitually, users tend to use technology.

2.9.5 Updated Delone and Mclean Information System Success Model (ISSM)

The updated DeLone and McLean ISSM is used to measure the success of IS at the individual or organisational level. The Update DeLone and McLean ISSM (Figure 2.7) underlines six dimensions of IS success: 1. System Quality (For example, ease of use, system flexibility) 2. Information Quality (For instance: relevance, understandability, accuracy), 3. Service quality (For example: responsiveness, accuracy, reliability, technical), 4. SyU (For example: amount of use, frequency of use), 5. User satisfaction (users' level of satisfaction with reports, websites, and support services), and 6. Net benefits (For example, improved decision-making, improved productivity, increased sales) (Petter, DeLone, & McLean, 2008).

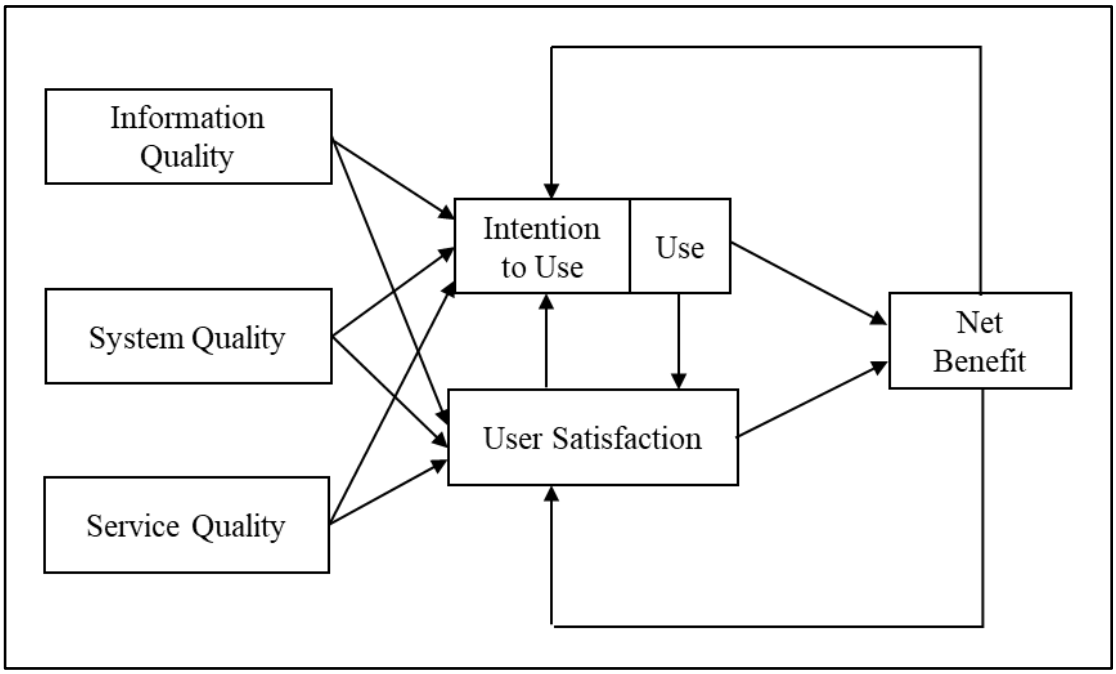


Figure 2.7 Updated D&M IS Success Model

IS should contribute to the success of the individuals, groups, or organisations that use it. Thus, ISSM raises three problems: what qualifies as a "benefit?" Who is it for? And at what analytical stage? Since the initial word "impacts" can be positive or negative, this can lead to confusion about whether the findings are good or bad.

"Net benefits" is essential because no result is entirely positive or entirely without adverse effects. The IS is developed with characteristics that exhibit varying degrees of scheme and data quality. Next, by using the system, customers and executives experience these characteristics and are either happy or unhappy with the system or its data products. The use of the scheme and its data products then affects the individual user in carrying out his or her job, and these individual effects generate organisational effects jointly (DeLone & McLean, 2003). Mason proposed a hierarchy of impact (influence) levels: from receiving information, through understanding it, applying it to a specific problem, and changing decision behaviour, to a change in organisational performance. Mason proposed that one technique of measuring the I/S effect was to determine whether the system output caused the recipient (i.e., the decision-maker) to modify their behaviour (Mason, 1978).

Theories and models related to SMU and job performance, such as the UGT, TAM, TRA, TPB, UTAUT, and the Updated DeLone and McLean ISSM, provide valuable insights into user behaviour and system adoption. U&G emphasises the active role of users in selecting media to fulfil cognitive, emotional, and social needs (Katz et al., 1973; Ruggiero, 2000). TAM and TRA focus on perceived usefulness and ease of use as predictors of technology adoption, while social influence and user experience further enhance acceptance (Davis, 1989; Rauniar et al., 2014). TPB extends TRA by adding perceived behavioural control, which influences intentions and usage behaviour (Ajzen, 1991; van Zoonen et al., 2014). UTAUT integrates these dimensions and highlights performance expectancy, social influence, and facilitating conditions as critical to technology acceptance, with UTAUT2 adding factors like hedonic value and habit (Venkatesh et al., 2012). Finally, ISSM evaluates the success of IS based on system quality, user satisfaction, and net benefits, emphasising the system's potential to enhance decision-making and productivity (DeLone & McLean, 2003). These frameworks collectively demonstrate social media's role in improving AP by fostering collaboration, knowledge sharing, and networking among academicians.

While UGT and IS-based models provide important foundations for understanding academic SMU and performance outcomes, they offer limited insight into the relational mechanisms that transform use into sustained professional benefits. In academic environments characterised by collaboration, trust, and knowledge exchange, these relational resources are critical. Consequently, the present study

extends existing theoretical perspectives by integrating SC as a mediating mechanism, as elaborated in Section 2.8, to explain how socially oriented SMU contributes to AP.

2.10 Application of Theory and Model on Social Media Use Research

This section reviews how major media-use and IS theories have been applied in prior social media research to explain user motivations, system adoption, and performance outcomes across educational, organisational, and professional contexts. The review highlights both the explanatory strengths and limitations of these theories in capturing the multidimensional and relational nature of SMU, thereby informing the integrated theoretical approach adopted in the present study.

2.10.1 Uses and Gratifications Theory (UGT) and Motivations for Social Media Use

UGT has been pivotal in understanding the motivations behind media consumption and the gratifications users derive from it. This theoretical lens offers nuanced insights into how individuals engage with social media across contexts, including cognitive needs, workplace applications, education, and psychological well-being. Hussain et al. (2020) examined the alignment between gratifications sought and gratifications obtained among information professionals who use social media for cognitive purposes, such as acquiring knowledge. Their findings revealed a significant gap between users' expectations and actual outcomes, suggesting that social media often fails to adequately meet cognitive needs. These discrepancies highlight the need for users to critically evaluate and adjust their social media practices to enhance their utility and effectiveness.

Meanwhile, Kumar and Yadav (2021) combined UGT and the Means-End Chain (MEC) Theory to explore university students' use of Facebook Groups for learning. By adopting the Student Technology Use Hierarchical Framework (STUH), they found that Facebook’s interactive features help fulfil higher-level cognitive and decision-making needs. Similarly, Kalam et al. (2023) investigated student motivations for SMU and its impact on AP. Their study revealed that non-academic learning and video clip-watching positively influenced AP, while entertainment-driven use surprisingly enhanced AP despite not directly driving SMU. These findings underscore

the role of motivational alignment in leveraging social media for educational outcomes. Furthermore, recent research has identified the roles of content quality (Ma et al., 2019; Sundjaja et al, 2024), social influence (Gogan et al, 2018; Luan & Zhong, 2025; Sundjaja et al, 2024), and entertainment (Hsu & Lin, 2023; Oh et al., 2024) in driving user satisfaction. Enhanced satisfaction improved knowledge retention and user stickiness, underscoring the importance of curated and targeted educational content on social media platforms.

2.10.2 Application of UGT in Educational and Professional Contexts

On the other hand, UGT has also been applied to assess social media's impact in professional settings. Ma et al. (2021) analysed how public and private SMU affects employee job satisfaction and work efficiency. Public platforms benefited both work- and social-related motivations, whereas private platforms contributed only to social satisfaction. In another study, Turulja, Delalić, and Bajgoric (2022) distinguished between cognitive and SUs of social media in the workplace. CU enhanced innovative behaviour and job performance, whereas SU had an adverse effect, highlighting the dual-edged nature of workplace social media engagement. Studies have Extended UGT (EUGT) to strategic communication, exploring differences in motivations across multi-platform users. For instance, Facebook and Instagram users are primarily driven by self-status seeking and entertainment, while Facebook and Pinterest users focus more on information-seeking and future-oriented activities (Jin et al., 2017). Cross-cultural studies further demonstrate UGT's applicability in peer-to-peer community building, with individualised motivations remaining significant across cultures, although relational motivations vary by cultural context (Anderson et al., 2023). More recent work has proposed an EUGT that incorporates environmental factors and user predispositions alongside traditional gratifications. Xu et al. (2023) demonstrated that environmental cues and pre-existing attitudes significantly shape engagement in video game streaming. Meanwhile, Adistri et al. (2024) identified entertainment, education, and social interaction as primary motivations for TikTok use, highlighting its role in satisfying complex psychological, cognitive, and social needs. Collectively, these distinctions offer valuable insights for organisations aiming to tailor their social media strategies to diverse stakeholder groups. Research by Lee et al. (2022) delved into factors driving the sustainable use of SNS, identifying entertainment value, social

influence, and trust as key motivators. The mediating role of trust was particularly significant, shaping user attitudes and long-term engagement. These findings provide actionable guidance for platform designers to enhance user retention by fostering trust and positive user experiences.

However, Sun, Liu, and Zhang (2020) explored the implications of excessive ESM use, focusing on communication visibility (message transparency and network translucence). While gratifications related to social and informational needs drive excessive use, perceived hedonic value did not have a significant impact. These findings emphasise the importance of managing ESM use to balance productivity and prevent overuse. Bhatiasevi (2024) applied UGT to examine the effects of SMU on the social relationships and psychological well-being of adults and older adults in Thailand. The findings highlighted the positive role of entertainment value, social enhancement, and interpersonal connectivity in fostering social and emotional health. Conversely, self-discovery motivations negatively influenced SMA, suggesting a complex interplay of user intent and outcomes.

2.10.3 Technology Acceptance Model (TAM) in Social Media Adoption and Use

The TAM has been widely applied to understand the factors influencing SMA and its use across various contexts. TAM has demonstrated its utility in explaining how social media facilitates collaborative learning and AP in higher education. Alenazy et al. (2019) validated TAM at Universiti Teknologi Malaysia, showing that perceived usefulness and ease of use significantly enhanced researchers' collaborative authoring via social media. Similarly, Al-Qeisi and Eletter (2022) highlighted that usefulness, enjoyment, and ease of use were key drivers of SMA in Jordanian learning environments, contributing to improved student performance. These studies highlight TAM’s relevance in guiding institutions to harness social media’s potential for educational purposes.

The adaptability of TAM has enabled researchers to integrate complementary theories and variables, thereby deepening its explanatory power. For example, Al-Rahmi et al. (2018) combined TAM with Constructivism Theory to investigate the role of social media in collaborative learning among Malaysian research students. Their findings underscored social media's interactive and learner-centred dynamics while identifying gender disparities, with female students expressing lower satisfaction with

perceived usefulness and ease of use. This dual-theoretical approach validated TAM's constructs and illuminated its synergy with theories addressing social engagement and learning behaviours. Furthermore, TAM's extensions, such as incorporating psychological ownership (Zhao et al., 2016) and social dynamics, such as fear of missing out (Bailey et al., 2018), have provided nuanced insights into social media's influence on user engagement and loyalty.

TAM's applicability extends beyond education to business and crisis adaptation contexts. For instance, Mukminin et al. (2022) applied TAM to explore the adoption of social media for English language teaching in Indonesia during the COVID-19 pandemic, identifying PEU and usefulness as critical factors for effective integration. Similarly, Fakhreldin et al. (2024) used TAM alongside the Task Technology Fit (TTF) framework to assess the impact of social media on Micro, Small, and Medium Enterprises (MSMEs) in Egypt. Their findings highlighted the positive influence of social media on MSME performance, emphasising the need for supportive ecosystems in emerging markets. These applications reinforce TAM’s versatility in addressing diverse challenges, from enhancing education to driving business performance and crisis resilience.

2.10.4 Unified Theory of Acceptance and Use of Technology (UTAUT / UTAUT2)

The UTAUT framework has been pivotal in analysing technology adoption at individual and organisational levels. Albanna et al. (2022) extended UTAUT by integrating new constructs, such as management commitment, and by assessing the impact of social media on Nonprofit Organisations (NPOs) in Jordan. Results emphasised the significant roles of performance expectancy, effort expectancy, and facilitating conditions in enhancing awareness and community engagement, although no significant impact on fundraising was observed. In the context of higher education, Al-Rahmi et al. (2022) combined UTAUT and TTF to investigate SMU for teaching and learning. Their findings highlighted that social and technological characteristics, behavioural intention, and task-technology fit positively influenced AP. This underscores the role of social media in promoting active learning and knowledge sharing. Esteve del Valle et al. (2017) also applied UTAUT2 to understand faculty use of social media in teaching. The study identified performance expectancy, habit, and facilitating conditions as key determinants, with older educators indicating greater

adoption rates. Similarly, Riady et al. (2022) analysed teachers' SMU during COVID-19 and found that facilitating conditions were the strongest predictor, alongside demographic factors that moderated adoption behaviours.

2.10.5 Behavioural and Social Theories Explaining Social Media Use

Various theoretical frameworks have been applied to understand the impact of SMU in different contexts. The TPB has been applied to understand SMU in various contexts. Studies have discovered that TPB components, including attitude, subjective norm, and perceived behavioural control, significantly influence social media purchase behaviour and high-level use of social networking websites (Sharma et al., 2020; Pelling & White, 2009). However, researchers have identified limitations in TPB's explanatory power, leading to model extensions. Identity-related constructs, such as social identity expressiveness and self-identity, have enhanced TPB's predictive ability for work-related SMU and high-level social networking website use (Zoonen et al., 2014; Pelling & White, 2009). Additionally, factors such as social media trustworthiness and past behaviour have been highlighted to affect attitudes and intentions (Sharma et al., 2020; Pelling & White, 2009). These studies suggest that while TPB provides a valuable framework for understanding SMU, incorporating additional variables can enhance its explanatory power across diverse social media contexts. Social Learning Theory has been employed to highlight the role of social media in learning positive behaviours, such as health-related behaviours, with studies in Cameroon, Uganda, and Nigeria revealing a significant relationship between SMU, locus of control, and mental health outcomes (Kituyi & Kyeyune, 2024; Kituyi et al., 2020). Technological determinism theory posits that technology is the primary driver of societal change, shaping human behaviour and social structures (Hauer, 2017). This concept is particularly relevant in the context of social media, which has transformed various aspects of society, including communication, education, and commerce (Hauer, 2017). McLuhan's assertion that "we shape our tools, and they in turn shape us" underscores the reciprocal relationship between technology and society (Azam Jan et al., 2020). Social media platforms have created a global village, connecting people across cultures and boundaries and homogenising user experiences (Azam Jan et al., 2020).

SCT, on the other hand, provides a valuable framework for understanding SMU and its impact on various behaviours. Studies have applied SCT to explore factors influencing health-related SMU during COVID-19 (Elkefi, 2023), political engagement among Hispanics and Latinos (Velasquez & Quenette, 2018), and information sharing about colon cancer (Yoon & Tourassi, 2014). Personal factors such as age, ethnicity, and health perceptions, as well as environmental factors such as social isolation, affect SMU for health purposes (Elkefi, 2023). In the political context, social media network expression and political efficacy contribute to increased offline engagement (Velasquez & Quenette, 2018). Habit strength is a significant determinant of social media usage (Khang et al., 2014). Additionally, topics with tangible benefits generate more social media traffic, highlighting the potential for effective health campaigns (Yoon & Tourassi, 2014).

2.10.6 Organisational and Knowledge-Based Theoretical Perspectives

Beyond that, research on SMU in organisations through the lens of Absorptive Capacity Theory yields several key insights. Studies indicate that firms employ social media for various purposes, including knowledge acquisition, transformation, and exploitation (Boateng et al., 2021; Hu & Schlagwein, 2013). SMU types have been identified: broadcast, dialogue, collaboration, knowledge management, and sociability (Schlagwein & Hu, 2017). These use types differentially impact an organisation's absorptive capacity, with dialogue and collaboration enhancing the ability to recognise, assimilate, and exploit new external knowledge (Hu & Schlagwein, 2013; Schlagwein & Hu, 2017). SMU can increase transparency, moderation, and multidirectional interactions, influencing capabilities such as connectedness, socialisation tactics, cross-functionality, and receptivity (Ooms et al., 2015). However, not all SMU types equally contribute to absorptive capacity and organisational performance, highlighting the importance of strategic implementation (Schlagwein & Hu, 2017).

2.10.7 Integrative Theoretical Positioning for the Present Study

This study integrates constructs from IS theories and media-use theories to more accurately capture the multidimensional nature of SMU among academicians. Traditional IS models such as the TAM (Davis, 1989), the UTAUT (Venkatesh et al.,

2012), and the updated DeLone and McLean ISSM (Petter et al., 2008) provide robust predictors of system adoption and continued use through indicators such as frequency, duration, and intensity of use. Still, their reliance on unidimensional usage measures overlooks the diverse purposes and social contexts of academic SMU. To address this limitation, the study incorporates UGT to operationalise SMU across cognitive, social, and professional dimensions. This integration allows the measurement of "how much" social media is used and "how" and "why" it is used, for example, for research information seeking, professional networking, scholarly visibility, or stress relief. Such an approach responds to calls in recent literature for multidimensional operationalisations of SMU in academic contexts (Arshad & Akram, 2018; Hussain et al., 2020) and enables a more nuanced analysis of its relationship with AP. This ultimately provides a theoretical foundation for the mediating role of SC discussed in Section 2.8.

2.11 Variable and Dimension in Literature: Academicians' Social Media Use and Job Performance

The preceding sections have established the theoretical landscape by integrating IS theories such as ISSM, UTAUT, TAM, UGT, and SCT. However, to shift from a conceptual understanding to a measurable framework, it is necessary to examine how these variables have been operationalised and dimensioned in existing scholarly discourse. The section provides a critical review of the literature concerning the specific dimensions of academic SMU and the multifaceted nature of AP.

2.11.1 Academicians' Performance

Job performance is a multidimensional construct encompassing the behaviours and outcomes employees contribute to organisational goals. In general management literature, performance is often framed in terms of task performance, which refers to the execution of core job duties, and contextual performance, which includes behaviours that foster a positive organisational environment, such as collaboration and Organisational Citizenship Behaviours (OCB). Additionally, counterproductive behaviours, such as withdrawal or deviance, can undermine overall performance (Harari, Reaves, & Viswesvaran, 2016). Traditional performance indicators have

included efficiency, attendance, and quality of work (Ivancevich, 1976), though contemporary frameworks also emphasise innovation, safety, adaptability, and interpersonal contributions as essential dimensions (Lanaj, Chang, & Johnson, 2012).

In academia, the performance construct needs to be contextualised to reflect the unique responsibilities of academic staff. Scholars such as Sukirno (2020) have argued that AP extends beyond general job performance to encompass teaching, research, publication, and social engagement, collectively capturing the dual emphasis on knowledge dissemination and creation. Similarly, Higgins (1989) and Balabonienė and Večerskienė (2014) highlighted both internal indicators, such as student success and graduation rates, and external measures, such as research productivity and graduates' employability, as central to evaluating academic effectiveness. This multidimensionality reflects the dual mission of HEIs: ensuring quality learning experiences while advancing scholarly contributions.

Therefore, performance evaluation in higher education is tied closely to academic roles. Arnăutu and Panc (2015) emphasised teaching quality, research productivity, and preparedness as indicators of lecturer effectiveness. Ahmad Kharman Shah and Cox (2017) stressed that performance also extends to digital visibility and professional reputation in the era of academic social media. Nielsen's (2020) case study of academic promotion practices further underscored the primacy of research impact as a central performance criterion, especially in tenure and promotion decisions. However, teaching and service remain important supporting roles.

In Malaysia, the Malaysia Qualification Agency (MQA) shapes AP frameworks for academicians, which positions academic staff as the core drivers of educational quality. According to the MQA (2014), the roles and responsibilities of academicians encompass teaching, supervision, research, consultancy, publication, administration, and service to society, reflecting the expectation that academics contribute not only within the classroom but also in advancing institutional and societal goals. Similarly, Masron, Ahmad, and Rahim (2012), in their study at USM, identified teaching, supervision, research, publication, and consultation as the core performance dimensions of academicians. Comm and Mathaisel (2000) further reinforced that teaching, research, and service are historically the pillars of AP globally.

Malaysian universities have operationalised these performance categories in various ways. For example, Basarudin, Yeon, Yaacob, and Abd Rahman (2016) grouped academic workload into teaching and supervision, research and consultation,

administrative work, publication, and community service. Similarly, Mohamad Ishak, Suhaida, and Yuzainee (2009), in a study at UNITEN, developed performance indicators that include research and innovation, teaching and supervision, writing and publication, consultancy, and services. These dimensions are also reflected in academic promotion processes, where teaching, research, administration, and community engagement are considered. However, the volume and impact of research output often remain the most influential factors (Md. Yunus et al., 2015; Nielsen, 2020). Building on this body of literature and aligning with the appraisal frameworks used by Malaysian HEIs such as UiTM, this study adopts seven key dimensions of AP, teaching, supervision, research, publication, consultation, administration and management, and social services. By integrating these dimensions, the study captures the holistic nature of AP, reflecting both global academic benchmarks and the specific requirements of Malaysian higher education.

2.11.2 Social Media Use

Academicians have integrated social media into their daily communication for research work. Research scholars use social media to search for information, upload photos, share photos, files, music, and videos, seek jobs, and socialise with friends. Other than that, research scholars can also create profiles and search for other scholars with the same interests (Madhusudhan, 2012). Meanwhile, for research and scholarly communications, academics use social networking tools to exchange data and information, build new connections, and communicate with other academics for professional development (Chen & Bryer, 2012; Gruzd et al., 2012; Tiryakioglu & Erzulum, 2011). Social media helps academics in their professional work, from searching for information to managing publications.

Social media is also used to maintain a professional image in the academic community (Ferguson & Wheat, 2015; Dermentzi, Papagiannidis, Osorio Toro, et al., 2016). As supported by Lutz and Hoffmann (2017), social media was used for information, communication, and self-promotion purposes. Academicians also use social media to support class (Moran, Seaman, &Tinti-Kane, 2011, cited in Lapoe et al., 2017), to share and discuss content, coordinate with research partners, and promote other academic works, as well as connect to other academicians with similar backgrounds (Lapoe et al., 2017). Social media can strengthen connections, get updates

about topics in the field, and promote one's own scholarly work (Gruzd, 2012). Meishar-Tal and Pieterse (2017) highlighted motives for using academic networks that are Self-promotion and ego bolstering, belonging to a professional community, acquiring professional knowledge, interaction with professionals, and escapism. Burns, V. F., Blumenthal, A., and Sitter (2020) highlighted SMU in conducting and promoting research. In the case of Twitter, it enhances the impact and reach of scholarship and promotes research equity by enabling people to engage and publicly discuss. In a study by (Radford, M. L., Kitzie, V., Mikitish, S., Floegel, D., Radford, G. P., & Connaway, 2020), social media enables scholars to connect with researchers with similar interests and provides an opportunity to view people's research interests and publications.

Other than that, social media is also used to seek and access information. Through social media, users can get informed on a topic or interest. As stated by (Ahmad Kharman Shah & Cox, 2017), Twitter is a platform that keeps people updated on the latest news and personal interests. Information access depends on the information pushed to academics, based on who they follow and who follows them.

Social media has also become a repository for storing documents, and is effectively used for sharing documents (del Valle, M. E., Gruzd, A., Haythornthwaite, C., Paulin, D., & Gilbert, 2017). In the case of Twitter, it was valued for its ability to support a broad community of interest around interviewees' subject areas. This also meant it was a valued information source, especially in the context of the creation, usage, and sharing of scholarly information (Ahmad Kharman Shah & Cox, 2017). Academic networks, in contrast, are chiefly used for information consumption and are perceived more as databases than as places to establish social or professional relations and interact with others (Meishar-Tal & Pieterse, 2017).

There is a time when social media provides a way to take a break from tiring work or to fill gaps in time. Twitter is used to take a break from boring or taxing work (Ahmad Kharman Shah & Cox, 2017) and used for leisure activities (Meishar-Tal & Pieterse, 2017). However, it also may lead to poor AP if social media is used heavily for entertainment. It could lead to procrastination and low concentration in academic activities (Ahmad Kharman Shah & Cox, 2017). Thus, social media plays a role in the academic sphere; it impacts the teaching and learning process, supports the search, retrieval, and dissemination of information, and can serve as a promotional tool and even provide a g-index score for academics.

Table 2.14
Social Media Use Dimensions

Dimensions	Sub-dimension	Study
Social Use	Communication	(Lapoe et al., 2017);(Nisar, Prabhakar, & Strakova, 2019);(Cocchio & Awad, 2014); (Murthy & Lewis, 2015b); (Vasquez et al., 2015); (Thelwall & Kousha, 2015); (Haustein, 2018); (Arshad & Akram, 2018); (C. Qi, 2018); (Tajudeen, Jaafar, & Ainin, 2018); (Madhusudhan, 2012b);
	Collaboration	(Cocchio & Awad, 2014); (Murthy & Lewis, 2015b); (Vasquez et al., 2015); (Meishar-Tal & Pieterse, 2017); (Arshad & Akram, 2018); (C. Qi, 2018); (Drummond, McGrath, & O'Toole, 2018); (Kaplan & Haenlein, 2010b); (Madhusudhan, 2012b); (Van Noorden, 2014)
	Interaction	(Ariel & Avidar, 2015); (Sloan, Quan-Haase, McCay-Peet, & Quan-Haase, 2017); (Meishar-Tal & Pieterse, 2017); (C. Qi, 2018); (Tajudeen et al., 2018); (Nisar et al., 2019);
	Engagement	(Mangold & Faulds, 2009); (Bal, Grewal, Mills, & Ottley, 2015); (Guesalaga, 2016); (Sapkota & Vander Putten, 2018); (C. Qi, 2018); (Madhusudhan, 2012b)
Cognitive Use	Information/knowledge sharing/dissemination	(Murthy & Lewis, 2015b); (Vasquez et al., 2015); (Elsayed, 2015); (Oh & Syn, 2015); (Ariel & Avidar, 2015); (Thelwall & Kousha, 2015); (Pieterse, 2016); (Sloan et al., 2017); (Hinojosa & Cleveland, 2017b); (Meishar-Tal & Pieterse, 2017); (Haustein, 2018); (Arshad & Akram, 2018); (Drummond et al., 2018); (Kaplan & Haenlein, 2010b); (Madhusudhan, 2012b); (Van Noorden, 2014)
	Information searching	(Jang, 2016); (Felt, 2016); (Meishar-Tal & Pieterse, 2017); (Tajudeen et al., 2018); (Drummond et al., 2018);
	Information consumption	(Pieterse, 2016); (Meishar-Tal & Pieterse, 2017); (Tajudeen et al., 2018); (Drummond et al., 2018)
Hedonic Use	Entertainment	(Cao & Yu, 2019)
System Use	Frequency	(Murthy & Lewis, 2015b); (Elsayed, 2015); (Pieterse, 2016); (Meishar-Tal & Pieterse, 2017); (Haustein, 2018); (Madhusudhan, 2012b); (Junco, 2012)
	Duration	(Elsayed, 2015); (Madhusudhan, 2012b); (Junco, 2012)
	Intensity	(Fusi & Feeney, 2018); (Stojanovic, Andreu, & Curras-Perez, 2018); (L. Yu, Cao, Liu, & Wang, 2018)

Table 2.14 outlines the multidimensional nature of SMU by categorising it into four key dimensions, SU, CU, HU, and SyU, each comprising several sub-dimensions drawn from a wide range of empirical studies. The SU dimension highlights the interpersonal and collaborative functions of social media, encompassing communication (e.g., direct messaging and information exchange), collaboration (e.g., shared academic projects), interaction (e.g., two-way engagement through comments and feedback), and engagement (e.g., participation in discussions or scholarly discourse). These sub-dimensions are supported by studies such as those by Lapoe et al. (2017), Murthy and Lewis (2015), and Meishar-Tal and Pieterse (2017), who collectively illustrated the importance of social media in fostering academic connectivity and knowledge sharing. The CU dimension reflects how users search for, consume, and disseminate knowledge-related information. This includes information sharing (Murthy & Lewis, 2015), searching (Jang, 2016), and consumption (Pieterse, 2016), emphasising social media's role as a conduit for academic and professional knowledge flows. HU, though less emphasised in academic contexts, captures the entertainment and relaxation motivations behind social media engagement, as explored by Cao and Yu (2019). Finally, the SyU dimension considers the behavioural metrics of use, such as frequency (Murthy & Lewis, 2015), duration (Elsayed, 2015), and intensity (Fusi & Feeney, 2018), which offer insights into users' time investment and habitual engagement. These dimensions provide a robust and comprehensive framework for understanding how academicians utilise social media, thereby offering a foundation for investigating its influence on outcomes such as SC and performance. This typology also helps distinguish between different usage patterns across platforms and academic roles, enabling more nuanced analysis of digital engagement in higher education contexts.

2.11.3 Social Capital

SC is outlined as the aggregate of the precisely manageable resources associated with possession of a sturdy network of extra or less institutionalised relationships of mutual acquaintance or recognition (Bourdieu, 1986, p. 248), as cited in Tzanakis, 2013). Empirical research has assessed the significance of the approach in micro-blogging, that is, strategically identifying what to post, what to share, and whom to

share with on an open platform, where the message can go viral throughout the network (Qi, Monod, Fang, & Deng, 2018).

The idea of SC is the network of relationships that creates valued capital. The capital is greatly set in networks of reciprocal acquaintance. Three dimensions of SC are identified as structural, relational, and cognitive dimensions (Nahapiet & Ghoshal, 1998). SC is 'the sum of the real and practicable sources embedded within, accessible through, and derived from the network of relationships possessed with the aid of an individual or social unit (Nahapiet & Ghoshal, 1998, p. 243 as cited in Chang & Hsu, 2016). SSC refers to the connections between individuals (Wasko & Faraj, 2005; van den Hooff & Huysman, 2009). RSC, on the other hand, is the assets that are rooted in ongoing interpersonal relationships (van den Hooff & Huysman, 2009). CSC relates to shared code and languages among parties (Nahapiet & Ghoshal, 1998). When discussing SMU, it is important to study bridging and bonding between individuals. Bridging SC involves exposure to the information and resources from weak ties, such as colleagues (Steinfield, Ellison, Lampe, & Vitak, 2012). Bridging SC will extend the opportunities and understanding to the new information and resources (Putnam, 2000), as cited in Ellison, Steinfield, & Lampe, 2007). Meanwhile, bonding SC is a strong relationship that develops between people with similar backgrounds and interests (Ellison et al., 2007).

2.12 Conceptual Framework

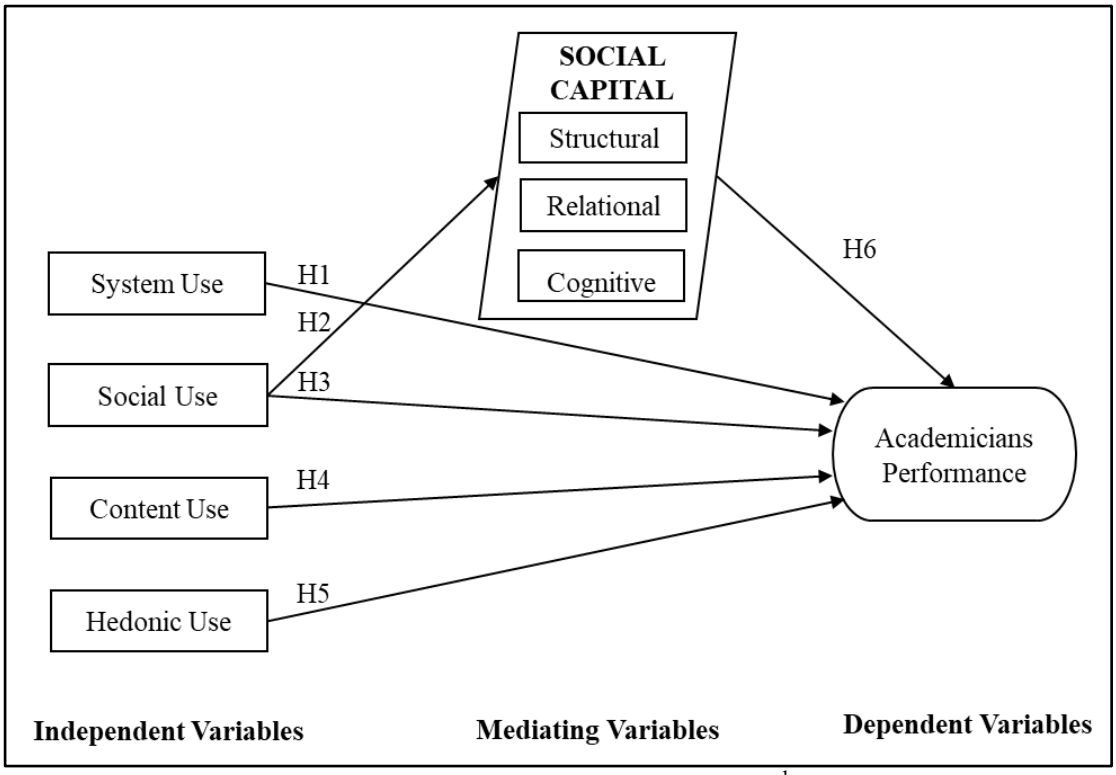


Figure 2.8 Conceptual Framework[1]

This study (refer to Figure 2.8) conceptualises SMU as a multidimensional construct encompassing social, content, hedonic, and SyU. Prior models such as TAM and UTAUT provide valuable foundations for understanding technology adoption, but extensions are required to capture the complexity of academic contexts (Masood et al., 2022; Guo et al., 2025). SU refers to interactions, collaborations, and engagements that foster academic and professional relationships (Arshad & Akram, 2018; Hou et al., 2024). CU involves accessing, sharing, and exchanging academic knowledge through digital platforms (Meishar-Tal & Pieterse, 2017; Borazon & Hsueh-Hua, 2023). Although primarily entertainment-driven, HU can indirectly influence academic outcomes by affecting satisfaction and engagement (Badr et al., 2024). SyU reflects the intensity and frequency of usage behaviours, indicating the embeddedness of SMU in academic routines (Junco, 2012; Kuş, 2025). By adopting these four dimensions, the

[1] The dimension originally referred to as 'Cognitive Use' in prior studies (e.g., Al-Rahmi et al., 2015) was relabelled as 'Content Use' in this study to reflect the nature of content interaction within social media platforms and to reduce terminological overlap with Cognitive Social Capital.

present framework emphasises how different patterns of SMU may strengthen SC and, subsequently, influence AP.

SC is defined in this study as the resources derived from academic networks and collaborative relationships (Bourdieu, 1986; Nahapiet & Ghoshal, 1998). Following Nahapiet and Ghoshal's (1998) framework, it is examined through three dimensions: structural capital (network ties and access to collaborators), relational capital (trust, reciprocity, and professional recognition), and cognitive capital (shared values and academic goals). In higher education, these dimensions facilitate mentoring, collaborative research, and disciplinary cohesion (Claridge, 2020; Yoon & Lee, 2022). With the rise of social media, scholars increasingly mobilise SC digitally through platforms such as ResearchGate and LinkedIn, which enhance collaboration, visibility, and knowledge transfer (Tajudeen et al., 2023; Majhi et al., 2025). Within this framework, SC is positioned as a mediating construct, linking SMU to AP by explaining how digital interactions are transformed into professional resources.

In Malaysian higher education, AP is formally evaluated based on teaching, supervision, research, consultation, publication, administrative/management tasks, and community service (Ishak et al., 2009; Aida Suraya Md. Yunus & Pang, 2015; Basarudin et al., 2016). These dimensions align with the MQA and institutional assessment systems such as SETARA, ensuring that individual achievement contributes to institutional excellence. Accordingly, this study adopts a seven-dimensional view of AP (teaching, supervision, research, consultation, publication, administration, and service) to reflect the holistic criteria used in Malaysia. This operationalisation enables a systematic examination of how SMU and SC jointly shape academians' professional effectiveness.

2.12.1 Hypotheses

H1: There is a relationship between SyU and AP.
H2: There is a relationship between SU and AP.
H3: There is a relationship between CU and AP.
H4: There is a relationship between HU and AP.
H5: There is a relationship between SC and AP.
H6: There is a relationship between SU and SC.

H7: There is a relationship between SU and AP as mediated by SC.

2.12.2 Explanation of Hypotheses

Based on the preceding discussion of the various models and variables related to SMU, and, in line with the current study, Figure 2.9 presents the conceptual model and the relationships among the constructs and the hypotheses.

2.12.2.1 System Use and Academician Performance

SyU refers to the habitual or technical engagement with social media platforms, often measured through indicators such as frequency of use, duration, and intensity (Murthy & Lewis, 2015; Elsayed, 2015). This dimension aligns closely with traditional IS research, emphasising the quantitative aspects of technology interaction, including time spent online and the number of interactions. In the context of higher education, consistent engagement with digital tools can enhance accessibility, visibility, and integration into professional environments.

Studies have demonstrated that frequent interaction with social media improves digital presence and facilitates communication among peers and students (Ansari & Khan, 2020; Jena, 2015). Nonetheless, these studies often treat social media as a single construct, failing to differentiate between types of use. In contrast, this study isolates SyU to examine its specific impact on AP, which encompasses teaching, research, supervision, and administrative duties.

While SyU may not directly influence complex tasks like research output or curriculum development, it is a foundational step toward more purposeful engagement. For example, academicians who regularly access platforms such as LinkedIn or Twitter may gradually transition from passive observers to active contributors, improving their professional productivity (Al Kurdi, 2024). Additionally, frequency of use has been linked to improved familiarity with digital tools, indirectly supporting job effectiveness by enabling better navigation of online learning environments and virtual collaboration spaces.

The TAM provides a theoretical foundation for this hypothesis, highlighting how PEU and frequency of access influence user behaviour and eventual performance outcomes (Davis, 1989). According to TAM, perceived usefulness and ease of use are

key determinants of continued usage behaviour. While initially developed for static systems, TAM has been adapted to explore SMA, particularly in structured educational contexts (del Valle et al., 2017).

Further support comes from the UTAUT, which identifies performance expectancy, effort expectancy, and social influence as critical factors shaping technology usage intentions (Venkatesh et al., 2003). Although UTAUT was initially designed for general technology adoption, it has been applied in academic settings to understand how regular platform interaction affects professional outcomes (Riady et al., 2022).

Therefore, this hypothesis posits a positive relationship between SyU and AP (H1). Empirical findings in related fields further support this hypothesis. A study found that habitual use of workplace social media platforms positively influenced job performance, particularly when users were familiar with the interface and had developed routines around their digital activities (Lee & Kwahk, 2010; Cui et al, 2020; Mohd Noor & Shahrom, 2021). Similarly, Junco (2012) observed that while frequency alone did not guarantee enhanced productivity, it did contribute to increased digital fluency, indirectly supporting task efficiency. This leads to the following hypothesis:

H1: There is a relationship between SyU and AP.

2.12.2.2 Social Use and Academician Performance

SU refers to using social media platforms for interpersonal communication, collaborative interaction, and professional networking. This dimension of use goes beyond mere access or frequency of engagement; it involves active participation in online discussions, maintaining connections with peers, joining academic groups, and leveraging digital networks for resource sharing and collaboration. The theoretical foundation for this hypothesis is drawn from SCT, which posits that individuals derive value from their relationships and network structures (Putnam, 2000; Nahapiet & Ghoshal, 1998). These relational resources are significant in academic environments, as they contribute to research partnerships, mentorship opportunities, student feedback, and institutional collaboration.

Empirical studies have demonstrated that SU enhances AP by fostering peer learning, increasing professional visibility, and facilitating collaborative research (Gruzd et al., 2012; Shah et al., 2017). For instance, academicians who engage in meaningful interactions on platforms such as LinkedIn, ResearchGate, or Twitter often experience increased recognition within their field, which can lead to invitations to co-authorship, speaking engagements, and leadership roles in academic communities. These outcomes influence performance metrics, such as publication rates, teaching evaluations, and institutional contributions.

The UGT further supports this hypothesis by suggesting that users actively select media based on personal and professional needs (Ruggiero, 2000; Turulja et al., 2022). According to UGT, academicians may use social media for information consumption, to belong to a scholarly community, gain peer recognition, and seek emotional support. These gratifications align closely with job-related performance indicators, where network strength, reputation, and collaboration play key roles in career advancement and productivity.

In addition, Kietzmann et al. (2011) proposed the honeycomb framework of social media, identifying relationships as one of its core functions. Their model highlights how identity management, presence, and group formation help users cultivate valuable connections, reinforcing that relational engagement via social media contributes to professional success. This perspective is especially relevant in higher education, where digital networking has become essential to academic life.

Studies focusing on social media integration in educational settings have shown that SU enhances knowledge exchange and interdisciplinary collaboration (Murthy & Lewis, 2015; Manca & Ranieri, 2016). For example, academicians using Facebook Groups or Slack channels for course coordination reported improved teaching delivery, student interaction, and peer feedback. These benefits translate into better classroom engagement, more efficient curriculum development, and greater access to teaching resources, all of which are components of AP. Moreover, Sun and Shang (2014) posited that social-related use of social media indirectly increases work-related use by improving familiarity and comfort with the platform. Over time, this leads to higher engagement in professional activities, including research promotion, student advising, and conference participation. Their findings indicate that 40% of the impact of social-related use on work-related use is mediated through SC, reinforcing the importance of SU in shaping professional outcomes.

From an organisational behaviour perspective, Esteve Del Valle et al. (2017) observed that social networking sites and document-sharing platforms enhance knowledge storage and dissemination, mainly when used for peer-to-peer learning and mentorship. This implies that relational engagement via social media builds trust and shared understanding, both of which are foundational elements of SC and critical for enhancing performance in academic roles.

In Malaysian higher education, the role of SU remains underexplored despite its potential to improve professional connectivity and support academic development. While prior studies have focused on general adoption patterns (Jena, 2015), few have examined how specific types of use affect performance. This study addresses that gap by testing whether SU significantly affects AP, particularly in research collaboration, student engagement, and peer mentoring.

AP is conceptualised in this study as a multidimensional construct comprising teaching, research and publication, supervision, and consultation. SMU can potentially influence each of these domains in distinctive ways. In the context of teaching, social media platforms facilitate timely communication, resource sharing, and collaborative learning with students, thereby enhancing pedagogical effectiveness. For research and publication, social media fosters scholarly networking, co-authorship opportunities, and the dissemination of findings through academic forums such as ResearchGate or LinkedIn. Within the domain of supervision, social media enables continuous informal guidance, progress monitoring, and quick feedback exchange between supervisors and postgraduate students. Lastly, in consultation, social media platforms offer avenues for engaging with industry partners, disseminating expert knowledge, and expanding professional visibility beyond institutional boundaries. These interactions contribute to a more connected, responsive, and impactful academic role.

Given this context, H2 hypothesises that SU significantly influences AP, as measured across multiple dimensions of professional effectiveness. This hypothesis is supported by both theoretical models and empirical evidence showing that purposeful networking and collaborative interaction improve job satisfaction and productivity (Wang et al., 2020; Schlagwein & Hu, 2016). This leads to the following hypothesis:

H2: There is a relationship between SU and AP.

