UNIVERSITI TEKNOLOGI MARA

DEVELOPMENT AND VALIDATION OF THE WORKPLACE COVID-19 KNOWLEDGE AND STIGMA SCALE (WOCKSS) AND ITS APPLICATION IN ANALYSING STIGMA DYNAMICS AMONG FACTORY WORKERS USING SOCIAL NETWORK ANALYSIS

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ABSTRACT

The COVID-19 pandemic not only posed major public health challenges but also intensified social issues such as stigma, particularly within workplace settings. In Malaysia, the manufacturing sector was disproportionately affected, creating an important context for examining workplace stigma. This study aimed to develop, validate and perform reliability assessment of the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS) and to investigate how workplace COVID-19 stigma is shaped and distributed through social networks. The study was conducted in two phases using a cross-sectional design. Phase 1 focused on the development and validation of WoCKSS, a Malay-language instrument comprising two domains, namely knowledge and stigma. The stigma domain was structured around three constructs, which were stereotype, fear and prejudice. Content and face validation were conducted with expert panels and target respondents. Construct validity was assessed using Item Response Theory (IRT) for the knowledge domain and Exploratory and Confirmatory Factor Analyses (EFA and CFA) for the stigma domain. The final instrument retained 14 knowledge items and 7 stigma items, each demonstrating strong psychometric performance, including acceptable item difficulty and discrimination, unidimensionality for the knowledge domain, and robust internal consistency based on McDonald's omega. Phase 2 applied the validated instrument among 179 factory workers in Negeri Sembilan and incorporated both egocentric and sociocentric perspectives from Social Network Analysis (SNA). In the egocentric analysis, multiple logistic regression (MLogR) identified age and job position as significant predictors of workplace stigma, with younger and administrative employees reporting higher stigma levels. Binary logistic multilevel modelling (MLM) further indicated that the influence of alters on ego's stigma-related judgements was shaped primarily by relationship type, with family members exerting the strongest influence. Sociocentric analysis was conducted using Exponential Random Graph Modelling (ERGM) and the Quadratic Assignment Procedure (QAP). ERGM results showed that tie formation was influenced by reciprocity and homophily based on gender, job position and stigma status. QAP demonstrated that dyads with similar eigenvector centrality and coreness were more likely to share the same stigma status, indicating that structural influence and embeddedness within the network core were important correlates of stigma similarity. In conclusion, the findings show that workplace COVID-19 stigma is shaped not only by individual attributes but also by relational structures and positional dynamics within workplace networks. The integration of psychometric validation with both egocentric and sociocentric network approaches provides a comprehensive understanding of how stigma is socially structured and sustained within organisational settings.

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LIST OF SYMBOLS

Symbols

χ^2	Chi-square
B	Regression Coefficient
r	Correlation Coefficient
q	Freely Estimated Parameters
R_0	Basic Reproduction Number
α	Alpha
R^2	Coefficient of Determination

LIST OF ABBREVIATIONS

Abbreviations

1-PL	One-Parameter Logistic
2-PL	Two-Parameter Logistic
2-PL IRT	Two-Parameter Logistic IRT
AIC	Akaike Information Criterion
AIDS	Acquired Immune Deficiency Syndrome
aOR	Adjusted Odd Ratio
AUC	Area Under the Curve
B.1.1.529	Omicron Variant
B.1.1.7	Alpha Variant
B.1.351	Beta Variant
B.1.617.2	Delta Variant
BIC	Bayesian Information Criterion
CEDISC	COVID-19 Experienced Discrimination Scale
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CI	Confidence Interval
CISS	COVID-19 Infection Stigma Scale
COINS	COVID-19 Internalised Stigma Scale
COVID-19	Corona Virus Disease 2019

Abbreviations

COVID-PSS	COVID-19 Public Stigma Scale
COVISS-HCW	COVID-19 Stigma Scale for Healthcare Workers
CSS	COVID-19 Stigma Scale
CSS-M	COVID-19 Stigma Scale-Modified
CVI	Content Validity Index
DASS-21	Depression Anxiety and Stress Scale 21
df	Degree of Freedom
DOSH	Department of Occupational Safety and Health
DV	Dependent Variable
E16-COVID19-S	16-Item COVID-19 Stigma Scale
EFA	Exploratory Factor Analysis
ERGM	Exponential Random Graph Modelling
FA	Factor Analysis
FVI	Face Validity Index
H1N1	Influenza A Virus Subtype H1N1
H5N1	Influenza A Virus Subtype H5N1
HCW	Healthcare Workers
HIV	Human Immunodeficiency Virus
HLM	Hosmer-Lemeshow Test
HSDF	Health Stigma And Discrimination Framework
I-CVI	Item Content Validity Index