2.12.2.3 Content Use and Academician Performance

CU refers to the purposeful engagement with social media for knowledge creation, information sharing, and scholarly discussion. It reflects how academicians use digital platforms to enhance their professional expertise, disseminate academic content, and engage in intellectual exchange. In higher education, CU plays a crucial role in shaping how academicians access, process, and apply knowledge, directly influencing teaching quality, research output, and institutional contributions.

Theoretically, this hypothesis is supported by the UGT, which emphasises that users actively select media based on personal and professional needs (Ruggiero, 2000; Turulja et al., 2022). Specifically, academicians seeking knowledge acquisition, professional development, and research visibility are more likely to use social media content. These gratifications align with career advancement goals and AP expectations, with scholarly impact often measured by publication records, citation counts, and research collaborations.

Empirical studies have indicated that CU enhances job performance by improving access to resources and fostering continuous learning (Vásquez et al., 2015; Meishar-Tal & Pieterse, 2017). For example, platforms such as ResearchGate, LinkedIn, and Academia.edu enable scholars to publish working papers, track citations, and receive peer feedback, thereby boosting academic productivity. According to Lim et al. (2020), these platforms also support digital scholarship, enabling researchers to connect with global networks and stay updated on emerging field trends. The honeycomb framework of social media functionality proposed by Kietzmann et al. (2011) further reinforced this hypothesis. The model identifies identity management, presence, personal identity, and reputation building as key functions of social media that support professional outcomes. These features enable academicians to curate their online profiles, establish credibility, and engage in meaningful scholarly discussions, all contributing to performance evaluation criteria such as research dissemination, teaching innovation, and service to the academic community.

In Malaysian HEIs like UiTM, AP is typically evaluated using multi-dimensional KPIs, including:

- Teaching effectiveness
- Supervision and mentoring
- Research output (e.g., publications, grants)

- Administrative and leadership roles
- Community or professional service

These metrics are often tied to promotion decisions and tenure evaluations, making the CU of social media a relevant study area. By leveraging platforms for information dissemination, peer review, and collaboration, academicians can improve their visibility, impact, and networking opportunities, all valued in performance appraisals.

Murthy and Lewis (2015) explored how social media supports knowledge-sharing behaviours among professionals and found that CU significantly contributes to work-related outcomes, particularly when integrated into daily practice. Their findings suggested that purposeful social media activity, such as posting summaries of research articles, commenting on peers' work, or organising virtual symposiums, enhances individual productivity and collective knowledge growth within academic communities.

Sun and Shang (2014) observed that social media usage patterns evolve from hedonic to content over time, especially among professionals seeking to build reputations and advance careers. In higher education, academicians may transition from casual browsing to active contribution, leading to improved performance indicators such as citation rates, co-authorship opportunities, and student engagement.

Further empirical evidence comes from Shah et al. (2017), who studied integrating social media into academic practices and found that CU leads to better research visibility, increased scholarly interaction, and enhanced academic reputation. These factors were strongly associated with higher performance ratings, especially in institutions where online presence and digital engagement are increasingly valued alongside traditional metrics.

Additionally, Jordan and Weller (2018) noted that professional branding and the showcasing of expertise via social media platforms positively influence academic recognition. Academicians who consistently share insightful commentary, lecture materials, or policy recommendations on digital platforms are often perceived as thought leaders, which aligns with institutional expectations for public engagement and knowledge transfer.

This hypothesis is also supported by the Updated DeLone and McLean ISSM, which includes system usage and user satisfaction as determinants of performance outcomes (DeLone & McLean, 2003). While initially developed for e-commerce systems, ISSM has been adapted to assess how digital tools, including social media, contribute to job effectiveness and organisational success (Kotsenas et al., 2018).

The CU of social media represents one of the most valuable applications of digital networking in academic settings. Supported by UGT and empirical findings, this hypothesis posits that CU significantly influences AP (H3), particularly in research dissemination, teaching enhancement, and professional visibility. This leads to the following hypothesis:

H3: There is a relationship between CU and AP.

2.12.2.4 Hedonic Use and Academician Performance

HU refers to the leisure-oriented, entertainment-driven, or non-academic engagement with social media. This dimension of use aligns with the UGT, which posits that individuals engage with media based on their gratifications, such as escape, relaxation, and self-expression (Katz, Gurevitch, & Haas, 1973; Ruggiero, 2000). In contrast to CU or SU, HU does not primarily aim at professional development or knowledge exchange but rather at personal enjoyment and digital leisure.

Theoretically, this hypothesis examines whether entertainment-based usage patterns detract from academic responsibilities and negatively influence performance outcomes. While some studies argue that HU motivates continued platform engagement by offering emotional satisfaction (Arshad & Akram, 2018), others suggest that excessive non-academic usage leads to distraction, time wastage, and reduced focus on core duties (Balakrishnan & Raj, 2016; Kuss & Griffiths, 2017).

In higher education, academicians must balance professional obligations with personal digital behaviours. However, suppose a significant portion of time is spent on non-productive activities such as watching videos, browsing memes, or engaging in informal discussions. In that case, it may reduce the time available for teaching preparation, research writing, or administrative tasks. This concern has been echoed in qualitative feedback from users who reported difficulty managing work-life boundaries due to frequent exposure to entertainment content during working hours.

Empirical studies have linked high levels of HU to reduced productivity across various professions. For instance, Junco (2012) found that students who engaged more with non-academic Facebook usage had lower GPAs, suggesting that distraction from educational goals can impact performance metrics. Similarly, Balakrishnan and Raj (2016) observed that excessive recreational use of social media among professionals was associated with lower job satisfaction and reduced task efficiency. These findings imply that hedonic gratification may motivate continued use but could also lead to diminished work-related outcomes. The honeycomb framework of social media functions proposed by Kietzmann et al. (2011) further supported this notion by identifying entertainment and self-expression as key purposes of social media usage. While these elements enhance user engagement, they do not directly contribute to knowledge creation, networking, or task completion, which are critical components of AP.

Additionally, Sun and Shang (2014) explored how different types of SMU affect work-related outcomes, finding that HU increases familiarity with platforms, but it does not significantly enhance professional effectiveness. Their study indicated that HU often precedes utilitarian use, but only when users transition toward purposeful engagement does it result in measurable benefits. This suggests that HU may serve as a gateway to platform adoption but, by itself, does not enhance performance.

Malaysian HEIs, such as UiTM, evaluate AP using multidimensional KPIs. Given these expectations, HU may conflict with professional demands, especially if academicians spend significant time on social media for entertainment rather than scholarly or instructional purposes. Prior studies (e.g., Cao & Yu, 2019) have highlighted how habitual scrolling through non-academic content reduces attention span and affects task prioritisation, both of which are essential for academic roles requiring deep concentration and structured workflows.

HU emphasises passivity, consumption, and self-gratification; as such, this type of use is unlikely to contribute meaningfully to peer learning, research collaboration, or academic networking. Murthy and Lewis (2015) examined how academics use social media and found that those who predominantly engaged in HU were less likely to integrate digital tools into their professional practice. They noted that while habitual use enhances digital fluency, it often remains superficial unless it transitions into information sharing, networking, or content creation.

This hypothesis assumes that HU may have a negative or neutral effect on AP, though the nature of the relationship remains to be empirically tested. If supported, it would highlight the importance of responsible social media integration in academic environments, particularly in institutions where digital behaviour is increasingly monitored and assessed for professional outcomes.

Therefore, H4 proposes that there is a relationship between HU and AP, potentially harmful or insignificant, depending on how frequently academicians engage in non-academic activities via social media. This leads to the following hypothesis:

H4: There is a relationship between HU and AP.

2.12.2.5 Social Capital and Academicians' Performance

The conceptual model for this study positions SC as a critical determinant of AP within HEIs. Grounded in SCT (Coleman, 1988; Putnam, 2000; Nahapiet & Ghoshal, 1998) and supported by the Resource-Based View (Barney, 1991), the model argues that the quality and structure of academic staff networks provide access to valuable resources, such as information, collaboration opportunities, and trust, that directly influence their performance outcomes. In knowledge-intensive environments like universities, performance is multidimensional, encompassing teaching, supervision, research, consultation, publication, and service contributions (Basarudin, Yeon, Yaacob, & Abd Rahman, 2016; Ishak, Suhaida, & Yuzainee, 2009).

SC enhances these performance dimensions through structural, relational, and cognitive components (Nahapiet & Ghoshal, 1998). Structural ties broaden academicians' access to collaborators, funding opportunities, and scholarly communities, directly supporting research, consultation, and publication activities. RSC, built on trust and reciprocity, facilitates mentorship, peer learning, and supervisory quality (Mondal, Sharma, & Panackal, 2025; Yoon & Lee, 2022). Meanwhile, CSC provides shared norms and common academic language that improve classroom communication, foster interdisciplinary teaching innovations, and align research goals (Ancillai, Donnini, & Panni, 2025). Collectively, these dimensions create a supportive environment for academicians to excel in core performance criteria emphasised by Malaysian HEIs.

In Malaysia, universities, including UiTM, systematically assess academic staff performance across teaching, supervision, research and publication, consultation, and community service (Aida Suraya Md. Yunus & Pang, 2015; Basarudin et al., 2016). The MQA and the SETARA rating framework further institutionalise these criteria as benchmarks of academic quality and institutional excellence. Within this framework, SC becomes an essential intangible resource that enables academicians to fulfil institutional expectations and progress in their careers. For instance, collaborative networks enhance research outputs and publication visibility, while strong collegial relationships improve teaching practices and student supervision outcomes.

Empirical studies reinforce this linkage between SC and job performance in academic and non-academic contexts. Negoro et al. (2025) noted that RSC and SSC significantly mediated the relationship between proactive behaviours and performance. Similarly, Majhi, Mukherjee, and Anand (2025) demonstrated that social media enhances professional performance only when interactions translate into SC that builds absorptive capacity. In higher education, these findings suggest that AP, measured through consultation, research, publication, supervision, and teaching, depends on individual capability and the quality of professional networks and trust-based relationships.

Therefore, building upon theoretical foundations and empirical insights, this study posits that SC positively influences AP in Malaysian higher education. The conceptual model proposes that structural, relational, and CSC interact to improve teaching effectiveness, supervisory quality, research productivity, consultation engagement, and publication output. This leads to the following hypothesis:

H5: There is a relationship between SC and AP.

2.12.2.6 Social Use and Social Capital

SU refers to social media for interpersonal interaction, professional networking, and collaborative communication. It captures the relational dimension of social media engagement, where users leverage digital platforms to build connections, exchange information, and establish trust-based relationships. This aligns with SCT, which emphasises that individuals derive value from their networks through access to resources, shared norms, and mutual understanding (Putnam, 2000; Nahapiet &

Ghoshal, 1998). In academic settings, SU enables academicians to maintain professional ties, collaborate on research, and engage in scholarly discussions beyond institutional boundaries.

The concept of SC encompasses three main components: structural, relational, and cognitive. SSC relates to the network structures and connections available to individuals. RSC involves trust, norms, and cooperation within those networks. CSC pertains to shared language, vision, and values among network members. The SU of social media has been suggested to influence all these dimensions by facilitating frequent interactions, enabling collaboration, and fostering shared understandings among peers (Murthy & Lewis, 2015).

Empirical studies have demonstrated that SU of LinkedIn, ResearchGate, and Twitter enhances professional visibility and facilitates academic outreach (Gruzd et al., 2012; Lapoe et al., 2017). These platforms allow academicians to follow colleagues' work, participate in virtual conferences, and engage in discussions that strengthen professional bonds. For example, Wang et al. (2020) found that digital networking significantly contributes to SC development, particularly by enabling access to expert knowledge and peer support. This supports the view that interpersonal use of social media leads to the formation of valuable relational resources.

Further evidence comes from Schlagwein and Hu (2016), who categorised SMU into types such as broadcast, dialogue, and sociability, each contributing to relationship-building in different ways. Broadcast functions allow for disseminating updates on academic activities, dialogue fosters two-way communication, and sociability enhances informal interaction, all of which are essential for building professional rapport and collaborative networks.

From a theoretical standpoint, UGT also supports this hypothesis. UGT suggests that users actively select media based on their needs, including belonging to a community, seeking recognition, and establishing relationships (Ruggiero, 2000). When applied to academic contexts, this theory implies that academicians are drawn to social media for content consumption and for relational benefits that contribute to SC (Turulja et al., 2022).

Additionally, Kietzmann et al. (2011) proposed the honeycomb framework of social media functionality, identifying relationships as one of the core purposes of platform usage. Their model highlights how features such as identity management,

presence, and groups help users cultivate meaningful connections, reinforcing the role of SU in enhancing SC.

In organisational and educational settings, Esteve Del Valle et al. (2017) observed that social networking sites and document-sharing platforms are essential tools for storing and disseminating knowledge, mainly when used for peer-to-peer learning and mentorship. This further supports the idea that relational engagement via social media enhances resource sharing and trust, both foundational elements of SC.

Moreover, Sun and Shang (2014) explored the indirect effects of social-related use on work-related outcomes, finding that non-academic interactions often lead to greater familiarity with the platform, thereby promoting more structured and purposeful use. This pathway explains how SU can gradually evolve into meaningful professional engagement, strengthening the foundation of SC over time.

Academic environments benefit from SU because it allows for peer feedback, co-authorship opportunities, and mentorship networks that may not be possible within traditional institutional frameworks. Shah et al. (2017) noted that platforms like LinkedIn and ResearchGate enhance visibility and reputation, which are important for career advancement and research impact.

This hypothesis is therefore supported by multiple theoretical perspectives and empirical findings, indicating that SU of social media contributes meaningfully to the formation of SC, which in turn plays a significant role in shaping academic outcomes. This leads to the following hypothesis:

H6: There is a relationship between SU and SC.

2.12.2.7 Social Use and Academician Performance as mediated by Social Capital

This hypothesis explores a mediated pathway in which the SU of social media influences AP through the development of SC. Unlike direct effects, this hypothesis posits that the impact of SU on AP is not immediate. Instead, it occurs indirectly through relational resources built through digital engagement.

From a theoretical perspective, this hypothesis is grounded in SCT, which posits that individuals gain value from their networks of relationships, including access to information, support, and collaborative opportunities (Putnam, 2000; Nahapiet &

Ghoshal, 1998). In academic environments, SC is essential for professional advancement, as it enhances:

- Peer collaboration
- Research dissemination
- Student interaction
- Institutional reputation

These outcomes are components of AP, particularly when evaluated using multidimensional KPIs such as teaching quality, research output, supervision, and administrative contributions. Empirical studies have demonstrated that digital networking primarily improves performance by accumulating relational resources (Wang et al., 2020; Ali-Hassan et al., 2015). For instance, academicians who engage in meaningful interactions on platforms such as LinkedIn, ResearchGate, or Twitter often experience increased recognition within their field, leading to invitations to co-authorship, speaking engagements, and leadership roles in academic communities.

The mediating role of SC has been tested across multiple contexts. Sun and Shang (2014) found that social-related use of social media indirectly increases work-related use by improving familiarity and comfort with the platform. Their study indicated that 40% of the impact of social-related use on work-related use was mediated through SC, reinforcing its importance in shaping professional outcomes.

Esteve Del Valle et al. (2017) further observed that social networking sites and document-sharing platforms enhance knowledge storage and dissemination, particularly for peer-to-peer learning and mentorship. This implies that relational engagement via social media builds trust and shared understanding, both of which are foundational elements of SC and critical for enhancing performance in academic roles.

In addition, Esteve Del Valle et al. (2017) noted that social media facilitates two types of use, social-related and work-related. While social-related use helps users become familiar with the platform, the work-related use, supported by SC, leads to measurable performance improvements. Studies such as those by Alajmi and Alasousi (2023) have empirically validated the mediating role of SC in the relationship between SMU and job performance. Their findings suggest that while social media usage may not directly improve productivity, the professional networks and trust relationships formed through these platforms contribute significantly to performance outcomes.

Furthermore, Wang et al. (2020) demonstrated that social media enables employees to build and maintain professional relationships, access valuable information, and secure network-based support. These activities increase SC, which improves job performance by granting access to critical resources and opportunities.

In the context of higher education, SC encompasses three key dimensions:

- SSC: Network structures and connections
- RSC: Trust, norms, and cooperation
- CSC: Shared language, vision, and values

SU of social media (e.g., posting updates, participating in discussions, following peers' work) supports all three dimensions by:

- Facilitating network expansion
- Encouraging trust-building through consistent interaction
- Promoting shared understanding through scholarly communication

Murthy and Lewis (2015) explored how academics use social media and found that those who engaged in purposeful networking experienced improved visibility, recognition, and collaboration over time. This aligns with the idea that SU fosters relational development, enhancing AP. Jordan and Weller (2018) also highlighted the role of professional branding and the showcasing of expertise via social media platforms. Academicians who consistently share insights and engage in dialogue develop stronger online reputations, which can lead to increased citations, invited talks, and funding opportunities, all indicators of academic success.

This hypothesis also draws support from the TAM and UGT. According to UGT, users select media based on personal and professional needs, including belonging to a community, seeking recognition, and gaining emotional support (Ruggiero, 2000; Turulja et al., 2022). Over time, these gratifications translate into stronger professional identities embedded in SC and reflected in performance evaluations. The honeycomb framework of social media functions proposed by Kietzmann et al. (2011) identifies relationships and reputation-building as core purposes of platform use. These features enable academicians to cultivate meaningful connections, eventually enhancing performance metrics such as research visibility, teaching effectiveness, and service to the institution.

This study tests whether SU enhances AP primarily by promoting SC development (H7). If supported, it would indicate that social media's most significant contribution lies not in direct usage; rather, it stems from the networks and trust it helps build. This mediated pathway offers a more nuanced understanding of how digital behaviour translates into professional outcomes. It suggests that institutions should encourage purposeful networking and structured engagement rather than simply general adoption. This leads to the following hypothesis:

H7: There is a relationship between SU and AP as mediated by SC.

2.13 Summary

Chapter 2 provides a comprehensive literature review to establish the theoretical and empirical foundation of this study. It begins by exploring the concept of social media, including its definitions, elements, categories, characteristics, and role in academia, culminating in a contextual definition of academic SMU for this research. A distinction is drawn between SMU and broader IT use to highlight their unique features. The chapter then examines AP, focusing on its dimensions within Malaysian HEIs, particularly UiTM. It discusses the relationship between SMU and job performance, emphasising the mediating role of SC. Various theoretical models, such as the UGT, TAM, and UTAUT, are reviewed and applied to explain social media's impact. Finally, the chapter outlines key variables, then presents a conceptual model and hypotheses that serve as the basis for this study.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the research methodology for examining the relationship between Social Media Use (SMU) and Academician's Performance (AP) among academicians. It outlines the research design, sampling techniques, questionnaire development, data collection processes, and the plan for data analysis. Additionally, the chapter details the variables and measurement tools used in the study. Together, these sections form a structured approach for gathering and analysing data to effectively address the Research Objectives (ROs).

3.2 Conceptual Framework of the Study

The structural model in this study delineates the predictive relationships between multidimensional SMU, Social Capital (SC), and AP. Grounded in the behavioural attributes operationalised in the survey instrument, the following subsections elucidate the theoretical logic underpinning hypotheses H1 through H7.

3.2.1 Direct Relationships (H1–H6)

The conceptual framework posits that purposeful engagement with social media for technical, social, and informational objectives directly facilitates professional productivity.

H1: The influence of System Use (SyU) on AP

Derived from survey attributes assessing the frequency and intensity of use, this path suggests that habitual engagement with academic platforms fosters digital habituation. A high frequency of visits to social media platforms by Universiti Teknologi MARA (UiTM) academicians ensures that they become technically

proficient and deeply integrated into the digital scholarly ecosystem, thereby enhancing the efficiency and execution of daily academic responsibilities.

H2: The influence of Social Use (SU) on AP

This hypothesised path posits that SU serves as a strategic driver for professional advancement among UiTM academicians. Within the university's ecosystem, engagement in digital networking and the fostering of new professional relationships significantly elevate an academician's global visibility and scholarly reputation. By actively participating in specialised social groups and academic communities on digital platforms, academicians can cultivate a diverse network of peers who share similar research interests. This communicative interaction acts as a vital precursor to excellence in research and consultation, as it facilitates expanded peer support and the seamless exchange of scholarly knowledge across institutional boundaries. Consequently, these expanded social ties empower UiTM academicians to strengthen their collaborative potential, ultimately leading to superior performance in meeting their professional and institutional objectives.

H3: The influence of Content Use (CU) on AP

This hypothesised path suggests that, for UiTM academicians, purposeful engagement with digital content is a vital mechanism for professional excellence. Within the university’s performance framework, the capacity to create, share, and search for scholarly information directly augments teaching expertise by enabling the integration of real-time, industry-relevant insights into the curriculum. Furthermore, this cognitive engagement facilitates the development of specialised knowledge essential to high-quality supervision across various academic levels and strengthens professional relationships with industry partners by disseminating expert content. By maintaining a presence at the forefront of their respective disciplines on social media platforms, academicians are better equipped to meet institutional Key Performance Indicators (KPIs), particularly by enhancing research quality and academic visibility. Ultimately, the effective utilisation of digital content ensures that scholarly output remains contemporary, relevant, and aligned with the university's strategic goals.

H4: The influence of Hedonic Use (HU) on AP

In contrast to utilitarian dimensions, HU is operationalised through attributes such as taking breaks, filling time gaps, and relaxation. The underlying logic suggests that while these behaviours fulfil affective needs, they potentially divert cognitive resources from institutional KPIs. Consequently, the study theorises a non-positive relationship, as entertainment-seeking behaviour does not inherently contribute to the core pillars of teaching, research, or supervision.

H5: The influence of SC on AP

This hypothesised path suggests that professional productivity among UiTM academicians is significantly driven by the integration of structural, relational, and Cognitive Social Capital (CSC). Within the UiTM context, a robust network characterised by trust, mutual integrity, and shared intellectual priorities effectively mitigates the common barriers to collaborative research. By cultivating strategic ties with peers across different universities, academicians gain access to vital work-related information and specialised advisory support. These external linkages facilitate high-impact cross-institutional publications and enhance the success rate of competitive grant applications. Consequently, the accumulation of these relational assets is a critical determinant of elevating overall AP and institutional competitiveness.

H6: The influence of SU on SC

This hypothesis posits that social media serves as a fundamental catalyst for the accumulation of SC within the academic profession. Behavioural attributes, such as collaborative engagement and digital networking, act as the primary drivers in establishing structural ties and fostering institutional trust. For academicians at UiTM, these digital interactions are essential for transforming informal acquaintances into reliable professional networks. The model suggests that in the absence of active social interaction, the critical relational resources, such as mutual reciprocity and shared scholarly norms, cannot be effectively accumulated. Consequently, social media usage

facilitates the development of the social infrastructure necessary for long-term academic excellence and collaborative success.

3.2.2 The Mediation Mechanism (H7)

H7: The influence of SU on AP as mediated by SC

This hypothesis encapsulates the mediation logic in which SC serves as the transformative engine that converts digital social interaction into tangible AP. Within the UiTM context, the study posits that professional networking and collaborative interaction on social media do not automatically lead to superior performance. Instead, these interactions must first be distilled into structural, relational, and CSC. For instance, an academician's effort in fostering new relationships significantly impacts high-level performance metrics, such as exceeding publication KPIs or securing industry consultancy, only when those connections are translated into relational resources, including institutional trust, mutual reciprocity, and shared scholarly norms. Thus, SC acts as the vital bridge that ensures digital engagement yields substantive professional outcomes.

3.3 Research Paradigm

A research paradigm provides the philosophical foundation that guides how a study is conceptualised, designed, and conducted (Park, Konge, & Atino, 2020; Ryan, 2018). Paradigms are typically defined by their ontological, epistemological, and methodological assumptions (Guba & Lincoln, 1994) and serve as a lens through which researchers approach inquiry. Paradigms serve as a lens through which researchers approach their inquiry, shaping the choice of methods and interpretation of findings.

This study is grounded in the positivist paradigm, which assumes that reality is objective, stable, and measurable through empirical observation. The positivist worldview emphasises testing theories, identifying causal relationships, and using structured instruments to collect quantifiable data (Creswell, 2014). In line with this paradigm, the present research adopts a quantitative approach to examine the dimensions of SMU, SC, and AP. The focus is on developing and validating measurement models and testing hypothesised relationships using statistical techniques.

The positivist paradigm is particularly appropriate for this study because it allows the application of established theories (e.g., the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and Social Capital Theory (SCT)) within a higher education context. Positivism enables generalisation of findings from a representative sample to a larger population, thereby contributing to theory testing and refinement (Neuman, 2014). By employing structured instruments, factor analysis, and structural modelling, the study aligns with the positivist emphasis on objectivity, reliability, and replicability (Saunders et al., 2009).

3.4 Research Methodology

This study adopted a quantitative research methodology, which emphasises objective measurement and statistical analysis of numerical data to test hypotheses and validate theoretical relationships (Creswell & Creswell, 2018). Quantitative methods were chosen because they enable the researcher to examine relationships among variables, generalise findings to a larger population, and provide statistical evidence for model testing (Hair et al., 2019). In the context of this research, a quantitative approach is appropriate, as it facilitates the validation of measurement models and the assessment of relationships among SMU, SC, and AP. The research began by identifying the dimensions of SMU through an extensive literature review. Based on the theoretical definitions, measurement items were generated to represent each dimension. The measurement of SMU was then empirically validated through Exploratory Factor Analysis (EFA) to identify the underlying factor structure and refine the scale, followed by Confirmatory Factor Analysis (CFA) to test the validity and reliability of the measurement model in the study context (Byrne, 2016; Worthington & Whittaker, 2006). Similarly, SC was measured using an adapted version of established instruments, ensuring that the items were contextually relevant to academicians in Malaysian Higher Education Institutions (HEIs). AP was operationalised based on a theoretical definition, and measurement items were developed accordingly. As with SMU, EFA and CFA were applied to AP measures to ensure construct validity and reliability (Hair et al., 2019). This structured quantitative approach allows for rigorous testing of the conceptual framework, ensuring that the constructs are both theoretically sound and empirically supported before proceeding to structural model analysis.

3.5 Research Design

This study employed a quantitative research design, integrating theoretical and empirical procedures, to develop and validate measurement models for SMU, SC, and AP. The process began with the generation of theoretical items for each construct, with dimensions defined based on established literature (DeVellis, 2017). These definitions served as the foundation for creating an initial pool of measurement items. Following this, expert validation was conducted to establish content validity, ensuring the items were representative, relevant, and clear (Lynn, 1986). Feedback from experts was used to refine and improve the measurement items before proceeding to large-scale data collection. Once data were collected, EFA was employed for each construct to identify the latent factor structure and assess whether the items aligned with the theorised dimensions (Worthington & Whittaker, 2006). EFA facilitated the empirical identification and removal of weak or cross-loading items, enhancing the reliability of the measurement model. Subsequently, CFA was conducted to validate the factor structure, assess construct validity (including convergent and discriminant validity), and confirm the suitability of the models for further structural modelling (Hair et al., 2019; Singh, Abdul Ghani, & Teoh, 2009). This sequential approach, from theoretical conceptualisation to empirical validation, was applied consistently to all constructs in the study, ensuring that the final measurement models were conceptually sound and statistically robust. The overall research process is illustrated in Figure 3.1, which outlines the study's step-by-step flow.

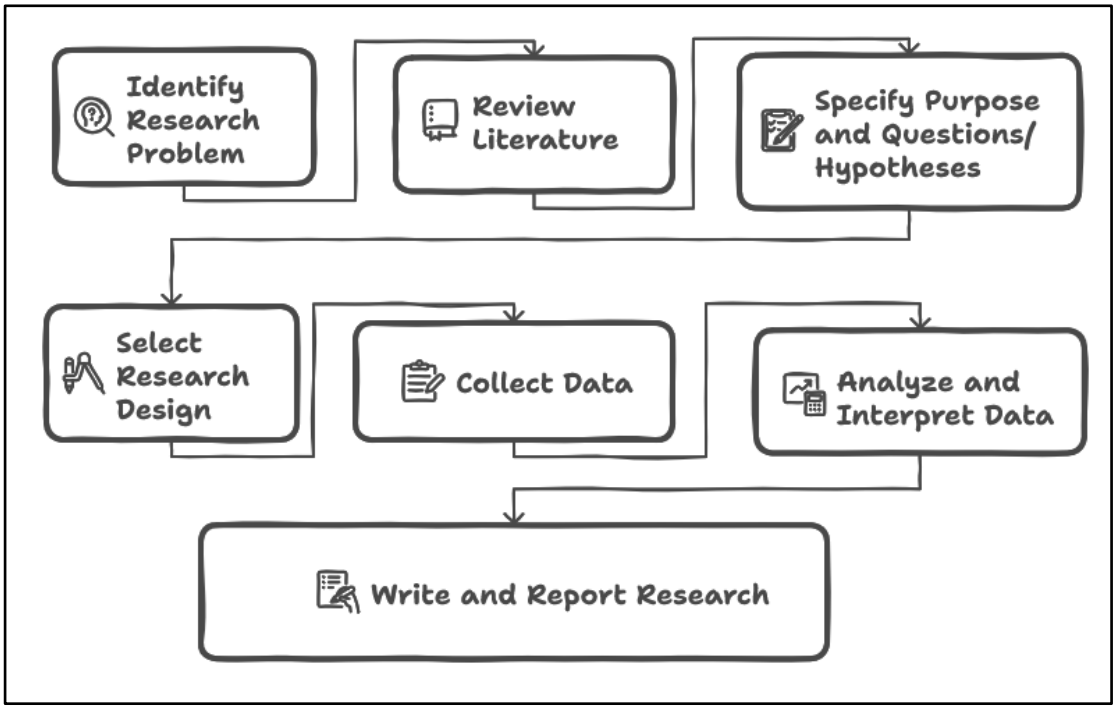


Figure 3.1 The Research Design Process Adapted from (Creswell & Creswell, 2018)

3.6 Sampling

In quantitative research, ensuring that the sample size is adequate to detect statistically significant effects is critical to study design. An a priori power analysis was conducted using the statistical software in GPower version 3.1 to determine this study's minimum required sample size. The analysis was based on the F test for linear multiple regression (fixed model, R^2 deviation from zero), which is suitable for testing the significance of multiple predictors in explaining variance in a dependent variable.

Following established guidelines in the social sciences, a medium effect size ($f^2 = 0.15$) was assumed, consistent with Cohen's (1988) conventions. The analysis was set to detect effects at an alpha level (α) of 0.05, with a desired statistical power of 0.95 ($1 - \beta$), which exceeds the minimum threshold of 0.80 recommended by Gefen, Rigdon, and Straub (2011). Four predictors were specified in the model, corresponding to the four dimensions of SMU examined in the study.

Based on Figure 3.2, the power analysis results indicated a noncentrality parameter (λ) of 19.35, with a critical F value of 2.4448, and degrees of freedom for the numerator and denominator set at 4 and 124, respectively. Based on these parameters, the minimum required sample size was 129 participants, yielding an actual power of

0.9506. This means the study had a 95.06% probability of detecting an actual effect, if one exists, thus minimising the risk of Type II error.

The sample collected for this study exceeded the minimum threshold, ensuring that the statistical analyses, including hypothesis testing and Structural Equation Modelling (SEM), were supported by a sample of sufficient size with adequate power. This strengthens the credibility and generalisability of the study's findings.

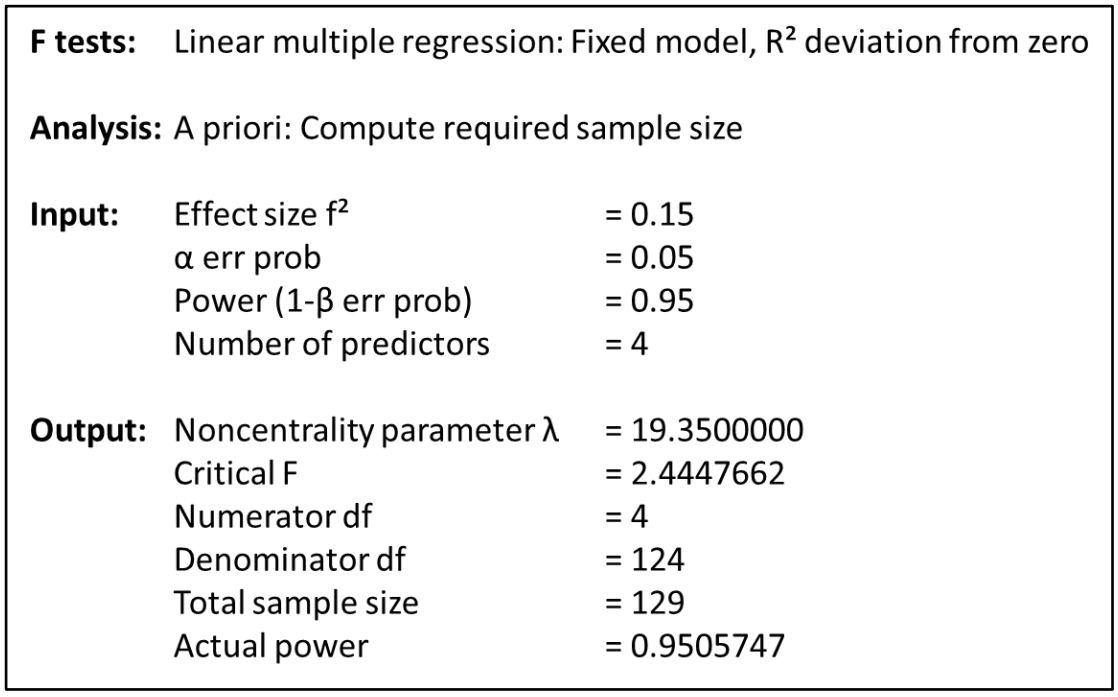


Figure 3.2 A Priori Power Analysis for Determining Minimum Sample Size in Multiple Regression

3.7 Questionnaire Development

This study employs a questionnaire to collect data. The questionnaire is used to study new and emerging contexts in the form of problems, tasks, or environmental conditions that have not been measured before. This study also employs a questionnaire to collect data to modify the existing theory. The questionnaire research involves item development, scale development, and scale evaluation. Firstly, item development involves identifying the domain, generating items, and ensuring content validity. Secondly, in scale development, pre-testing will be conducted during the administration, including sampling and survey administration, item reduction, and factor extraction. Lastly, scale evaluation will involve tests of dimensionality,

reliability, and factorial and external validity (Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H. R., & Young, 2018).

3.7.1 Justification for Mixed Scaling

To minimise Common Method Variance (CMV) and response bias, the questionnaire incorporated both 5-point and 7-point Likert scales. While most items used a standard 5-point format (e.g., Strongly Disagree – Strongly Agree), certain constructs, particularly those measuring abstract or nuanced perceptions, used a 7-point scale (e.g., 1 (Strongly Disagree) to 7 (Strongly Agree)).

This variation in response format reduces patterned responding and increases discriminant validity, aligning with best practices in survey design (Podsakoff et al., 2003; Malhotra et al., 2006). It also allowed for greater granularity in capturing subtle differences in perceived impact and usage levels.

3.7.1.1 Phase 1: Item Development

Items were generated based on theoretical definitions and existing validated scales. SyU (B1_SyU) was measured via frequency, duration, and intensity of platform interaction. SU (B2_SU) focused on communication, collaboration, and peer networking. CU (B3_CU) included knowledge sharing, content creation, and scholarly discussion. HU (B4_HU) reflected entertainment-driven usage. SC comprised structural, relational, and cognitive dimensions. Lastly, AP (D_AP) was evaluated across teaching, supervision, consultation, research, and publication. All items were carefully worded to reflect local academic realities and underwent expert validation and pilot testing. In this study, three experts, senior academicians with extensive teaching, research, and management experience, reviewed the items for clarity, relevance, and representativeness. The number of experts was determined according to methodological guidelines, which state that a minimum of three qualified experts is sufficient to ensure content validity (Lynn, 1986; Polit & Beck, 2006). This is further supported by Rubio et al. (2003), who emphasised that the quality and expertise of the panel are more critical than the size. Hence, selecting three experts with strong quantitative and subject-matter expertise provided confidence that the items demonstrated adequate face and content validity. Following expert validation, a pilot study was conducted to statistically assess

the reliability and validity of the measurement items, ensuring their suitability for the main data collection. Pilot studies are widely recommended in instrument development to evaluate item performance and methodological rigour (Hazzi & Maaldaon, 2015), while also providing guidance on appropriate sample sizes for preliminary testing (Johanson & Brooks, 2010; Kunselman, 2024).

3.7.1.2 Phase 2: Scale Development

During the pre-testing phase, the draft questionnaire was administered to 30 academicians at UiTM to assess comprehension, usability, and face validity. Feedback was used to rephrase ambiguous items, remove redundant ones, and ensure that the scale formats matched the measured constructs. After pre-testing, the final questionnaire comprised 69 items, distributed across six latent constructs.

3.7.1.3 Phase 3: Scale Evaluation

Following scale development, the instrument underwent rigorous validation:

- Convergent validity was assessed via AVE and outer loadings.
- Discriminant validity was evaluated using the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker criterion.
- Internal consistency was checked using Cronbach's Alpha and rho_C.

All constructs demonstrated strong psychometric properties, confirming the instrument's suitability for structural model testing.

3.7.2 Summary of Questionnaire Structure

Table 3.1 summarises the questionnaire structure used in this study, outlining the sections, their purposes, and the constructs measured. The questionnaire is divided into five main parts. Part A focuses on collecting demographic information of the respondents, including age, gender, campus, and years of experience. Part B examines academicians' social media usage patterns by measuring SyU, SU, CU, and HU. Part C evaluates the development of SC among academicians, covering the structural,

relational, and cognitive dimensions. Part D measures AP across key functional areas, namely teaching, research, supervision, administration, and service. Finally, Part E consists of an open-ended question designed to identify perceived problems related to SMU among academicians. Overall, Table 3.1 provides a clear overview of how the questionnaire components align with the study objectives and research constructs.

Table 3.1
Overview of Questionnaire Sections

Section	Purpose	Constructs Measured
Part A	Collect demographic information	Age, gender, Campus, Year of Experience
Part B	Assess social media usage patterns.	System Use (B1_SyU), Social Use (B2_SU), Content Use (B3_CU), Hedonic Use (B3_HU)
Part C	Evaluate social capital development.	Structural (C1_SSC), Relational (C2_RSC), Cognitive Social Capital (C3_CSC)
Part D	Measure academician performance	Teaching, Research, Supervision, Administration, Service
Part E	To identify problems of social media use among academicians	Open-ended question.

3.7.3 Sample Item from the Questionnaire

Table 3.2 below presents a sample of items from the final questionnaire. These items were designed to reflect both frequency and purpose of use, distinguishing between productive and non-productive engagement with social media.

Table 3.2
Sample Item

Constructs	Sample Items
System Use (B1_SyU)	Please rate in the range of scale 1(Never) to 5 (Every time) for the following statement about the frequency of social media site visits per week. Please rate in the range of scale 1(Never use) to 5 (Frequently use) for the following statement about how often you use social media.
Social Use (B2_SU)	SU1. I use social media to foster new relationships at work. SU2. I use social media to network with fellow academics from other institutions.

Constructs	Sample Items
	SU3. I use social media to maintain a close relationship with my colleagues.
	SU4. I use social media to explore social groups that share similar interests.
	SU5. I use social media to make acquaintances with individuals with the same interests.
Content Use (B3_CU)	CU1. I use social media to share useful information
	CU2. I use social media to search for relevant content based on my needs.
	CU3. I use social media to access useful information.
	CU5. I use social media to create content based on my interests.
	CU6. I use social media to create content based on my knowledge.
Hedonic Use (B3_HU)	HU1. I use social media to take a break from work.
	HU2. I use social media to fill a time gap.
	HU3. I use social media to get myself relaxed.
	HU4. I use social media as a source of entertainment.
Structural Social Capital (C1_SSC)	SSCE1. I have many acquaintances I consider friends
	SSCE2. I have established a good rapport with many acquaintances
	SSCE3. I have many acquaintances who support me through my personal problems
	SSCE4. I have many acquaintances with whom I feel comfortable disclosing my personal information
	SSCE5. I have many acquaintances I socially meet outside work
	SSCI1. I have many acquaintances whom I seek for work-related information
	SSCI2. I have many acquaintances whom I ask for work-related advice.
	SSCI3. I know many acquaintances whom I can approach whenever I need work-related advice.
	SSCI4. I provide answers to work-related questions posed by my acquaintances.
	SSCI5. I willingly provide work-related input to many of my acquaintances.
Relational Social Capital (C2_RSC)	RSC1. I have skilled acquaintances whom I trust.
	RSC2. I trust my acquaintances.
	RSC3. Generally, I rely on the acquaintances I work with.
	RSC4. I can work well with my acquaintances.
	RSC5. My acquaintances and I are confident in each other.
	RSC6. My acquaintances show high integrity.
Cognitive Social Capital (C3_CSC)	CSC1. I understand the information from my contacts.
	CSC2. I share my knowledge with my contacts.
	CSC3. It is easy to understand my contacts.
	CSC4. Sometimes it is challenging to understand my contacts.
	CSC5. There are different work priorities between my acquaintances and

Constructs	Sample Items
	me.
	CSC6. There is compatibility between information acquaintances and me.
	CSC7. I found it difficult to understand my acquaintances.
	APT5. I have an appropriate teaching method for the students.
	APT6. I have expertise in my area of teaching.
	APC2. I am well-known in my area of expertise.
	APC4. I have established a good relationship with the industry
Academician Performance (D_AP)	APS2. I conduct supervision at various academic levels.
	APS4. I have the skills to supervise the students.
	APP1. I will publish according to the university's KPI.
	APP2. I will publish based on my KPI.
	APP3. I am willing to publish more than my KPI.
	APP5. I predict to publish more than my KPI.
	APR3. I look forward to applying for a research grant.

3.8 Data Collection

Prior to the main data collection, expert validation was conducted with three senior academicians to refine the questionnaire items and ensure face validity. This step strengthened the clarity, relevance, and alignment of the measurement items with the academic context before survey administration (DeVellis, 2017; Hair, Black, Babin, & Anderson, 2019). A structured questionnaire was administered to academicians at UiTM for the primary data collection. The survey targeted academicians who actively use social media and are affiliated with different UiTM campuses across Malaysia. The questionnaire was distributed via official email channels to multiple campuses to ensure adequate geographic representation. A stratified random sampling technique was employed, with campus location as the primary stratification factor (Neuman, 2014; Saunders, Lewis, & Thornhill, 2009). This approach enabled the inclusion of respondents from all UiTM campuses while minimising sampling bias. Demographic data were also collected, including campus affiliation, age, gender, and years of academic experience. A total of 215 responses were received, of which 206 were valid and retained for further analysis. This exceeded the minimum sample size determined

by power analysis, enhancing the robustness of the study's findings (Cohen, 1992; Faul, Erdfelder, Buchner, & Lang, 2009).

3.8.1 Sampling Technique

A stratified random sampling technique was employed in this study to ensure that respondents were representative of the diverse academic staff across UiTM campuses in Malaysia. In stratified sampling, the population is divided into mutually exclusive subgroups (strata), and participants are randomly selected within each stratum (Cochran, 1977; Lohr, 2019). In this context, each UiTM campus represented a stratum, reflecting the institution's nationwide geographical spread. This method was selected to minimise sampling bias and to increase the likelihood that the final sample would capture the heterogeneity of academicians across different locations (Levy & Lemeshow, 2013). To determine the minimum sample size required for adequate statistical power, an a priori power analysis was conducted using GPower 3.1. It is important to note that *G*Power does not calculate sampling based on the total population size but instead estimates the minimum required number of respondents based on key statistical parameters: effect size, significance level (α), desired statistical power, and the number of predictors (Faul, Erdfelder, Buchner, & Lang, 2009). The results indicated that at least 129 responses were required to achieve a statistical power of 0.95, thereby minimising the likelihood of Type II error. A total of 215 responses were collected via the online survey platform, of which 206 were valid and included in the final analysis, exceeding the minimum sample size suggested by *G*Power. While some campuses contributed relatively fewer respondents than larger campuses, the inclusion of academicians from all strata ensured the representativeness of the overall population. The literature emphasises that, in disproportionate stratified sampling, including all subgroups is more critical than maintaining proportionality, particularly when subgroup-level comparisons are not the primary RO (Kish, 1965; Levy & Lemeshow, 2013). Thus, the adopted strategy was both statistically sufficient and methodologically appropriate to address the objectives of this study.

3.8.2 Survey Administration

The final questionnaire was hosted on Google Forms and distributed via institutional email. From April to August 2024, participants were asked to complete the survey, and reminder emails were sent during data collection to improve response rates. The Google Forms interface was designed to ensure clarity and ease of completion:

- Each section was clearly labelled (Part A–E)
- Instructions were included at the beginning of each section
- Clear navigation and formatting
- Logical grouping of constructs
- Mobile-friendly layout for accessibility

Reminder emails were sent every two weeks during the data collection period to encourage participation and increase the response rate.

3.8.3 Sample Item from the Questionnaire

Before data collection, the research was conducted in line with UiTM's ethical research practices, which did not mandate formal ethics approval for this study. Nevertheless, ethical standards such as informed consent, voluntary participation, and data confidentiality were fully upheld.

- Voluntary participation
- Informed consent
- Confidentiality and anonymity
- Non-coercion
- Data protection

Although formal ethics approval was not mandated by UiTM for this particular cohort and study type, the research was conducted in full adherence to ethical standards in social science research. All participants were informed of the study's purpose, their voluntary participation, and the confidentiality of their responses.

A clear informed consent statement was included at the beginning of the questionnaire (Figure 3.3). No identifying personal data was collected. Responses were anonymised and securely stored for academic use only. The study adhered to the principles of respect, beneficence, and non-maleficence, ensuring participants' rights and dignity were always protected. Participants were informed about the study's purpose and assured that their responses would be used solely for research.



SOCIAL MEDIA USE (SMU) AND ITS IMPACT ON ACADEMICIAN PERFORMANCE IN MALAYSIA

Dear Professor/ Associate Professor/Dr./Mr./Mrs./Ms.

My name is Zuraidah binti Arif, and I am a Ph.D. student at the School of Information Science, College of Computing, Informatics, and Mathematics, Universiti Teknologi MARA. I would like to invite you, Professor/ Associate Professor/Dr./Mr./Mrs./Ms. to participate in this survey on social media use and its impact on academician performance in Malaysia. This survey consists of four sections, demographic, social media use, social capital, and academician performance.
The purpose of this study is to study the way social media use impacts Malaysian academician performance. Your kindness in completing the questionnaire is very much appreciated. This questionnaire will take approximately 13 – 15 minutes to complete. Your responses are greatly valued. There is no right and wrong answer. Your responses will be strictly confidential for academic purposes only. If you have any queries or concerns about the questionnaire, please do not hesitate to contact me at 011-56658028.

Thank you for taking the time to participate in this research.
جَزَاكَ اللهُ خَيْرًا
May Allah reward you [with] goodness

ZURAIDAH BINTI ARIF
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College Of Computing, Informatics, and Mathematics
Universiti Teknologi MARA
Phone: +6011156658028
Email: zuraidah_arif@uitm.edu.my

Figure 3.3 Sample from Questionnaire

3.8.4 Sample Item from the Questionnaire

Upon collecting the Table 3.2 data, it was exported from Google Forms into Statistical Package for the Social Sciences (SPSS) 26 for initial screening. Missing values were identified and handled using pairwise deletion. Outliers were assessed

using Mahalanobis distance and Cook's D statistic (Hair, Black, Babin, & Anderson, 2019). Straight-lining responses were flagged and removed if more than 10% of items showed identical responses. After screening, the dataset was imported into SmartPLS 4 for further analysis, including construct validation, structural modelling, and mediation testing.

3.9 Pilot Test

Before the main data collection, a pilot test was conducted to examine the survey instrument's clarity, reliability, and feasibility. Pilot testing is a critical step in instrument development, as it allows researchers to identify issues with wording, structure, and reliability before large-scale administration (DeVellis, 2017; Bryman & Bell, 2015). A total of 30 academicians participated in the pilot study, which is consistent with the recommended range of 10 to 30 respondents for pilot testing in social science research (Hertzog, 2008; Johanson & Brooks, 2010). The pilot test also provided preliminary reliability evidence, ensuring the constructs were suitable for further validation in the main study (Hair et al., 2019).

3.9.1 Pilot Test Results

A pilot test was conducted with 30 participants to evaluate the reliability of the measurement items. According to Nunnally and Bernstein (1994) and Hair et al. (2019), a Cronbach's Alpha value of 0.70 or above is acceptable for internal consistency. The results in Table 3.3 indicate that all constructs exceeded this threshold. For SMU, reliability values ranged from 0.755 to 0.886 across system, social, content, and hedonic dimensions. For SC, Cronbach's Alpha values ranged from 0.781 to 0.967, while AP dimensions recorded values between 0.740 and 0.915. These findings indicate that the measurement items demonstrate satisfactory reliability for the main study. Since the primary purpose of a pilot test is to ensure clarity, feasibility, and reliability (Hertzog, 2008; Johanson & Brooks, 2010), further validation, such as EFA, will be performed using the larger primary study dataset.

Table 3.3
Sample Item (N=30)

Construct	Dimension	Cronbach's Alpha	Number of Items
Social Media Use	System	0.765	3
	Social	0.886	5
	Content	0.79	5
	Hedonic	0.755	5
Social Capital	Structural	0.96	10
	Relational	0.967	6
	Cognitive	0.781	7
Academicians' Performance	Supervision	0.915	5
	Teaching	0.826	6
	Consultation	0.74	4
	Research	0.866	6
	Publication	0.895	6
	Administration & Management	0.914	6
	Social Service	0.87	4

Note. Reliability was assessed using Cronbach's Alpha. Values above 0.70 indicate acceptable internal consistency (Nunnally & Bernstein, 1994; Hair et al., 2019).

3.10 Plan for Data Analysis

This section outlines the step-by-step data analysis procedures (Figure 3.4) used to test the research hypotheses and answer the Research Questions (RQs).

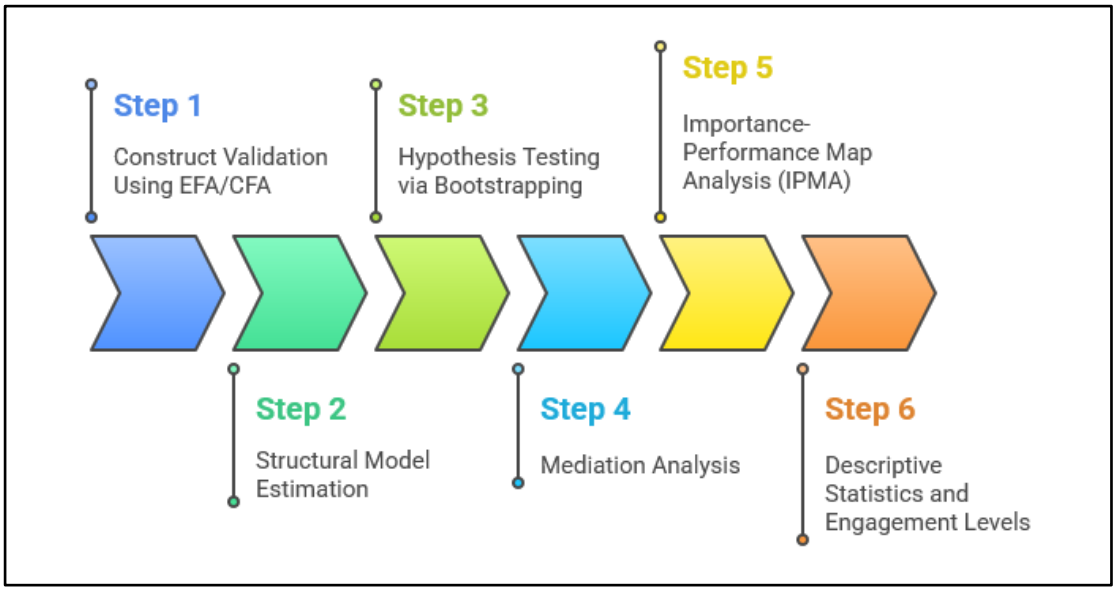


Figure 3.4 Data Analysis Procedure

3.10.1 Step 1: Descriptive Statistics and Engagement Levels

Descriptive statistics were computed in SPSS 26 to provide an overview of engagement across each dimension of SMU and AP. The analysis included measures of central tendency (mean), variability (standard deviation), and distributional properties (skewness and kurtosis), alongside frequency distributions. These statistics provided contextual support for interpreting the measurement model results presented in Section 4.3 and the Importance-Performance Map Analysis (IPMA) in Section 4.7, particularly in understanding usage intensity patterns and relative construct performance. Descriptive analysis also served as a preliminary step to ensure that the data met assumptions of normality and to contextualise subsequent inferential analyses (Hair, Black, Babin, & Anderson, 2019; Tabachnick & Fidell, 2019).

3.10.2 Step 2: Construct Validation Using EFA/CFA

3.10.2.1 Exploratory Factor Analysis (EFA)

EFA was conducted in SPSS to examine each construct's underlying factor structure and assess unidimensionality. The EFA results informed the retention of items, which were subsequently validated using CFA in the SmartPLS environment. Item retention followed established guidelines:

- Factor loadings ≥ 0.50 (with ≥ 0.70 considered ideal; Hair, Hult, Ringle, & Sarstedt, 2017; Tabachnick & Fidell, 2019)
- Absence of substantial cross-loadings
- Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy > 0.60 (Kaiser, 1974)
- Bartlett's Test of Sphericity $p < 0.05$ (Bartlett, 1954)

EFA was critical for refining the dependent variable, AP. The analysis revealed a clear four-factor solution corresponding to Teaching, Supervision, Research & Publication, and Consultation. These dimensions are conceptually aligned with AP benchmarks outlined in Malaysian higher education performance frameworks, such as the UiTM Academic Staff Performance Appraisal System. Consequently, AP was

modelled as a Higher-Order Construct (HOC) using the Repeated Indicator Approach in SmartPLS. This allowed for a more theoretically robust and empirically supported representation of the multifaceted nature of AP.

3.10.2.2 Confirmatory Factor Analysis (CFA)

CFA was conducted using SmartPLS 4 to assess the measurement model's reliability and validity. Three types of validity were examined:

- Convergent Validity:
  - Assessed using outer loadings (≥ 0.70; items between 0.40–0.70 may be retained if Average Variance Extracted (AVE) and CR are adequate) (Hair, Hult, Ringle, & Sarstedt, 2018; Hair, Risher, Sarstedt, & Ringle, 2019)) and (AVE ≥ 0.50) (Hair et al., 2017; Hair et al., 2022).
- Discriminant Validity:
  - Discriminant validity was primarily verified using the HTMT ratio. Following Henseler et al. (2015) and Hair et al. (2022), a threshold of < 0.90 was utilised (or < 0.85 for a more conservative assessment) to ensure each construct is conceptually unique.
  - The square root of the AVE for each construct was compared against its correlations with other constructs, ensuring the square root of the AVE is higher than any inter-construct correlation (Hair et al., 2017; Hair et al., 2022).
- Internal Consistency Reliability:
  - Internal consistency reliability was primarily assessed using Composite Reliability (rho_c), with a required threshold of ≥ 0.70 (Hair et al., 2022). Additionally, rho_a was monitored to ensure a consistent estimate of reliability, as it provides a more precise representation of construct stability in PLS-SEM (Hair et al., 2019; Hair et al., 2022).

3.10.3 Step 3: Structural Model Estimation

The structural model was assessed using the Partial Least Squares (PLS) algorithm in SmartPLS, which estimates the relationships among latent constructs and evaluates the model's explanatory power (Hair et al., 2017; Hair et al., 2022). Structural model estimation involved computing path coefficients (β) to assess the strength and direction of hypothesised relationships, R^2 values to indicate the variance explained in the endogenous constructs, and f^2 effect sizes to evaluate the relative contribution of each exogenous variable to the model (Cohen, 1988; Hair et al., 2022). In line with best practices in PLS-SEM, bootstrapping with 5,000 subsamples was employed to test the statistical significance of the path coefficients and indirect effects, providing t-values, p-values, and bias-corrected confidence intervals (Chin, 1998; Nitzl, Roldán, & Cepeda, 2016).

The hypothesised structural paths tested in this study were as follows: (1) SyU → AP, (2) SU → AP, (3) CU → AP, (4) HU → AP, (5) SC → AP, and (6) SU → SC. In addition to these direct effects, the model also examined the mediating role of SC in the relationship between SU and AP (SU → SC → AP). This approach ensured both direct and indirect effects were captured, providing a comprehensive understanding of how different dimensions of SMU, together with SC, contribute to AP.

3.10.4 Step 4: Hypothesis Testing via Bootstrapping

Bootstrapping was performed with 5,000 subsamples to assess statistical significance, in line with Hair, Hult, Ringle, and Sarstedt's (2022) recommendation that at least 5,000 resamples provide stable estimates and accurate standard errors. This procedure generated three key outputs:

- t-values where significance is typically established at $t \geq 1.96$ for a two-tailed test at $\alpha = 0.05$ (Hair et al., 2022; Kline, 2015).
- p-values with significance determined at $p < 0.05$ as the conventional threshold in behavioural and social science research (Cohen, Cohen, West, & Aiken, 2013; Hair et al., 2022).
- Bias-corrected confidence intervals are particularly relevant for testing mediation effects, as they provide more accurate estimates of indirect effects

and do not assume normality of the sampling distribution (Preacher & Hayes, 2008; Hayes, 2018).

This multi-criteria approach ensured rigorous and reliable hypothesis testing, strengthening the validity of the causal inferences drawn from the structural model.

3.10.5 Step 5: Mediation Analysis

Mediation was assessed using the Baron and Kenny (1986) framework, supplemented with the bootstrapping procedure in SmartPLS. Following recommended guidelines (Hair, Hult, Ringle, & Sarstedt, 2017; Nitzl, Roldán, & Cepeda, 2016), the procedure involved:

- Testing the direct effect (c-path): SU → AP.
- Estimating the a-path: SU → SC.
- Estimating the b-path: SC → AP.
- Assessing the indirect effect: SU → SC → AP.
- Applying bootstrapping with 5,000 subsamples to generate t-values, p-values, and bias-corrected confidence intervals for significance testing (Hair et al., 2022).
- Calculating the Variance Accounted For (VAF) to determine the type of mediation. A VAF of less than 20% indicates no mediation, between 20% and 80% indicates partial mediation, and above 80% indicates full mediation (Hair et al., 2017).

This procedure ensured that both direct and indirect pathways were rigorously tested and that the extent of mediation was clearly classified.

3.10.6 Step 6: Importance-Performance Map Analysis (IPMA)

IPMA was conducted within SmartPLS to derive practical implications. IPMA compared construct importance (based on β-coefficients) and construct performance (based on mean scores). This allowed for identifying:

- Constructs with high importance but low performance → Suggested areas for improvement
- Constructs with high importance and high performance → Indicated effective implementation
- Constructs with low importance but high performance → Highlighted potential over-investment

3.11 Tools of Data Analysis

This study employed two complementary software tools, IBM SPSS 26 and SmartPLS 4, to ensure comprehensive and rigorous data analysis. Each served distinct yet interrelated purposes aligned with the ROs.

IBM SPSS was first used for data screening and preliminary analysis. Tasks included handling missing values, testing normality, assessing internal consistency reliability (Cronbach's alpha), and conducting EFA to uncover the underlying factor structure of items. SPSS is widely recognised for its robust handling of large datasets and ease of implementation, making it a standard choice for initial data diagnostics and descriptive statistics (Pallant, 2020). By applying SPSS before structural modelling, the study ensured that only valid, reliable, and well-structured data entered the PLS-SEM stage, thereby reducing the risk of model misspecification (Hair et al., 2017; Kline, 2016). In this regard, SPSS served as a data screening tool to ensure the dataset's reliability and readiness.

SmartPLS was then employed for CFA, measurement model validation, and hypothesis testing via SEM. The choice of SmartPLS was particularly appropriate as the study's constructs were multidimensional and conceptualised as HOCs. For example, SMU and SC were captured through multiple subdimensions, while AP was modelled using several subdomains. PLS-SEM is especially effective in this context, as it supports the estimation of Hierarchical Component Models (HCMs) while simultaneously overseeing complex structural relationships (Hair, Hult, Ringle, & Sarstedt, 2022; Sarstedt, Hair, Cheah, Becker, & Ringle, 2019).

HOCs provide a means of modelling abstract multidimensional concepts while retaining their specific subdimensions. In this study, SC and AP were modelled as Type I reflective-reflective HOCs, in which both the HOC and its lower-order components (LOCs) are reflective. This specification is most suitable when dimensions represent

distinct but correlated manifestations of a common underlying concept (Becker, Klein, & Wetzels, 2012; Sarstedt et al., 2019). Evaluating reflective HOCs requires establishing reliability and validity at both the LOC and HOC levels, and SmartPLS offers an efficient implementation through repeated indicators and a two-stage approach.

The selection of SmartPLS is further supported by the ongoing methodological debate between Covariance-Based SEM (CB-SEM) and PLS-SEM. While CB-SEM is often preferred for theory testing and model fit assessment, PLS-SEM is particularly suited to prediction-oriented studies, models with formative or composite constructs, and conditions involving non-normal data distributions or moderate sample sizes (Hair et al., 2021; Dash & Paul, 2021). The introduction of PLSc-SEM (consistent PLS) has addressed earlier concerns regarding parameter bias in reflective models, further strengthening PLS-SEM's methodological credibility (Dijkstra & Henseler, 2015a, 2015b; Sarstedt, Ringle, & Hair, 2017). Comparative evidence demonstrates that SmartPLS offers methodological flexibility by combining prediction-oriented PLS-SEM and factor-consistent PLSc-SEM approaches, yielding results comparable to CB-SEM while remaining robust under challenging data conditions (Rigdon, 2016; Sarstedt et al., 2022).

Moreover, PLS-SEM was particularly advantageous for addressing this study's objectives, namely, testing the mediating role of SC and validating multidimensional constructs. Unlike CB-SEM, which assumes multivariate normality and requires larger sample sizes, PLS-SEM allows robust testing under moderate sample conditions and in models that integrate reflective and formative specifications (Gefen, Rigdon, & Straub, 2011). Thus, SmartPLS provided the methodological rigour necessary to model the complexity of the relationships among SMU, SC, and AP more effectively than CB-SEM approaches. The systematic sequence of steps employed in the SEM analysis is summarised in Table 3.4.

Table 3.4
Procedural Steps for Data Analysis in SEM

Step	Procedure	Software Used
1. Data Screening & Preparation	Handling missing data, outlier detection, and normality checks	SPSS
2. Reliability & EFA	Internal consistency, reliability, and Exploratory Factor Analysis	SPSS
3. Measurement Model (CFA)	Convergent & discriminant validity checks	SmartPLS
4. Structural Model Assessment	Path coefficients, R^2, effect size (f^2), predictive relevance (Q^2)	SmartPLS
5. Mediation & Higher-Order Constructs	Testing mediating effects, estimating hierarchical component models	SmartPLS
6. Advanced Analysis	Importance-Performance Map Analysis (IPMA)	SmartPLS

In addition to the above, the SEM procedure involves a more theoretical and conceptual sequence, as highlighted by Dash and Paul (2021), as outlined in Table 3.5. Their framework underlines the transition from construct definition to empirical validation, ensuring that SEM analysis is statistically sound and theoretically grounded.

Table 3.5
Steps Involved in the Process of SEM (Adapted from Dash & Paul, 2021)

Step	Description	References
Step 1: Individual Constructs	Define latent variables (constructs) clearly in the hypothesised model. Constructs must be grounded in theory (structural and measurement). Theories serve as the primary foundation to define constructs.	Hair Jr. et al. (2020); Maydeu-Olivares et al. (2018); Bentler (1990)
Step 2: Preparing for CFA	Specify the measurement model. Assign observed indicators to constructs and draw a path diagram. Include indicator loadings and error terms as appropriate.	Dash et al. (2021); Dash & Chakraborty (2021); Shi & Maydeu-Olivares (2020)
Step 3: Running CFA	Assess reliability (Composite Reliability ≥ 0.70; values ≥ 0.60 acceptable in exploratory research), convergent validity (indicator loadings ≥ 0.70 preferred; 0.40–0.70 acceptable if justified; AVE ≥ 0.50), and discriminant validity (no cross-loadings, constructs remain distinct). Ensure unidimensionality. Assess data normality (skewness/kurtosis between -2 and +2). Evaluate model fit indices (absolute,	Hair et al. (2017, 2011, 2010); Chin (1998); Malhotra et al. (2006); Hu & Bentler (1999)

Step	Description	References
	incremental, parsimonious). Modify the model if necessary.	
Step 4: Structural Modelling	Establish theoretical linkages among constructs. Test hypothesised paths and evaluate structural relationships using path coefficients. Assess the overall model fit and compare it with alternative models. Validate underlying theories with empirical data.	Mueller & Hancock (2018); Hair Jr. et al. (2017); Hayes et al. (2017); Ullman & Bentler (2003)
Step 5: Findings	Draw conclusions based on statistical results and study objectives. Provide theoretical and practical recommendations derived from the validated model.	Dash et al. (2021); Hair et al. (2010)

Overall, SPSS was used for data screening and exploratory analysis, while SmartPLS was employed for confirmatory and structural modelling of HOCs. This approach reflects best practices in contemporary research methodology, where preliminary statistical checks (SPSS) are combined with advanced predictive modelling (PLS-SEM/PLSc-SEM) to ensure reliability, validity, and robustness of findings (Hair et al., 2019; Hair et al., 2021; Dash & Paul, 2021; Kline, 2016).

3.12 Variables and Measurement

This study conceptualises and operationalises its core constructs based on established theoretical foundations and newly developed items. Table 3.6 presents the primary variables, their corresponding dimensions, conceptual definitions, and sources of measurement.

Table 3.6
Summary of Constructs and Measurement

Variable	Dimension	Definition	Measurement Source
Social Media Use (SMU)		SMU refers to how academicians engage with social media platforms for various purposes, including communication, knowledge sharing, entertainment, and frequency of use.	-
	Social Use (SU)	The use of social media for communication, collaboration, and networking with peers or groups. It includes forming new connections, maintaining relationships, and participating in collaborative work such as research.	Adapted and rephrased from Ali-Hassan et al. (2015)
	Content Use (CU)	Social media is used to search, consume, and share knowledge and information for academic purposes.	Adapted and rephrased from Ali-Hassan et al. (2015)
	Hedonic Use (HU)	The use of social media for personal enjoyment, relaxation, and entertainment purposes.	Adapted and rephrased from Ali-Hassan et al. (2015)
	System Use (SyU)	The extent of social media usage is measured in frequency, duration, and intensity of interaction with social media platforms.	Adapted and rephrased from Venkatesh et al. (2003); modified for academic context
Social Capital (SC)		Social Capital is the network of relationships that facilitates collective action and access to resources within academic communities.	-
	Structural Social Capital (SSC)	Networking relationships between individuals or groups with diverse backgrounds, where connections are not based on prior experience.	Adapted from Ali-Hassan et al. (2015)
	Relational Social Capital (RSC)	Networking relationships based on familiarity or past experiences (e.g., among co-workers, classmates, or colleagues).	Adapted from Ali-Hassan et al. (2015)
	Cognitive Social Capital (CSC)	The shared understanding, language, and interpretation among individuals includes the ability to communicate effectively within a community of practice.	Adapted from Ali-Hassan et al. (2015)
Academician Performance (AP)		Academician performance is defined as the professional achievements of academicians across teaching, research, supervision, consultation, publication, and community service.	Adapted from the SETARA rating system; Pekeliling Timbalan Naib Canselor (Penyelidikan dan Inovasi), Bilangan 01 Tahun 2020

3.13 Chapter Summary

This chapter outlined the research methodology adopted to investigate the impact of SMU on AP in Malaysian HEIs. It described the philosophical underpinnings of the study, which employed a positivist paradigm and a quantitative research design. The chapter explained the multi-phase approach used to develop and validate the research instrument, beginning with item generation based on theory and literature, followed by expert review, pilot testing, and refinement based on EFA and CFA using SmartPLS. The constructs measured in the study included four dimensions of SMU (SyU, SU, CU, and HU), three sub-dimensions of SC (Structural, Relational, and Cognitive), and the dependent variable, AP, consisting of sub-dimensions such as teaching, research and publication, supervision, and consultation. Each construct was measured using validated or adapted items, with care taken to ensure contextual relevance and content validity. The sampling strategy employed stratified random sampling, with campus location as the primary stratification factor to ensure geographic and disciplinary representation. Data were collected via an online questionnaire distributed to academicians across multiple UiTM campuses. Ethical research practices were maintained throughout the study, including obtaining informed consent, voluntary participation, and maintaining the confidentiality of responses. The next chapter, Chapter 4, presents the results of the data analysis, including descriptive statistics, measurement model validation, structural model testing, and mediation analysis.

CHAPTER 4
RESULTS

4.1 Introduction

This chapter presents empirical findings on the relationship between Social Media Use (SMU), Social Capital (SC), and Academicians' Performance (AP) in Malaysian Higher Education Institutions (HEIs). Data analysis was conducted using SPSS and SmartPLS, incorporating measurement and structural model assessments via Partial Least Squares Structural Equation Modelling (PLS-SEM). The measurement model was evaluated for indicator reliability, internal consistency, convergent validity (via AVE), and discriminant validity (via Heterotrait-Monotrait Ratio (HTMT), along with multicollinearity checks (Variance Inflation Factor (VIF)). Once validity and reliability were confirmed, the structural model was tested to examine direct effects, explanatory power (R^2), and effect sizes (f^2). Mediation analysis assessed the role of SC as an intermediary between SMU and AP. The chapter begins with the respondents' demographic profile, followed by descriptive analysis and qualitative insights from open-ended responses. It continues with evaluations of the measurement and structural models, mediation analysis, and Importance-Performance Map Analysis (IPMA). It concludes with a summary of the hypothesis testing results. This chapter presents the results of the data analysis, following the step-by-step plan outlined in Section 3.9. Table 4.1 summarises the alignment between the data analysis plan and the reported results. Although the findings are reported thematically for clarity, the sequence of analysis strictly adheres to the procedures specified in Chapter 3, beginning with construct validation, followed by structural model estimation, hypothesis testing, mediation analysis, importance-performance map analysis, and descriptive assessment.

Table 4.1
Alignment Between Data Analysis Plan and Reported Results

Chapter 3: Analysis Plan	Description	Corresponding Chapter 4 Section
Step 1: Descriptive Statistics	Demographics, construct levels, engagement	Sections 4.3.1 – 4.3.4
Step 2: Construct Validation	Assessment of the reliability and	Section 4.4 Measurement

Chapter 3: Analysis Plan	Description	Corresponding Chapter 4 Section
(EFA/CFA)	validity of constructs	Model Testing
Step 3: Structural Model Estimation	Examination of path relationships and model fit	Section 4.5 Structural Model Testing
Step 4: Hypothesis Testing (Bootstrapping)	Testing the significance of hypothesised relationships	Sections 4.5.2 and 4.8
Step 5: Mediation Analysis	Testing the mediating role of social capital	Section 4.6 Mediation Analysis
Step 6: IPMA	Importance-Performance Map Analysis	Section 4.7 IPMA

4.2 Data Preparation Procedures

Prior to proceeding with the primary statistical analysis and hypothesis testing, a rigorous data preparation phase was conducted to ensure the integrity and quality of the dataset. This preliminary stage is critical in quantitative research, as the accuracy of the structural model results depends heavily on the cleanliness of the underlying data. The following subsections detail the systematic procedures undertaken to refine the raw survey responses, moving from the initial assessment of response rates to more complex statistical screenings. These procedures include data cleaning, outlier identification, normality testing, and evaluation of Common Method Variance (CMV), all of which establish a robust foundation for subsequent measurement and structural model evaluations.

4.2.1 Response Rate

The survey was distributed online via Universiti Teknologi MARA's (UiTM) official email channels via Google Forms, yielding 215 responses. After screening for completeness and removing invalid cases, 206 responses were retained for analysis, resulting in a valid response rate of 95.8%. This figure is considered very high compared to typical online survey studies in higher education, which often range between 30% and 60% (Nulty, 2008) and exceed the general acceptability benchmark of 30% for professional populations (Baruch & Holtom, 2008). The high return rate can be attributed to institutional email distribution, the relevance of the study topic, and

reminder emails sent during the collection period (April-August 2024). Importantly, the final valid sample size (n = 206) exceeded the minimum requirement of 129 respondents determined a priori through a power analysis (Faul, Erdfelder, Buchner, & Lang, 2009), ensuring sufficient statistical power. Overall, the high response rate supports the reliability and representativeness of the findings and reduces the likelihood of non-response bias.

4.2.2 Data Cleaning

Following data collection, a thorough data cleaning process was conducted to ensure the dataset's accuracy, consistency, and quality before further statistical analysis. A total of 206 valid responses were processed in SPSS, enabling systematic screening and correction of potential issues. The dataset did not contain any missing values, as all respondents provided complete answers to the questionnaire. Therefore, no imputation or deletion techniques (e.g., listwise or pairwise deletion) were necessary. This completeness is attributed to the online survey design, which required respondents to answer each question before proceeding to the next.

No logical inconsistencies or contradictory responses were identified during the screening process. All respondents demonstrated coherent answering patterns, such as consistent alignment between social media usage behaviour and frequency indicators. Hence, no cases were excluded due to response inconsistency. No data entry errors (such as typos, reversed scales, or mislabelled categories) were detected. Using an online survey platform minimised the risk of manual entry errors, and the structured format ensured that all responses were recorded accurately. The questionnaire did not include reverse-scored items. Therefore, no special procedures were required to identify or correct careless responding based on such items. Data cleaning was performed using IBM SPSS Statistics 26, where descriptive statistics and frequency distributions were generated to detect anomalies. No advanced filters or syntax were required, as the dataset was largely clean and well-structured from the outset.

While formal outlier detection was performed in Section 4.2.3, a preliminary check during data cleaning revealed no extreme or unusual response patterns that would compromise the validity of the results. However, a small number of duplicate responses were initially received and removed before the cleaning stage, ensuring that only one

response per participant was retained. Overall, the data cleaning process confirmed the high quality of the collected data, enabling reliable and meaningful subsequent analyses.

4.2.3 Assessment of the Outliers

A preliminary assessment of outliers was conducted to ensure the integrity and reliability of the dataset before performing PLS-SEM analysis using SmartPLS. Given that PLS-SEM is a variance-based technique known for its robustness against minor violations of normality (Hair et al., 2017), there was no need for formal outlier removal. As part of basic data screening, univariate outliers were assessed by examining standardised z-scores for all observed indicators. Any value exceeding ±3.29 standard deviations was considered an extreme univariate outlier (Tabachnick & Fidell, 2019). Despite this, no such extreme values were identified in the dataset. Furthermore, multivariate outliers were not formally tested due to the relatively small sample size (n = 206) and PLS-SEM's resilience to such issues. Hair et al. (2017) noted that PLS-SEM is particularly suitable for studies with limited sample sizes and is less sensitive to outliers than Covariance-Based SEM (CB-SEM) methods. Therefore, no cases were excluded based on outlier analysis, and all 206 valid responses were retained for further analysis using SmartPLS.

4.2.4 Assessment of Normality

A preliminary assessment of univariate normality was performed to evaluate the distribution of observed indicators prior to conducting PLS-SEM using SmartPLS. This analysis involved examining skewness and kurtosis statistics for each indicator associated with the study's constructs: SMU (System Use (SyU), Social Use (SU), Content Use (CU), Hedonic Use (HU), Structural Social Capital (SSC), Relational Social Capital (RSC), and Cognitive Social Capital (CSC)), and AP (Teaching, Supervision, Consultation, and Research & Publication).

Table 4.2 presents the skewness and kurtosis values along with their respective standard errors for all observed indicators. The results show that several items exhibited deviations from univariate normality, with skewness values exceeding ±1 and kurtosis values outside the commonly recommended thresholds (Kline, 2015; Tabachnick & Fidell, 2019). Such deviations are frequently observed in survey-based research,

particularly in studies involving social media usage and behavioural constructs. Formal normality tests, such as the Kolmogorov-Smirnov or Shapiro-Wilk tests, were not emphasised in this study. This is due to the fact that PLS-SEM does not require the data to be normally distributed, and the presence of non-normality does not bias parameter estimates in variance-based modelling approaches (Hair et al., 2017). Furthermore, the application of nonparametric bootstrapping procedures during model estimation yields robust standard errors and significance testing even when the data deviate from normality assumptions.

Consequently, no data transformation was applied. The distributional characteristics of the data were considered acceptable for subsequent measurement model assessment, structural model evaluation, and hypothesis testing using PLS-SEM.

Table 4.2
Descriptive Statistics of Skewness and Kurtosis for Observed Indicators

Construct	Item	Skewness		Kurtosis	
		Statistic	Std. Error	Statistic	Std. Error
System use	B1_SyU_1SM_Frq	-0.892	0.169	0.71	0.337
	B1_SyU_1SM_Int	-0.757	0.169	0.143	0.337
Social use	B2_SU1	-1.121	0.169	0.911	0.337
	B2_SU2	-1.354	0.169	2.082	0.337
	B2_SU3	-1.349	0.169	1.691	0.337
	B2_SU4	-1.312	0.169	2.305	0.337
	B2_SU5	-1.366	0.169	2.348	0.337
Content use	B3_CU1	-1.743	0.169	4.382	0.337
	B3_CU2	-1.87	0.169	5.573	0.337
	B3_CU3	-2.149	0.169	8.493	0.337
	B3_CU4	-1.422	0.169	2.137	0.337
Hedonic use	B3_HU1	-1.743	0.169	3.299	0.337
	B3_HU2	-1.569	0.169	2.641	0.337
	B3_HU3	-1.385	0.169	2.183	0.337
	B3_HU4	-1.412	0.169	2.155	0.337
Structural social capital	C1_SSCE1	-0.932	0.169	0.609	0.337
	C1_SSCE2	-1.222	0.169	1.781	0.337
	C1_SSCE3	-0.543	0.169	-0.451	0.337
	C1_SSCE4	-0.153	0.169	-0.933	0.337
	C1_SSCE5	-0.268	0.169	-0.971	0.337

Construct	Item	Skewness		Kurtosis	
		Statistic	Std. Error	Statistic	Std. Error
	C1_SSCI1	-1.097	0.169	0.945	0.337
	C1_SSCI2	-1.088	0.169	0.579	0.337
	C1_SSCI3	-1.052	0.169	0.554	0.337
	C1_SSCI4	-1.166	0.169	1.136	0.337
	C1_SSCI5	-1.179	0.169	1.188	0.337
Relational Social Capital	C2_RSC1	-1.424	0.169	2.758	0.337
	C2_RSC2	-0.985	0.169	1.388	0.337
	C2_RSC3	-0.874	0.169	0.461	0.337
	C2_RSC4	-1.385	0.169	2.392	0.337
	C2_RSC5	-1.306	0.169	2.254	0.337
	C2_RSC6	-1.308	0.169	2.267	0.337
Cognitive Social Capital	C3_CSC1	-1.559	0.169	4.118	0.337
	C3_CSC2	-1.705	0.169	4.255	0.337
	C3_CSC3	-1.082	0.169	1.805	0.337
	C3_CSC5	-0.897	0.169	1.239	0.337
	C3_CSC6	-0.983	0.169	1.651	0.337
	C3_CSC7	-0.274	0.169	-0.683	0.337
Supervision	D_APS2_A	-0.674	0.169	-0.236	0.337
	D_APS4_A	-0.35	0.169	0.116	0.337
Teaching	D_APT5	-0.187	0.169	-1.056	0.337
	D_APT6	-0.535	0.169	-0.727	0.337
consultation	D_APC2	-0.599	0.169	-0.364	0.337
	D_APC4	-0.363	0.169	-0.668	0.337
Research and Publication	D_APP1	-1.329	0.169	3.282	0.337
	D_APP2	-1.352	0.169	3.406	0.337
	D_APP3	-0.564	0.169	-0.185	0.337
	D_APP5	-0.593	0.169	-0.313	0.337

4.2.5 Common Method Variance (CMV)

A correlation matrix was generated using the PLS Algorithm output in SmartPLS to assess the potential presence of CMV. Table 4.3 presents the bivariate correlations among all latent constructs in the final measurement model, including SyU, SU, CU, HU, SC, and AP.

As recommended by Podsakoff et al. (2003), correlation coefficients exceeding 0.70 may indicate common method bias. In this study, the highest correlation was observed between SU and CU at r = 0.518, followed by CU and SyU at r = 0.396. These values remain well below the critical threshold of 0.70, suggesting that CMV is not a serious concern.

Moreover, procedural remedies such as ensuring anonymity, using balanced item wording, and separating the measurement of predictor and criterion variables were applied during data collection. These design choices, combined with the correlation results, confirm that CMV is unlikely to threaten the validity of the findings.

Table 4.3
Construct Correlations from SmartPLS

	AP	**CU**	**HU**	**SC**	**SU**	**SyU**
AP	1	0.348	-0.046	0.327	0.375	0.258
CU	0.348	1	0.205	0.282	0.518	0.396
HU	-0.046	0.205	1	0.206	0.16	0.279
SC	0.327	0.282	0.206	1	0.401	0.202
SU	0.375	0.518	0.16	0.401	1	0.306
SyU	0.258	0.396	0.279	0.202	0.306	1

4.3 Descriptive Analysis

Following the rigorous data preparation and screening procedures detailed in the previous section, the focus now shifts to an exploratory evaluation of the dataset. The descriptive analysis serves as an essential precursor to the inferential statistics by providing a comprehensive profile of the study's participants and their general engagement patterns. This section first outlines the demographic characteristics of the UiTM academicians involved in the study, followed by a detailed examination of the mean scores and standard deviations for the core constructs: SMU, AP, and SC. By analysing these central tendencies, the study establishes an empirical baseline that contextualises the subsequent structural model testing and hypothesis evaluation.

4.3.1 Respondents' Demographic Profile

This section summarises the demographic characteristics of the 206 academicians who participated in the study. The key demographic variables analysed include gender, age, years of experience (see Table 4.5), and campus/branch location (Table 4.4). The sample consisted of respondents from both genders. Most participants were female (55.3%, n = 114), while male respondents accounted for 44.7% (n = 92). This indicates a slightly higher participation rate among female academicians. Respondents ranged in age from 24 to 67, with a mean age of 42.63. The most frequently reported age was 38 years, which was the mode value. Most respondents fell within the 31–50 years range, indicating that the sample primarily represents mid-career to senior-level academicians. The respondents' teaching or working experience varied from 1 to 43 years, with a mean of 13.8 years. The most common experience level was 13 years, although multiple modes were observed due to varied career paths. Most respondents had 6–10 years of experience (47.6%), suggesting that the sample comprises mostly mid-level professionals with substantial experience in academic work environments. Respondents across Malaysia were drawn from various UiTM campuses. The most significant number of responses came from Kedah (16.0%, n = 33), followed by Sarawak (12.1%, n = 25) and Melaka (13.6%, n = 28). Other campus locations showed varying response rates; the full distribution is presented in Table 4.4 below. This diverse geographic representation supports the generalisability of the findings across different regions in Malaysia.

Table 4.4
Response Rate

Campus Location	Frequency	Percentage
Johor	12	5.80%
Kedah	33	16.00%
Kelantan	18	8.70%
Melaka	28	13.60%
Negeri Sembilan	21	10.20%
Pahang	10	4.90%
Perak	12	5.80%
Perlis	6	2.90%
Pulau Pinang	7	3.40%
Sabah	5	2.40%

Campus Location	Frequency	Percentage
Sarawak	25	12.10%
Selangor	18	8.70%
Terengganu	11	5.30%

Table 4.5
Demographic Overview (N=206)

Variable	Category / Range	N	%	Descriptive Statistics
Gender	Male	92	44.7	–
	Female	114	55.3	–
Age (years)	–	–	–	Mean = 42.63, Median = 40, Mode = 38, SD = 7.392, Min = 24, Max = 67
Experience (years)	–	–	–	Mean = 13.8, Median = 14, Mode = 13, SD = 7.313, Min = 1, Max = 43
Campus Location	Most frequent: Kedah	33	16.0	–

4.3.2 Social Media Use (Construct Descriptive Analysis)

This section presents the descriptive analysis of SMU, the independent variable in this study. SMU was measured using multiple indicators across four dimensions: SyU, SU, CU, and HU. The SyU dimension assesses how frequently, for how long, and to what extent respondents use social media. As presented in Table 4.6, the majority of respondents reported using social media “Every Time” (46.1%), indicating that most respondents use social media consistently, followed by "Almost Every Time" (38.8%), indicating consistent engagement with social media platforms. Only one respondent reported "Never" or "Almost Never" using social media, suggesting widespread adoption among the sample.

Table 4.6
Frequency Descriptive Analysis

Frequency		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never	1	.5	.5	.5
	Almost Never	1	.5	.5	1.0
	Occasionally/Sometimes	29	14.1	14.1	15.0
	Almost Every Time	80	38.8	38.8	53.9
	Every Time	95	46.1	46.1	100.0
	Total	**206**	**100.0**	**100.0**	

Respondents generally reported a high intensity of use, as depicted in Table 4.7, with over one-third (36.4%) indicating they use social media "Almost Every Time," and nearly half (44.7%) reporting "Frequent Use." These results support the assumption that social media has become an integral part of many academicians' daily routines.

Table 4.7
Intensity Descriptive Analysis

Intensity		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never	1	.5	.5	.5
	Almost Never	1	.5	.5	1.0
	Occasionally/Sometimes	37	18.0	18.0	18.9
	Almost Every Time	75	36.4	36.4	55.3
	Every Time	92	44.7	44.7	100.0
	Total	**206**	**100.0**	**100.0**	

SyU's composite mean score (see Table 4.8) was 4.27 (SD = 0.779). This indicates that, on average, academicians reported a relatively high level of system-oriented social media engagement in their academic work. The high frequency and intensity of SyU observed among the respondents suggest that social media platforms are already well integrated into academicians' daily routines. This pattern aligns with the Technology Acceptance Model (TAM), which posits that technologies perceived as useful and easy to use are more likely to be adopted and consistently utilised (Davis, 1989). Empirical studies in higher education contexts have similarly shown that perceived usefulness and ease of use encourage sustained social media engagement for academic-related activities (Alenazy et al., 2019; Al-Qeisi & Eletter, 2022). The

findings indicate that, at the system level, social media has moved beyond initial adoption and is now a normalised digital infrastructure among academicians.

Table 4.8
Composite Score for System Use

Construct	Statistic	Value
System Use	Mean	4.27
	Std. Deviation	0.779

Based on Table 4.9, WhatsApp was the most frequently used platform (35.0%, n = 72), likely due to its utility in communication and messaging within academic settings. This was followed by Google Scholar (17.5%, n = 36) and Telegram (13.6%, n = 28), supporting academic collaboration and information sharing. Only a small percentage of respondents reported using professional networking platforms such as LinkedIn (3.4%) or ResearchGate (8.7%). Similarly, Facebook (8.3%) and YouTube (4.9%) were used less frequently than communication-focused tools such as WhatsApp and Telegram. It is also worth noting that only a few respondents reported using platforms such as Instagram, TikTok, and Twitter, indicating limited use of social media for short-form content or public academic discussions.