Abbreviations

I-FVI	Item Face Validity Index
IBM	International Business Machines Corporation
ICC	Intraclass Correlation Coefficient
ICCs	Item Characteristic Curve
IDAF-4C+	Index of Dental Anxiety and Fear Scale
IRT	Item Response Theory
JKJAV	Jawatankuasa Khas Jaminan Akses Bekalan Vaksin COVID-19
KAP	Knowledge, Attitude and Practice
KMO	Kaiser-Meyer-Olkin
KR-20	Kuder–Richardson Formula 20
LNAM	Linear Network Autocorrelation Model
MAP	Velicer's Minimum Average Partial
MCMC	Markov Chain Monte Carlo
MCO	Movement Control Order
MI	Modification Indices
ML	Maximum Likelihood
MLM	Binary Logistic Multilevel Modelling
MLogR	Multiple Logistic Regression
MLR	Maximum Likelihood Robust
MR-QAP	Multiple Regression Quadratic Assignment Procedure
mRNA	Messenger Ribonucleic Acid

Abbreviations

nAGQ	Adaptive Gauss-Hermite Quadrature
P.1	Gamma Variant
PAF	Principal Axis Factoring
PC	Principal Component
PCA	Principal Component Analysis
PCC	Post COVID-19 Condition
PCCSQ	Post COVID-19 Condition Stigma Questionnaire
PE	Parameter Estimate
PLWHA	People Living With HIV and AIDS
POIS	Preventing Outbreak at Ignition Site
QAP	Quadratic Assignment Procedure
RM	Ringgit Malaysia
RMSEA	Root Mean Square Error of Approximation
ROC	Receiver Operating Characteristic
S-CVI/AVE	Scale-Level Content Validity Index/Average
S-CVI/UA	Content Validity Index/Unweighted Average
S-FVI/AVE	Scale-Level Face Validity Index/Average
S-FVI/UA	Scale Face Validity Index
S19-HCP	Stigma-19 - Healthcare Providers
SARS	Severe Acute Respiratory Syndrome
SARS-CoV-2	Severe Acute Respiratory Syndrome Corona Virus 2

Abbreviations

SD	Standard Deviation
SE	Standard Error
SNA	Social Network Analysis
SPM	Sijil Pelajaran Malaysia
SPSS	Statistical Package for The Social Sciences
SRMR	Standardised Root Mean Square Residual
STFC	Selangor Task Force for COVID-19
TB	Tuberculosis
TLI	Tucker-Lewis Index
TRF	Test Response Function
UA	Universal Agreement
UNAIDS	Joint United Nations Programme on HIV/AIDS
VIF	Variance Inflation Factor
VOC	Variants of Concern
VSS	Very Simple Structure
WHO	World Health Organization
WoCKSS	Workplace COVID-19 Knowledge And Stigma Scale
WOS	Web of Science

CHAPTER 1
INTRODUCTION

1.1 Research Background

The outbreak of coronavirus disease 2019 (COVID-19) began in Wuhan, China, in late 2019 and rapidly spread worldwide. The World Health Organization (WHO) declared COVID-19 a pandemic on 11 March 2020 after it caused widespread illness and death across many countries (World Health Organization, 2020d). Following the initial reports of pneumonia of unknown aetiology in Wuhan, transmission was linked to person-to-person spread through respiratory droplets and contaminated surfaces, with airborne transmission later recognised, particularly in poorly ventilated indoor settings (Du et al., 2020; World Health Organization, 2020b, 2020c). Beyond its effects on health systems, economies, and daily life, the pandemic also produced major social consequences, including fear, misinformation, and stigma, which created barriers to disease control and recovery (Bagcchi, 2020; The Joint United Nations Programme on HIV/AIDS (UNAIDS), 2020). These consequences were not distributed randomly, but were shaped by how individuals and groups were perceived, connected, and positioned within their social environments.

Globally, COVID-19 disrupted ordinary social activities and work structures (Bloom et al., 2020). Movement restrictions, uncertainty about infection risk, and a constant flow of information through social and digital media increased public anxiety (Brooks et al., 2020; Zarocostas, 2020). In many places, individuals who were infected or suspected of being infected were labelled and avoided (Bagcchi, 2020; Chew et al., 2021; Jayakody et al., 2021). Such reactions reflected the tendency to separate people into categories of "safe" and "unsafe" and to assign blame to those perceived as sources of danger (Link & Phelan, 2001). Similar patterns were observed during earlier outbreaks such as SARS and Ebola, where fear of infection contributed to stereotyping and discrimination (Person et al., 2004). COVID-19 revived these patterns on a broader scale, showing that stigma is a recurring feature of infectious disease crises. However, although stigma during outbreaks has been widely documented, its operation within workplace settings remains less clearly theorised, especially in relation to the social and structural conditions through which it is reinforced.