The dominance of WhatsApp in this study aligns with prior research that highlights its effectiveness as a real-time academic communication and collaboration tool, particularly in postgraduate supervision, research coordination, and informal knowledge exchange (Lee et al., 2023; Van Staden & Nel, 2023). The substantial use of Google Scholar further reflects academicians' preference for platforms that support academic identity management, citation tracking, and research discoverability, consistent with findings by Adhikari et al. (2020) and López-Hermoso et al. (2020). In contrast, the relatively low usage of academic social networking platforms such as ResearchGate and LinkedIn suggests that, while these platforms offer visibility and networking opportunities, they are not yet fully embedded in daily academic workflows. This finding contrasts with studies conducted in Western research-intensive contexts where ResearchGate plays a more central role in scholarly engagement (Keng & Cheng, 2023), indicating possible contextual and cultural differences in platform adoption. Similarly, the limited use of Facebook, YouTube, Instagram, TikTok, and Twitter supports earlier evidence that academicians tend to prioritise platforms with direct task-

oriented benefits over those associated with entertainment or public discourse (Davidovitch & Belichenko, 2018; Rauchfleisch et al., 2023). This pattern reinforces the argument that academicians' SMU is largely instrumental rather than exploratory or public-facing. The frequency of platform usage is presented below:

Table 4.9
Social Media Platforms

Platform	Frequency	Percentage
WhatsApp	72	35.00%
Google Scholar	36	17.50%
Telegram	28	13.60%
ResearchGate	18	8.70%
Facebook	17	8.30%
YouTube	10	4.90%
LinkedIn	7	3.40%
Scopus	7	3.40%
Academic.edu	3	1.50%
Instagram	3	1.50%
TikTok	2	1.00%
Twitter	2	1.00%
Mendeley	1	0.50%
Total	**206**	**100%**

As shown in Table 4.10, respondents reported high levels of agreement across all items, indicating active use of social media for professional networking and relationship-building. The highest-rated item was SU4 ("I use social media to explore social groups who share similar interests"), indicating that social media is key in connecting academicians with like-minded professionals. Items related to maintaining workplace relationships (SU3) and building new connections (SU1) also received favourable ratings, suggesting that social media is perceived as a valuable tool for academic collaboration and peer interaction. These findings imply that academicians use social media for purposes beyond casual or entertainment, particularly for social and professional development. The high levels of agreement observed for SU are consistent with prior studies that emphasise social media's role in facilitating academic interaction, collaboration, and professional networking (Lapoe et al., 2017; Murthy & Lewis, 2015; Meishar-Tal & Pieterse, 2017). Similar to these studies, academicians in

this study actively use social media to identify communities of shared interest and maintain professional relationships.

Respondents demonstrated strong engagement in sharing, searching, and accessing applicable content, with particularly high scores for CU3 ("I use social media to access useful information") (M = 6.40). High scores suggest that academicians actively use social media as a platform for knowledge sharing to consume and disseminate scholarly content. The strong engagement in CU aligns with prior research highlighting social media's role as a tool for knowledge access and dissemination in academic contexts (Murthy & Lewis, 2015; Jang, 2016; Pieterse, 2016). Consistent with these studies, academicians in this sample actively use social media to locate, consume, and share scholarly information. Notably, the exceptionally high mean score for accessing useful information suggests that content-related motivations may be more salient than interactional or entertainment-driven uses, reinforcing the argument that academicians prioritise task-relevant outcomes over casual engagement.

Academicians frequently use social media for hedonic purposes, especially to take breaks, relax, and fill time gaps. The highest-rated HU was HU1 ("I use social media to take a break from work"), with a mean score of 5.89, highlighting the role of social media as a stress-relief mechanism during academic duties. Consistent with prior research that conceptualises SyU in terms of frequency, duration, and intensity (Murthy & Lewis, 2015; Fusi & Feeney, 2018), respondents in this study demonstrated high habitual engagement with social media. However, the descriptive findings alone suggest that the intensity of use does not differentiate between productive and unproductive engagement, reinforcing the need to examine how social media is used rather than how much it is used.

Table 4.10
Descriptive Analysis of Social Media Use

Social Media Use	Item	Mean	Std. Deviation
System Use	B1_SyU_Frq	4.30	0.762
	B1_SyU_Int	4.24	0.796
Social Use	SU1. I use social media to foster new relationships at work.	5.32	1.412
	SU2. I use social media to network with fellow academics from other institutions.	5.61	1.275
	SU3. I use social media to maintain close relationships with	5.58	1.425

Social Media Use	Item	Mean	Std. Deviation
	my colleagues.		
	SU4. I use social media to explore social group who share similar interests.	5.66	1.207
	SU5. I use social media to make acquaintances with individuals with the same interests.	5.54	1.271
Content Use	CU1. I use social media to share useful information	6.05	1.094
	CU2. I use social media to search for relevant content based on my needs.	6.29	0.928
	CU3. I use social media to access useful information.	6.40	0.830
	CU5. I use social media to create content based on my interests.	5.68	1.363
Hedonic Use	HU1. I use social media to take a break from work.	5.89	1.281
	HU2. I use social media to fill a time gap.	5.79	1.270
	HU3. I use social media to get myself relaxed.	5.78	1.264
	HU4. I use social media as a source of entertainment.	5.83	1.220

4.3.3 Academicians' Performance (Construct Descriptive Analysis)

This section presents a descriptive analysis of the AP construct based on 10 final retained indicators, grouped into four core sub-dimensions: Supervision, Teaching, Consultation, and Research and Publication. These items were selected based on their psychometric strength and theoretical relevance during the measurement model evaluation. All items were measured using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The descriptive statistics in Table 4.11 provide insights into how academicians perceive their performance across these functional areas.

Respondents generally agreed with their supervisory abilities in the supervision dimension. The mean score for APS2 (“I conduct supervision at various academic levels”) was 3.89, and APS4 (“I have skills to supervise the students”) scored slightly higher at 4.28, indicating confidence in supervisory competencies, though with some variation in engagement across academic levels. Meanwhile, teaching: The teaching dimension yielded the highest mean scores, reflecting high confidence in pedagogical practices. APT5 (“I have an appropriate teaching method for the students”) had a mean of 4.43, and APT6 (“I have expertise in my area of teaching”) scored 4.49,

demonstrating strong self-perceived teaching proficiency. On the other hand, regarding consultation, respondents reported moderate engagement. APC2 ("I am well-known in my area of expertise") had a mean of 3.46, while APC4 ("I have established good relationships with industry") scored 3.36, suggesting room for increased industry engagement and visibility. Lastly, research and publication: Respondents strongly aligned with these responsibilities. APP1 ("I will publish according to university KPI") and APP2 ("I will publish based on my KPI") had high mean values of 4.16 and 4.19, respectively. Meanwhile, APP3 ("I am willing to publish more than my KPI") and APP5 ("I predict to publish more than my KPI") received moderately lower scores (3.66 and 3.67), indicating that, while institutional requirements are prioritised, there is a moderate drive to exceed expectations.

The high mean scores observed for teaching and supervision are consistent with previous research showing that academicians generally exhibit strong confidence in pedagogical competence and supervisory skills, particularly in institutions where teaching load and postgraduate supervision form central components of academic roles (Comm & Mathaisel, 1998; Lim et al., 2024). These findings suggest that core academic responsibilities remain well-established and prioritised, reflecting institutional expectations rather than individual variability. In contrast, respondents reported a strong commitment to meeting institutional publication Key Performance Indicators (KPIs). The moderately lower scores for willingness to exceed these requirements suggest a performance orientation that is compliance-driven rather than expansion-driven. This finding echoes earlier studies that argue that publication behaviour in public universities is often shaped by formal performance metrics, leaving limited incentive to exceed minimum expectations (Masron et al., 2012; SETARA Rating, 2020). In contrast, consultation-related activities recorded comparatively lower mean scores, indicating limited engagement with industry or external stakeholders. This pattern is consistent with prior research, which notes that consultation and industry linkage activities, while recognised in AP frameworks, are often underdeveloped due to limited institutional incentives, time constraints, and unclear evaluation criteria (Che Omar et al., 2017). The lower emphasis on consultation may also explain why social media's role in enhancing performance is uneven across academic dimensions.

The descriptive results indicate that academicians report stronger performance in teaching, supervision, and research and publication compared to consultation activities. This pattern aligns with prior studies, which consistently identify teaching

and research as the core performance domains in public HEIs, where academic appraisal systems are closely tied to instructional quality and publication output (Masron et al., 2012; Che Omar et al., 2017; SETARA Rating, 2020). These findings suggest that academicians are confident in core academic duties such as teaching, supervision, and publishing, while consultation activities may benefit from institutional support or incentives. This overview sets the stage for more detailed structural modelling in subsequent sections.

Table 4.11
Descriptive Statistics of Retained Academician Performance Indicators

Sub-Dimension	Item Code	Statement	Mean	Std. Deviation
Supervision	D_APS2_A	I conduct supervision at various academic levels.	3.89	0.984
	D_APS4_A	I have the skills to supervise the students.	4.28	0.606
Teaching	D_APT5	I have an appropriate teaching method for the students.	4.43	0.543
	D_APT6	I have expertise in my area of teaching.	4.49	0.565
Consultation	D_APC2	I am well-known in my area of expertise.	3.46	1.142
	D_APC4	I have established a good relationship with the industry.	3.36	1.142
Research & Publication	D_APP1	I will publish according to the university's KPI.	4.16	0.799
	D_APP2	I will publish based on my KPI.	4.19	0.795
	D_APP3	I am willing to publish more than my KPI.	3.66	1.074
	D_APP5	I predict to publish more than my KPI.	3.67	1.086

4.3.4 Social Capital (Mediating Variable Descriptive Analysis)

This section presents the descriptive analysis of SC, which is included as a mediating variable to examine how SMU may influence AP through relational networks and trust. SC was measured using 19 Likert-scale items grouped into three sub-dimensions: SSC, RSC, and CSC. Each item was rated on a 7-point scale, ranging from 1 = Strongly Disagree to 7 = Strongly Agree. A total of 206 valid responses were analysed.

Based on Table 4.12, respondents reported relatively high levels of SSC, particularly in establishing rapport (M = 5.30) and seeking work-related information (M = 5.17). However, scores related to personal support (SSCE3, M = 4.43) and disclosing

personal information (SSCE4, M = 3.93) were slightly lower, suggesting potential areas for improvement in deeper interpersonal relationships. Meanwhile, respondents demonstrated strong relational ties, with mean scores exceeding 5.0 for all items. This indicates high trust, reliance, and confidence within their professional networks. On the other hand, CSC yielded mixed results. Respondents reported high levels of understanding (CSC1, M = 5.70) and knowledge sharing (CSC2, M = 5.67), indicating effective communication and mutual comprehension. However, some challenges were noted in understanding differences in work priorities (CSC5, M = 5.32) and compatibility (CSC7, M = 4.21), suggesting potential areas for further development in cognitive alignment.

The relatively high levels of SSC observed in this study, particularly in rapport-building and work-related information seeking, align with Nahapiet and Ghoshal's (1998) conceptualisation of SSC as access to network connections. The comparatively lower scores for personal support and self-disclosure suggest that these connections function primarily as professional or weak ties rather than deep interpersonal bonds. This pattern reflects Putnam's (2000) notion of bridging SC, where individuals leverage broad networks to access information and resources rather than emotional support, a trend also observed in academic SMU (Ellison et al., 2007). On the other hand, the consistently high mean scores across all RSC indicators indicate strong levels of trust, mutual respect, and confidence among academicians. This finding is consistent with Wasko and Faraj (2005) and van den Hooff and Huysman (2009), who argued that sustained professional interaction fosters relational assets even in digitally mediated environments. Unlike bonding SC rooted in personal intimacy, the trust observed here appears to be professionally grounded, reinforcing the functional role of social media in maintaining reliable academic networks rather than close personal relationships. Meanwhile, the mixed results observed for CSC reflect a nuanced pattern consistent with Nahapiet and Ghoshal's (1998) framework. While respondents reported high levels of shared understanding and effective knowledge exchange, lower scores related to compatibility and alignment of work priorities suggest that shared language does not necessarily translate into shared goals. This partial cognitive alignment echoes Ellison et al. (2007), who noted that digitally mediated networks often support information exchange more effectively than deeper consensus-building. Overall, the findings indicate that academicians possess strong SSC and RSC through professionally oriented networks that support trust and information exchange, while CSC, although generally

high, reveals areas where deeper alignment and shared priorities can still be strengthened.

Table 4.12
Descriptive Statistics for Social Capital Items by Sub-Dimension

Social Capital	Item	Mean	Std. Deviation
Structural Social Capital	SSCE1. I have many acquaintances I consider friends	5.25	1.337
	SSCE2. I have established a good rapport with many acquaintances	5.30	1.267
	SSCE3. I have many acquaintances who support me through my personal problems	4.43	1.590
	SSCE4. I have many acquaintances with whom I feel comfortable disclosing my personal information	3.93	1.666
	SSCE5. I have many acquaintances I meet socially outside work	4.09	1.755
	SSCI1. I have many acquaintances whom I seek for work-related information	5.17	1.506
	SSCI2. I have many acquaintances whom I ask for work-related advice.	5.10	1.569
	SSCI3. I know many acquaintances whom I can approach whenever I need work-related advice.	5.02	1.583
	SSCI4. I provide answers to work-related questions posed by my acquaintances.	5.21	1.459
	SSCI5. I willingly provide work-related input to many of my acquaintances.	5.33	1.440
Relational Social Capital	RSC1. I have skilled acquaintances whom I trust.	5.55	1.175
	RSC2. I trust my acquaintances.	5.26	1.248
	RSC3. Generally, I rely on the acquaintances I work with.	4.99	1.435
	RSC4. I can work well with my acquaintances.	5.47	1.232
	RSC5. My acquaintances and I are confident in each other.	5.36	1.205
	RSC6. My acquaintances show high integrity.	5.38	1.223
Cognitive Social Capital	CSC1. I understand the information from my contacts.	5.70	0.971
	CSC2. I share my knowledge with my contacts.	5.67	1.100
	CSC3. It's easy to understand my contacts.	5.35	1.111
	CSC5. There are different work priorities between my acquaintances and me.	5.32	1.137
	CSC6. There is compatibility between information acquaintances and me.	5.33	1.067

Social Capital	Item	Mean	Std. Deviation
	CSC7. I found it difficult to understand my acquaintances.	4.21	1.518

4.3.5 Insights from Open-Ended Response

To complement the quantitative findings, Part E of the survey invited academicians to describe in their own words the problems they encounter when using social media. These findings directly address Research Objective 6 (RO6), which aimed to explore the challenges faced by academicians when using social media. Table 4.13 shows that 20 problem themes were identified through thematic analysis of the open-ended responses, with examples of responses. Table 4.14 presents the frequencies of themes based on responses by the academician. Respondent is free to express the problem and concern about SMU. These themes reflect various concerns and experiences related to SMU in academic settings. The most prominent challenges are summarised in Figure 4.1 based on response frequency.

Table 4.13
Coded Theme

No.	Theme	Description	Examples from Responses
1	Information Overload	Excessive and irrelevant information causes difficulty in filtering and accessing relevant content.	"Information overload," "too much unrelated information," "overflow of information," "too many social media platforms," "difficult to find the right information quickly," "too much unwanted information," "rabbit hole leading away from objectives."
2	Data Privacy and Security Concerns	Issues related to data privacy, security breaches, and personal information exposure.	"Privacy concerns," "data mining," "security problems such as scams and phishing," "preference for anonymity," "ethical concerns," "identity theft risks," "privacy setting loopholes," "location settings exposing personal information."

No.	Theme	Description	Examples from Responses
3	Access and Connectivity Issues	Problems with accessing social media due to poor or unstable internet connections.	"Internet connection issues," "low wireless coverage," "lagging," "access restrictions in certain areas like campuses," "unstable connection causes browsing issues," "prefer to be in a place with a good internet connection."
4	Mental Health and Productivity Challenges	Negative impacts on mental health and productivity, including addiction, anxiety, and procrastination.	"Social media addiction," "anxiety from comparing to others," "procrastination," "excessive use leading to wasted time," "distractions from work," "tying self-worth to likes and comments," "mental health deterioration due to overexposure."
5	Misinformation and Fake News	Spread of false or misleading information on social media platforms.	"Fake news," "misinformation," "lack of credibility," "difficulty verifying sources," "misleading advertisements," "AI-generated content making credibility hard to judge," "viral information with no due diligence," "false historical information."
6	Disruptive Advertisements	Overwhelming and irrelevant advertisements are disrupting the user experience.	"Too many advertisements," "pop-ups," "misleading marketing campaigns," "advertisements distracting focus."
7	Blurring Personal and Professional Boundaries	Challenges in separating personal and professional lives, especially for academicians.	"Uncomfortable sharing personal updates with colleagues," "ethical concerns," "managing reputation risks," "balancing academic and social contexts," "mixture of personal and professional," "prefer to stay passive to avoid issues."
8	Lack of Engagement and Interaction	Lack of meaningful interaction or response on social media platforms.	"Low engagement despite high impressions," "limited knowledge sharing," "superficial academic discourse," "lack of interaction or engagement from expected community," "knowledge sharing not as active as expected."

No.	Theme	Description	Examples from Responses
9	Inappropriate and Culturally Sensitive Content	Issues with inappropriate content and ethical dilemmas in using social media.	"Inappropriate content for Malaysian culture," "unethical use of social media," "ethical concerns in public service," "negative connotations on youth, politics, and trends."
10	Adapting to Rapid Technological Changes	Difficulties in adapting to new technologies or platforms.	"Too fast-paced technological development," "difficulty understanding CSS/HTML," "lack of workshops for mastering platforms," "too fast development of new applications like AI."
11	Social Media-Induced Procrastination	Social media is a distraction and causes time wastage.	"Spending too much time scrolling," "procrastination," "difficulty managing time on social media," "distraction from focus," "carried away by feeds and videos."
12	Credibility and Reliability of Information	Challenges in identifying credible and reliable information.	"How to tell credible content," "AI-generated/manipulated content," "distinguishing factual from personal perspectives," "reliability of sources," "sharing incorrect information."
13	Health Implications of Prolonged Social Media Use	Physical and mental health issues arising from prolonged SMU.	"Anxiety," "depression," "social isolation," "negative impacts on mental health," "cyberbullying causing psychological harm," "mental distress from comparing to others."
14	Access to Academic Resources and Publications	Difficulty accessing relevant academic materials or journals.	"Limited access to paywalled content," "subscription issues," "lack of access to full articles," "difficult to find latest publications on legal studies."
15	Positive Experiences and No Challenges Reported	Respondents indicated no problems with SMU.	"No problem," "everything is fine," "no issues."
16	Limited Audience Segmentation by Age	Limited audience segmentation by age on social media platforms.	"Not all social media platforms represent all targeted ages."
17	Miscommunication from Language and Short-form Usage	Miscommunication due to language and short-form usage.	"Inappropriate content for Malaysian culture," "unethical use of social media," "ethical concerns in public service," "negative connotations on youth, politics, and trends."

No.	Theme	Description	Examples from Responses
18	Tailoring Content to Audience Competency	Tailoring content to the audience's academic or competency level.	"The right content to suit my students' level of competency."
19	Trust Issues in Social Media Interactions	Trust issues regarding social media interactions and information.	"Trust," "difficulty trusting information," "sharing incorrect information," "concerns about credibility and accuracy of sources."
20	Device Compatibility and Technological Advancement Issues	Device compatibility and technology advancement issues.	"Device breaks because it cannot support," "knowledge on device and apps," "technical issues due to advancing technology."

Table 4.14
Frequencies of Themes

Theme		Frequency
E_PROB1	Information Overload	21
E_PROB2	Data Privacy and Security Concerns	19
E_PROB3	Access and Connectivity Issues	18
E_PROB4	Mental Health and Productivity Challenges	11
E_PROB5	Misinformation and Fake News	11
E_PROB6	Disruptive Advertisements	8
E_PROB7	Blurring Personal and Professional Boundaries	7
E_PROB8	Lack of Engagement and Interaction	6
E_PROB9	Inappropriate and Culturally Sensitive Content	3
E_PROB10	Adapting to Rapid Technological Changes	10
E_PROB11	Social Media-Induced Procrastination	22
E_PROB12	Credibility and Reliability of Information	11
E_PROB13	Health Implications of Prolonged Social Media Use	8
E_PROB14	Access to Academic Resources and Publications	6
E_PROB15	Positive Experiences and No Challenges Reported	61
E_PROB16	Limited Audience Segmentation by Age	2
E_PROB17	Miscommunication from Language and Short-form Usage	2
E_PROB18	Tailoring Content to Audience Competency	1
E_PROB19	Trust Issues in Social Media Interactions	5
E_PROB20	Device Compatibility and Technological Advancement Issues	3

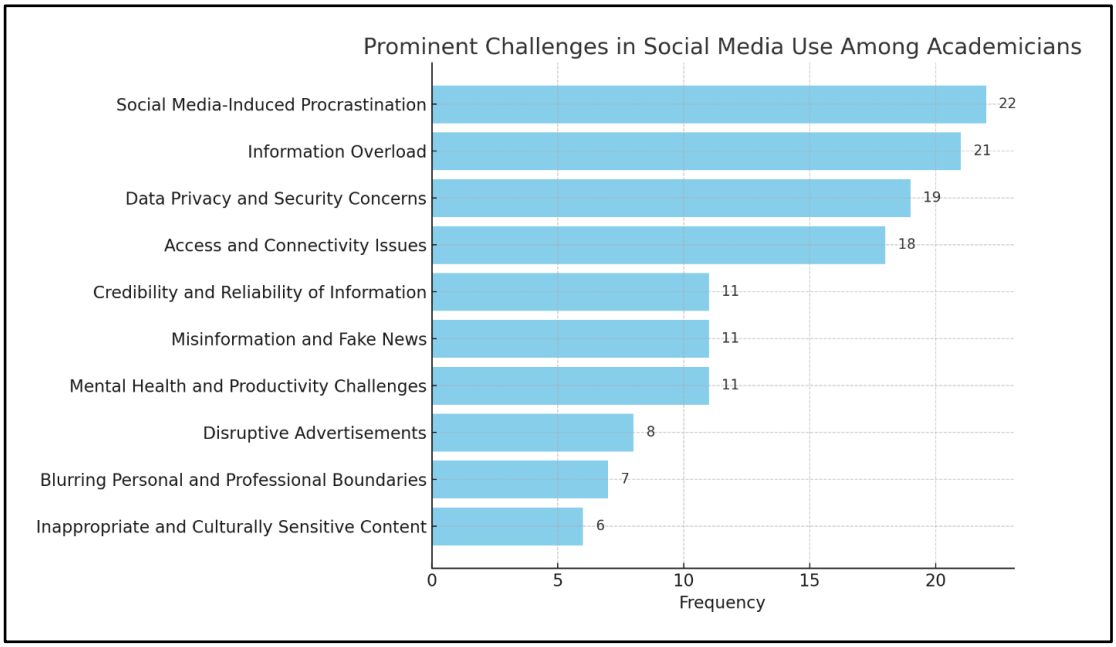


Figure 4.1 Summary of the Most Prominent Challenges

Based on Figure 4.1, the most frequently reported problem was social media-induced procrastination, with 22 respondents acknowledging difficulties managing time and productivity due to excessive scrolling and distraction. This was closely followed by information overload (n = 21), in which respondents reported being overwhelmed by excessive, irrelevant, or redundant content, making it challenging to filter useful information. Data privacy and security concerns (n = 19) also emerged as a significant issue, with respondents expressing fears over personal information exposure, scams, and data misuse. Likewise, access and connectivity issues (n = 18) were common, particularly in settings with unstable internet connections or platform restrictions within campuses. Additional themes, such as mental health impacts, misinformation, and lack of credibility of content, were each reported by 11 respondents, underscoring the psychological and informational risks posed by unregulated or excessive SMU. Although less frequently mentioned, concerns such as disruptive advertisements, blurred personal and professional boundaries, and culturally inappropriate content highlight the nuanced, context-specific nature of the social media challenges faced by academicians in Malaysia.

The issues identified in the open-ended responses both align with and extend prior literature on SMU in the workplace and academic settings. While existing studies predominantly emphasise the positive role of social media in enhancing communication, collaboration, and job performance (Cao et al., 2012; Dittes &

Smolnik, 2019; Huang & Zulkifli, 2023), the present findings highlight the costs of unmanaged and excessive use, particularly in academic contexts. Problems such as social media-induced procrastination and information overload, which were most frequently reported by respondents, are consistent with earlier research identifying distraction, technostress, and cognitive overload as negative consequences of intensive social media engagement (Yin et al., 2018; Permana et al., 2023). Similarly, concerns regarding data privacy and security echo prior studies that caution against the risks of exposure, misuse of personal data, and reduced trust when social media platforms are used without clear organisational guidance (Wang & Beh, 2025).

In contrast to studies that report improved productivity and job fulfilment when SMU is purposeful and supported by organisational policies (Moyo & Nkhahle, 2024; Chen et al., 2024), the current findings suggest that such enabling structures may be insufficient or unevenly implemented in the academic environment. Issues related to connectivity constraints, blurred personal-professional boundaries, and mental health impacts further indicate that the academic use of social media differs from corporate settings, where enterprise platforms and formal usage norms are more established. Collectively, these findings support the existing literature's position that SMU is neither inherently beneficial nor inherently harmful; rather, its outcomes depend on context, the intensity of use, and institutional regulation, reinforcing the need for strategic, guided social media practices in Malaysian higher education. These insights reinforce and contextualise the quantitative findings, providing a deeper understanding of the multifaceted barriers that may hinder effective and productive SMU among academic staff.

4.4 Measurement Model Testing

In accordance with Step 2 of the data analysis plan outlined in Section 3.9.1, this section reports the results of construct validation using reliability and validity assessments. The initial measurement model comprised 69 items across all constructs. However, during the measurement model evaluation using PLS-SEM, 21 items were deleted, resulting in a final set of 48 indicators.

The decision to remove items was based on empirical evidence and theoretical justification, in line with recommended practices (Hair et al., 2022; Sarstedt et al., 2019; Ringle et al., 2012). Specifically, items with outer loadings below the 0.708 threshold

were considered for removal, particularly if their removal increased Composite Reliability (CR) or Average Variance Extracted (AVE) (Hair et al., 2022). This refinement process was notably evident in the AP construct, where several items were identified as redundant or conceptually inconsistent.

Although the overall deletion rate exceeded 20% (30.4%), this level of refinement is considered acceptable in reflective measurement models, provided it enhances model parsimony and construct validity. Hair et al. (2022) noted that even items with loadings above 0.70 may be removed if they reduce explanatory power or discriminant validity. Sarstedt et al. (2019) further cautioned that higher-order models with too many indicators may suffer from multicollinearity, leading to inflated standard errors and reduced precision in parameter estimates. The final retained items met all threshold criteria for convergent validity (AVE > 0.50), internal consistency reliability (CR > 0.70), and indicator reliability, thus ensuring the robustness of the final measurement model.

4.4.1 Indicator Reliability (Outer Loading)

Indicator reliability was assessed by examining the outer loadings of each indicator on its respective latent construct. According to Hair et al. (2022), a loading value of 0.708 or higher is recommended, as it indicates that the construct explains at least 50% of the indicator's variance, thereby ensuring that the indicator shares more variance with its associated latent variable than with the measurement error. In this study, the outer loadings for the majority of constructs exceeded the 0.708 threshold, demonstrating strong indicator reliability.

However, for the AP dimensions, several loadings ranged between 0.578 and 0.701. Following the guidelines of Hair et al. (2022), these items were retained for the final model because they contribute to the content validity of the performance construct, and their retention did not adversely affect the AVE or Composite Reliability (CR), which remained well within the acceptable limits. This approach ensures that the multidimensional nature of AP, encompassing teaching, research, and consultation, is fully captured without compromising the model's statistical robustness.

The results in Table 4.16 demonstrate that all retained items in the final model exhibit outer loadings above or near the acceptable threshold. These indicators were selected after removing items with low factor loadings during the measurement model

refinement process. The retained indicators demonstrate strong item reliability and make significant contributions to their respective constructs. For example, in the SyU construct, both indicators, frequency and intensity of use, showed high loadings above 0.90, indicating strong reliability. Similarly, SU, CU, and HU indicators exceeded the 0.70 threshold. All items under the SC dimensions (structural, relational, and cognitive) also demonstrated strong indicator reliability.

Meanwhile, the AP construct, consisting of four sub-dimensions (Supervision, Teaching, Consultation, and Research & Publication), retained only items with outer loadings above the acceptable threshold in the final model. As shown in Table 4.15, most items reported outer loadings well above the 0.70 threshold. A few indicators had loadings between 0.60 and 0.70, such as D_APS2_A ($\lambda = 0.627$), D_APT6 ($\lambda = 0.605$), D_APT5 ($\lambda = 0.620$), and D_APP2 ($\lambda = 0.631$), yet these were retained due to their theoretical relevance and their contribution to construct coverage in the AP Higher-Order Construct (HOC).

Since SC and AP were modelled as HOCs, indicator reliability was assessed at their respective Lower Order Components (LOCs) level. Outer loadings for all LOCs are presented accordingly to reflect item reliability. The results affirm that the retained indicators reliably represent their respective constructs, supporting the validity of subsequent analyses in the structural model.

Table 4.15
Outer Loading Result

Construct (LOC)	**Indicator**	**Outer Loading (λ)**
System Use (SyU)	B1_SyU_Frq	0.923
	B1_SyU_Int	0.943
Social Use (SU)	B2_SU1	0.848
	B2_SU2	0.829
	B2_SU3	0.806
	B2_SU4	0.716
	B2_SU5	0.745
Content Use (CU)	B3_CU1	0.79
	B3_CU2	0.791
	B3_CU3	0.77
	B3_CU4	0.807
	B3_CU5	0.784

Construct (LOC)	Indicator	Outer Loading (λ)
Hedonic Use (HU)	B3_HU1	0.867
	B3_HU2	0.911
	B3_HU3	0.929
	B3_HU4	0.866
Structural Social Capital (SSC)	C1_SSCE1	0.793
	C1_SSCE2	0.802
	C1_SSCE3	0.706
	C1_SSCE4	0.7
	C1_SSCE5	0.742
	C1_SSCI1	0.889
	C1_SSCI2	0.872
	C1_SSCI3	0.84
	C1_SSCI4	0.874
	C1_SSCI5	0.863
Relational Social Capital (RSC)	C2_RSC1	0.87
	C2_RSC2	0.932
	C2_RSC3	0.836
	C2_RSC4	0.936
	C2_RSC5	0.954
	C2_RSC6	0.936
Cognitive Social Capital (CSC)	C3_CSC1	0.754
	C3_CSC2	0.811
	C3_CSC3	0.725
	C3_CSC6	0.856
	C3_CSC7	0.690
Supervision	D_APS2_A	0.627
	D_APS4_A	0.701
Teaching	D_APT5	0.62
	D_APT6	0.605
Consultation	D_APC2	0.578
	D_APC4	0.624
Research & Publication	D_APP1	0.648
	D_APP2	0.631
	D_APP3	0.662
	D_APP5	0.666

4.4.1.1 Indicator Reliability Final Model

This section evaluates the indicator reliability of the final measurement model using outer loadings. Outer loadings represent the strength of association between each observed indicator and its corresponding latent variable. According to Hair et al. (2022), an outer loading value of 0.708 or higher is recommended, as it indicates that the latent construct explains at least 50% of the indicator's variance. However, in line with the guidelines provided by Hair et al. (2019) and Hair et al. (2022), indicators with loadings between 0.40 and 0.70 may be retained if they are essential for the content validity of the construct and if their removal does not significantly increase the AVE or Composite Reliability (CR) above the required thresholds. This flexibility ensures that theoretically significant items, particularly within the AP construct, are preserved, thereby maintaining the model's conceptual integrity.

Table 4.16 presents the final model's outer loading values for all retained indicators. All items exceeded the minimum acceptable threshold, confirming adequate indicator reliability. This suggests the observed items are reliable measures of their respective latent constructs.

Table 4.16
Outer Loadings for Latent Variables (Final Model)

Construct	Indicator	Outer Loading
System Use (SysU)	B1_SyU_Frq	0.925
	B1_SyU_Int	0.942
Social Use (SU)	SU1	0.846
	SU2	0.822
	SU3	0.803
	SU4	0.723
	SU5	0.753
Content Use (CU)	CU1	0.795
	CU2	0.915
	CU3	0.91
Hedonic Use (HU)	HU1	0.824
	HU4	0.96
Structural Social Capital (SSC)	SSCE1	0.797
	SSCE2	0.807
	SSCE3	0.699

Construct	Indicator	Outer Loading
	SSCE4	0.692
	SSCE5	0.738
	SSCI1	0.889
	SSCI2	0.869
	SSCI3	0.839
	SSCI4	0.876
	SSCI5	0.866
Relational Social Capital (RSC)	RSC1	0.88
	RSC2	0.934
	RSC3	0.839
	RSC4	0.932
	RSC6	0.933
Cognitive Social Capital (CSC)	CSC1	0.872
	CSC2	0.886
	CSC3	0.827
	CSC6	0.794
Academicians' Performance (AP) – *Supervision*	D_APS2_A	0.662
	D_APS4_A	0.701
Academicians' Performance (AP) – *Teaching*	D_APT5	0.745
	D_APT6	0.761
Academicians' Performance (AP) – *Consultation*	D_APC2	0.578
	D_APC4	0.624
Academicians' Performance (AP) – *Research & Publication*	D_APP1	0.648
	D_APP2	0.631
	D_APP3	0.662
	D_APP5	0.666

4.4.2 Convergent Validity

Convergent validity evaluates how each construct correlates strongly with its respective indicators. According to Hair et al. (2022), convergent validity is confirmed when the AVE for each latent construct exceeds 0.50, indicating that the construct explains more than half of the variance in its observed variables. As shown in Table 4.17**,** all constructs in the final model exceeded the recommended threshold of AVE ≥ 0.50, with AVE values ranging from 0.561 (AP) to 0.875 (SyU). This confirms that the retained indicators adequately capture their respective constructs.

In addition to AVE, internal consistency reliability was evaluated using Cronbach's Alpha and Composite Reliability (ρc). Following the latest recommendations by Hair et al. (2022), all values met or exceeded the established thresholds (≥ 0.70). All values met or exceeded the recommended thresholds (Cronbach's Alpha ≥ 0.70; Composite Reliability ≥ 0.70), demonstrating strong reliability across all constructs.

Table 4.17
Convergent Validity Assessment

Construct	Average Variance Extracted (AVE)
AP (Academicians' Performance)	0.561
CU (Content Use)	0.652
HU (Hedonic Use)	0.814
SC (Social Capital)	0.772
SU (Social Use)	0.625
SyU (System Use)	0.875

4.4.3 Internal Consistency Reliability

Internal consistency reliability assesses the degree to which a set of items consistently measures the same latent construct. While convergent validity focuses on how sound indicators represent a construct, internal consistency emphasises the indicators' coherence. Hair et al. (2022) recommended that internal consistency is considered adequate when Cronbach's Alpha and Composite Reliability (ρc) exceed 0.70. In the final model, all constructs met or exceeded this threshold, as shown in Table 4.18. Cronbach's Alpha values ranged from 0.739 (AP) to 0.925 (HU), while Composite Reliability (ρc) ranged from 0.836 to 0.946. These results indicate that the measurement scales for each construct are stable and reliable, and the indicators within each construct are well-aligned.

Table 4.18
Internal Consistency Reliability Metrics

Construct	Cronbach's Alpha	Composite Reliability (rho_c)
AP (Academicians' Performance)	0.739	0.836
CU (Content Use)	0.82	0.882
HU (Hedonic Use)	0.925	0.946
SC (Social Capital)	0.852	0.91
SU (Social Use)	0.849	0.892
SyU (System Use)	0.857	0.933

4.4.4 Discriminant Validity

Discriminant validity was evaluated to ensure that each construct in the model represents a conceptually distinct entity, a critical criterion for establishing the structural model's construct validity. Following the latest guidelines for PLS-SEM (Hair et al., 2022), two methods were applied: the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the HTMT (Henseler et al., 2015). While both methods were examined, this study prioritises the HTMT ratio, as recent simulation studies have demonstrated it to be a more rigorous and reliable assessment of discriminant validity compared to the traditional Fornell-Larcker criterion (Hair et al., 2022; Henseler et al., 2015). A threshold of HTMT < 0.90 was utilised (with a more conservative target of < 0.85 for conceptually similar constructs) to confirm that each construct measures a unique phenomenon within the academic professional context.

4.4.4.1 Fornell-Larcker Criterion

According to the Fornell-Larcker Criterion, a construct's square root of AVE should be greater than its correlations with other constructs. As depicted in Table 4.19, the diagonal elements represent the square roots of AVE, which are all higher than the corresponding inter-construct correlations. This indicates that each construct shares more variance with its associated indicators than others, supporting discriminant validity.

Table 4.19
Fornell-Larcker Criterion

Construct	AP	CU	HU	SC	SU	SyU
AP	0.749					
CU	0.348	0.807				
HU	-0.046	0.205	0.902			
SC	0.327	0.282	0.206	0.879		
SU	0.375	0.518	0.16	0.401	0.79	
SyU	0.258	0.396	0.279	0.202	0.306	0.935

4.4.4.2 Heterotrait-Monotrait Ratio (HTMT)

HTMT is considered a more reliable method for assessing discriminant validity compared to traditional criteria. Methodological research suggests an HTMT ≤ 0.85 as a conservative criterion, while an HTMT ≤ 0.90 serves as an acceptable threshold for conceptually related constructs (Franke & Sarstedt, 2019; Hair et al., 2022). Given that the constructs in this study, such as the dimensions of SMU and SC, are theoretically linked, a 0.90 threshold was adopted to avoid overly conservative rejections of the model (Franke & Sarstedt, 2019). As reported in Table 4.20, all HTMT values remain below the 0.90 threshold, indicating strong evidence of discriminant validity and confirming that each construct represents a unique conceptual entity.

Table 4.20
HTMT Ratio

Construct	AP	CU	HU	SC	SU	SyU
AP						
CU	0.44					
HU	0.103	0.245				
SC	0.4	0.335	0.224			
SU	0.458	0.622	0.185	0.463		
SyU	0.328	0.474	0.31	0.233	0.356	

4.4.5 Conclusion of Measurement Model Testing

This section summarises the outcomes of the measurement model evaluation for the final model, comprising six latent constructs: SMU, SC, and AP, including their respective subdimensions. The final retained items were selected based on rigorous evaluation of indicator reliability, convergent validity, internal consistency, and discriminant validity. All retained indicators in the final model demonstrated acceptable outer loadings, mostly exceeding the threshold of 0.70. Some items, such as APP4 (λ = 0.536) and APR6 (λ = 0.665), had loadings between 0.50 and 0.70 but were retained due to strong theoretical justification and their contribution to construct meaning.

Convergent validity was confirmed, with all constructs showing AVE values above 0.50, ranging from 0.561 (AP) to 0.875 (SMU Intensity). This indicates that each construct explains at least 50% of the variance in its indicators. Internal consistency reliability was supported by Cronbach's Alpha values ranging from 0.739 to 0.925 and composite reliability (ρ_c) values all exceeding the recommended minimum of 0.70. These values confirm that the constructs were measured with consistency and stability. Discriminant validity was established using the Fornell-Larcker criterion and the HTMT ratio. Each construct's square root of AVE was greater than its correlations with other constructs, and all HTMT values were below the 0.90 threshold. This indicates that the constructs are empirically distinct and do not suffer from multicollinearity.

4.5 Structural Model Testing

Following the construct validation stage, Step 3 and Step 4 of the analysis plan are addressed through structural model estimation and hypothesis testing.

4.5.1 Variance Inflation Factor (VIF) Procedure

Before testing the structural relationships in the model, multicollinearity among indicators and constructs was assessed using the VIF. VIF values indicate the degree to which a predictor variable is linearly related to other predictors. According to Knock and Lynn (2012), a VIF value below 3.3 suggests acceptable levels of collinearity.

Table 4.21 presents the VIF values for each indicator in the outer model. All values were below the recommended threshold of 3.0, indicating that collinearity among measurement indicators is not a concern. This suggests that each observed item contributes uniquely to its respective construct. Although a few items (e.g., B3_HU2 and B3_HU3) exceeded the 3.0 guideline by a slight margin, they were retained based on their theoretical contribution and lack of negative impact on model validity.

Table 4.21
Outer Model VIF Values (Item-Level)

Item	VIF
B1_SyU_Frq	2.285
B1_SyU_Int	2.285
B2_SU1	2.664
B2_SU2	2.2
B2_SU3	2.359
B2_SU4	2.449
B2_SU5	2.477
B3_CU1	1.781
B3_CU2	3.339
B3_CU3	3.194
B3_CU4	1.388
B3_HU1	3.755
B3_HU2	4.765
B3_HU3	4.188
B3_HU4	2.42
C1_SSC	2.444
C2_RSC	2.655
C3_CSC	1.74
CONSLT.	1.459
RES.&PUB.	1.321
SUPERV.	1.747
TEACH.	1.593

Table 4.22 reports the VIF values for the structural paths in the inner model (i.e., between latent constructs). All values fall well below the critical threshold of 3.3, confirming that multicollinearity does not pose a concern for the predictive relationships in the structural model.

Table 4.22
Inner Model VIF Values (Final Model)

	VIF
CU -> AP	1.509
CU -> SC	1.503
HU -> AP	1.119
HU -> SC	1.098
SC -> AP	1.231
SU -> AP	1.528
SU -> SC	1.391
SyU -> AP	1.266
SyU -> SC	1.264

The VIF analysis confirms that there is no significant multicollinearity in either the outer or the inner model. Therefore, all measurement and structural paths can be interpreted reliably in subsequent model evaluation.

4.5.2 Significance and Relevance of Relationships

To evaluate the significance of the hypothesised relationships, this study employed the nonparametric bootstrapping procedure. Since PLS-SEM does not assume normality, bootstrapping is essential for deriving standard errors and t-statistics to assess the significance of path coefficients (Hair et al., 2022).

Following the recommendations of Hair et al. (2022) and Becker et al. (2023), a bootstrapping procedure with 5,000 subsamples was executed using the Percentile Bootstrap method. Although 10,000 subsamples are often recommended for final result preparation in SmartPLS 4 to ensure maximum stability, 5,000 subsamples are considered a robust, sufficiently large number that provides reliable estimates and prevents the conservative rejection of valid paths (Hair et al., 2017).

The significance level was set at 0.05. Consequently, a relationship is considered statistically significant if the t-value exceeds 1.96 (for a two-tailed test) and the p-value is less than 0.05. Additionally, 95% confidence intervals were examined; a path coefficient is deemed significant if the interval between the 2.5% and 97.5% quantiles does not include zero (Hair et al., 2022).

Table 4.23
Structural Model Path Coefficients

Hypothesis	Relationship	β (Original Sample)	t-value	p-value	Decision
H1	CU → AP	0.175	2.249	0.025	Supported
H2	HU → AP	-0.196	2.921	0.004	Supported (Negative)
H3	SC → AP	0.214	2.791	0.005	Supported
H4	SU → AP	0.186	2.122	0.034	Supported
H5	SU → SC	0.334	4.298	0.000	Supported
H6	SyU → AP	0.143	1.993	0.046	Supported

As shown in Table 4.23, all hypothesised relationships in the final structural model were statistically significant at $p < 0.05$, indicating the robustness of the model (see Figure 4.2). Specifically, SC presented a positive and significant influence on AP ($\beta = 0.214$, $p = 0.005$), supporting its role as a key mediator in the model. CU and SU also positively and significantly predicted AP, highlighting the relevance of targeted, relationship-building SMU. Interestingly, HU had a significant but negative effect on AP ($\beta = -0.196$, $p = 0.004$), suggesting that non-professional or leisure-oriented use may detract from academic productivity. SyU, measuring usage frequency and intensity, had a moderate but significant positive relationship with AP ($\beta = 0.143$, $p = 0.046$). Additionally, SU → SC (H5) showed a strong and significant relationship ($\beta = 0.334$, $p < 0.001$), indicating that SU of social media fosters the development of SC among academicians. These findings confirm the relevance and statistical significance of the structural paths, providing empirical support for the proposed research model. The strength of these relationships reinforces the conceptual framework linking different dimensions of SMU to SC and AP.

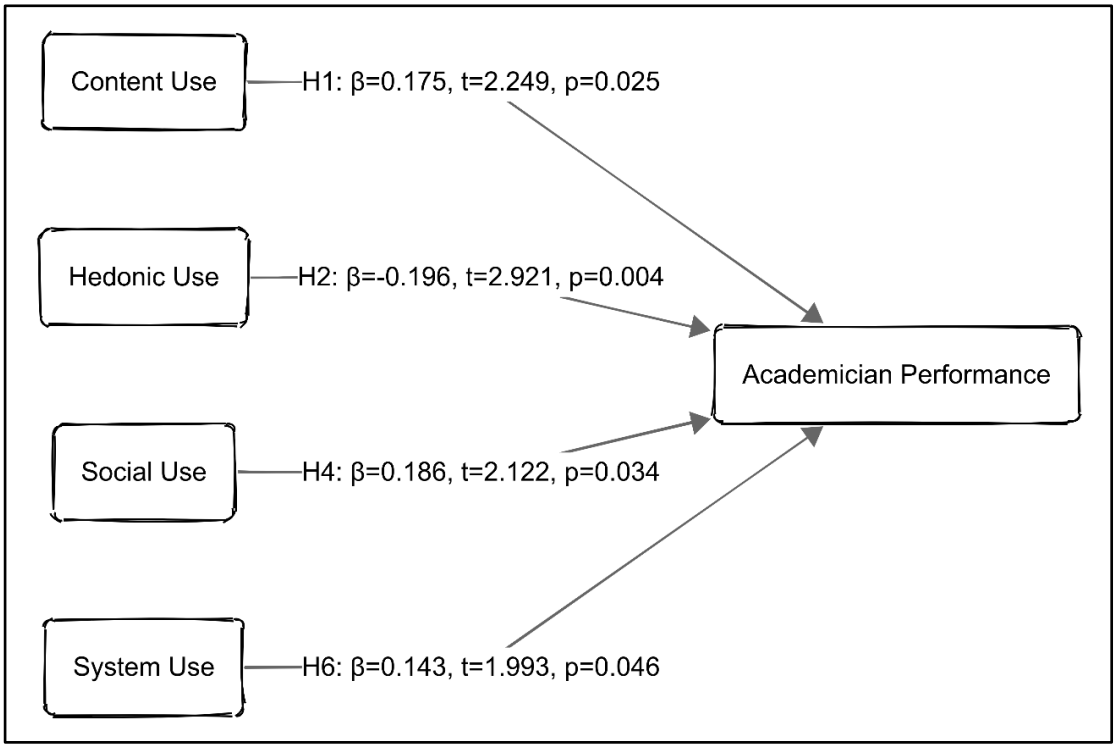


Figure 4.2 Structural Model Results for Direct Effects of Social Media Use Dimensions on Academician Performance

4.5.3 Predictive Relevance PLSpredict Results

To assess the out-of-sample predictive power of the structural model, the PLSpredict procedure was executed using a 10-fold, 10-repetition configuration. Following the guidelines by Shmueli et al. (2019), the evaluation was conducted at both the construct and indicator levels. As a preliminary step, the construct-level summary was examined. As shown in Table 4.24, both AP $Q^2_{predict}$ = 0.177 and SC $Q^2_{predict}$=0.099 yielded values greater than zero. According to Hair et al. (2022), $Q^2_{predict} > 0$ indicates that the model outperforms the most naive benchmark, namely the training sample mean. These results confirm that the proposed model possesses basic out-of-sample predictive capability for the key endogenous constructs.

Table 4.24
Construct-Level Predictive Relevance Summary

Construct	$Q^2_{predict}$	RMSE	MAE
Academician Performance (D_AP)	0.177	0.914	0.757
Social Capital (SC)	0.099	0.967	0.714

To assess the predictive power, a granular analysis at the indicator level was conducted by comparing PLS-SEM Root Mean Square Error (RMSE) values with those of the Linear Model (LM) benchmark. The LM benchmark represents a naive linear regression of the indicators. Following Shmueli et al. (2019), Predictive power is considered high when all PLS-SEM indicators yield lower RMSE values than the LM benchmark, medium when the majority are lower, and low when only a minority outperform the benchmark. As presented in Table 4.25, five indicators (D_APP1, D_APP2, D_APT1, D_APT3, and C3_CSC) exhibited lower RMSE values under the PLS-SEM model compared to the LM benchmark. Since only a minority of the indicators demonstrated superior predictive accuracy, the model is classified as exhibiting low predictive power at the indicator level.

Table 4.25
Indicator-Level Prediction Error Comparison

Construct / Indicator	$Q^2_{predict}$	PLS-SEM (RMSE)	LM (RMSE)
Academician Performance (D_AP)	**0.177**		
D_APC3	0.029	0.793	0.787
D_APP1	0.070	0.773	0.790
D_APP2	0.081	0.764	0.780
D_APR6	0.103	0.709	0.706
D_APS1_A	0.149	0.579	0.578
D_APS2_A	0.078	0.947	0.945
D_APS3_A	0.099	0.575	0.567
D_APS4_A	0.133	0.565	0.556
D_APS5	0.120	0.593	0.582
D_APT1	0.115	0.548	0.551
D_APT3	0.101	0.504	0.505
D_APT5	0.049	0.531	0.527
D_APT6	0.016	0.562	0.556
Social Capital (SC)	**0.099**		
C1_SSC	0.112	0.946	0.937
C2_RSC	0.059	0.975	0.970
C3_CSC	0.061	0.974	0.981

Overall, although the indicator-level predictive accuracy is modest, the positive construct-level Q^2 predict values indicate that the model retains meaningful out-of-sample predictive relevance. These findings suggest that the proposed model is

primarily explanatory, consistent with the study's theory-testing objective, while still demonstrating acceptable predictive capability for AP and SC.

4.5.4 Assessment of R^2 (Coefficient of Determination)

The coefficient of determination (R^2) assesses the model's explanatory power by indicating how much variance in the endogenous constructs is explained by the exogenous constructs. Adjusted R^2 is also reported as a function of the number of predictors in the model, offering a more conservative estimate of explanatory power. As shown in Table 4.26, the model explains 18.7% of the variance in SC and 24.6% of the variance in AP. While Hair et al. (2011) classified 0.25 as the threshold for weak explanatory power in PLS-SEM, both values exceed the 0.10 adequacy criterion proposed by Falk and Miller (1992) and fall within Cohen's (1988) moderate range (0.13-0.26). In line with Ozili's (2023) view that R2 between 0.10 and 0.50 is acceptable in a social science model with a significant predictor, the result can be interpreted as demonstrating adequate to moderate explanatory power.

Table 4.26
Explained Variance (R^2) and Adjusted R^2

Constructs	R-square	R-square adjusted
AP	0.246	0.228
SC	0.187	0.171

These findings suggest that the proposed model has reasonable explanatory power and is suitable for proceeding to further evaluation of hypotheses and mediation effects.

4.5.5 Assessment of Effect Size (f^2)

This section evaluates the practical relevance of the model's structural relationships using f^2 effect sizes. While p-values indicate whether a relationship is statistically significant, f^2 values provide insight into each predictor's magnitude and practical impact on the dependent variables. According to Hair et al. (2022), f^2 values are interpreted using this thresholds $f^2 \geq 0.02$ = small effect, $f^2 \geq 0.15$ = medium effect,

$f^2 \geq 0.35$ = large effect, and $f^2 < 0.02$ = negligible effect. Table 4.25 summarises the f^2 values for all relevant relationships.

Table 4.27
f^2 Effect Sizes for Predictor Variables

Predictor → Dependent Variable	f^2 Value	Interpretation
CU → AP	0.027	Small effect
HU → AP	0.045	Small effect
SC → AP	0.049	Small effect
SU → AP	0.03	Small effect
SU → SC	0.099	Approaching medium
SyU → AP	0.021	Small effect

As shown in Table 4.27, all direct relationships with AP exhibit small but meaningful effect sizes, with HU → AP ($f^2 = 0.045$) and SC → AP ($f^2 = 0.049$) showing the strongest practical influence. The strongest observed effect overall is from SU → SC ($f^2 = 0.099$), indicating that SU has a moderately substantial impact on SC development. Meanwhile, SyU has a negligible effect on SC ($f^2 = 0.001$) but retains a small effect on AP.

4.5.6 Social Capital as a Higher-Order Construct (HOC)

In this study, SC was modelled as a second-order reflective-reflective HOC to capture the multidimensional nature of academic social networks. The HOC comprises three first-order reflective constructs:

- SSC – representing network ties
- RSC – representing trust, norms, and obligations
- CSC – representing shared values and understanding

This modelling approach follows the reflective-reflective specification, in which the HOC is reflected by its underlying dimensions (SSC, RSC, and CSC), which in turn are reflected by their respective indicators. This is consistent with the Hierarchical Component Model (HCM) framework in PLS-SEM as detailed by Hair et al. (2022) and Sarstedt et al. (2019). The use of an HOC in this context reduces the number of path

relationships in the structural model, thereby increasing model parsimony and providing a more integrated view of the SC phenomenon.

4.5.6.1 Validation of the Higher-Order Construct

The outer loadings of the first-order constructs were examined to assess the validity of SC as a second-order construct. As indicated in Table 4.28, all higher-order loadings exceeded the 0.708 threshold (Hair et al., 2022), ranging from 0.842 to 0.907. These high values indicate that the dimensions are strongly integrated into the overarching construct.

Table 4.28
Outer Loadings of First-Order Constructs on Social Capital

First-Order Construct	Description	Outer Loading
C1_SSC	Structural Social Capital	0.894
C2_RSC	Relational Social Capital	0.907
C3_CSC	Cognitive Social Capital	0.842

Each first-order construct demonstrated excellent internal consistency and convergent validity, as presented in Table 4.29 Cronbach's Alpha and Composite Reliability (CR) values exceeded 0.70 (Nunnally & Bernstein, 1994; Hair et al., 2021), with this study reporting values above exceeded 0.85 and 0.90, respectively, while AVE values exceeded 0.50 (Fornell & Larcker, 1981; Hair et al., 2022), indicating that each construct explains more than half of the variance in its indicators.

Table 4.29
Construct Reliability and Convergent Validity of Lower-Order Constructs

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
C1_SSC	0.942	0.95	0.657
C2_RSC	0.944	0.957	0.818
C3_CSC	0.867	0.909	0.715

Discriminant validity was assessed using the HTMT ratio, as shown in Table 4.30, and the Fornell-Larcker criterion (see Table 4.31). All HTMT values were well below the conservative threshold of 0.85 and the liberal threshold of 0.90 (Henseler,

Ringle, & Sarstedt, 2015). All HTMT values between SC and other constructs (CU, HU, SU, SyU, D_AP) were well below the recommended threshold of 0.90, indicating sufficient discriminant validity.

Table 4.30
HTMT Ratios Between Social Capital and Other Constructs

Construct Pair	HTMT Value	Interpretation
CU ↔ SC	0.296	Acceptable
HU ↔ SC	0.212	Excellent
SU ↔ SC	0.456	Acceptable
SyU ↔ SC	0.204	Excellent
D_AP ↔ SC	0.32	Acceptable

Additionally, based on Table 4.31, the Fornell-Larcker analysis confirmed that the square root of AVE for each construct exceeded its correlations with other constructs, satisfying the criterion for discriminant validity (Fornell & Larcker, 1981).

Table 4.31
Fornell-Larcker Criterion Between Social Capital and Other Constructs

Construct	CU	D_AP	HU	SC	SU	SyU
CU	0.875					
D_AP	0.403	0.718				
HU	0.224	-0.009	0.893			
SC	0.25	0.279	0.189	0.881		
SU	0.472	0.317	0.158	0.398	0.791	
SyU	0.396	0.289	0.247	0.194	0.302	0.822

Finally, path coefficients were tested and validated via bootstrapping. In PLS-SEM, significance is established when t-values exceed 1.96 ($p < 0.05$), 2.58 ($p < 0.01$), or 3.29 ($p < 0.001$) (Hair et al., 2021). Path coefficients were estimated and validated via bootstrapping to test the impact of SC. Results in Table 4.32 confirm that SU → SC had a significant positive effect ($\beta = 0.346$, $p < 0.001$), and SC → D_AP also showed a significant positive effect ($\beta = 0.170$, $p = 0.022$). These findings support the mediating role of SC in linking SMU to AP.

Table 4.32
Path Coefficients Involving Social Capital

Relationship	β	*t*-value	*p*-value	Significant?
SU → SC	0.346	4.533	<0.001	Yes
SC → D_AP	0.17	2.298	0.022	Yes

The reflective-reflective measurement model for SC is psychometrically sound and statistically valid. Each first-order construct strongly reflects the HOC, and discriminant validity is established. This modelling approach provides a more holistic representation of how different facets of SC jointly contribute to AP and validates its inclusion as a key mediating construct in the structural model.

4.5.7 Academicians' Performance as a Higher-Order Construct (HOC)

In this study, AP was conceptualised as an HOC formed by four first-order dimensions: Teaching, Supervision, Consultation, and Research & Publication. This reflective-reflective HOC structure was adopted because the overall performance of academicians is best understood as the combined effect of these multiple, yet correlated, facets of academic responsibility (Becker, Klein, & Wetzels, 2012; Hair et al., 2017; Hair et al., 2022). Each first-order construct represents a key performance domain:

- Teaching (TEACH.): instructional delivery and engagement in academic settings
- Supervision (SUPERV.): mentoring and overseeing postgraduate or undergraduate students
- Consultation (CONSLT.): providing academic or industry consultation
- Research & Publication (RES.&PUB.): scholarly output through research and publication

The HOC for AP was modelled using the Repeated Indicator Approach in SmartPLS. In this approach, all indicators of the first-order constructs were repeated and assigned to the HOC AP. As shown in Table 4.33, all first-order constructs loaded significantly onto AP, with loadings ranging from 0.673 (Research & Publication) to 0.834 (Supervision). These values exceed the minimum recommended threshold of 0.60

(Chin, 1998), indicating that each dimension contributes to the HOC. Among the four, Supervision exhibited the strongest influence (0.834), followed by Consultation (0.755), Teaching (0.724), and Research & Publication (0.673). This suggests that while all domains are important, supervision and consultation play a powerful role in defining the perceived performance of academicians within the sampled context.

Table 4.33
Outer Loadings of First-Order Constructs on Academicians' Performance

First-Order Construct	Description	Outer Loading
CONSLT.	Consultation	0.755
RES.&PUB.	Research & Publication	0.673
SUPERV.	Supervision	0.834
TEACH.	Teaching	0.724

To validate the reflective-reflective modelling of AP as an HOC, the reliability and convergent validity of its first-order components, Consultation, Research and Publication, Supervision, and Teaching, were examined.Table 4.34 presents the results of this assessment. All constructs demonstrated high levels of internal consistency reliability, as indicated by Cronbach's Alpha values exceeding the recommended threshold of 0.70. Composite reliability (CR) values for all dimensions were also above the 0.70 cut-off, confirming the consistency of the items in measuring their respective constructs.

Furthermore, all AVE values were well above 0.50, indicating that each construct explains more than 50% of the variance in its indicators. The Teaching dimension showed the highest AVE (0.860), followed by Consultation (0.813), Supervision (0.784), and Research and Publication (0.716). These findings support strong convergent validity across all first-order constructs.

Together, these psychometric properties confirm that the first-order dimensions adequately represent the broader construct of AP. The results justify the modelling of AP as a second-order construct in the structural model.

Table 4.34
Construct Reliability and Convergent Validity of First-Order Constructs

Construct	Cronbach's Alpha	Composite Reliability (pc)
CONSLT.	0.772	0.897
RES.&PUB.	0.900	0.926
SUPERV.	0.724	0.879
TEACH.	0.838	0.925

Discriminant validity was assessed to ensure that the first four first-order dimensions of AP (i.e., Supervision, Teaching, Consultation, and Research & Publication) were empirically distinct from one another. Two standard criteria were used: the HTMT ratio and the Fornell-Larcker criterion.

As shown in Table 4.35, all HTMT values were below the threshold of 0.90 (Hair et al., 2022), indicating satisfactory discriminant validity. The highest HTMT value was observed between AP and Research & Publication (0.861), which remains within the acceptable range, suggesting that, while related, these constructs are not redundant. Other HTMT values, such as between Supervision and Teaching (0.770) and between Consultation and Teaching (0.436), also fell below the critical threshold, confirming that each dimension captures a unique aspect of AP.

Table 4.35
HTMT Ratios Between First-Order Constructs of AP

Construct Pair	HTMT Value
Consultation ↔ AP	0.829
Research & Publication ↔ AP	0.861
Supervision ↔ AP	0.738
Teaching ↔ AP	0.643

To evaluate the discriminant validity of the first-order constructs under the HOC AP, the Fornell-Larcker criterion was applied. This method compares the square root of the AVE for each construct with the correlations between that construct and all other constructs. Discriminant validity is established when the square root of AVE (diagonal values) is greater than the corresponding inter-construct correlations (off-diagonal values) (Fornell & Larcker, 1981; Hair et al., 2022).

As shown in Table 4.36, the diagonal values (square roots of AVE) are all greater than their respective inter-construct correlations, indicating that each construct shares more variance with its own indicators than with other constructs in the model. For example, the square root of AVE for Consultation is 0.902, which is higher than its correlations with AP (0.710), Research & Publication (0.465), Supervision (0.445), and Teaching (0.350). Similarly, the square root of AVE for Teaching is 0.927, which exceeds all its correlations with the other constructs. These results confirm that discriminant validity is established among the four first-order constructs of AP. Thus, each construct is empirically distinct and adequately represents its intended conceptual domain within the overall AP construct.

Table 4.36
Fornell-Larcker Criterion Between First-Order Constructs of AP

	AP	CONSLT.	RES.&PUB.	SUPERV.	TEACH.
AP	0.647				
CONSLT.	0.71	0.902			
RES.&PUB.	0.831	0.465	0.846		
SUPERV.	0.594	0.445	0.336	0.885	
TEACH.	0.549	0.35	0.294	0.6	0.927

The validation results confirm that AP can be modelled as a valid and reliable second-order construct, composed of four conceptually distinct yet empirically related domains. All first-order constructs demonstrate acceptable reliability, convergent validity, and discriminant validity. Since no hypotheses were formulated to test individual paths between the AP HOC and its subdimensions, no structural paths were estimated or reported. This modelling approach allows for a comprehensive and parsimonious representation of AP and supports its use in subsequent structural model testing involving other constructs in the study.

4.6 Mediation Analysis

Consistent with Step 5 of the analysis plan, this section examines the mediating role of SC. The section examines whether SC mediates the relationship between the SU of social media and AP. The mediation analysis used the bootstrapping procedure with 5,000 subsamples in SmartPLS. Both direct and indirect path coefficients were evaluated for statistical significance using t-values and p-values.

Table 4.37
Path Coefficients for Mediation Analysis

Path	Original Sample (β)	t-value	p-value	Significance
SU → AP	0.186	2.122	0.034	Significant
SU → SC	0.334	4.298	0.000	Significant
SU → SC → AP	0.072	2.271	0.023	Significant

As shown in Table 4.37, the direct effect of SU on AP was statistically significant (β = 0.186, p = 0.034), indicating that the SU of social media contributes positively to AP. Simultaneously, SU also had a significant indirect effect on AP through SC (β = 0.072, p = 0.023), indicating partial mediation. To assess the strength of the mediation, the Variance Accounted For (VAF) was calculated:

$$VAF = \frac{Indirect\ Effect\ (a \times b)}{Total\ Effect} \quad (4.1)$$

Indirect Effect (a × b) = SU → SC × SC → AP
= 0.334 × (0.072 / 0.334)
= 0.072,

Total Effect = Direct + Indirect
= 0.186 + 0.072
= 0.258,

VAF = 0.072 / 0.258
= 0.279 (or 27.9%).

According to Hair et al. (2017), a VAF between 20% and 80% indicates partial mediation. Thus, SC partially mediates the relationship between SU and AP. This means that while SU directly influences the AP, a portion of its effect is also channelled through enhancing SC. These findings indicate that the SU of social media contributes

to AP not only directly but also indirectly through the creation of SC. Table 4.38 presents a concise summary of the mediation analysis results. The significant indirect effect underscores the importance of social networks and relational resources in translating online engagement into meaningful academic outcomes. Figure 4.3 presents the mediation model.

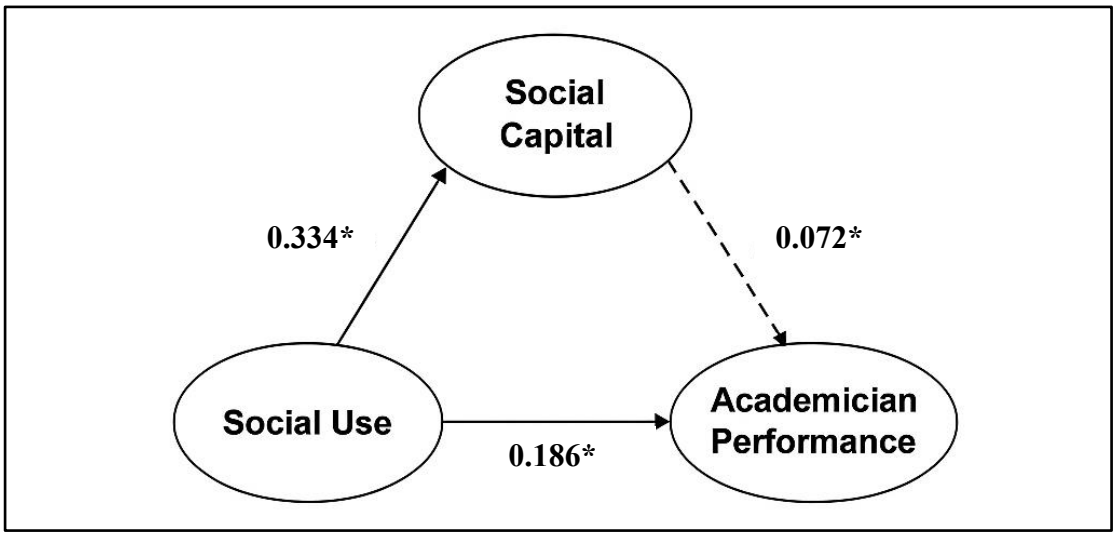


Figure 4.3 Mediation Path Diagram

Table 4.38
Summary of Mediation Effects

Path	Direct Effect (IV → DV)	Indirect Effect (IV → M → DV)	Total Effect	VAF (%)	Mediation Type
SU → SC → AP	0.186 (p = 0.034)	0.072 (p = 0.023)	0.186 + 0.072 = 0.258	0.072 / 0.258 × 100 = 27.9%	Partial Mediation

4.7 Importance-Performance Map Analysis (IPMA)

As outlined in Step 6 of the analysis plan, an IPMA was conducted to derive practical insights, with AP (D_AP) as the target construct to further enhance the interpretation of the PLS-SEM results. Unlike the basic PLS path model, IPMA considers the importance (total effects) and performance (average latent variable scores) of predictor constructs. This dual focus provides more actionable insights for practical decision-making.

4.7.1 Result of IPMA

The IPMA provides an extension to the standard PLS-SEM results by considering the average values of the latent variable scores (performance) alongside their total effects (importance). This analysis is crucial for identifying the most significant areas for strategic intervention (Hair et al., 2022; Ringle & Sarstedt, 2016).

As shown in Table 4.39 and Figure 4.4, SU emerged as the most important predictor (Total Effect = 0.277), followed by SC (Total Effect = 0.220). While SU has a moderate performance score (75.60), SC has the lowest performance in the model (69.30). According to the IPMA framework, constructs in the bottom-right area (high importance but relatively lower performance) are the primary targets for improvement. Therefore, enhancing the SC of academicians represents the most significant opportunity to boost overall performance, as it has high leverage but is currently low execution.

Table 4.39
Importance and Performance of Constructs Predicting Academicians' Performance

Construct	Total Effect (Importance)	Performance (%)
CU	0.168	85.699
HU	-0.223	80.130
SC	0.220	69.298
SU	0.277	75.596
SyU	0.148	81.776

CU and SyU are of moderate/high importance and high performance. With performance scores of 85.70 and 81.78, respectively, these constructs are already functioning effectively and should be maintained as foundational strengths.

A notable finding is that the negative importance of HU showed a negative total effect (-0.223) despite relatively high performance (80.130), suggesting that increasing hedonic engagement may reduce AP and should be monitored closely. SyU, with the lowest importance (0.148), displayed strong performance (81.776), indicating a stable support role.

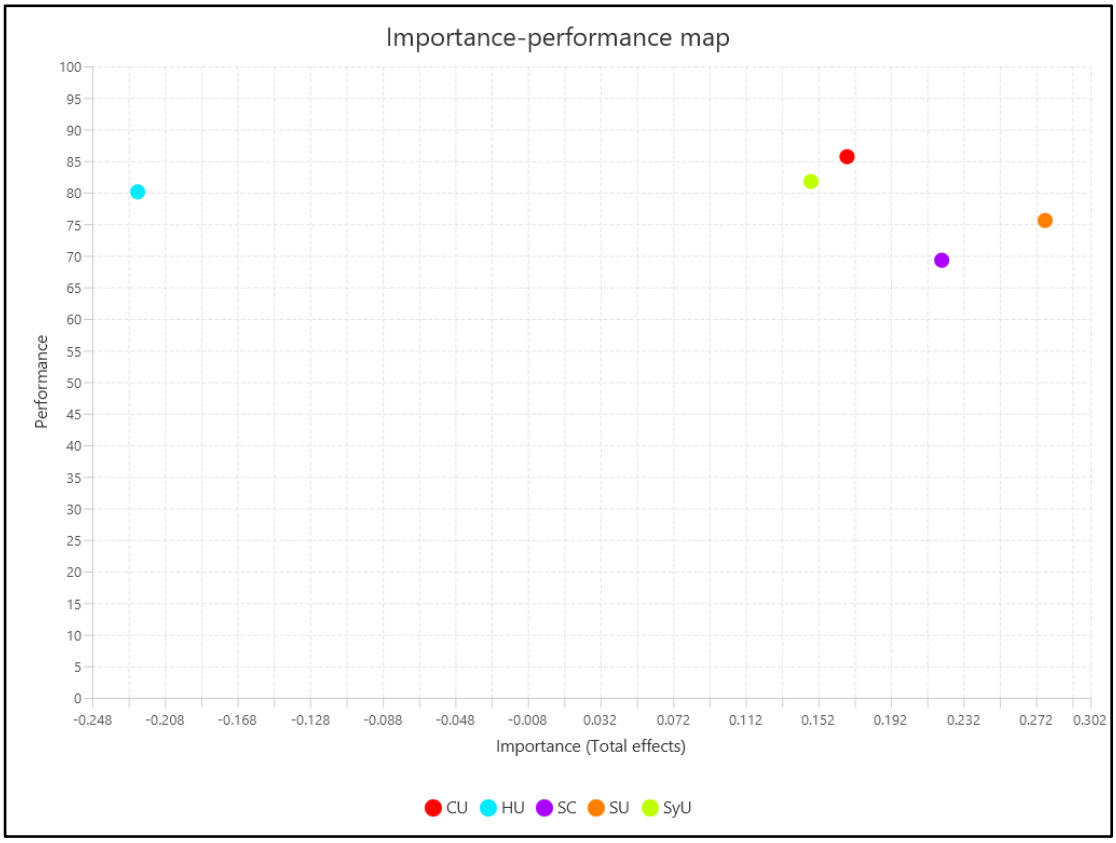


Figure 4.4 Importance-Performance Map Analysis (IPMA) for Academicians' Performance (AP)

The IPMA plot (see Figure 4.4) visually illustrates the relative positioning of each construct based on its importance (total effect) and performance (latent variable scores). Constructs in the top-right quadrant (e.g., CU and SyU) represent 'major strengths,' characterised by both high importance and high performance; these should be maintained to ensure continued academic success. Conversely, constructs with high importance but comparatively lower performance (e.g., SC and SU) are located in the bottom-right quadrant. These are identified as 'primary targets for improvement,' where strategic enhancements could yield the highest return in boosting AP. Finally, HU is situated on the left of the map with a negative total effect, suggesting that its role is counterproductive; thus, it should be de-emphasised in professional development strategies to prevent a decline in performance.

4.8 Hypotheses Testing Summary

This section summarises the hypotheses tested in the structural model as shown in Table 4.40, highlighting the relationships, path coefficients (β), t-values, p-values, and whether each hypothesis was supported based on the significance threshold of $p < 0.05$. The analysis also includes one indirect effect: assessing the mediating role of SC in the relationship between SU and AP.

Table 4.40
Summary of Hypothesis Testing

Hypothesis	Relationship	β	t-value	p-value	Significant (p < 0.05)	Decision
H1	System Use → Academicians' Performance	0.143	1.993	0.046	Yes	Supported
H2	Social Use → Academicians' Performance	0.186	2.122	0.034	Yes	Supported
H3	Content Use → Academicians' Performance	0.175	2.249	0.025	Yes	Supported
H4	Hedonic Use → Academicians' Performance	-0.196	2.921	0.004	Yes	Supported (Negative)
H5	Social Capital → Academicians' Performance	0.214	2.791	0.005	Yes	Supported
H6	Social Use → Social Capital	0.334	4.298	0	Yes	Supported
H7	SU → SC → AP (Mediation)	0.072	2.271	0.023	Yes	Supported (Partial Mediation)

The final structural model was established after validating the model's measurement and structural components using PLS-SEM. The model incorporates direct paths from four dimensions of SMU (SyU, SU, CU, and HU) to AP and the mediating role of SC in the relationship between SU and AP.

All hypothesised relationships included in the final model were statistically supported at the 0.05 significance level. HU significantly negatively affected performance, while SC emerged as a meaningful mediator. A visual representation of the final structural model is presented in Figure 4.5, illustrating the significant pathways and mediation effect observed in the study.

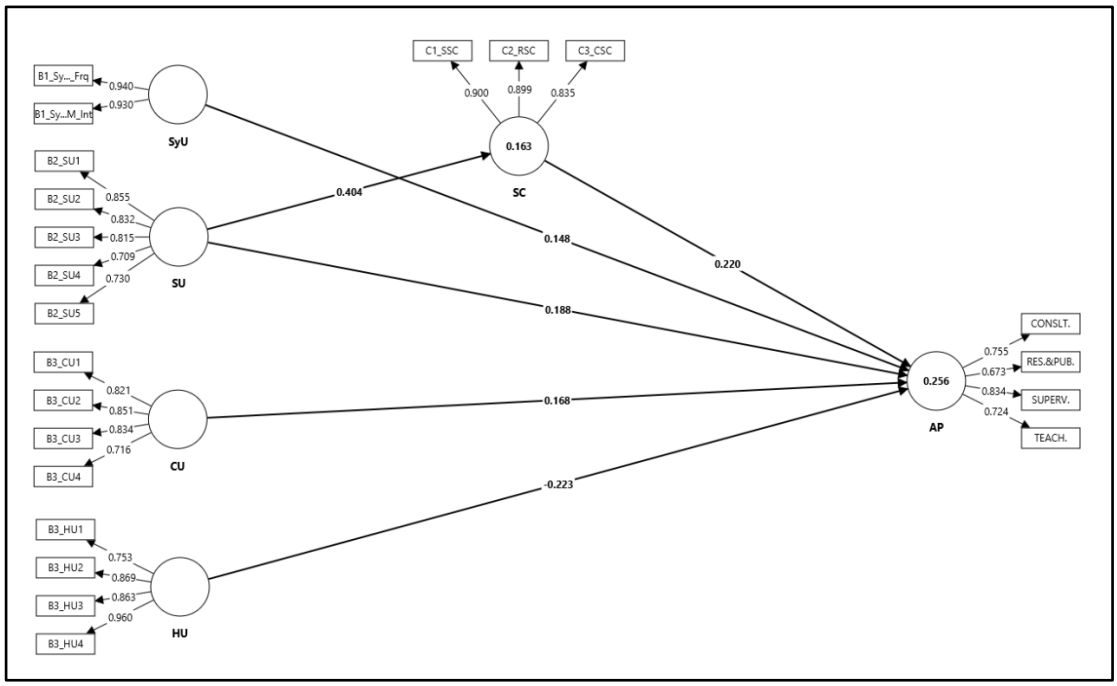


Figure 4.5 Structural Equation Model of Social Media Use, Social Capital, and Academicians' Performance with Mediation Path

(Note: SyU = System Use, SU = Social Use, CU = Content Use, HU = Hedonic Use, SC = Social Capital, SSC = Structural Social Capital, RSC = Relational Social Capital, CSC = Cognitive Social Capital, and AP = Academicians' Performance. All path coefficients are statistically significant at $p < 0.05$. The path from Hedonic Use (HU) to Academicians' Performance (AP) is negative ($\beta = -0.223$), indicating an inverse relationship.)

4.9 The Final Validated Model: Multidimensional Social Media Use-Performance Model with Social Capital Mediation

As the highlight of the theoretical advancements discussed in the preceding sections, this study presents a final, empirically validated structural framework (see Figure 5.1). This refined model represents the final product of the research, integrating the multidimensional nature of SMU with the mediating role of SC to explain AP outcomes.

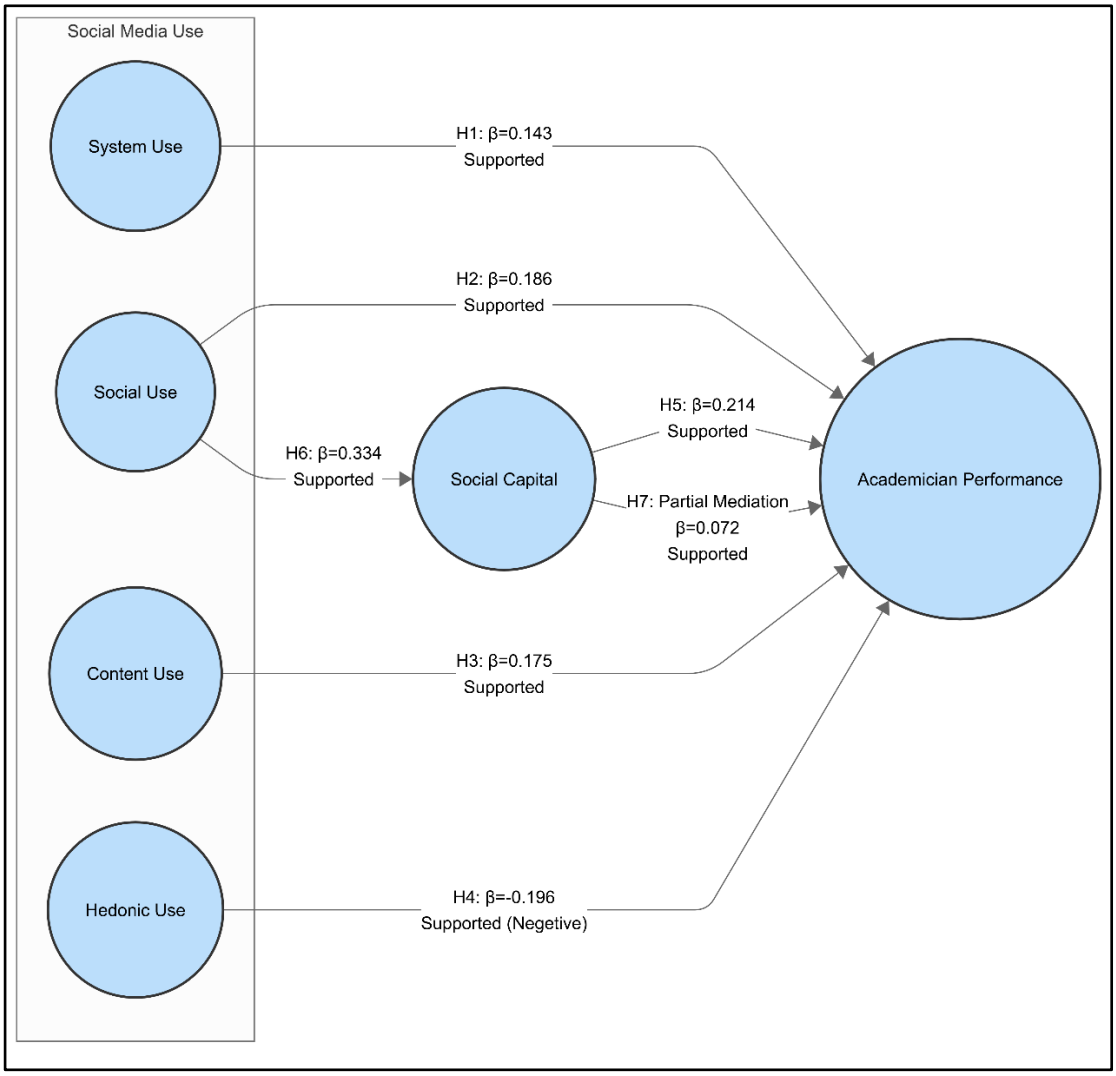


Figure 4.6 Multidimensional Social Media Use–Performance Model with Social Capital Mediation

The clean model highlights the core mechanisms through which SMU influences AP. Specifically, it demonstrates that system, social, and CUs contribute positively to performance, while HU exerts a negative influence. Importantly, the model confirms SC as an HOC that partially mediates the relationship between SU and AP, underscoring the importance of relational resources in academic digital environments. This validated framework constitutes the study's primary theoretical contribution, offering a coherent roadmap for future research on digital engagement and professional productivity in higher education.

4.10 Chapter Summary

This chapter presented the study's empirical results, including the measurement model assessment, structural model testing, mediation analysis, and IPMA. The findings establish the statistical validity and reliability of the constructs and confirm key relationships among dimensions of SMU, SC, and AP within the context of Malaysian higher education. All constructs demonstrated acceptable reliability, convergent validity, and discriminant validity. The structural model confirmed significant effects of SyU, SU, CU, and SC on AP, while HU showed a significant negative effect. SC was also found to mediate the relationship between SU and the AP. The final structural model was validated, and the IPMA results identified SU and CU as high-priority areas. These empirical outcomes provide the foundation for deeper interpretation and theoretical implications. A comprehensive discussion of these findings, including theoretical contributions, practical implications, and alignment with the ROs, is provided in Chapter 5.

CHAPTER 5
CONCLUSION

5.1 Introduction

Chapter 5 serves as the analytical culmination of the study, systematically transitioning from empirical validation to strategic implication by synthesising the findings of Universiti Teknologi MARA (UiTM) academicians to address the core Research Objectives (ROs). The chapter begins with a high-level summary of the structural model results before moving into an in-depth discussion that links the multidimensional nature of Social Media Use (SMU), specifically the system, social, content, and hedonic dimensions, to Academician's Performance (AP), with a primary focus on the pivotal mediating role of Social Capital (SC) as the engine for professional success. This narrative then elevates the discourse to highlight significant theoretical and methodological contributions, explaining how the study extends traditional IS models by integrating Social Capital Theory (SCT) into the digital academic landscape. To ensure practical relevance, the flow culminates in actionable institutional and policy recommendations to optimise digital literacy and governance at UiTM, while maintaining academic rigour by acknowledging limitations and proposing future research directions to advance the scholarly legacy of the work.

5.2 Summary of Results and Findings

This study investigated how multidimensional SMU influences AP, with SC examined as a mediating mechanism. Overall, the findings provide strong empirical support for the proposed research framework and address the study's ROs. The results indicate that SMU among UiTM academicians is widespread and serves multiple professional and personal purposes. System-oriented, social, and content-driven uses emerged as beneficial forms of engagement that support academic work, such as teaching, supervision, research, and professional collaboration. These findings reinforce prior literature that positions social media as an enabling technology for knowledge sharing, networking, and task efficiency within higher education contexts.

In contrast, Hedonic Use (HU) demonstrated a negative association with AP. This suggests that while social media can enhance productivity when used instrumentally, excessive leisure-oriented engagement may distract academicians from core academic responsibilities. This finding highlights the dual nature of SMU and underscores the importance of purposeful and regulated engagement in professional settings. SC was found to play a crucial role in explaining performance outcomes. Academicians who actively used social media for social interaction and professional networking reported stronger relational resources, including trust, reciprocity, and knowledge sharing. These relational assets, in turn, positively influenced AP, confirming SC as both a direct contributor and a partial mediator in the relationship between SMU and performance. This supports SCT and extends its application within the context of digital academic environments.

Collectively, the findings confirm the multidimensional nature of SMU and demonstrate that not all forms of use contribute equally to performance outcomes. The study addresses existing gaps in Information Systems (IS) and higher education literature by integrating usage dimensions, SC, and performance within a single empirical model. Importantly, the results highlight that effective SMU in academia is not merely a matter of access or frequency, but of how and why these platforms are used.

These insights provide a strong foundation for the practical implications discussed in the subsequent section, particularly in guiding institutions and academicians toward more strategic and productive use of social media in higher education. In conclusion, this research culminates in the development of a validated structural framework that advances the understanding of SMU in academic contexts. By refining the multidimensional relationships among usage types, SC, and performance, this study provides a coherent, theoretically grounded product. The final clean model, discussed as a primary contribution in Section 5.4, serves as a roadmap for future research and institutional strategies for effective social media engagement in higher education.

5.3 Discussion of Key Findings

With the measurement and structural models' statistical validity firmly established in the preceding chapter, this section shifts from empirical reporting to a critical interpretation of the results. The discussion seeks to contextualise the findings within the existing body of literature and the specific socio-professional landscape of UiTM.

5.3.1 Research Objective 1: To Identify Dimensions of Social Media Use Among Academicians

This study validated SMU as a multidimensional construct comprising System Use (SyU), Social Use (SU), Content Use (CU), and HU. Drawing upon Uses and Gratifications Theory (UGT), the Technology Acceptance Model (TAM), and the Information Systems Success Model (ISSM), these four dimensions were tested and confirmed through Confirmatory Factor Analysis (CFA). All measurement indicators demonstrated strong psychometric properties, with factor loadings above 0.70, Cronbach's alpha and composite reliability exceeding 0.70, and AVE values above 0.50, confirming convergent validity. This validation advances prior IS research, which often treats "use" as a unidimensional construct, typically measured by frequency, duration, or intensity (Venkatesh et al., 2003). The present study extends this view by capturing the diverse, context-specific characteristics of SMU within academia.

Among the four dimensions, SU emerged as the most prominent, reflected in high factor loadings and the highest descriptive mean scores. This indicates that academicians primarily use social media for professional networking, collaboration, and maintaining scholarly relationships. These findings strongly align with Boyd and Ellison's (2007) definition of social networking services and Kietzmann et al.'s (2011) honeycomb framework, which emphasise identity, conversations, relationships, and group presence as central to social media functionality. Empirical evidence from previous studies supports this interpretation, showing that platforms such as LinkedIn, ResearchGate, and academic blogs provide critical avenues for academicians to build networks, share ideas, and promote research visibility (Gruzd et al., 2012; Lapoe et al., 2017). Thus, SU's dominance highlights the central role of relationship-building in academic engagement with social media.

The study also found that CU was a strong and valid dimension, supported by both CFA results and moderate descriptive mean values. This dimension captures the use of social media for accessing, organising, and disseminating academic content, underscoring its role in knowledge management and scholarly communication. These findings are consistent with Högberg's (2018) functionalist perspective, which emphasises content creation and dissemination, and with prior work that identified Mendeley, ResearchGate, and Twitter as key platforms supporting academic information sharing and collaboration (Vásquez et al., 2015; Veletsianos, 2013). The validation of CU as a distinct dimension demonstrates that social media serves both social interaction and the cognitive and informational needs of academicians.

By contrast, SyU and HU, while empirically validated in the CFA, showed relatively lower descriptive means than SU and CU. SyU, measured through frequency and intensity of use, reflects the behavioural integration of social media into academic practice. This aligns with the TAM and DeLone and McLean's ISSM, which posit that perceived usefulness and system quality lead to sustained usage (Davis, 1989; DeLone & McLean, 2003). High SyU scores indicate that social media has become a normalised tool in academic work, consistent with successful technology adoption. HU, meanwhile, captures the entertainment and leisure aspects of social media engagement, resonating with UGT's proposition that users seek gratifications beyond utilitarian goals (Katz et al., 1973). Although less central than SU and CU, their inclusion strengthens the overall conceptualisation of SMU as a comprehensive, four-dimensional construct. These findings confirm that academicians' social media engagement is best understood through a multidimensional framework that balances technical, social, informational, and hedonic motives.

The results of the measurement model validation using factor loadings, AVE, and internal consistency reliability indicators confirmed that each of these four constructs represents a unique and empirically distinguishable dimension of SMU. Furthermore, each construct demonstrated satisfactory psychometric properties, with composite reliabilities (ρc) exceeding 0.84 and AVEs exceeding the 0.50 threshold, thereby validating the robustness of this multidimensional conceptual framework. Thus, Objective 1 was comprehensively addressed through theoretical synthesis and empirical modelling, resulting in a validated, granular framework for understanding how academicians use social media in various professional and personal capacities.

5.3.2 Research Objective 2: To Examine Which Dimensions of Social Media Use Influence Academicians' Performance

This section discusses the direct effects of the four multi-dimensions of SMU (i.e., SyU, SU, CU, and HU) on AP, as hypothesised in H1 through H4. The structural model estimation using PLS-SEM revealed statistically significant relationships for all four dimensions, albeit with varying effect sizes and directions. These findings validate the theoretical assumptions underlying the research framework and offer nuanced insights into how different social media engagement patterns influence academic productivity in Malaysian higher education.

$$H1: SyU \rightarrow AP$$

The first hypothesis (H1) posited that SyU, which refers to social media interaction frequency, duration, and intensity, would positively influence AP. The hypothesis was supported, with a path coefficient (β) of 0.143 ($t = 1.993$, $p = 0.046$), indicating a statistically significant but modest positive effect. This result is consistent with earlier research grounded in the TAM (Davis, 1989), emphasising the importance of Perceived Ease of Use (PEU) and continued interaction as precursors to performance benefits.

SyU in this study was conceptualised along technical and habitual dimensions, capturing regular log-ins, platform familiarity, and interaction frequency. These aspects contribute to what is commonly termed "digital readiness," which is foundational in leveraging more cognitively and socially meaningful uses of social media. For instance, academicians who are regularly active on platforms such as LinkedIn, Twitter, or ResearchGate are likely to become more comfortable with their features, enhancing their ability to utilise these tools for more complex professional functions such as networking, content sharing, or collaborative writing.

The finding supports the assertions of Ansari and Khan (2020), who found that habitual SMU improved communication among faculty and students, thereby enhancing the quality of teaching and supervision. Similarly, Al Kurdi (2024) demonstrated that sustained engagement with digital platforms eventually leads to more strategic, value-driven use among academics. However, this study's relatively low effect size suggests

that SyU, while necessary, may serve more as a prerequisite or facilitator than a direct driver of AP.

Furthermore, this finding aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003), which posits that effort expectancy and performance expectancy shape technology usage behaviour. In Malaysian higher education, where digital infrastructure and social media policies are still maturing across various institutions, mere usage may reflect a baseline level of digital literacy rather than an indicator of meaningful academic output. Hence, while SyU remains a significant predictor, its influence appears foundational rather than transformational.

H2: SU → AP

The second hypothesis (H2) investigated the direct relationship between SU and AP. SU encompasses interpersonal communication, professional networking, and relational engagement through digital platforms. The hypothesis was supported, with a path coefficient of 0.186 ($t = 2.122$, $p = 0.034$), demonstrating a statistically significant positive impact. Among the dimensions studied, SU emerged as one of the more influential predictors of the AP, corroborating theoretical propositions from SCT (Putnam, 2000; Nahapiet & Ghoshal, 1998) and the UGT (Ruggiero, 2000).

This finding reflects the growing role of social media in fostering collaborative and communicative environments among scholars. Platforms like LinkedIn, Facebook, academic groups, and ResearchGate facilitate peer-to-peer interaction, provide access to expert communities, and support ongoing academic discourse. The result is consistent with the study by Shah et al. (2017), which reported that social networking enhances career visibility, improves peer engagement, and increases co-authorship opportunities. Similarly, Wang et al. (2020) found that SU promotes trust-building and reciprocal learning, key elements of academic collaboration.

Theoretically, SU corresponds closely with SC's relational and structural components, which are instrumental in shaping professional outcomes. The SCT posits that trust-based relationships and network density can facilitate access to information, emotional support, and collective learning, all of which are essential in academia. In line with the honeycomb framework of social media functions by Kietzmann et al.

(2011), SU activates core functions such as “relationships” and “presence,” which translate into tangible academic benefits like mentorship, resource sharing, and institutional coordination.

In the Malaysian context, where collaborative culture in research and teaching is increasingly emphasised under national strategic plans such as MyRA and the Malaysian Education Blueprint, social connectivity via digital platforms enhances institutional visibility and supports interdisciplinary initiatives. Thus, the significant positive association observed in this study aligns with global findings and underscores the importance of purposeful relational engagement in local academic settings.

H3: CU → AP

The third hypothesis (H3) proposed that CU would significantly and positively influence AP. This dimension focuses on consuming, creating, and sharing knowledge-based content through social media platforms. The hypothesis was supported, with a path coefficient of 0.175 ($t = 2.249$, $p = 0.025$), indicating a significant direct relationship.

This result is theoretically grounded in the UGT, which posits that individuals actively choose media platforms to satisfy specific needs, such as knowledge acquisition, professional development, and peer recognition (Ruggiero, 2000). The findings also support the cognitive dimension of SCT, which emphasises the role of shared language, norms, and values in facilitating cooperative action (Nahapiet & Ghoshal, 1998).

Empirically, the results are consistent with the studies by Meishar-Tal and Pieterse (2017) and Lim et al. (2020), which found that academics who engage with research-driven content on platforms like Academia.edu, Google Scholar, and ResearchGate are more likely to participate in academic discourse, increase their citation counts, and improve their scholarly visibility. Vásquez et al. (2015) also reported that CU contributes to job-related learning and resource access, which are integral to performance in higher education.

At UiTM and similar institutions, CU supports several Key Performance Indicators (KPIs), including research productivity, teaching innovation, and community engagement. The digital dissemination of scholarly material, such as preprints, datasets,

teaching videos, or policy briefs, enables broader academic outreach and supports professional branding (Jordan & Weller, 2018). As the Malaysian research ecosystem increasingly emphasises metrics like citations and research grants, the ability to strategically use content-based platforms becomes a valuable competency.

Thus, the significant impact of CU on AP can be interpreted as evidence that academics who are consumers and contributors to digital knowledge ecosystems tend to perform better across teaching, research, and service domains. The findings underscore the utility of digital scholarship as both a personal and institutional advantage.

H4: HU → AP

The fourth hypothesis (H4) tested the relationship between HU and AP. This dimension captures leisure-driven, entertainment-focused, and non-academic interactions on social media. Interestingly, the hypothesis was supported, but the relationship was negative and statistically significant, with a path coefficient of –0.196 ($t = 2.921$, $p = 0.004$). This finding indicates that while HU is common, its influence on performance is detrimental, echoing concerns raised in previous literature about the potentially distracting nature of recreational SMU.

The result is in line with the studies by Balakrishnan and Raj (2016) and Kuss and Griffiths (2017), which found that non-purposeful social media usage can lead to decreased productivity, time mismanagement, and reduced job satisfaction. Junco (2012) reported similar findings among students, where excessive use of platforms for entertainment correlated with lower AP. Among academicians, these effects may manifest as decreased concentration, procrastination, and limited time for core responsibilities, such as research writing, student supervision, or curriculum development.

While the UGT accounts for leisure and escapism as legitimate media motivations, this study's findings suggest that such gratifications may have limited value in professional contexts. In fact, prolonged hedonic engagement may erode the boundaries between work and personal life, especially in remote or hybrid working environments with abundant digital distractions.

The negative relationship between HU and AP also aligns with the ISSM (DeLone & McLean, 2003), emphasising that system usage must be purposeful and task-aligned to yield positive outcomes. Sun and Shang (2014) noted that hedonic engagement could be an early-stage familiarity mechanism. However, unless it evolves into more strategic uses (such as CU or SU), it remains professionally unproductive.

Malaysian universities, where academicians are assessed based on detailed KPIs, including publications, teaching evaluations, and time allocated to community service, have become critical. HU, if not moderated, could undermine efforts to meet these benchmarks. Moreover, in institutions like UiTM, where digital behaviour is increasingly integrated into teaching and learning systems (e.g., u-future), the misalignment of online time with institutional goals poses a potential risk to academic productivity.

Collectively, the findings of H1 to H4 provide robust evidence that social media usage patterns significantly influence AP, though not uniformly. While SyU, SU, and CU each exert a positive effect, HU presents a cautionary tale about the unintended consequences of digital leisure in professional spaces. These differential effects reinforce the value of treating SMU as a multidimensional construct rather than a singular behaviour.

The results support foundational theories such as TAM, UGT, and SCT, while extending their applicability to the specific context of Malaysian higher education. In particular, the significant effects of SU and CU highlight the transformative potential of social media when used purposefully. Conversely, the negative association observed for HU calls for implementing digital well-being practices and institutional policies that help academics manage online engagement in a balanced manner.

Overall, the direct effects model presented in this study provides valuable insights into how different types of social media behaviour shape academic outcomes. As universities continue integrating digital tools into their operational and strategic frameworks, understanding these nuanced relationships becomes crucial for optimising Social Media Adoption (SMA), training, and policy development across Higher Education Institutions (HEIs).

5.3.3 Research Objective 3: To Determine the Level of Social Media Use and Academicians' Performance Among UiTM Academicians

The findings reveal that SMU among UiTM academicians is widespread and deeply embedded in their professional routines. Over 84% of respondents reported using social media either "Almost Every Time" or "Every Time," with a composite mean score of 4.27 (SD = 0.779) for SyU, indicating high frequency and intensity of engagement. This level of integration aligns with the TAM, which posits that perceived usefulness and ease of use drive sustained technology adoption (Davis, 1989; Alenazy et al., 2019). The dominance of platforms such as WhatsApp (35.0%), Google Scholar (17.5%), and Telegram (13.6%) reflects a strategic preference for tools that support real-time communication, knowledge retrieval, and academic identity management. These choices are not random but align with daily academic tasks, consistent with studies showing that instrumental use of social media enhances job performance by improving coordination and information access (Chen et al., 2024; Jafar et al., 2019). According to Media Synchronicity Theory (Dennis, 2008, as cited in Lee & Lee, 2020), platforms like WhatsApp offer high interactivity and message convergence, enabling users to reduce ambiguity in complex tasks, particularly valuable in collaborative supervision, research coordination, and administrative communication.

Beyond functional use, social media also serves hedonic and emotional purposes, revealing a dual role in academic life. High mean scores for items such as "I use social media to take a break from work" (M = 5.89) and "to get myself relaxed" (M = 5.78) indicate that academicians actively use these platforms for stress relief and psychological well-being. This aligns with UGT, which identifies tension release as a core motivation for media consumption (Katz et al., 1973; Ruggiero, 2000). However, this gratification-seeking behaviour carries risks. The Importance-Performance Map Analysis (IPMA) reveals a negative total effect of HU on AP (–0.223), despite its relatively high performance score (80.13%), suggesting that while such use is everyday, it may undermine productivity when unregulated. This finding echoes concerns raised by Yu et al. (2019) and Sendurur et al. (2015), who observed that excessive, entertainment-driven engagement can lead to distraction, procrastination, and reduced work focus. The open-ended responses substantiate this: 22 respondents explicitly cited social media-induced procrastination as a key challenge. In contrast, others mentioned

"information overload" and "time wastage," reinforcing the dual-edged nature of social media in professional environments (Turulja et al., 2022).

Regarding AP, respondents reported strong self-efficacy in core academic functions, particularly in teaching and research. The teaching dimension recorded the highest mean scores, with "I have expertise in my area of teaching" (M = 4.49) and "I have an appropriate teaching method for the students" (M = 4.43), indicating a high level of confidence in pedagogical competence. Similarly, research-related items such as "I will publish based on my KPI" (M = 4.19) align with institutional expectations. These results are consistent with the conceptualisation of job performance as the degree to which individuals achieve work-related goals and contribute to organisational success (Williams & Anderson, 1991; Janssen & Van Yperen, 2004). However, motivation to exceed KPIs was more moderate, as reflected in lower scores for "I am willing to publish more than my KPI" (M = 3.66) and "I predict to publish more than my KPI" (M = 3.67), suggesting that performance is largely compliance-driven rather than intrinsically motivated. Furthermore, performance in consultation activities was comparatively lower, particularly in establishing industry relationships (M = 3.36) and visibility in one's field (M = 3.46), indicating underdeveloped external engagement, a critical gap in knowledge transfer, and societal impact.

Most notably, the IPMA results highlight a critical disconnect between importance and performance. SU (total effect = 0.277) and SC (total effect = 0.220) emerged as the most influential predictors of AP, yet both scored below optimal levels in performance (75.60% and 69.30%, respectively). This suggests that while networking, collaboration, and trust-building are key performance drivers, academicians are not fully leveraging social media to achieve them. This underperformance in SC development is particularly significant, as Wang et al. (2020) argued that social media enables employees to access critical resources, build professional relationships, and enhance collaborative innovation. The low performance in Cognitive Social Capital (CSC) and Relational Social Capital (RSC) (e.g., understanding differences in work priorities, sharing personal support) further indicates that while structural connections exist, deeper, trust-based relationships are lacking. To maximise the benefits of social media, institutions must move beyond access and usage metrics and foster intentional, strategic engagement. As Moyo and Nkhahle (2024) emphasised, organisations should implement digital literacy programs, clear usage guidelines, and recognition mechanisms to encourage productive use while minimising

distractions. This includes promoting platforms such as ResearchGate and LinkedIn for scholarly visibility, training in effective collaboration through WhatsApp groups, and supporting digital well-being to prevent burnout.

5.3.4 Research Objective 4: To Identify the Challenges of Social Media Use in Academic Settings

This section discusses the findings related to RO4, which aimed to identify the challenges academicians face when using social media in academic settings. Thematic analysis of open-ended responses revealed 20 distinct challenge themes, with the most frequently reported being social media-induced procrastination (n = 22), information overload (n = 21), data privacy and security concerns (n = 19), and access and connectivity issues (n = 18). These findings, supported by qualitative and quantitative data, highlight the complex and often contradictory nature of social media engagement in higher education, where tools designed to enhance productivity can simultaneously become sources of distraction, stress, and professional risk.

One of the most prominent challenges identified was social media-induced procrastination, with 22 respondents explicitly stating that they struggle with time management due to excessive scrolling, feed distractions, or getting "carried away by videos." This aligns with prior research indicating that the hedonic and addictive design of social media platforms can lead to unproductive use, particularly in knowledge-intensive professions (Yu et al., 2019; Sendurur et al., 2015). From the UGT perspective, while users may initially seek relaxation or mental breaks (Katz et al., 1973), the gratification obtained often exceeds intended limits, resulting in behavioural overuse and diminished work focus. This paradox, in which a tool for stress relief ultimately contributes to work pressure, reflects a broader failure of self-regulation in digital environments.

The challenge of information overload is closely linked to procrastination, reported by 21 respondents. Academicians described being overwhelmed by "too much unrelated information," "overflow of content," and difficulty filtering relevant academic material from noise. This phenomenon is consistent with Zhang et al. (2022), who defined information overload as a state in which the volume of incoming information exceeds an individual’s processing capacity, leading to cognitive fatigue and decision paralysis. In academia, where precision and credibility are paramount, this excess of

unverified or redundant content can hinder research efficiency and scholarly judgment. The multiplicity of platforms, from WhatsApp groups to Twitter threads, further fragments attention and increases cognitive load, making it challenging to focus on core academic tasks.

Another significant concern was data privacy and security, raised by 19 respondents. Concerns included "privacy setting loopholes," "exposure of location data," "risks of identity theft," and fears of "data mining" by third parties. These findings resonate with growing global anxieties about digital surveillance and ethical use of personal information (Bhatiasevi, 2024). For public-sector academicians in Malaysia, who are bound by civil service ethics and institutional policies, the blurring of personal and professional boundaries on social media poses reputational and legal risks. As one respondent noted, "I prefer to stay passive to avoid issues," reflecting a cautious approach shaped by institutional norms and fear of misinterpretation. This aligns with the Theory of Planned Behaviour (TPB), which posits that perceived behavioural control and subjective norms (e.g., organisational culture) significantly influence social media engagement (Sharma et al., 2020).

Access and connectivity issues were also frequently cited (n = 18), particularly in rural campuses or areas with poor internet infrastructure. Respondents reported "lagging," "unstable connections," and "restricted access" within certain university zones, which disrupts real-time collaboration and limits participation in digital academic communities. This digital divide underscores inequities in access to technology across Malaysia's geographically dispersed higher education system. While urban-based academicians may seamlessly use platforms like Google Scholar or ResearchGate, those in remote locations face structural barriers that hinder equitable digital engagement. This concern challenges the assumption of universal connectivity in e-learning and digital scholarship policies.

Additional challenges included misinformation and fake news (n = 11), credibility of sources (n = 11), and mental health impacts (n = 8), such as anxiety and self-worth tied to online validation (e.g., likes and comments). These findings reflect the post-truth digital environment, where Artificial Intelligence (AI)-generated content and viral misinformation complicate the verification process (Nicely, 2024). As knowledge custodians, academics feel a heightened responsibility to discern credible information, yet many expressed uncertainty. This epistemological tension between

open knowledge sharing and academic rigour reveals a critical gap in digital literacy training within academic institutions.

Interestingly, 61 respondents reported no challenges, indicating that SMU is seamless and beneficial for a significant portion of the sample. This duality between those who experience severe challenges and those who do not suggests that individual differences (e.g., digital fluency, digital literacy) play a crucial role in shaping social media experiences (Adelakun et al., 2023). It also highlights the context-dependent nature of these challenges, which cannot be generalised across all academicians.

5.3.5 Research Objective 5: To Examine the Mediating Role of Social Capital Between Social Media Use and Academicians' Performance

RO5 examined whether SC mediates the relationship between SMU and AP. The findings confirmed a partial mediation effect, as SU was demonstrated to influence performance directly ($\beta = 0.186$, $p = 0.034$) and indirectly through SC ($\beta = 0.072$, $t = 2.271$, $p = 0.023$). This indicates that while social media engagement in academic contexts contributes directly to professional outcomes, its impact is significantly strengthened when it fosters the development of relational resources embedded in SC.

Theoretically, these results reinforce the propositions of SCT (Putnam, 2000; Nahapiet & Ghoshal, 1998), highlighting how trust, shared norms, and professional networks enhance access to information, collaboration, and opportunities. This study demonstrates that social interactions on platforms such as LinkedIn, ResearchGate, and Twitter provide a foundation for building the structural, relational, and cognitive dimensions of SC. These dimensions, in turn, translate into improved performance across teaching, research, supervision, and scholarly visibility.

This mediated relationship also supports prior empirical findings that underscore the importance of SC in linking digital engagement with professional performance. Studies such as Sun and Shang (2014), Esteve Del Valle et al. (2017), and Wang et al. (2020) found that the performance benefits of SMU are maximised when mediated by strong professional networks and trust-based relationships. Similarly, Ali-Hassan et al. (2015) and Alajmi and Alasousi (2023) demonstrated the significance of relational and knowledge-sharing communities in transforming social media engagement into meaningful professional outcomes.

In the context of Malaysian higher education, the findings offer an important contribution by showing how social media helps overcome institutional and geographical barriers, particularly in large multi-campus universities such as UiTM. Digital platforms are critical in sustaining collaboration and academic coherence by enabling connections across dispersed faculties and disciplines. Moreover, in a performance-driven, hierarchical academic culture, digital SC offers an accessible and influential mechanism for advancing professional outcomes.

From a theoretical perspective, validating this mediating role extends beyond SCT to the UGT and the honeycomb model of social media functionality (Kietzmann et al., 2011). While UGT explains why academicians engage in social media for recognition, validation, and community, the honeycomb model underscores how "relationships" and "reputation" are central to platform use. This study demonstrates that these theoretical dimensions converge in the digital academic environment, where relational and reputational gains translate into measurable performance.

RO5 is achieved by confirming that SC significantly mediates the relationship between SMU and AP. This partial mediation underscores that the benefits of social media extend beyond direct engagement, highlighting the critical role of relational assets in sustaining and enhancing academic productivity in Malaysian HEIs.

5.3.6 Research Objective 6: To Recommend Improvements to Enhance Effective Social Media Use Among Academicians

This study has demonstrated that SMU among academicians is a multidimensional phenomenon, shaped by individual motivations, institutional structures, and systemic forces. Drawing on evidence from descriptive analysis, measurement model validation, PLS-SEM, IPMA, and open-ended responses, this section presents strategic recommendations organised across three interconnected levels: User-Centric, Institutional, and Ecosystem-Level. This tri-level framework reflects the complex, interdependent nature of digital engagement in academia and supports the development of comprehensive, sustainable interventions.

At the user-centric level, the focus is on empowering individual academicians to engage with social media to enhance productivity, well-being, and professional identity. The structural model revealed a significant adverse effect of HU on AP ($\beta = -0.196$, $p = 0.004$), despite its high frequency of use (80.13% performance score). This

indicates a misalignment between gratification-seeking behaviour and productive outcomes, consistent with UGT (Katz et al., 1973). To address this, academicians should adopt self-regulatory strategies such as digital detox periods, time-tracking tools (e.g., Forest, RescueTime), and the Pomodoro Technique to minimise distraction and improve focus (Prakashkumar et al., 2023). Furthermore, the IPMA results show that CU (importance = 0.168, performance = 85.7%) and SU (importance = 0.277, performance = 75.6%) are key performance drivers. Academicians should shift from passive consumption to active knowledge curation, sharing research summaries, publishing preprints on ResearchGate, or engaging in scholarly discussions on LinkedIn and Twitter/X. This aligns with the concept of digital scholarship and supports professional visibility, peer feedback, and interdisciplinary collaboration (Jordan & Weller, 2018). A dual-account strategy, separating personal and professional profiles, can help maintain psychological boundaries and reduce role conflict, particularly in cultures where public service ethics are emphasised (Nguyen, 2021). By fostering digital mindfulness, academicians can transform social media from a source of distraction into a tool for lifelong learning and academic impact.

At the institutional level, universities must move beyond ad hoc adoption and establish intentional, structured frameworks for digital engagement. The measurement model confirmed SC as a Higher-Order Construct (HOC), with strong outer loadings (SSC = 0.894, RSC = 0.907, CSC = 0.842) and discriminant validity (Heterotrait-Monotrait Ratio (HTMT) < 0.90). Given its significant positive influence on performance ($\beta = 0.214$, $p = 0.005$), institutions should actively cultivate SC through digital means. First, digital literacy programs should be embedded in faculty development initiatives. These should go beyond technical skills, including critical evaluation of online content, awareness of algorithms, and ethical digital citizenship (UNESCO, 2018). Training should also cover task-technology fit, helping academicians match platforms to specific academic functions, e.g., using WhatsApp for supervision updates, Telegram for research groups, and YouTube for flipped teaching (Greenhow & Gleason, 2014). Second, institutions should develop social media governance policies aligned with national laws (e.g., Personal Data Protection Act 2010) and *Rukun Negara* principles, particularly *Kesopanan dan Kesusilaan* (Good Behaviour and Morality). These policies should define acceptable use, protect privacy, and prevent reputational risks without stifling academic freedom. Third, infrastructure equity is essential. The open-ended responses highlighted connectivity issues in specific

campuses, reflecting a digital divide. Universities must invest in campus-wide Wi-Fi, device subsidies, and mobile-responsive systems to ensure equitable access (Musa et al., 2020). Finally, institutions should recognise digital scholarship in performance appraisals to incentivise productive engagement by incorporating altmetrics (e.g., article views, shares, mentions) as optional but valid impact indicators (Thelwall & Kousha, 2015). This would encourage meaningful participation without penalising those who prefer traditional channels.

At the ecosystem level, the focus expands to the interconnected network of stakeholders, including government agencies, funding bodies, professional associations, and platform providers, that shape the digital landscape of higher education. The moderate R^2 value of 0.246 for AP suggests that while the model explains a meaningful portion of variance, external systemic factors, such as national KPIs, funding models, and cultural norms, also play a critical role. Therefore, the Ministry of Higher Education (MoHE) should revise national performance frameworks to recognise digital engagement as a formal component of academic contribution. This includes supporting open-access publishing, public scholarship, and online knowledge dissemination as legitimate forms of impact. A tiered recognition system could allow institutions to adopt digital metrics at their own pace, ensuring inclusivity and fairness. Additionally, the negative impact of HU, along with widespread reports of technostress and procrastination, calls for national-level initiatives to promote digital well-being. These could include public campaigns on healthy SMU, mental health support for academics, and partnerships with tech companies to design less addictive, education-friendly platforms. Finally, the fragmented platform landscape, with WhatsApp (35%), Google Scholar (17.5%), and ResearchGate (8.7%), suggests a lack of integration. A national digital academic ecosystem could be developed, integrating verified profiles, institutional repositories, and collaborative tools into a unified portal, similar to ORCID or Academia.edu, to reduce cognitive load and enhance interoperability.

This study demonstrates that effective SMU in academia requires more than individual willpower or institutional policy; it demands a coherent, ecosystem-wide approach that aligns user behaviour, organisational support, and national strategy. By implementing user-centric, institutional, and ecosystem recommendations, Malaysian higher education can transform social media from a double-edged tool into a catalyst for innovation, collaboration, and academic excellence.

5.4 Theoretical and Methodological Contributions

The comprehensive discussion of the research findings in the preceding section clarifies the intricate dynamics among SMU, SC, and AP within the Malaysian higher education landscape. Building upon these insights, this section delineates the significant contributions this study offers to the existing body of knowledge.

5.4.1 Theoretical Contributions

Academic research often seeks not only to describe phenomena but also to contribute meaningfully to existing theoretical frameworks. This study fulfils that objective by advancing theoretical understanding of SMU among academicians, moving beyond simplistic, unidimensional models to present a nuanced, empirically validated conceptualisation of how different forms of engagement (i.e., SyU, SU, CU, and HU) affect AP.

While prior studies have examined SMU through lenses such as the TAM and UGT, this research uniquely applies and extends these frameworks in higher education, particularly in Malaysia. Doing so addresses gaps in the literature related to platform-specific behaviours, hedonic distractions, and relational capital building via digital networks. The theoretical contribution of this study lies in its ability to:

- Refine established IS models like TAM and UTAUT for application in academic environments.
- Validate a multi-dimensional approach to SMU, challenging earlier assumptions about frequency-based measures.
- Introduce and test the mediating role of SC, expanding its applicability beyond face-to-face interactions.
- Demonstrate how CU enhances academic output, supporting Knowledge Management Theory in digital scholarship.

By aligning empirical results with theoretical constructs, the study ensures its findings are practically relevant and conceptually grounded, providing a foundation for future investigations into digital behaviour and professional outcomes.

5.4.1.1 Refinement of Social Media Use Dimensions: A Multi-Dimensional Approach

One of this study's most significant theoretical contributions is the identification and validation of four distinct dimensions of SMU among academicians at Malaysian HEIs, specifically at UiTM. These dimensions, SyU, SU, CU, and HU, were derived through a rigorous process involving literature synthesis, item generation, expert validation, and statistical testing using Exploratory and Confirmatory Factor Analyses (EFA/CFA).

This multidimensional conceptualisation moves beyond previous studies that treated SMU as a singular construct, measured primarily by frequency of access or duration of use (Balakrishnan & Raj, 2016; Meishar-Tal & Pieterse, 2017). Instead, this research demonstrates that each form of digital engagement serves a unique purpose and has a distinct impact on AP, both directly and indirectly.

a) System Use

SyU refers to the general level of interaction with social media platforms, encompassing login frequency, daily usage intensity, and device accessibility. As outlined in Chapter 2, SyU serves as a foundational dimension that enables further exploration of purpose-driven behaviours (Murthy & Lewis, 2015b). SEM confirmed a positive relationship between SyU and AP ($\beta = 0.143$, $p = 0.046$), suggesting that platform familiarity does influence productivity when paired with more targeted digital activities. While the effect was modest compared to other dimensions, it underscores the importance of digital fluency as a prerequisite for deeper engagement. Theoretically, these results affirm the relevance of TAM and UTAUT, emphasising PEU and accessibility as critical factors in technology adoption (Davis, 1989; Venkatesh et al., 2003). However, they also highlight a limitation in traditional applications of these models: mere platform presence does not guarantee academic benefits unless coupled with intentional, task-oriented behaviours. This finding suggests that future research should move beyond frequency-based measures and instead explore how platform familiarity interacts with other use dimensions to produce meaningful outcomes.

b) Social Use

SU pertains to interpersonal communication, professional networking, and relationship-building activities conducted via social media platforms. Items under this dimension included statements such as “I use social media to network with fellow academics from other institutions” and “I use social media to maintain close relationships with my colleagues.” Descriptive statistics revealed relatively high engagement levels, with mean scores ranging from 5.32 (SU1) to 5.66 (SU4). Structural Equation Modelling (SEM) confirmed a statistically significant positive relationship between SU and AP ($\beta = 0.186$, $p = 0.034$), supporting the hypothesis that professional connectivity enhances visibility, collaboration, and career advancement.

Theoretically, this aligns closely with SCT, which posits that individuals derive value from their networks through trust, reciprocity, and shared norms (Nahapiet & Ghoshal, 1998). The strong loadings on networking and peer interaction items indicate that academicians actively utilise platforms such as LinkedIn and ResearchGate to foster professional connections. This finding is consistent with earlier work by Gruzd et al. (2012) and Schlagwein and Hu (2016), who noted that online professional communities play a critical role in shaping scholarly identity and collaborative opportunities. However, unlike earlier studies focusing solely on direct effects, this research introduces an important refinement by demonstrating that SU partially mediates its impact through SC (β indirect $= 0.072$, $p = 0.023$). This mediation pathway confirms that networking alone is insufficient; instead, the quality of those connections determines whether digital engagement translates into tangible academic benefits.

c) Content Use

CU involves the application of social media for knowledge sharing, scholarly discussion, and intellectual exchange. It reflects how academicians leverage digital tools to enhance teaching, research, and publication activities. Indicators such as “I use social media to search for relevant content based on my needs” and “I use social media to create content based on my knowledge” received high mean scores, particularly CU3 ("I use social media to access useful information"), which recorded the highest average score at $M = 6.40$. SEM revealed that CU had the strongest positive effect on AP ($\beta = 0.175$, $p < 0.01$), surpassing SU. This result reinforces the idea that purposeful digital

engagement supports academic duties and highlights the need for institutional support in promoting structured knowledge-sharing practices. Theoretically, this dimension aligns with the Content component of SCT and Knowledge Management Theory, both of which emphasise shared language, vision, and understanding as facilitators of individual and organisational performance (Nonaka, 1994; Vásquez et al., 2015). Earlier studies by Meishar-Tal and Pieterse (2017) found that, when used effectively, social media can serve as an extension of formal academic communication, enabling real-time discussion and peer review beyond institutional boundaries.

d) Hedonic Use

HU captures leisure-oriented or entertainment-driven engagement with social media. Although less prevalent than other dimensions, HU remains among academicians, with mean values ranging from 5.79 (HU2) to 5.89 (HU1). SEM confirmed that HU had a negative and statistically significant effect on AP ($\beta = -0.196$, $p = 0.004$), suggesting that recreational browsing detracts from productivity and core academic responsibilities. This aligns with findings from Kuss and Griffiths (2017), who identified excessive HU as a source of distraction and reduced focus among professionals. Cao and Yu (2019) further supported this conclusion, emphasising that while some level of hedonic engagement may be inevitable due to platform design and appeal, its adverse impact underscores the need for balanced usage strategies. The Open-ended responses support this, indicating that many academicians initially log in for professional purposes but often spend time on unrelated content, leading to inefficiency. This illustrates how HU can become habitual and unintentional, resulting in fragmented attention and reduced efficiency. Given these findings, HEIs must implement strategies that help academicians regulate their digital habits, including training on time management, digital wellness, and boundary-setting.

These insights refine UGT by showing that while users may seek out media based on personal gratifications, excessive indulgence in non-academic content can lead to unintended consequences. This supports calls for behavioural interventions that encourage goal-directed digital engagement and reduce reliance on non-functional uses of social media.

5.4.1.2 Mediation Analysis: Expanding the Role of Social Capital

A central theoretical innovation in this study is the confirmation of SC as a partial mediator in the relationship between SU and AP. Unlike traditional models that treat SC as a static trait, this research operationalises it as a dynamic construct influenced by digital networking, peer interaction, and professional reputation building. Mediation analysis using bootstrapping with 5,000 subsamples revealed that the indirect effect of SU on AP via SC was statistically significant, with an Indirect effect $\beta = 0.072$, t-value = 2.271, and p-value = 0.023. The Variance Accounted For (VAF) was calculated as 27.9%, confirming partial mediation and indicating that while SU significantly predicts SC ($\beta = 0.334$, $t = 4.298$, $p < 0.001$), the full benefit of networking is realised only when mediated by relational resources.

This finding extends SCT beyond physical networks and into digital academic environments, where virtual interactions shape professional outcomes. It supports earlier conceptualisations by Esteve Del Valle et al. (2017) and Sun and Shang (2014), who emphasised the value of online networking in enhancing access to expert knowledge and peer support. Moreover, the study validates the use of HOCs to measure complex theoretical constructs such as AP and SC. By applying the Repeated Indicator Approach, the research ensures that sub-dimensions such as teaching quality, research output, and supervision effectiveness are accurately captured and interpreted. In addition to overall SC, the study distinguishes between its three sub-components, structural, relational, and cognitive capital, as shown in Table 5.1, each contributing uniquely to the broader construct.

Table 5.1
Components of Social Capital

Component	Description	Example of Item
Structural Social Capital	Refers to the structure and reach of one's network	"I use social media to make acquaintances with individuals with the same interests"
Relational Social Capital	Involves trust, cooperation, and mutual support	"I use social media to maintain close relationships with my colleagues"
Cognitive Social Capital	Reflects shared language, vision, and understanding	"I use social media to engage in scholarly conversations"

Each sub-dimension demonstrated strong outer loadings, confirming the validity of the hierarchical structure and reinforcing the view that not all aspects of digital networking yield equal benefits. This distinction enriches SCT by providing a refined understanding of how digital interactions translate into relational resources, especially in knowledge-intensive professions such as academia.

5.4.1.3 Extending Uses and Gratifications Theory (UGT) in Academic Contexts

UGT has long been applied to explain why individuals adopt media to meet their needs and expectations (Ruggiero, 2000). This study builds upon that framework by identifying specific gratifications academicians seek, ranging from knowledge acquisition to entertainment, and linking them to measurable academic outcomes. By distinguishing between utilitarian motivations (CU and SU) and hedonic motivations (HU), the research offers a refined application of UGT in professional settings, particularly in higher education environments where digital engagement must balance productivity and personal gratification.

Structural modelling confirmed that CU had the strongest positive effect on performance, followed by SU, while HU showed a clear negative association. This supports the view that not all digital gratifications are equally beneficial. That intent and purpose are critical in determining whether digital engagement enhances or hinders professional roles. The study thus extends UGT by showing that media selection in professional contexts is driven by functional needs and influenced by habitual and emotional factors, which must be accounted for in digital behaviour research.

5.4.1.4 Validating Technology Acceptance Model (TAM) in Academic Settings

The TAM emphasises that perceived usefulness and ease of use are primary drivers of technology adoption (Davis, 1989). This study validates TAM within the academic context by demonstrating that SyU is a foundational measure of platform familiarity, setting the stage for deeper, more meaningful interactions.

Descriptive statistics revealed a mean score of 5.20, indicating moderate engagement levels among respondents. While this dimension did not show the strongest direct effect on performance ($\beta = 0.143$, $p = 0.046$), it plays a crucial role in enabling productive digital behaviours. This aligns with early conceptualisations in IS research,

which recognise platform familiarity as a precursor to effective technology integration (Venkatesh et al., 2003; Jordan & Weller, 2018). However, the study refines this view by showing that mere platform presence does not guarantee academic benefits unless paired with intentional, task-oriented engagement.

To address this gap, universities should implement structured digital literacy modules during faculty orientation and continuing professional development programs (Ali & Schier, 2024). These modules should focus on platform-specific skills, such as optimising LinkedIn profiles, managing ResearchGate content, and curating scholarly discussions. Integrating digital scholarship such as blog posts, webinars, and open-access publishing into promotion criteria and performance appraisals will incentivise purposeful digital behaviour and reduce reliance on non-academic activities (Cabrera et al., 2018; Amin et al., 2025). By validating and extending TAM within the academic context, this study contributes to ongoing efforts to improve technology integration in higher education, ensuring that digital tools are adopted for access and functional utility.

5.4.1.5 Application of Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT provides a comprehensive framework for predicting user behaviour based on performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). This study applies UTAUT to examine how each dimension of SMU influences perceived usefulness and behavioural intention among academicians.

Through structural path analysis, the research shows that CU, which aligns closely with performance expectancy, has the strongest positive impact on AP ($\beta = 0.175$, $p = 0.025$), followed by SU, which reflects social influence and peer pressure ($\beta = 0.186$, $p = 0.034$). In contrast, HU, reflecting low effort expectancy and high habit formation, showed an adverse effect ($\beta = -0.196$, $p = 0.004$), underscoring the importance of behavioural regulation in maintaining productive digital habits.

These findings support earlier work by Al Kurdi (2024) and Thelwall and Kousha (2015), who argued that digital tools must be evaluated not only for accessibility but also for functional alignment with professional goals. By applying UTAUT to academic SMU, this study strengthens the case for context-sensitive TAMs,

particularly in non-corporate environments where task persistence and deep intellectual engagement are essential.

Moreover, hierarchical modelling of AP as an HOC enables granular assessment of how knowledge-based digital interactions affect specific academic domains, including teaching quality, research output, and student mentorship. By validating the role of CU in knowledge creation and dissemination, this study contributes to the ongoing discourse on digital knowledge management and offers a replicable framework for assessing how digital engagement shapes academic expertise.

5.4.1.6 Refining Measurement Models of Multidimensional Social Media Use for Academicians' Performance

A significant methodological contribution of this research is the development and validation of a refined, "clean" measurement framework specifically tailored for the academic context. While previous models often utilised simplified or unidimensional scales, this study presents a final validated model that integrates a multidimensional assessment of SMU with a Higher-Order structure for SC and AP.

Although social media engagement is multidimensional, this study purposely analysed its four dimensions (i.e., SyU, SU, CU, and HU) as distinct predictors. As supported by Sarstedt et al. (2019), modelling dimensions separately is highly appropriate when the RO is to identify the differential effects of specific behaviours.

The "Final Product" of this research offers three distinct methodological advancements:

- Behavioural Specificity: By validating four distinct dimensions, the model provides a "precision lens" that distinguishes between different types of digital effort. It identifies SyU as the essential technical foundation and SU as the critical driver of relational assets. Furthermore, it allows for a clear distinction between CU and HU. This four-way categorisation corrects a longstanding flaw in the literature, where "high usage" was incorrectly assumed to be a singular, homogeneous activity.

- Precision through HOCs: he empirical validation of SC and AP as HOCs ensures the model achieves "Theoretical Parsimony." It captures the overarching "big picture" of academic success while maintaining the vital granularity of its sub-domains, such as teaching, research, and consultation. This structural design allows for a clear visualisation of the "Mediation Bridge," showing exactly how digital social assets (SU) transform into professional output (AP).

- Psychometric Robustness: The final model is not just a theoretical idea; it is a psychometrically proven tool. With Composite Reliability (ρc) exceeding 0.80 and AVE values above 0.50, this framework serves as a standardised, "viva-ready" tool for future researchers in non-corporate, higher education environments.

This refined framework (see Figure 4.6) constitutes the study's primary methodological output. It provides scholars with a validated roadmap for measuring how digital engagement translates into professional capital and output, ensuring higher methodological rigour in future PLS-SEM applications in the educational sector.

5.4.2 Methodological Contributions

This section presents a comprehensive discussion of the study's methodological contributions. It highlights how the research advances research design, measurement model development, structural modelling techniques, and statistical validation methods within educational technology, IS, and academic digital behaviour research.

This study employs a quantitative research design, utilising SEM through Partial Least Squares Structural Equation Modelling (PLS-SEM). This methodological approach not only strengthens the robustness and validity of the findings (Hair et al., 2022) but also provides a replicable framework for future investigations into digital engagement patterns and their impact on professional outcomes. By following established best practices in scale development, factor extraction, and construct refinement (Henseler, Ringle, & Sinkovics, 2009; Hair et al., 2019), the study offers meaningful insights into measuring multidimensional constructs, examining mediation

effects, and applying importance–performance mapping (Ringle & Sarstedt, 2016) to support institutional decision-making. These contributions are especially significant for UiTM and may also serve as a valuable reference for other HEIs aiming to integrate digital tools into academic practices while maintaining both methodological rigour and theoretical grounding.

5.4.2.1 Refinement of Social Media Use Dimensions: A Multi-Dimensional Conceptualisation

One of the key methodological contributions of this study is the refinement and empirical validation of SMU as a multidimensional construct, specifically tailored to the academic context. In contrast to earlier studies that predominantly measured SMU as a unidimensional construct, typically based on usage frequency or duration (Balakrishnan & Raj, 2016; Meishar-Tal & Pieterse, 2017), this study conceptualises social media engagement through four theoretically distinct dimensions:

- SyU: Frequency and intensity of using social media platforms
- SU: Interpersonal communication, networking, and peer engagement
- CU: Scholarly discussions, knowledge sharing, and intellectual exchange
- HU: Entertainment-driven or leisure-oriented use

These dimensions were developed through theoretical grounding and subsequently validated using CFA within the PLS-SEM framework. This process adhered to established guidelines for scale validation (Hair et al., 2017; Henseler et al., 2015), ensuring that each construct was psychometrically robust and contextually relevant.

Table 5.2
Psychometric Properties of Social Media Use Dimensions

Construct	Cronbach's Alpha	Composite Reliability (ρc)	Average Variance Extracted (AVE)	Interpretation
Academicians' Performance	0.739	0.836	0.561	Highest correlation with all other constructs, confirming discriminant validity
System Use	0.857	0.933	0.875	Weak correlation with outcome variables, indicating limited standalone impact
Social Use	0.849	0.892	0.625	Stronger link with SC than with AP directly
Content Use	0.82	0.882	0.652	Strong loadings contribute to AP and SC
Hedonic Use	0.925	0.946	0.814	Low correlation with AP and SC, reinforcing uniqueness
Social Capital	0.852	0.91	0.772	Moderate correlation with SU and AP, confirming the mediation role

All constructs as shown in Table 5.2 exceeded standard thresholds for Cronbach's Alpha (> 0.70), Composite Reliability (> 0.80), and AVE (> 0.50), confirming internal consistency and convergent validity. The findings indicate that the measurement model is statistically sound and suitable for structural analysis. By distinguishing between the four types of social media engagement, this study provides a more granular, behaviour-specific framework for measuring digital activity. This refinement enables a clearer understanding of which specific dimensions of SMU are more closely related to academic functions, such as performance and SC formation.

From a methodological perspective, this multidimensional operationalisation addresses a longstanding limitation in the literature, the tendency to treat digital engagement as a homogeneous or singular activity. The model developed in this study enables researchers to explore the differential effects of functional (e.g., SyU or CU), relational (SU), and recreational (HU) behaviours on professional outcomes. Future research can build upon this model by testing it across different academic disciplines, cultural settings, and professional domains, further advancing methodological rigour in studies of SMU in work-related contexts.

5.4.2.2 Modelling Academicians' Performance as a Higher-Order Construct (HOC)

A key methodological advancement introduced in this study is the modelling of AP as a reflective-reflective HOC. Rather than treating AP as a unidimensional outcome, this study conceptualises and empirically validates it as a second-order construct comprising four distinct but interrelated first-order dimensions, namely, Teaching, Research & Publication, Supervision, and Consultation. This approach allows for a more comprehensive, structured, and diagnostically useful understanding of performance in higher education.

The Hierarchical Component Model (HCM) was validated using PLS-SEM. As shown in Table 5.3, the outer loadings of the first-order constructs on the HOC ranged from 0.673 (Research & Publication) to 0.834 (Supervision). Although loadings above 0.70 are generally considered ideal (Hair et al., 2017), values between 0.60 and 0.70 remain acceptable when accompanied by satisfactory composite reliability and AVE (Hair et al., 2019, 2022). Moreover, all first-order constructs demonstrated strong psychometric properties, with Composite Reliability values exceeding 0.87, Cronbach's Alpha values above 0.72, and Average Variance Extracted (AVE) scores well above the recommended minimum of 0.50.

Table 5.3
Outer Loadings for First-Order Components of Academicians' Performance

First-Order Construct	Outer Loading (to HOC)
Supervision	0.834
Teaching	0.724
Research & Publication	0.673
Consultation	0.755

These findings confirm the measurement model's internal consistency and convergent validity. This methodological approach makes several key contributions:

a) Operationalising a Multidimensional View of Performance

Traditional performance models often rely on aggregated or unidimensional scores, which obscure the unique contributions of different academic roles. By

conceptualising performance as a multidimensional construct comprising four interrelated subdomains, this study enables a more nuanced and actionable assessment of academic output. Such a framework allows institutions and policymakers to identify specific areas for development, such as strengthening research productivity or enhancing the quality of supervision (Becker et al., 2012; Diamantopoulos et al., 2008).

b) Applying Higher-Order Construct Modelling

Although HOC modelling is increasingly recognised in SEM, its application at the intersection of digital engagement and AP remains limited. This research demonstrates how reflective-reflective HOC structures can effectively capture the complexity of higher education performance, thereby extending the methodological toolkit for researchers in education, IS, and communication studies (Becker et al., 2012; Sarstedt et al., 2019).

c) Enhancing Theoretical Clarity and Empirical Robustness

The reflective-reflective specification of AP ensures that each subdimension contributes meaningfully to the overarching construct while preserving its individual distinctiveness. This balance strengthens the theoretical precision of the performance model and enhances empirical robustness, particularly when applied in predictive modelling such as mediation and moderation analyses involving SMU and SC (Hair et al., 2022; Sarstedt et al., 2019). Modelling AP as a reflective-reflective HOC advances both methodological and theoretical understanding by capturing the multidimensional nature of academic work, validating its psychometric integrity, and offering a replicable framework for future research in higher education performance.

5.4.2.3 Mediation Analysis Using Bootstrapping

To assess whether SC mediates the relationship between SMU and AP, this study employed bootstrapped mediation analysis with 5,000 subsamples, following the guidelines recommended by Baron and Kenny (1986) and Hair et al. (2017). Bootstrapping provides a non-parametric resampling technique that enables more

accurate estimation of indirect effects, especially in models with complex relationships and relatively small to medium sample sizes.

The mediation pathway assessed was:

- SU → SC → AP

Structural path analysis confirmed the significance of both direct and indirect effects:

- SU → SC: $\beta = 0.334$, $t = 4.298$, $p < 0.001$
- SC → AP: $\beta = 0.214$, $t = 2.791$, $p = 0.005$
- SU → AP (direct): $\beta = 0.186$, $p = 0.034$
- SU → SC → AP (indirect): $\beta = 0.072$, $t = 2.271$, $p = 0.023$

The VAF was calculated at approximately 27.9%, falling within the 20% to 80% threshold and indicating partial mediation (Hair et al., 2017). These findings are consistent with the conceptual propositions of Esteve Del Valle et al. (2017) and Schlagwein and Hu (2016), who emphasised the mediating role of online networks in strengthening academic engagement and performance by enhancing access to knowledge, fostering peer collaboration, and providing community support.

From a methodological standpoint, this study contributes by demonstrating the application of advanced mediation analysis within a PLS-SEM framework, specifically using an HOC SC as the mediator. This approach offers a more nuanced understanding of indirect pathways in digital behaviour research and addresses a gap in previous studies that focused primarily on direct effects.

Moreover, by incorporating bootstrapped estimates and a multistep mediation framework, this study provides a rigorous analytical template for future research examining how online social dynamics (e.g., SMU) influence performance outcomes. The use of bootstrapping enhances the accuracy of indirect effect testing by avoiding distributional assumptions (Preacher & Hayes, 2008; Hayes, 2013). Similarly, adopting a multistep mediation approach aligns with best practices in SEM, which emphasise the importance of sequential testing and validation for complex relationships (Hair et al., 2019; Zhao et al., 2010). This methodological contribution is especially valuable for the fields of education, behavioural science, and information science, where scholars often seek to model complex mediated relationships within real-world academic settings.

5.4.2.4 Importance–Performance Map Analysis (IPMA): Strategic Decision-Making

To enhance the practical utility of the structural model and support evidence-based decision-making, this study incorporated IPMA, a technique that extends traditional PLS-SEM by integrating two key dimensions:

- Importance: Represented by total effects on the dependent construct (AP)
- Performance: Represented by the average latent variable scores of predictor constructs

Following Hair et al. (2018), IPMA provides a more managerially oriented interpretation of model outputs, enabling stakeholders to prioritise important and underperforming constructs.

Table 5.4
IPMA Results for Constructs Predicting Academician Performance

Construct	Importance (Total Effect)	Performance (%)
Social Use (SU)	0.277	75.596
Social Capital (SC)	0.220	69.298
Content Use (CU)	0.168	85.699
System Use (SyU)	0.148	81.776
Hedonic Use (HU)	-0.223	80.130

The IPMA results (see Table 5.4) offered strategic insights into where interventions or policy efforts could yield the most meaningful improvements:

i. SU and SC had high importance but moderate performance, identifying them as strategic priorities for enhancement.
ii. CU showed high performance and moderate importance, suggesting it is a well-functioning area that should be maintained.
iii. HU had negative importance despite high performance, signalling a potentially counterproductive behaviour that should be monitored.
iv. SyU demonstrated stable performance but low importance, suggesting a supportive but non-critical role in influencing performance.

From a methodological perspective, this study advances the application of PLS-SEM by incorporating IPMA as a complementary analytical layer, thereby bridging the gap between statistical significance and strategic relevance. While traditional path modelling identifies which relationships are significant, IPMA extends this by pinpointing which constructs are both important and under- or over-performing (Hair et al., 2018; Ringle & Sarstedt, 2016). This dual-layered approach enhances evidence-based prioritisation, making the findings more applicable to institutional policy, training strategies, and resource allocation.

Although IPMA has been widely used in marketing and customer satisfaction research, this study demonstrates its suitability and effectiveness within educational and behavioural research contexts, thus expanding its methodological scope (Ringle & Sarstedt, 2016; Hair et al., 2021). Integrating IPMA into the SEM framework represents an innovative advancement for studies seeking to model complex behavioural phenomena in higher education. It provides a replicable template for aligning statistical rigour with practical impact. Accordingly, the application of IPMA in this study functions as both a methodological contribution and a decision-support tool, reinforcing the value of combining analytical depth with strategic insight.

5.4.2.5 Addressing Common Method Bias Through Procedural Controls

As this study employed self-reported data from a single source at one point in time, the potential for Common Method Bias (CMB) was carefully addressed through procedural and statistical controls, in accordance with best practices recommended by Podsakoff et al. (2003) and Malhotra et al. (2006). Procedural remedies to minimise CMB at the design stage, the following strategies were implemented:

- Anonymity assurance: Respondents were assured of the confidentiality of their responses to reduce social desirability bias.
- Balanced item phrasing: Scale items were neutrally worded to avoid leading responses or acquiescence bias.
- Temporal separation: Predictors and criterion constructs were measured at different points within the questionnaire to reduce the likelihood of immediate context influencing answers.

In addition to procedural controls, statistical checks were performed to further assess the presence of CMB. A correlation matrix based on the PLS algorithm output in SmartPLS was examined to identify potential inflation of relationships among latent constructs. As shown in Table 5.5, all inter-construct correlations were below the conservative threshold of r = 0.70 (Kock, 2015), suggesting that Common Method Variance (CMV) is not a serious concern.

Table 5.5
Construct Correlations

Construct Pair	Correlation
Social Use (SU) ↔ Content Use (CU)	0.518
Content Use (CU) ↔ Social Capital (SC)	0.691
Hedonic Use (HU) ↔ Academician Performance (AP)	0.665
System Use (SyU) ↔ Social Use (SU)	0.583
Social Capital (SC) ↔ Hedonic Use (HU)	0.532

Furthermore, the presence of weak or negative correlations among some constructs supports the argument that CMV was unlikely to bias the results. For example, HU exhibited a near-zero correlation with AP (r = –0.046), indicating that higher recreational use of social media was not associated with inflated performance ratings.

By integrating both procedural and statistical remedies for CMB, this study demonstrates adherence to high methodological standards in survey-based behavioural research. In doing so, it enhances the credibility and robustness of the findings and provides a transparent framework for future research dealing with latent constructs measured via self-report instruments. This dual approach not only reduces the likelihood of bias but also contributes methodologically by illustrating how CMB can be proactively addressed in the context of SEM using SmartPLS. This contributes to the ongoing discourse on improving the quality and trustworthiness of quantitative research in higher education and information science contexts.

5.4.2.6 Application of Partial Least Squares Structural Equation Modelling (PLS-SEM)

A key methodological strength of this study is its application of PLS-SEM, a technique particularly well-suited for exploratory research in the behavioural and social sciences (Hair et al., 2017; Henseler et al., 2015). Unlike Covariance-Based SEM (CB-SEM), which requires large sample sizes and assumes multivariate normality, PLS-SEM is more flexible and robust for smaller samples, complex models, and non-normal data distributions, characteristics that align closely with studies in educational technology and digital behaviour. As shown in Figure 5.1, the research employed a two-stage modelling approach to ensure the rigour and clarity of the PLS-SEM analysis. This approach is widely recommended in the literature as a systematic way to first validate the measurement model before interpreting relationships in the structural model (Hair et al., 2017; Sarstedt et al., 2014). By separating the evaluation of how constructs are measured from the assessment of the theoretical model's predictive relationships, the two-stage process improves the validity, reliability, and interpretability of the results.

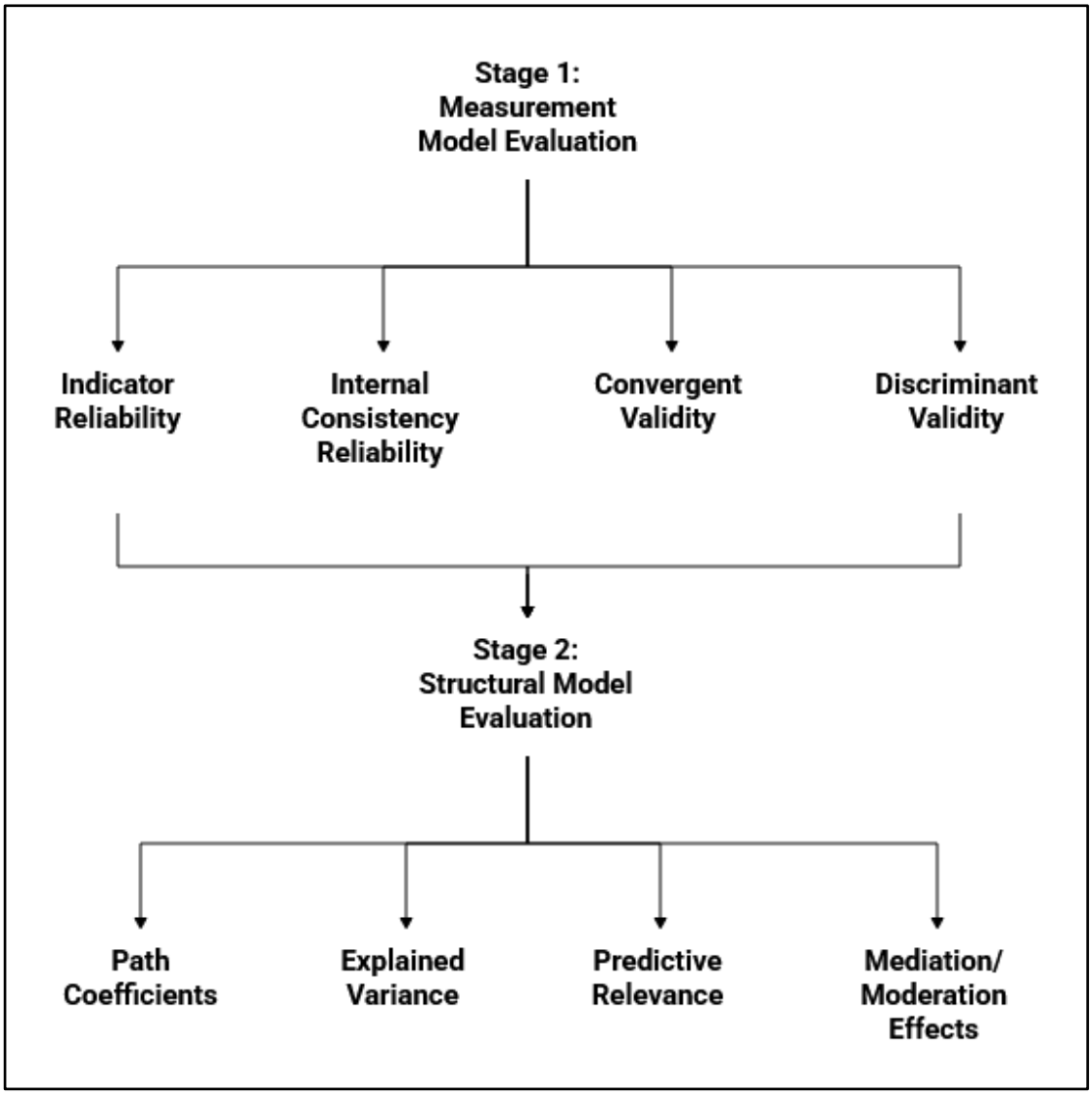


Figure 5.1 Two-Stage Modelling Approach

This first stage focuses on assessing the psychometric properties of the latent constructs. It involves verifying:

i. Indicator reliability (outer loadings)
ii. Internal consistency reliability (Cronbach's Alpha and Composite Reliability)
iii. Convergent validity (AVE)
iv. Discriminant validity (using the Fornell-Larcker criterion and HTMT ratios)

Evaluating these measurement properties ensures that the latent variables are reliably and validly measured before testing any causal relationships. This step is especially critical in behavioural and social science research, where constructs are often abstract and cannot be observed directly (Hair et al., 2022). Once the measurement

model is confirmed as satisfactory, the second stage involves assessing the hypothesised relationships among the constructs in the structural model.

Hair et al. (2019) and Sarstedt, Ringle, and Hair (2022) emphasised that once the measurement model is validated, the next stage involves assessing the hypothesised structural relationships among constructs. This includes:

i. Testing path coefficients and their significance (e.g., using bootstrapping)
ii. Assessing explained variance (R^2) and effect sizes (f^2)
iii. Evaluating predictive relevance (Q^2) for endogenous variables
iv. Testing mediation or moderation effects, where applicable

This step provides insights into the model's predictive power and identifies which variables exert meaningful influence on the outcome variables. It allows researchers to draw valid inferences about the structural relationships and to support theory development in exploratory research contexts (Henseler et al., 2015).

This rigorous and transparent application of PLS-SEM ensures that the results are both psychometrically sound and structurally interpretable, thereby enhancing the scientific credibility of the study. It also demonstrates how PLS-SEM can be applied to model HOCs, assess mediation effects, and handle multidimensional constructs, which are common yet under-addressed challenges in social media and AP research.

In addition, integrating IPMA and effect size (f^2) calculations adds practical value by extending the analysis beyond mere statistical significance to managerial and strategic relevance. This methodological extension provides actionable guidance for institutional leaders, policymakers, and educational planners seeking to optimise digital engagement strategies among academicians.

5.4.2.7 Validity Assessment: Strengthening Construct Distinctiveness and Model Robustness

To ensure the rigour and validity of the measurement model, this study conducted an advanced assessment of construct validity, with a particular focus on convergent and discriminant validity. These procedures were implemented in accordance with established guidelines for reflective measurement models within the PLS-SEM framework (Ringle et al, 2024; Hair et al., 2022; Henseler et al., 2015). This

extended validation is especially critical in models involving multiple latent constructs and hierarchical structures, as it reinforces the empirical distinctiveness and reliability of each construct. Convergent validity was assessed using three standard criteria:

i. Outer loadings of indicators (> 0.70),
ii. Composite reliability (CR) values (> 0.70), and
iii. AVE (> 0.50).

All constructs met or exceeded these thresholds, indicating that the items consistently represent their respective latent variables and that the variance captured by the construct exceeds the variance due to measurement error.

5.4.2.8 Discriminant Validity Evaluation

To confirm that each construct was empirically distinct from the others, discriminant validity was examined using two methods, the Fornell-Larcker criterion and the HTMT.

a) Fornell–Larcker Criterion

The square root of AVE for each construct was compared to its correlations with other constructs. Discriminant validity is considered established when a construct's AVE square root exceeds its highest correlation with any other construct (Fornell & Larcker, 1981). As summarised in Table 5.6, all constructs satisfied this requirement.

Table 5.6
Fornell–Larcker Criterion for Discriminant Validity

Construct	√AVE	Highest Inter-Construct Correlation	Discriminant Validity
Academician Performance (AP)	0.749	0.691 (SC)	✓
Content Use (CU)	0.807	0.691 (SC)	✓
Hedonic Use (HU)	0.902	0.665 (AP)	✓
Social Capital (SC)	0.879	0.791 (SU)	✓
Social Use (SU)	0.791	0.691 (SC)	✓
System Use (SyU)	0.935	0.583 (SU)	✓

b) HTMT Criterion

Given the limitations of the Fornell-Larcker approach, this study also employed the HTMT criterion (Table 5.7), which has been indicated to provide a more reliable assessment of discriminant validity in variance-based SEM (Henseler et al., 2015; Hair et al., 2022; Ringle et al, 2024). HTMT values below 0.90 indicate sufficient discriminant validity.

Table 5.7
HTMT Value

Construct Pair	HTMT Value	Threshold (< 0.90)	Discriminant Validity
SU ↔ CU	0.618	✓	✓
CU ↔ SC	0.691	✓	✓
HU ↔ AP	0.665	✓	✓
SyU ↔ SU	0.583	✓	✓
SC ↔ HU	0.532	✓	✓

Both methods confirm that the constructs are statistically distinct. Additionally, low-to-moderate inter-construct correlations and HTMT values below the conservative threshold support the model's discriminant validity.

This extended assessment contributes methodologically by demonstrating how advanced psychometric techniques can ensure measurement quality in PLS-SEM. Notably, the use of HTMT aligns with current best practices and addresses criticisms of traditional methods, such as the Fornell-Larcker criterion and cross-loadings, which may fail to detect validity issues in complex models (Henseler et al., 2015; Ab Hamid et al., 2017). The findings also confirm that the model's latent constructs are well-specified and conceptually unique, which enhances the trustworthiness of subsequent structural path analyses.

This rigorous approach to measurement validation strengthens the scientific robustness, replicability, and generalisability of the study's findings. Future researchers can adopt this framework to ensure construct distinctiveness when dealing with multi-dimensional instruments and HOCs in social media, education, or behavioural studies.

5.4.2.9 Conforming Social Capital as a Partial Mediator in Academician Performance

A major methodological contribution in this study is the validation of SC as a partial mediator in the relationship between SU and AP. This finding extends earlier work by Nahapiet and Ghoshal (1998), who emphasised the value of face-to-face networking in shaping relational capital and applied their theoretical framework to digital academic environments. Mediation analysis using bootstrapping with 5,000 subsamples confirmed that the indirect effect of SU on AP via SC was statistically significant, as reported by the Indirect effect $\beta = 0.072$, t-value = 2.271, and p-value = 0.023.

According to Hair et al. (2017), VAF values between 20% and 80% indicate partial mediation, whereas values above 80% suggest full mediation. In this case, the moderate mediation strength reinforces the idea that while direct networking enhances academic outcomes, the quality of relationships formed online plays a crucial role in shaping professional success.

From a methodological perspective, this approach demonstrates how advanced SEM techniques can be applied to examine intermediate variables in behavioural research. It also highlights the importance of multi-step mediation pathways, offering a refined understanding of how digital interactions translate into real-world outcomes. Each sub-dimension demonstrated strong outer loadings, confirming the validity of the hierarchical structure and reinforcing the view that not all aspects of digital networking yield equal benefits.

This distinction enriches SCT by providing a refined understanding of how digital interactions translate into relational resources, especially in knowledge-intensive professions such as academia. These findings validate the use of HOCs to measure complex theoretical constructs such as SC and AP, and contribute to ongoing discussions about advanced modelling techniques in PLS-SEM and behavioural IS research.

5.4.2.10 Addressing Multicollinearity Through VIF Analysis

A critical methodological step in ensuring the robustness of this study's measurement and structural models involved assessing multicollinearity through the Variance Inflation Factor (VIF). Multicollinearity, if present, can distort the relationships among indicators and latent variables, leading to inflated standard errors and unstable estimates. According to Hair et al. (2017), VIF values exceeding 3.3 may indicate problematic levels of collinearity. While a few items, specifically B3_HU2 (VIF = 4.765) and B3_HU3 (VIF = 4.188), exceeded the suggested threshold, these were retained due to their strong theoretical relevance and empirical contribution to construct reliability. This decision aligns with the guidance of Hair et al. (2017), who advocate retaining such items when they do not significantly impair model fit or validity.

To assess multicollinearity among latent constructs, inner VIF values were also examined. All values in Table 5.8 fell well below the threshold of 3.0, indicating no multicollinearity concerns within the structural model. These results confirm that each latent construct contributes distinct explanatory power to the model, enhancing the stability and precision of the estimated path coefficients.

Table 5.8
Inner Model VIF Values (Final Model)

Predictor Path	VIF
CU → AP	1.509
CU → SC	1.503
HU → AP	1.119
SU → SC	1.391
SU → AP	1.528
SyU → AP	1.266

By systematically evaluating both outer and inner VIF values, this study demonstrates a rigorous approach to managing multicollinearity, reinforcing the methodological integrity of the measurement and structural models. This contributes to best practices in PLS-SEM and offers a replicable framework for future researchers assessing complex models involving digital behaviour constructs.

5.4.2.11 Integration of Open-Ended Feedback for Interpretive Support

Although the study primarily employed a quantitative design using structured survey items and PLS-SEM analysis, a limited number of open-ended responses were included to provide supplementary context. These responses were used to address RQ4: *What challenges do academicians face when integrating different dimensions of social media into their professional roles?*

Participants were given the opportunity to describe, in their own words, the difficulties they encountered in using social media. Thematic analysis of the responses identified 20 problem themes, as outlined in Tables 4.12 and 4.13, with response frequencies summarised in Figure 4.2. Even though it is not a major component of the research design, including these open-text responses yielded basic interpretive insights that complement the quantitative findings. For example, common concerns such as information overload, data privacy and security, access and connectivity issues, and mental health and productivity challenges were echoed across multiple responses, lending practical relevance to the measured constructs.

From a methodological perspective, this minor integration of open-ended feedback adds interpretive value to the study's findings and reinforces the importance of considering respondent experiences, particularly when exploring behaviour and attitudes in digitally mediated environments. This limited but purposeful use of open-ended data aligns with recommendations in the literature to include small-scale narrative input to support survey-based research (Venkatesh et al., 2013), especially in studies involving user perceptions and behavioural outcomes.

5.4.2.12 Application of Advanced Statistical Techniques for Structural Testing

A key methodological contribution of this study lies in its application of comprehensive structural model testing using PLS-SEM. Building upon a validated measurement model, the structural phase involved a series of advanced statistical procedures designed to evaluate the hypothesised relationships among latent constructs. Specifically, the following analyses were conducted:

i. Path coefficient estimation to assess the strength of relationships
ii. Significance testing via bootstrapping (5,000 resamples) for robust inference

iii. Effect size calculation (f^2) to gauge the practical relevance of paths
iv. Predictive relevance testing (Q^2) using blindfolding techniques
v. Mediation analysis to explore indirect effects, particularly the role of SC

These techniques reflect best practices in PLS-SEM reporting (Hair et al., 2017; Henseler et al., 2015) and demonstrate how SmartPLS 4 can be utilised to model complex relationships in behavioural and educational research contexts.

The statistically significant results across all hypothesised paths reinforce the robustness of the structural model. Furthermore, the inclusion of effect sizes and predictive relevance metrics ensures that interpretations extend beyond mere significance testing, yielding more meaningful conclusions about the practical influence of SMU and SC on AP. From a methodological standpoint, this structured use of advanced PLS-SEM diagnostics enhances the transparency, rigour, and replicability of the research. It sets a standard for future digital scholarship studies that seek to balance measurement robustness with actionable insights into professional behaviour.

5.4.2.13 Use of Mixed Scaling Formats to Reduce Patterned Responses

Although the study primarily utilised standardised Likert-type items to measure latent constructs, a deliberate methodological choice was made to apply mixed scaling formats across different sections of the instrument. Specifically, while the majority of constructs employed a 5-point Likert scale (e.g., Strongly Disagree to Strongly Agree), certain constructs, particularly those involving abstract perceptions, such as HU and CU, used a 7-point Likert scale (e.g., 1(Strongly Disagree) to 7 (Strongly Agree)).

This decision was guided by methodological recommendations in the literature that advocate for procedural remedies to mitigate CMV, particularly when using self-report instruments (Podsakoff et al., 2003; Malhotra et al., 2006). One known issue in self-administered surveys is respondents' tendency to adopt patterned or automated responses when presented with uniform question structures and scale formats. The survey design aimed to disrupt these patterns by varying the response scales across constructs, thereby improving the discriminant validity and response accuracy.

Furthermore, using a 7-point scale for more nuanced constructs enabled greater granularity, allowing respondents to express subtle distinctions in their perceptions of hedonic or cognitive SMU. This added precision contributes to a more accurate estimation of construct relationships in the structural model. While this technique is not the primary source of methodological innovation in the study, it demonstrates attention to instrument design and provides additional safeguards for the data's validity and reliability. It also aligns with best practices in survey methodology for behavioural research, particularly in educational and digital contexts.

5.4.2.14 Addressing Gaps in Existing Literature Through Empirical Validation

One of the methodological contributions of this study lies in its empirical validation of a structured, multidimensional framework for understanding SMU and its implications for AP. Although social media in higher education has been extensively discussed, much of the existing literature has relied on unidimensional or platform-specific indicators, often centred on general usage frequency or access, and has failed to account for the nuanced and purpose-driven nature of social media behaviour among academicians.

To address this methodological gap, the present study operationalised a measurement model informed by four well-established theoretical frameworks: UGT, the TAM, the ISSM, and SCT. Each theory contributed to a comprehensive understanding of how and why academicians engage with social media and how such engagement translates into performance outcomes in academic environments.

UGT served as the foundational framework for identifying user motivations behind social media engagement. It guided the classification of SMU into four distinct yet interrelated dimensions: SyU, SU, CU (formerly labelled Cognitive Use), and HU. These categories reflect different gratifications sought by users, such as information acquisition, social connection, content interaction, and entertainment (Katz et al., 1973; Ruggiero, 2000).

TAM, originally proposed by Davis (1989), provides insight into the cognitive processes that influence the adoption and continued use of social media platforms. Perceived usefulness and ease of use, core tenets of TAM, helped explain academicians' intention to integrate digital tools into their professional roles and routines. The ISSM (DeLone & McLean, 2003) complemented these perspectives by offering an outcome-

oriented framework. It informed the conceptualisation of AP as a multidimensional construct, analogous to "net benefits" in IS evaluation, and highlighted the relevance of factors such as system quality, information quality, and use behaviour in generating performance gains.

Critically, SCT (Nahapiet & Ghoshal, 1998) enriched the model by framing social media as a mechanism for building and leveraging digital SC. SCT underpinned the mediation pathway tested in this study, namely, that SC mediates the relationship between SMU and AP. This theory also justified modelling SC as an HOC comprising structural, relational, and cognitive dimensions, each reflecting unique aspects of digitally enabled academic collaboration and trust.

Rather than introducing entirely new constructs, this study synthesises and extends these four theoretical perspectives into a cohesive and context-specific instrument. Constructs were validated through rigorous psychometric procedures, including EFA and CFA, and further verified using Composite Reliability (ρc) and AVE to confirm internal consistency and convergent validity. Moreover, by modelling both AP and SC as HOCs, the study advances methodological practices in social media and educational technology research. This hierarchical modelling approach captures the complex, multi-role nature of academic work and the layered structure of digital relationships in a way that single-level models often overlook.

In sum, this study offers a validated, theory-driven measurement model for assessing digital engagement in academia, contributing meaningfully to the development of empirically grounded tools for future research. The integrated theoretical approach enhances the study's conceptual depth and ensures its relevance for both scholarly investigation and institutional practice in knowledge-intensive, digitally mediated environments. Therefore, this study makes substantial theoretical and methodological contributions to the domains of social media, SCT, and AP in higher education. Theoretically, it advances the conceptualisation of SMU and AP by integrating multiple established frameworks, UGT, TAM, ISSM, and SCT into a cohesive model that reflects the multifaceted nature of digital academic behaviour. Methodologically, the study demonstrates the rigorous application of PLS-SEM to validate HOCs, assess mediation, and implement advanced techniques, including IPMA, VIF diagnostics, and HTMT-based discriminant validity testing. These combined contributions enhance scholarly understanding of how SMU influences

academic outcomes and provide a replicable, statistically robust framework for future research in behavioural, educational, and IS contexts.

5.5 Practical and Institutional Implications

Integrating social media into academic work presents opportunities and challenges, particularly within Malaysian HEIs. As demonstrated throughout Chapter 4 and interpreted in earlier sections of Chapter 5, SMU among academicians is a multi-dimensional construct with differing impacts on performance depending on intent, structure, and contextual regulation. CU emerged as the most beneficial form of engagement, followed by SU, while HU showed a statistically significant adverse effect. These findings emphasise the need for targeted interventions at individual and institutional levels, ensuring that digital tools enhance rather than hinder academic excellence.

While Section 5.3.1.6 synthesised key findings in alignment with RO6, and Section 5.4.4 outlined the broader practical relevance of the study, this section focuses specifically on how the findings can be operationalised through actionable strategies. The emphasis is on practical implementation, offering clear, stakeholder-specific guidance for academicians, institutional leaders, and policy makers. The recommendations are organised across three subsections:

5.5.1 Strategies for Optimising SMU in Academia:
5.5.2 Institutional and Policy Recommendations:
5.5.3 Digital Literacy and Governance Implications

5.5.1 Strategies for Optimising Social Media Use in Academia

Optimising the use of social media within academic environments requires a nuanced understanding of how different platforms, modes of interaction, and behavioural patterns contribute to or detract from academic productivity and professional development. Drawing from the empirical results of this study, including the structural model's demonstration of significant positive effects of CU ($\beta = 0.175$, $p = 0.025$) and SU ($\beta = 0.186$, $p = 0.034$) and the negative effect of HU ($\beta = -0.196$, $p = 0.004$), it becomes evident that academic stakeholders must adopt a strategic approach

to digital engagement. This section outlines five key strategies that individual academicians can implement to maximise the benefits of social media while minimising its potential downsides, based on data-driven insights and supported by recent scholarship.

5.5.1.1 Strategic Content Engagement for Academic Visibility and Recognition

In optimising SMU, academicians should prioritise CU to elevate their research visibility, engage in scholarly dialogue, and disseminate knowledge beyond institutional boundaries. Platforms such as Google Scholar, ResearchGate, Mendeley, and Academia.edu offer academic-centric environments where faculty can publish preprints, post updates about ongoing projects, and curate specialised reading lists (Jordan & Weller, 2018). These practices contribute to increased citation visibility and peer recognition, aligning with the growing importance of altmetrics in academic appraisal (Thelwall & Kousha, 2015). For instance, faculty members who regularly upload working papers or post-publication commentary on ResearchGate often receive feedback that informs further iterations of their work. Moreover, curating scholarly content for public consumption, whether through thematic blogs, curated bibliographies, or discipline-specific summaries, positions academicians as thought leaders in their fields (Sugimoto et al., 2017). By strategically prioritising CU, academicians not only extend the reach and impact of their scholarly contributions but also reinforce their professional identity within and beyond academic communities. This approach cultivates greater academic visibility, fosters meaningful peer engagement, and amplifies the societal relevance of research outputs. Ultimately, effective content engagement through academic-oriented social platforms serves as a practical and impactful strategy for enhancing performance in key domains such as research productivity, academic reputation, and scholarly influence, core dimensions of academic excellence.

5.5.1.2 Enhancing Academician Performance through Social Use of Social Media

Second, the SU of platforms such as LinkedIn, Twitter/X/X, Telegram, and ResearchGate offers significant potential to enhance lecturers' professional performance in higher education settings. Social media facilitates informal, yet

impactful, academic networking and collaboration, which can lead to measurable improvements across key performance areas, including research productivity, teaching innovation, consultation practices, and supervision effectiveness. In this study, SU demonstrated a significant indirect effect on AP through SC ($\beta = 0.072$, $p = 0.023$), reinforcing its strategic role in building academic relationships and fostering collaborative culture among scholars.

Academics today increasingly turn to social media communities for resource sharing, feedback exchange, and peer support. For instance, Gomez-Vasquez (2021) analysed the #AcademicChatter community on Twitter and revealed that academics, particularly early-career researchers and doctoral students, used the platform to discuss research challenges, share opportunities, and provide mutual encouragement. These interactions fostered trust and reinforced a culture of openness and collegiality, both crucial to productive academic environments. Likewise, Davidson et al. (2011) highlighted how social networking technologies, when integrated into faculty-level initiatives, supported the development of interprofessional competencies and collaboration across academic disciplines, thereby creating sustainable networks for educational innovation.

Furthermore, Chuang and Chiu (2016) found that self-presentation motivations among Wikipedia contributors contributed positively to collaborative information exchange, suggesting that academics who use social media to manage professional identity also strengthen their capacity for knowledge sharing. This is particularly relevant for lecturers aiming to expand their scholarly visibility and research outreach. Participation in digital communities not only supports professional development but also enhances performance through increased access to research collaborations, conference opportunities, and interdisciplinary dialogues (Lyttle et al., 2025).

In the Malaysian context, Ha and Kim (2014) found that lecturers and students who used Twitter for mobile learning reported enhanced engagement and information exchange, suggesting that social media can foster meaningful academic interactions beyond the classroom. Similarly, Ha, Jung, and Kim (2013) demonstrated that SMU in university classes contributed to collaborative relationships and student performance, reinforcing its educational utility. For lecturers, such tools may enable them to improve course delivery, engage in continuous learning, and strengthen bonds with both peers and students.

Knoll and Ifrah (2023) added that social media supports the formation of physician and patient communities, emphasising its role in professional learning and knowledge dissemination, principles easily transferable to the academic setting. Kazemian and Grant (2023) reviewed challenges of internal social networking in higher education but concluded that when properly adopted, such networks enhance communication and knowledge exchange, ultimately benefiting academic output.

Collectively, these findings confirm that SU of social media is more than a peripheral engagement activity; it is a powerful enabler of AP. For lecturers in Malaysian public universities who are assessed across domains such as research, teaching, supervision, and consultancy, leveraging social media to build SC translates into tangible professional gains. These platforms act as catalysts for cross-institutional collaborations, grant applications, co-authorships, and pedagogical enhancement. Therefore, integrating SMU strategically into academic workflows can enhance individual and institutional performance outcomes in higher education.

5.5.1.3 Managing Hedonic Social Media Use for Academic Productivity

Managing HU through behavioural self-regulation is essential for sustaining academic productivity and psychological well-being among academicians. While social media platforms offer avenues for leisure, stress relief, and emotional engagement, excessive hedonic engagement, such as mindless scrolling, viewing entertainment content, or prolonged passive browsing, has been shown to negatively impact cognitive performance and time management (Wirtz et al., 2021; Cao & Yu, 2019). In this study (Section 4.3.5), lecturers reported challenges such as "difficulty managing time on social media," "distraction from focus," and being "carried away by feeds and videos," which align with the concept of technostress and emotional exhaustion described in recent literature (Yu et al., 2023; Brooks et al., 2020). Such behavioural patterns are often habitual and reinforced by the gratification of immediate pleasure, leading to diminished self-regulatory control (Köse, 2020; Garibaldi et al., 2022).

To address this, academic staff should consider integrating digital well-being interventions and time-regulation strategies into their daily routines. Tools such as RescueTime, StayFocusd, or Forest, as shown in Plate 5.1, can help monitor and limit screen time by tracking usage patterns and blocking non-essential apps during designated work hours. As illustrated in Plate 5.1, these interventions range from

specialised analytics within the 'Stay Focus' interface to native smartphone settings that enforce strict time limits via 'Set app limit' functions. Furthermore, users can mitigate long-duration usage by customising 'break reminder' menus within specific application settings, such as YouTube, or by utilising the 'Freedom' feature to schedule structured sessions like 'Focused Mornings.' Techniques like the Pomodoro Technique, which combines focused intervals with structured breaks, have been demonstrated to improve task engagement and reduce digital distractions (Mark et al., 2018; Prakashkumar et al., 2023). Moreover, adopting digital self-regulation tools that offer purposeful redirection, such as To-Do List reminders or gamified alternatives like Garden Mode, has been shown to mitigate the habitual pull of hedonic content (Prakashkumar et al., 2023).

An additional strategy is to maintain dual-account separation, with one account dedicated to professional and academic networking and the other to personal interests. This approach creates clear psychological and functional boundaries, reducing the tendency to blur leisure with scholarly tasks and enhancing intentionality in SMU (Nguyen, 2021; Verduyn et al., 2022). Academicians are encouraged to engage in reflective practices to assess their motivations for SMU, as motives rooted in entertainment without purpose can contribute to emotional fatigue and a decline in job performance (Ali-Hassan et al., 2015; Janicke-Bowles et al., 2022).

Importantly, promoting digital mindfulness, where users are consciously aware of their engagement and the value derived, can reinforce positive usage patterns and discourage addictive or escapist behaviours. Overall, embedding structured behavioural strategies and leveraging self-monitoring tools are key to managing HU of social media, thereby sustaining focus, productivity, and well-being in academic work environments.

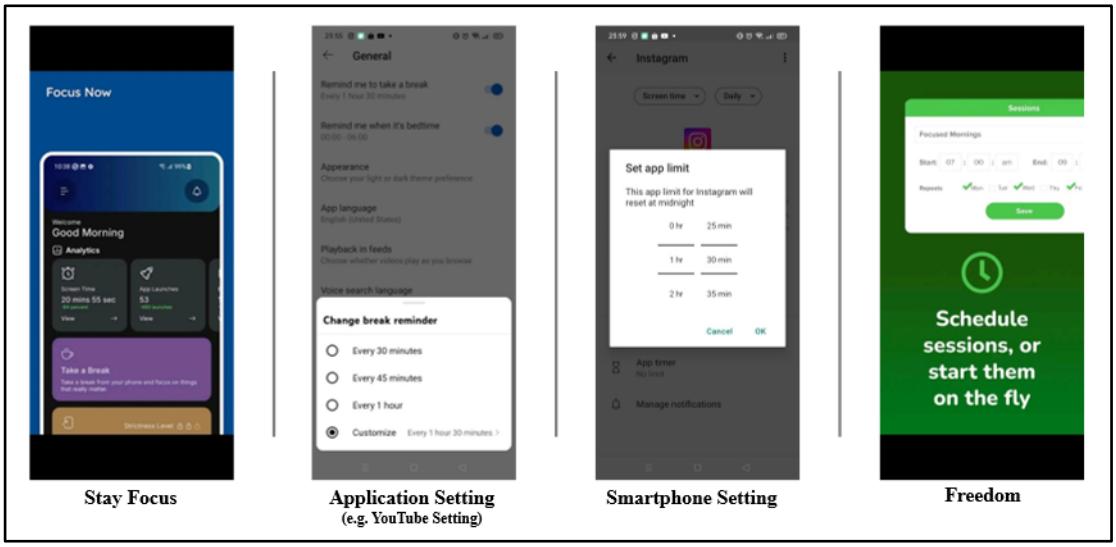


Plate 5.1 A Sample of Digital Self-Regulation Tools

5.5.1.4 Strategising System Use

To optimise AP, the SyU of social media must shift from passive, unstructured interaction to intentional, task-aligned engagement. The modest yet significant effect size in this study ($\beta = 0.143$, $p = 0.046$) suggests that the performance benefit arises not from the volume of system interactions but from the strategic and purposeful use of social media systems in daily academic work.

One robust strategy is the integration of social media platforms into structured academic workflows, for example, using tools like ResearchGate for real-time publication sharing, LinkedIn for disseminating teaching achievements, or Google Scholar alerts to automate literature monitoring. These platforms can be embedded into institutional learning management systems (LMS) or task dashboards to ensure SyU aligns with academic outputs (Ali-Hassan et al., 2015; Cao & Yu, 2019).

Moreover, scheduling intentional "academic social media blocks" (e.g., 20–30 minutes daily for research networking, journal updates, or posting professional content) can balance frequency and intensity. This approach aligns with Self-Regulation Theory and the active-passive use model, which emphasise that purposeful engagement, not high usage frequency, leads to better outcomes (Verduyn et al., 2022; Nguyen, 2021).

Finally, institutions should promote task-technology fit, ensuring academicians are trained to match specific social media tools with distinct performance areas, such as using YouTube channels for flipped teaching, Telegram for consultation groups, and WhatsApp for supervision updates (Greenhow & Gleason, 2014; Brooks et al., 2020).

This reduces the cognitive strain of multitasking across fragmented platforms (Yu et al., 2023) while optimising the use-performance relationship. Thus, optimising SyU requires a deliberate balance between frequency and intensity of engagement, oriented toward academic productivity rather than habitual or non-purposeful interactions.

5.5.2 Institutional and Policy Recommendations

HEIs play a central role in optimising SMU by shaping policies, infrastructure, and professional norms that align with emerging digital practices. As shown in this study, specific dimensions of SMU, such as SyU, SU, CU, and HU, have differential impacts on AP, both directly and through the mediating effect of SC. Therefore, institutional strategies must be rooted in these empirical insights and designed to support responsible, performance-enhancing engagement.

5.5.2.1 Establishing Governance and Ethical Standards

To optimise SyU and SU, institutions should develop comprehensive social media governance frameworks that align with national legislation such as the Communications and Multimedia Act 1998 (Act 588), Personal Data Protection Act 2010 (Act 709), and the Electronic Government Activities Act 2007 (Act 680). Following the 2024 amendments to the Communications and Multimedia Act, which require platforms with over 8 million users to implement more rigorous content moderation and safety measures (Malaysian Communications and Multimedia Commission, 2024), universities must ensure that academic engagement through platforms like YouTube, Facebook, or X (Twitter) adheres to both ethical and legal standards.

Beyond legal compliance, governance frameworks should be informed by national philosophical values, particularly the five principles of the *Rukun Negara* (Kementerian Perpaduan Negara, 2023).

i. *Kepercayaan kepada Tuhan* (Belief in God): Encourages spiritual accountability in digital interactions.
ii. *Kesetiaan kepada Raja dan Negara* (Loyalty to King and Country):

Promotes responsible content sharing that reflects national unity.

iii. *Keluhuran Perlembagaan* (Supremacy of the Constitution): Upholds the legal boundaries of speech and privacy online.

iv. *Kedaulatan Undang-Undang* (Rule of Law): Reinforces adherence to digital regulations and institutional codes of conduct.

v. *Kesopanan dan Kesusilaan* (Good Behaviour and Morality): Supports civility, respect, and ethical discourse in academic SMU.

Internal institutional policies should reflect these values by incorporating clear codes of conduct for academic staff. This includes defining acceptable usage, maintaining professional boundaries online, and encouraging constructive academic dialogue. Such orientation to *Rukun Negara* not only prevents misuse and digital misconduct but also fosters SSC and RSC, both of which are essential for sustaining trust and productive scholarly collaboration.

5.5.2.2 Recognising Digital Scholarship in Performance Appraisal

Although this study found that CU significantly contributes to improved AP, it is important to recognise that not all academicians actively engage with social media platforms for scholarly purposes. Despite the growing academic presence on platforms such as ResearchGate, LinkedIn, and Twitter/X, a significant proportion of academic staff, especially in certain disciplines or age cohorts, remain hesitant or infrequent users due to concerns over time, relevance, or digital literacy (Jordan & Weller, 2018; Manca & Ranieri, 2017).

Nonetheless, for those who do actively contribute to knowledge dissemination online, their efforts often remain unrecognised within traditional performance appraisal systems. Digital outputs such as public scholarship, professional networking, online lectures, open-access resource sharing, and engagement in academic discussions contribute meaningfully to institutional visibility and public impact. Incorporating alternative metrics (altmetrics), such as article views, downloads, social media shares, and mentions in online discussions, can provide a more holistic assessment of scholarly influence that extends beyond conventional citation indices (Thelwall & Kousha, 2015).

To ensure fairness and inclusivity, institutions could adopt a tiered approach in which digital scholarship is recognised as an optional but valid dimension of academic contribution. This would allow those with strong digital engagement to be credited accordingly, without penalising those who engage through more traditional channels. At the same time, institutions should offer capacity-building initiatives to encourage wider participation in digital scholarship over time.

In alignment with the AP HOC validated in this study, comprising teaching, research, publication, supervision, and consultation, recognising social media-based scholarly activities can enhance AP across multiple dimensions. Furthermore, national-level endorsement, such as through the Ministry of Higher Education's performance-based funding models or KPI structures, would provide stronger incentives for institutional reform and alignment.

Thus, while integrating digital scholarship into performance appraisal must be approached cautiously, recognising the evolving nature of academic contribution and offering structured support can lead to more equitable and future-ready evaluation systems.

5.5.2.3 Ensuring Digital Access and Infrastructure Equity

Access to reliable systems and platforms is foundational for optimal SyU and academic participation. This study identified digital inequalities across campuses, particularly in under-resourced areas. Institutions must upgrade infrastructure, including campus-wide Wi-Fi, mobile-responsive learning systems, and device subsidies, to enable seamless access to academic platforms (Musa et al., 2020).

These measures contribute to inclusive performance optimisation and are consistent with Malaysia's social inclusion principles and the Persons with Disabilities Act 2008. They also ensure that digital engagement is equitable across demographics, strengthening institutional SC and collaborative academic networks.

5.5.3 Digital Literacy and Governance Implications

The rise of social media in academia underscores the urgency for HEIs to strengthen their digital governance and literacy frameworks. This section addresses three focus areas essential for fostering responsible and effective engagement with

social media in academia: (1) Enhancing Academicians' Digital Literacy, (2) Strengthening Digital Governance and Ethical Awareness, and (3) Encouraging Algorithmic and Platform Awareness.

5.5.3.1 Enhancing Academicians' Digital Literacy

The multidimensional nature of SMU requires academicians to possess a high level of digital competence. Findings from this study highlight challenges such as time mismanagement, information overload, and the potential spread of misinformation, indicating a gap in critical digital literacy among some academicians. To address this, institutions should embed structured digital literacy programs within ongoing professional development schemes. These programs should teach academicians not only how to use social media effectively but also how to discern credible information sources, manage their digital identities, and use platforms ethically and strategically (Law et al., 2018).

As advocated by previous scholars, such literacy programs must go beyond technical skills and emphasise reflective, ethical, and context-sensitive practices (Alexander et al., 2019; Littlejohn & Seely Brown, 2020). A strategic approach would involve modular training, mentoring, and peer-to-peer sharing initiatives tailored to the varied digital proficiencies of academic staff. This empowers them to use social media to enhance collaboration, engagement, and visibility in ways that align with institutional values.

5.5.3.2 Strengthening Digital Governance and Ethical Awareness

Digital governance refers to the policies, norms, and strategies that shape responsible digital engagement in institutions. Despite the growing reliance on digital platforms, many HEIs lack clear and comprehensive social media governance structures. This study supports the need for academic institutions to develop transparent and inclusive digital governance frameworks that guide the ethical, professional, and effective use of social media tools.

Such frameworks should include articulated codes of conduct, data protection protocols, and ethical guidelines for online interaction, addressing issues such as academic freedom, cyberbullying, misrepresentation, and digital surveillance. As

Manca (2020) emphasised, digital governance in academia should not be perceived as a control mechanism, but rather as an enabling structure that ensures equitable access, promotes digital well-being, and supports academic autonomy in online environments.

Furthermore, the study emphasises that ethical concerns, such as using social media for personal gain or disseminating unverified content, can erode academic credibility and institutional reputation. Institutions must encourage academicians to critically reflect on their digital practices and align their online presence with the principles of academic integrity and public trust (Kimmons & Veletsianos, 2016).

5.5.3.3 Encouraging Algorithmic and Platform Awareness

Another critical dimension of digital literacy is understanding the role of algorithms and platform design in shaping what content academicians see, share, and engage with. Encouraging algorithmic and platform awareness helps academicians understand how opaque, AI-driven processes shape content visibility and user engagement. This knowledge is essential for critically navigating platform dynamics, promoting scholarly content ethically, and resisting potential manipulation through engagement-based metrics or biased recommendation systems. While social media offers unprecedented opportunities for visibility and connection, its algorithm-driven logic can promote echo chambers, reinforce biases, and prioritise popularity over academic rigour.

This study suggests that fostering algorithmic awareness is essential for academicians to navigate digital spaces effectively and consciously. Institutions should consider integrating training on the algorithmic behaviours of digital platforms into broader digital literacy efforts. By doing so, academicians can better understand how algorithms curate content, influence attention, and potentially amplify or limit academic visibility. As Boyd (2014) and Gillespie (2018) argued, a critical understanding of algorithms empowers users to resist passive consumption, exercise agency, and engage in more intentional knowledge dissemination. Academics who grasp how platform dynamics work are better positioned to manage their online presence, avoid manipulation by trending topics, and engage in meaningful academic discourse.

5.6 Study Limitations and Future Research Directions

Despite its theoretical contributions and empirical robustness, this study acknowledges several limitations that may constrain the generalisability, methodological scope, and theoretical depth of its findings. Understanding these limitations is critical for framing the conclusions within their appropriate boundaries and identifying pathways for future research. Accordingly, this section is structured into three interrelated dimensions (i.e., conceptual and framework limitations, methodological constraints, and avenues for future scholarly inquiry). Each subsection elaborates on specific issues encountered in the research design and implementation, and proposes strategic responses to enrich subsequent investigations of SMU and AP.

While this study contributes valuable insights into the relationship between SMU and AP in Malaysian HEIs, it is essential to acknowledge its methodological and contextual limitations. These limitations do not undermine the findings' validity but offer opportunities for refinement and expansion in future investigations. By identifying these constraints, this research ensures transparency in reporting, enhances theoretical generalisability, and supports continuous improvement in digital behaviour studies within academic environments.

5.6.1 Conceptual and Framework Limitations

The first category of limitations pertains to the conceptual scope and theoretical frameworks adopted in this study. One prominent limitation is the focus on a limited set of SMU dimensions: SyU, SU, CU, and HU. While these categories were adapted and refined from previous models and validated through exploratory and confirmatory analyses, they may not fully capture the evolving nuances of digital behaviour, particularly as new platforms and user modalities emerge. For instance, recent literature has pointed to other potentially salient categories, such as instrumental use (e.g., task delegation via AI bots), identity performance (e.g., self-branding on TikTok), and surveillance awareness (e.g., monitoring student behaviour), which were not considered in the present study (Conde-Caballero et al., 2023; Mohamed et al., 2024).

This study used three well-known theories, the TAM, the UGT, and the SCT, to understand how different ways of using social media affect AP. However, the detailed relationships between these theories were not fully explored. For example, while TAM

includes ideas like "perceived usefulness" and UGT includes types of "gratifications" such as entertainment or information seeking, this study did not separately examine how these specific elements influence performance. Instead, the study looked at the overall effects of each dimension of SMU. As a result, the model may have missed important insights about how and why certain types of SMU lead to better outcomes, especially in a diverse cultural setting like Malaysia.

In addition, the study treated SC as a broad concept comprising three parts: structural, relational, and cognitive capital. While this approach helped understand social media's overall role in academic networking and collaboration, it did not consider how different social media platforms might support different types of SC. For example, Facebook might help build friendships (relational capital), while ResearchGate might support academic knowledge sharing (cognitive capital), and WhatsApp might be more useful for organising tasks (structural capital). By not accounting for these platform-specific patterns, the model assumes that all platforms contribute to SC in the same way, which may not reflect actual usage. Future studies should develop models that account for how specific platforms operate, enabling us to better understand the unique value each platform brings to AP and collaboration.

Finally, "AP" was measured through four subdimensions: Research & Publication, Teaching, Supervision, and Consultation. While these dimensions align with the academic KPIs in Malaysian public universities, they may not be equally applicable across diverse institutional settings, including private universities, community colleges, and international higher education systems. As academia becomes increasingly digitised, future research must consider how alternative metrics, such as online engagement analytics or open-access dissemination, can be integrated into performance frameworks.

5.6.2 Methodological Limitations

The current study utilised a cross-sectional design to examine the relationships among various dimensions of SMU, SC, and AP within Malaysian HEIs. While this design enabled timely and efficient data collection from a large sample, it has inherent limitations regarding causality and temporal dynamics. As widely acknowledged in the research methodology literature, cross-sectional studies provide only a snapshot of associations at a given point in time and are thus limited in establishing causal

directionality (Creswell & Creswell, 2018). This limitation becomes particularly significant in behavioural and social sciences, where media use and performance evolve and are subject to contextual fluctuations.

In this regard, Taris, Kessler, and Kelloway (2021) offered a compelling critique of cross-sectional designs in occupational health psychology, which is highly relevant to the academic setting of this research. They asserted that while cross-sectional designs are useful for identifying patterns and correlations, they are inherently incapable of demonstrating causality because they lack temporal precedence. Their argument emphasised that accurate causal inference requires longitudinal methods, particularly repeated-measures designs that capture intra-individual changes over time. Without observing changes in antecedents and outcomes across different time points, researchers cannot determine whether a cause truly precedes its effect. The authors further critiqued "time-separated" designs, which measure variables at different times without repetition, arguing that such approaches do little to advance causal understanding beyond that of standard cross-sectional methods.

Although time-separated data collection may reduce common method bias, it does not address the central issue of temporal causality (Podsakoff et al., 2003; Taris et al., 2021). Moreover, as diary or panel study designs gain traction in occupational and behavioural research, it becomes evident that most fail to capitalise on their full analytical potential. Taris et al. (2021) noted that many so-called longitudinal studies pool daily or wave-based data and analyse them cross-sectionally, thereby missing opportunities to explore growth, lag effects, and intra-individual variability. These observations highlight a broader methodological limitation that is not unique to this study but is generally symptomatic of social science research. Future investigations into the evolving interplay between SMU, SC, and AP would benefit greatly from rigorous longitudinal designs or mixed-method approaches that integrate temporal data and experimental validation.

Beyond causality, the reliance on self-reported data, though common in social science research, introduces potential biases, including social desirability bias, recall inaccuracies, and CMV (Podsakoff et al., 2003). Although procedural remedies such as construct separation, anonymity assurances, and statistical tests for common method bias were implemented, the study still lacked objective validation mechanisms such as digital trace data or behavioural analytics. Future studies could significantly enhance the robustness of findings by incorporating system-generated data, such as usage logs,

screen-time analytics, or AI-assisted content analysis. These digital footprints would provide more accurate reflections of social media usage patterns and reduce the likelihood of inflated associations arising from respondents' self-perceptions.

Additionally, the study was conducted within a single institution, UiTM, which, despite being one of the largest and most demographically diverse public universities in Malaysia, limits the generalisability of the results. Institutional differences in digital infrastructure, professional development policies, research culture, and leadership dynamics may influence how academicians utilise and perceive social media. Consequently, the findings, while indicative of patterns within UiTM, may not fully represent the Malaysian higher education sector. Broader multi-site studies or stratified sampling across various institutional types (e.g., research universities, teaching-focused institutions, private colleges) are needed to achieve greater ecological validity.

Lastly, the study lacked an experimental component to assess the impact of specific interventions. While statistical associations were examined and theoretically grounded recommendations were proposed, the actual effects of implementing these strategies, such as digital literacy programs, platform access initiatives, or psychological well-being tools, were not empirically validated. As such, future research should explore the use of experimental or quasi-experimental designs to test the efficacy of practical interventions derived from the theoretical model. For instance, studies could evaluate whether structured digital training programs improve content engagement efficacy or whether social media governance workshops enhance responsible online behaviours. Embedding such applied strategies within a longitudinal evaluation framework could bridge the gap between theoretical advancement and practical impact.

5.6.3 Future Research Opportunities

Building on the limitations discussed above, several promising avenues for future research can be identified. First, future studies should employ longitudinal or experience sampling methods to track digital behaviour over time. Such approaches would capture changes in platform use, performance perception, and SC accumulation, offering more nuanced insights into causality and behavioural trajectories.

Second, integrating qualitative methods such as interviews, focus groups, or diary studies would deepen contextual understanding, especially regarding individual motivations, digital identity construction, and cultural meanings of platform use. These

methods would complement quantitative models and uncover latent variables that are not easily captured by survey instruments.

Third, building on the theoretical and contextual limitations discussed, future research should deepen the understanding of how TAM, UGT, and SCT interact in academic digital environments by disaggregating and explicitly modelling their core constructs. For example, future studies could explore how perceived usefulness and ease of use (TAM) mediate the relationship between SyU/CU and performance, or how specific gratifications such as self-expression, knowledge acquisition, and social connection (UGT) predict different forms of engagement. In addition, further studies should adopt platform-sensitive models to examine whether and how SC's structural, relational, and cognitive components are uniquely fostered across platforms such as WhatsApp, Facebook, ResearchGate, or YouTube. Multi-Group Analysis (MGA) in SmartPLS, qualitative interviews, or mixed-method approaches could yield richer insights into the contextual and cultural nuances that shape platform-specific digital behaviours in higher education. Such refined conceptual models would enhance theoretical contributions and offer more precise, targeted recommendations to academics, institutions, and policymakers in digitally mediated academic settings.

Fourth, intervention-based research is highly encouraged. Studies could experimentally test the effects of digital literacy training, time-management applications, or AI-assisted academic tools (e.g., citation generators, plagiarism detectors) on performance outcomes. These experiments would offer practical insights for institutions seeking to improve academic productivity through digital engagement.

Fifth, comparative studies across institutions and countries would reveal how institutional cultures, national policies, and digital infrastructures mediate the relationship between SMU and AP. Such studies would help determine whether the findings from Malaysian public universities are transferable to private universities or institutions in other developing or developed countries.

Sixth, future research should systematically explore the intersection between social media and AI. As Mohamed et al. (2024) noted, AI-driven algorithms significantly influence content visibility, personalisation, and user interaction. Future studies should investigate how algorithmic curation affects academic engagement, content diversity, and exposure to scholarly opportunities. Moreover, issues related to misinformation, echo chambers, and ethical AI design should be explored in higher education.

Seventh, expanding the performance model to include alternative indicators, such as online influence (e.g., Altmetrics), digital public engagement, and participation in open-access knowledge ecosystems would better capture the multifaceted nature of academic impact in the digital age. These indicators may be particularly relevant for early-career scholars and educators in interdisciplinary or emerging fields.

Finally, future studies should aim to inform policy design and institutional strategy by producing empirically validated models that can be integrated into national performance appraisal systems, institutional digital transformation plans, and faculty development programs. In doing so, research can help create a more digitally inclusive, ethically grounded, and productivity-enhancing academic ecosystem.

5.7 Conclusions

This chapter has synthesised and interpreted the study's key empirical findings, framed them within relevant theoretical perspectives, and outlined their implications for scholarship, institutional practice, and future research. Drawing upon the integration of the TAM, UGT, and SCT, the study has provided nuanced insights into how different dimensions of SMU, SyU, SU, CU, and HU affect AP in the Malaysian higher education context. Moreover, the research has validated the mediating role of SC, modelled as an HOC encompassing structural, relational, and cognitive components, thereby deepening our understanding of the mechanisms through which digital engagement translates into professional outcomes.

This conclusion also responds directly to key theoretical and empirical gaps identified in the literature, particularly the lack of validated, multidimensional measures of SMU, the absence of context-specific frameworks for AP, and the limited investigation of SC as a mediating mechanism. The study thus contributes to bridging the disconnect between traditional IS models, which typically emphasise usage metrics like frequency or duration, and the more complex, socially embedded realities of digital engagement in academia.

The discussion in this chapter confirms that CU and SU contribute positively to performance. In contrast, HU has a negative association, and SyU presents mixed outcomes depending on context. These findings reflect a maturing academic digital culture where purposeful engagement with social media platforms, particularly for knowledge sharing, academic collaboration, and research dissemination, catalyses

performance enhancement. SC emerged as a crucial intermediary variable, supporting the theoretical proposition that digital networks must be accompanied by trust, reciprocity, and shared norms to yield meaningful professional benefits. The significance of SC as a mediator also reinforces the importance of relational infrastructure within digital ecosystems, suggesting that network structure alone is insufficient without quality interactions and shared understanding.

The chapter further emphasised the practical and institutional implications of these findings. At the individual level, academicians must strategically curate their digital presence, engage with platforms aligned to their academic goals, and develop digital literacy and content management competencies. Universities should craft inclusive, adaptable digital policies at the institutional level, invest in training programs, and support platform-specific best practices. In the broader governance landscape, national policymakers must revise digital frameworks to accommodate AI-driven platforms, privacy concerns, platform accountability, and the ethical complexities of online academic life. These multi-level recommendations aim to build a resilient academic ecosystem that balances innovation with integrity.

Notwithstanding its contributions, the study acknowledges key limitations, most notably, the cross-sectional design, reliance on self-reported data, and institutional scope confined to UiTM. These constraints limit causal inference and generalisability, but they also offer avenues for future inquiry. The chapter has articulated a research agenda that calls for longitudinal and experimental designs, including behavioural analytics, and the development of platform-sensitive conceptual models to explore how different social media environments may cultivate or constrain SC and performance differently. The methodological critique also resonates with recent scholarly discussions on the pitfalls of overreliance on cross-sectional and time-separated studies in social science research.

In summation, this chapter has demonstrated that when employed purposefully, social media can be a powerful instrument for academic growth. However, its benefits depend on contextual, relational, and policy dimensions. The study's integration of TAM, UGT, and SCT offers a theoretically grounded and empirically validated framework for understanding the complex interplay between technology use and academic productivity. The findings contribute to scholarly debates and offer actionable insights for academicians, university administrators, and policymakers committed to fostering a digitally competent and high-performing academic workforce in Malaysia

and beyond. As digital transformations continue to shape higher education globally, this study affirms the need for deliberate, evidence-based strategies to harness the potential of social media while mitigating its risks.

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APPENDICES

APPENDIX 1

Questionnaires Response Sample

SOCIAL MEDIA USE (SMU) AND ITS IMPACT ON ACADEMICIAN PERFORMANCE IN MALAYSIA

Dear Professor/ Associate Professor/Dr./Mr./Mrs./Ms.

My name is Zuraidah binti Arif, and I am a Ph.D. student at the School of Information Science, College of Computing, Informatics, and Mathematics, Universiti Teknologi MARA. I would like to invite you, Professor/ Associate Professor/Dr./Mr./Mrs./Ms. to participate in this survey on social media use and its impact on academician performance in Malaysia. This survey consists of four sections, demographic, social media use, social capital, and academician performance.
The purpose of this study is to study the way social media use impacts Malaysian academician performance.
Your kindness in completing the questionnaire is very much appreciated. This questionnaire will take approximately 13 – 15 minutes to complete. Your responses are greatly valued. There is no right and wrong answer. Your responses will be strictly confidential for academic purposes only. If you have any queries or concerns about the questionnaire, please do not hesitate to contact me at

Thank you for taking the time to participate in this research.
جزاك الله خيرًا
May Allah reward you [with] goodness

ZURAIDAH BINTI ARIF

School of Information Science,
College Of Computing, Informatics, and Mathematics

Universiti Teknologi MARA
Phone: · --- --- ----
Email: zuraidah_arif@uitm.edu.my

The respondent's email (**hasyimah511@uitm.edu.my**) was recorded on submission of this form.

PART A: DEMOGRAPHIC

I identify myself as *

- (●) Female
- ( ) Male

I am ____ years old. *

38

I have served my current institution for _____ years. *

10

Which UiTM branch are you currently serving? *

- ○ 1. Johor Branch
- ◉ 2. Kedah Branch
- ○ 3. Kelantan Branch
- ○ 4. Melaka Branch
- ○ 5. Negeri Sembilan Branch
- ○ 6. Pahang Branch
- ○ 7. Perak Branch
- ○ 8. Perlis Branch
- ○ 9. Pulau Pinang Branch
- ○ 10. Sabah Branch
- ○ 11. Sarawak Branch
- ○ 12. Selangor Branch
- ○ 13. Terengganu Branch

PART B: SOCIAL MEDIA USE

Social media use (SMU) is the use of social media in the perspective of system, social, cognitive, and hedonic use.

SYSTEM USE (SyU)

System use (SU) is the use of social media in the perspective frequency, duration, and intensity.
The next questions requests information regarding your preferred, the second, and the third social media applications used for academic purposes.

Select your preferred social media application used for academic purposes. *

Telegram

SyU1. FREQUENCY *

Based on your preferred social media application.

Please rate in the range of scale 1(Never) to 5 (Every time) for the following statement about the frequency of social media site visits per week.

5. Every time

SyU2. DURATION *

Based on your preferred social media application.

I spend approximately ____ hours per week on the following social media sites

10-15 hours per week |

SyU2. INTENSITY *

Based on your preferred social media application.
Please rate in the range of scale 1(Never use) to 5 (Frequently use) for the following statement about how often you use social media.

5. Frequently use

Select your second (2) social media application used for academic purposes. *

YouTube

Based on your response, please rate in the range of scale 1(Strongly disagree) to 7 (Strongly agree) for the following statement. *

	1. Strongly disagree	2. Disagree	3. Somewhat disagree	4. Neither agree or disagree	5. Somewhat agree	6. Agree	7. Strongly Agree
SU1. I use social media to foster new relationship at work.	○	○	○	○	○	◉	○
SU2. I use social media to network with fellow academics from other institutions.	○	○	○	○	○	◉	○
SU3. I use social media to maintain close relationship with my colleagues.	○	○	○	○	○	◉	○
SU4. I use social media to explore social group who share similar interest.	○	○	◉	○	○	○	○
SU5. I use social media to make acquaintance with	○	○	◉	○	○	○	○

Based on your response ABOVE, please rate in the range of scale 1(Strongly disagree) to 7 (Strongly agree) for the following statement. *

	1. Strongly disagree	2. Disagree	3. Somewhat disagree	4. Neither agree or disagree	5. Somewhat agree	6. Agree	7. Strongly Agree
CU1. I use social media to share useful information	○	○	○	○	○	○	◉
CU2. I use social media to search for relevant content based on my needs.	○	○	○	○	○	○	◉
CU3. I use social media to access useful information.	○	○	○	○	○	○	◉
CU5. I use social media to create content based on my interest.	◉	○	○	○	○	○	○
CU6. I use social media to create content based on my knowledge.	◉	○	○	○	○	○	○

Based on your response ABOVE, please rate in the range of scale 1(Strongly disagree) to 7 (Strongly agree) for the following statement. *

	1. Strongly disagree	2. Disagree	3. Somewhat disagree	4. Neither agree or disagree	5. Somewhat agree	6. Agree	7. Strongly Agree
HU1. I use social media to take a break from work.	○	○	○	○	○	○	◉
HU2. I use social media to fill a time gap.	○	○	○	○	○	○	◉
HU3. I use social media to get myself relaxed.	○	○	○	○	○	○	◉
HU4. I use social media a source of entertainment.	○	○	○	○	○	○	◉
HU5. I use social media to play games.	◉	○	○	○	○	○	○

PART C: SOCIAL CAPITAL.

Social capital (SC) is defined as a networking relationship exists inside an individual.

Acquaintances is someone who is known but who is not a close friend or the state of knowing someone in a personal or social way.

STRUCTURAL SOCIAL CAPITAL (SSC)
Structural social capital (SSC) is defined as a networking relationship between individuals or group with different background, the relationship is not based on prior experience.

Please rate in the range of scale 1 to 7 for the following statement. *

	1. Strongly disagree	2. Disagree	3. Somewhat disagree	4. Neither agree or disagree	5. Somewhat agree	6. Agree	7. Strongly agree
SSCE1. I have many acquaintances I consider friends	◉	○	○	○	○	○	○
SSCE2. I have established good rapport with many acquaintances	◉	○	○	○	○	○	○
SSCE3. I have many acquaintances who support me through my personal problems	◉	○	○	○	○	○	○
SSCE4. I have many acquaintances that I feel comfortable in disclosing my personal information	◉	○	○	○	○	○	○
SSCE5. I have many acquaintances I socially meet outside work	◉	○	○	○	○	○	○
SSCI1. I have many acquaintances that I seek for work related information	◉	○	○	○	○	○	○
SSCI2. I have many acquaintances whom I ask for work-related advice.	◉	○	○	○	○	○	○
SSCI3. I know many acquaintances whom I can approach whenever I need work-related advice.	◉	○	○	○	○	○	○
SSCI4. I provide answers to work-	◉	○	○	○	○	○	○

related questions posed by my acquaintances.							
SSCI5. I willingly provide work-related input to many of my acquaintances.	◉	○	○	○	○	○	○

RELATIONAL SOCIAL CAPITAL (RSC)

Relational social capital (RSC) is defined as a networking relationship between individuals or group which share the same background. The relationship is started with prior experience for example co-workers, classmates, and teachers.

Please rate in the range of scale 1 to 7 for the following statement. *

	1. Strongly disagree	2. Disagree	3. Somewhat disagree	4. Neither agree or disagree	5. Somewhat agree	6. Agree	7. Strongly agree
RSC1. I have skilled acquaintances whom I trust.	◉	○	○	○	○	○	○
RSC2. I trust my acquaintances.	◉	○	○	○	○	○	○
RSC3. Generally, I rely on the acquaintances I work with.	◉	○	○	○	○	○	○
RSC4. I can work well with my acquaintances.	◉	○	○	○	○	○	○
RSC5. my acquaintances and I are confident in each other.	◉	○	○	○	○	○	○
RSC6. my acquaintances show high integrity.	◉	○	○	○	○	○	○

COGNITIVE SOCIAL CAPITAL (CSC)

Cognitive social capital (CSC) is defined as the ability of an individual to understand the message received by another person. It also involves the ability of an individual to express or share their understanding with the community of practice.

Please rate in the range of scale 1 to 7 for the following statement. *

	1. Strongly disagree	2. Disagree	3. Somewhat disagree	4. Neither agree or disagree	5. Somewhat agree	6. Agree	7. Strongly agree
CSC1. I understand the information from my contacts.	○	○	○	○	○	○	◉
CSC2. I share my knowledge with my contacts.	○	○	○	○	○	○	◉
CSC3. It easy to understand my contacts.	○	○	○	○	○	○	◉
CSC4. Sometimes it is challenging in understanding my contacts.	○	○	○	○	○	◉	○
CSC5. There are different work priorities between my acquaintances and I.	○	○	○	○	○	○	◉
CSC6. There is compatibility between information acquaintances and I..	○	○	○	○	○	◉	○
CSC7. I found it difficult to understand my acquaintances.	○	○	○	○	○	○	◉

PART D: ACADEMICIAN PERFORMANCE

Academician performance (AP) is defined as a set of activities that is teaching and supervision, research and consultations, publication, administrative and management work, and social services which were used to measure academician's performance in the higher education institutions.

Please rate in the range of scale *1 (Strongly disagree) to 5 (Strongly agree) for the following statement.* *

	1. Strongly disagree	2. Disagree	3. Neither agree or disagree	4. Agree	5. Strongly agree
APS1. I have appropriate qualifications to supervise the students.	○	○	○	◉	○
APS2. I conduct supervision at various academic levels.	○	○	○	◉	○
APS3. I have knowledge to supervise the students.	○	○	○	◉	○
APS4. I have skills to supervise the students.	○	○	○	◉	○
APS5. I have expertise in my area of specializations.	○	○	○	◉	○
APT1. I have qualifications to teach students at the undergraduate level.	○	○	○	◉	○
APT2. I have a qualification to teach students at the post-graduate level.	○	◉	○	○	○
APT3. I have knowledge to teach the students.	○	○	○	◉	○
APT4. I have appropriate ICT skills to supervise the students.	○	○	○	◉	○
APT5. I have an appropriate teaching method for the students.	○	○	○	◉	○
APT6. I have expertise I my area of teaching	○	○	○	◉	○
APC1. I have on-going consultation project with industry.	◉	○	○	○	○
APC2. I am well-known in my area of expertise.	○	○	○	◉	○
APC3. I have considerable experience in my area of expertise.	○	○	○	◉	○
APC4. I have established good relationship with industry	○	◉	○	○	○

APR1. I have an on-going research project.	○	○	○	◉	○
APR2. I have a research proposal ready for submission.	○	○	○	◉	○
APR3. I look forward to applying for a research grant.	○	○	○	◉	○
APR4. I am looking forward to executing the new research project.	○	○	○	◉	○
APR5. I am looking forward to executing new research collaborations.	○	○	○	◉	○
APR6. I have knowledge in my area of research.	○	○	○	◉	○
APP1. I will publish according to university KPI.	○	○	○	◉	○
APP2. I will publish based on my KPI.	○	○	○	◉	○
APP3. I am willing to publish more than my KPI.	○	◉	○	○	○
APP4. I will make sure my article is published in an indexed journal.	○	○	○	◉	○
APP5. I predict to published more than my KPI.	○	◉	○	○	○
APP6. I am looking forward for opportunity to publish in any type of publication.	○	○	○	◉	○
APA1. I have appropriate qualifications to hold administrative and management post.	◉	○	○	○	○
APA2. I have knowledge to hold the administrative and management post.	◉	○	○	○	○
APA3. I have skills to hold the administrative and management post.	◉	○	○	○	○
APA4. I have experience in administrative and	◉	○	○	○	○

management post.					
APA5. I am currently holding an administrative and management post.	◉	○	○	○	○
APA6. I held related administrative and management post	◉	○	○	○	○
APS1. I will contribute to the communities.	○	○	○	◉	○
APS2. I am always involved in social, and community work every year.	○	○	○	◉	○
APS3. I transfer my knowledge to the community.	○	○	○	◉	○
APS4. I am sharing my expertise to the community	○	○	○	◉	○

PART E: PROBLEMS OF SOCIAL MEDIA USE AMONG ACADEMICIANS

This part is intended to find the problems that you encounter in social media use.

APPENDIX 2

Survey Questions

PART A: DEMOGRAPHIC

1. Email: _____

2. I identify myself as
   - Female
   - Male

3. I am ____ years old.

4. I have served my current institution for _____ years.

5. Which UiTM branch are you currently serving?
   - 1. Johor Branch
   - 2. Kedah Branch
   - 3. Kelantan Branch
   - 4. Melaka Branch
   - 5. Negeri Sembilan Branch
   - 6. Pahang Branch
   - 7. Perak Branch
   - 8. Perlis Branch
   - 9. Pulau Pinang Branch
   - 10. Sabah Branch
   - 11. Sarawak Branch
   - 12. Selangor Branch
   - 13. Terengganu Branch

PART B: SOCIAL MEDIA USE

Social media use (SMU) is the use of social media in the perspective of system, social, cognitive, and hedonic use.

SYSTEM USE (SyU)

is the use of social media in the perspective frequency, duration, and intensity.

1. Select your preferred social media application used for academic purposes.
   - Academic.edu
   - Blog/Weblog
   - Facebook
   - Google Scholar
   - Instagram
   - LinkedIn
   - Mendeley
   - ORCID
   - Publons
   - ResearchGate

- Scopus
- Telegram
- Tiktok
- Twitter
- WhatsApp
- YouTube
-

2. SyU1. FREQUENCY
   Based on your preferred social media application.
   Please rate in the range of scale 1(Never) to 5 (Every time) for the following statement about the frequency of social media site visits per week.
   - Never use
   - Almost never
   - Occasionally/Sometimes
   - Almost every time
   - Frequently use

3. SyU2. DURATION
   Based on your preferred social media application.
   I spend approximately ____ hours per week on the following social media sites
   - Not at all
   - 0-5 hours per week
   - 5-10 hours per week
   - 10-15 hours per week |
   - 15-20 hours per week
   - 20-25 hours per week
   - more than 25 hours per week

4. SyU2. INTENSITY *
   Based on your preferred social media *application.*
   Please rate in the range of scale 1(Never use) to 5 (Frequently use) for the following statement about how often you use social media.
   - Never use
   - Almost never
   - Occasionally/Sometimes
   - Almost every time
   - Frequently use

SOCIAL USE (SU)

Social use (SU) is defined as the use of social media from the aspect of social. It involves communication, interactions, and connection (for example connection with people or making new connections) between individual and group. It also involves the use of social media for collaborative research or work.

Based on your response, please rate in the range of scale 1(Strongly disagree) to 7 (Strongly agree) for the following statement.

1. *Strongly disagree*
2. *Disagree*
3. *Somewhat disagree*
4. *Neither agree or disagree*
5. *Somewhat agree*
6. *Agree*
7. *Strongly Agree*

Social Use							
SU1. I use social media to foster new relationships at work.	1	2	3	4	5	6	7
SU2. I use social media to network with fellow academics from other institutions. SU3. I use social media to maintain a close relationship with my colleagues.	1	2	3	4	5	6	7
SU4. I use social media to explore social groups who share similar interests.	1	2	3	4	5	6	7
SU5. I use social media to make acquaintances with individuals with the same interests.	1	2	3	4	5	6	7

CONTENT USE (CU)

Content use (CU) is defined as the use of social media for information searching, information consumption, information and knowledge sharing.

Based on your response, please rate in the range of scale 1(Strongly disagree) to 7 (Strongly agree) for the following statement.

1. *Strongly disagree*
2. *Disagree*
3. *Somewhat disagree*
4. *Neither agree or disagree*
5. *Somewhat agree*
6. *Agree*
7. *Strongly Agree*

Content Use							
CU1. I use social media to share useful information	1	2	3	4	5	6	7
CU2. I use social media to search for relevant content based on my needs.	1	2	3	4	5	6	7
CU3. I use social media to access useful information.	1	2	3	4	5	6	7
CU5. I use social media to create content based on my interests.	1	2	3	4	5	6	7
CU6. I use social media to create content based on my knowledge.	1	2	3	4	5	6	7

HEDONIC USE (HU)

Hedonic use (HU) is the use of social media for entertainment and relaxing purpose.

Based on your response, please rate in the range of scale 1(Strongly disagree) to 7 (Strongly agree) for the following statement.

1. *Strongly disagree*
2. *Disagree*
3. *Somewhat disagree*
4. *Neither agree or disagree*
5. *Somewhat agree*
6. *Agree*
7. *Strongly Agree*

Hedonic Use							
HU1. I use social media to take a break from work.	1	2	3	4	5	6	7
HU2. I use social media to fill a time gap.	1	2	3	4	5	6	7
HU3. I use social media to get myself relaxed.	1	2	3	4	5	6	7
HU4. I use social media a source of entertainment.	1	2	3	4	5	6	7

PART C: SOCIAL CAPITAL.

Social capital (SC) is defined as a networking relationship exists inside an individual.

Acquaintances is someone who is known but who is not a close friend or the state of knowing someone in a personal or social way.

STRUCTURAL SOCIAL CAPITAL (SSC)

Structural social capital (SSC) is defined as a networking relationship between individuals or group with different background, the relationship
is not based on prior experience.

Please rate in the range of scale 1 to 7 for the following statement

1. Strongly disagree
2. Disagree
3. Somewhat disagree
4. Neither agree or disagree
5. Somewhat agree
6. Agree
7. Strongly agree

Structural Social Capital							
SSCE1. I have many acquaintances I consider friends	1	2	3	4	5	6	7
SSCE2. I have established good rapport with many acquaintances	1	2	3	4	5	6	7
SSCE3. I have many acquaintances who support me through my personal problems	1	2	3	4	5	6	7
SSCE4. I have many acquaintances that I feel comfortable in disclosing my personal information	1	2	3	4	5	6	7
SSCE5. I have many acquaintances I socially meet outside work	1	2	3	4	5	6	7

SSCI1. I have many acquaintances that I seek for work related information	1	2	3	4	5	6	7
SSCI2. I have many acquaintances whom I ask for work-related advice.	1	2	3	4	5	6	7
SSCI3. I know many acquaintances whom I can approach whenever I need work-related advice.	1	2	3	4	5	6	7
SSCI4. I provide answers to work-related questions posed by my acquaintances.	1	2	3	4	5	6	7
SSCI5. I willingly provide work-related input to many of my acquaintances.	1	2	3	4	5	6	7

RELATIONAL SOCIAL CAPITAL (RSC)

Relational social capital (RSC) is defined as a networking relationship between individuals or group which share the same background. The relationship is started with prior experience for example co-workers, classmates, and teachers.

Please rate in the range of scale 1 to 7 for the following statement

1. Strongly disagree
2. Disagree
3. Somewhat disagree
4. Neither agree or disagree
5. Somewhat agree
6. Agree
7. Strongly agree

Relational Social Capital							
RSC1. I have skilled acquaintances whom I trust.	1	2	3	4	5	6	7
RSC2. I trust my acquaintances.	1	2	3	4	5	6	7
RSC3. Generally, I rely on the acquaintances I work with.	1	2	3	4	5	6	7
RSC4. I can work well with my acquaintances.	1	2	3	4	5	6	7
RSC5. my acquaintances and I are confident in each other.	1	2	3	4	5	6	7
RSC6. my acquaintances show high integrity.	1	2	3	4	5	6	7

COGNITIVE SOCIAL CAPITAL (CSC)

Cognitive social capital (CSC) is defined as the ability of an individual to understand the message received by another person. It also involves the ability of an individual to express or share their understanding with the community of practice.

Please rate in the range of scale 1 to 7 for the following statement

1. Strongly disagree
2. Disagree
3. Somewhat disagree
4. Neither agree or disagree
5. Somewhat agree
6. Agree
7. Strongly agree

Cognitive Social Capital							
CSC1. I understand the information from my contacts.	1	2	3	4	5	6	7
CSC2. I share my knowledge with my contacts.	1	2	3	4	5	6	7
CSC3. It easy to understand my contacts.	1	2	3	4	5	6	7
CSC4. Sometimes it is challenging in understanding my contacts.	1	2	3	4	5	6	7
CSC5. There are different work priorities between my acquaintances and I.	1	2	3	4	5	6	7
CSC6. There is compatibility between information acquaintances and I.	1	2	3	4	5	6	7
CSC7. I found it difficult to understand my acquaintances.	1	2	3	4	5	6	7

PART D: ACADEMICIAN PERFORMANCE

Academician performance (AP) is defined as a set of activities that is teaching and supervision, research and consultations, publication, administrative and management work, and social services which were used to measure academician's performance in the higher education institutions.

Please rate in the range of scale 1 (Strongly disagree) to 5 (Strongly agree) for the following statement.

1. Strongly disagree
2. Disagree
3. Neither agree or disagree
4. Agree
5. Strongly agree

Academician Performance					
APS1. I have appropriate qualifications to supervise the students.	1	2	3	4	5
APS2. I conduct supervision at various academic levels.	1	2	3	4	5
APS3. I have knowledge to supervise the students.	1	2	3	4	5
APS4. I have skills to supervise the students.	1	2	3	4	5
APS5. I have expertise in my area of specializations.	1	2	3	4	5
APT1. I have qualifications to teach students at the undergraduate level.	1	2	3	4	5
APT2. I have a qualification to teach students at the postgraduate level.	1	2	3	4	5
APT3. I have knowledge to teach the students.	1	2	3	4	5
APT4. I have appropriate ICT skills to supervise the students.	1	2	3	4	5
APT5. I have an appropriate teaching method for the students.	1	2	3	4	5
APT6. I have expertise I my area of teaching	1	2	3	4	5
APC1. I have on-going consultation project with industry.	1	2	3	4	5

APC2. I am well-known in my area of expertise.	1	2	3	4	5
APC3. I have considerable experience in my area of expertise.	1	2	3	4	5
APC4. I have established good relationship with industry	1	2	3	4	5
APR1. I have an on-going research project.	1	2	3	4	5
APR2. I have a research proposal ready for submission.	1	2	3	4	5
APR3. I look forward to applying for a research grant.	1	2	3	4	5
APR4. I am looking forward to executing the new research project.	1	2	3	4	5
APR5. I am looking forward to executing new research collaborations.	1	2	3	4	5
APR6. I have knowledge in my area of research.	1	2	3	4	5
APP1. I will publish according to university KPI.	1	2	3	4	5
APP2. I will publish based on my KPI.	1	2	3	4	5
APP3. I am willing to publish more than my KPI.	1	2	3	4	5
APP4. I will make sure my article is published in an indexed journal.	1	2	3	4	5
APP5. I predict to published more than my KPI.	1	2	3	4	5
APP6. I am looking forward for opportunity to publish in any type of publication.	1	2	3	4	5
APA1. I have appropriate qualification to hold administrative and management post.	1	2	3	4	5
APA2. I have knowledge to hold the administrative and management post.	1	2	3	4	5
APA3. I have skills to hold the administrative and management post.	1	2	3	4	5
APA4. I have experience in administrative and management post.	1	2	3	4	5
APA5. I am currently holding an administrative and management post.	1	2	3	4	5
APA6. I held related administrative and management post	1	2	3	4	5
APS1. I will contribute to the communities.	1	2	3	4	5
APS2. I am always involved in social, and community work every year.	1	2	3	4	5
APS3. I transfer my knowledge to the community.	1	2	3	4	5
APS4. I am sharing my expertise to the community.	1	2	3	4	5

PART E: PROBLEMS OF SOCIAL MEDIA USE AMONG ACADEMICIANS

This part is intended to find the problems that you encounter in social media use.

Please state the problems that you encounter in social media use.

……
……
……
……
……

AUTHOR'S PROFILE



Zuraidah Arif obtained a Master's in Library Science (Sarjana (Master), and a Bachelor of Science in Information Studies (Hons) (Library & Information Management), from Universiti Teknologi MARA, Cawangan Shah Alam. Currently, she holds the position of Senior Lecturer at Universiti Teknologi MARA Cawangan Kedah.

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