Health-related stigma develops when people associate a disease with moral or social failure. Goffman (1963) described stigma as a process that discredits a person in the eyes of others, leading to exclusion or discrimination. Later frameworks emphasised that stigma is shaped by social and structural power, whereby some groups are able to label others as undesirable, irresponsible, or threatening (Link & Phelan, 2001; Parker & Aggleton, 2003). During infectious outbreaks, such judgements may intensify because people seek to identify who is responsible for spreading infection or breaking public health rules. Early COVID-19 studies showed that particular nationalities, occupations, and neighbourhoods were unfairly blamed for transmission (Bagcchi, 2020). The term “infodemic” was introduced to describe the rapid spread of misinformation that fuelled fear and hostility towards particular groups (World Health Organization, 2020a; Zarocostas, 2020). These developments suggest that stigma is not merely an individual attitude, but a socially produced and potentially networked phenomenon shaped by interaction, communication, and power. In workplace settings, stigma may therefore emerge through interpersonal judgement, organisational hierarchy, group norms, and unequal power relations. In this study, workplace stigma is approached as a relational phenomenon embedded within broader organisational and structural contexts.

In Malaysia, the pandemic’s pattern reflected these global challenges but had specific local features. This country experienced several infection waves that affected both urban and rural communities (Ang et al., 2023). The Ministry of Health reported that most clusters were linked to workplaces, particularly in the manufacturing and construction sectors, which together accounted for more than 90% of identified workplace clusters (Solhi, 2021). Factory settings often involve dense working arrangements, shared transportation, and on-site dormitories, making physical distancing difficult. These conditions not only facilitated transmission but also contributed to stigma among workers who were infected or quarantined (Ang et al., 2023). Workers returning from isolation were sometimes treated with suspicion, avoided by colleagues, or informally blamed for productivity loss (Rosni, 2022; Yong & Sia, 2021). These features make factory settings an important context for examining how stigma may be shaped not only by fear of infection, but also by workplace proximity, repeated interaction, and group norms.

The effects of such stigma were substantial for both individuals and organisations. Fear of being judged discouraged some workers from reporting symptoms or undergoing testing, while those who had recovered from COVID-19 often experienced shame, guilt, and social rejection (Bhanot et al., 2021; Rewerska-Juśko & Rejdak, 2022). Studies from other countries similarly showed that stigma was associated with anxiety, depression, and low self-esteem among affected individuals (Rewerska-Juśko & Rejdak, 2022; Yuan et al., 2021). At the organisational level, stigma weakened team relationships, reduced morale, and disrupted communication and cooperation (Schubert et al., 2021). These findings show that workplace stigma affects not only psychological wellbeing but also workplace functioning, safety, and trust.

The Malaysian government introduced several measures to control the spread of COVID-19, such as movement control orders (MCO), vaccination campaigns, and workplace safety guidelines (Bunyan, 2020; Department of Occupational Safety and Health Malaysia [DOSH], 2020; The Secretariat of the Special Committee for Ensuring Access to Covid-19 Vaccine Supply (JKJAV), 2021). Over time, management of the virus shifted from crisis response to endemic control. In July 2024, COVID-19 was reclassified as a respiratory illness similar to other common viral infections, and home surveillance orders were no longer required for infected individuals (Ministry of Health Malaysia, 2024). Although this policy change reflects the transition to endemic management, it does not remove the importance of understanding residual stigma, which may continue to affect social acceptance, disclosure, and workplace relationships. The persistence of such stigma in the endemic phase strengthens the need for context-specific tools and frameworks that can identify and explain these attitudes within workplace settings.

Workplace stigma is particularly concerning because it arises in environments that depend on cooperation, communication, and trust. In factory settings, workers often operate in close proximity, interact repeatedly, and sometimes share accommodation, making them especially vulnerable to gossip, exclusion, and blame when infection occurs (Schubert et al., 2021). Similar patterns have been reported among healthcare workers, where those exposed to COVID-19 patients were often avoided or discriminated against, resulting in stress, reduced performance, and psychological distress (Ampon-Wireko et al., 2022; Grover et al., 2020; Schubert et al., 2021). These findings show that workplace stigma affects not only individual wellbeing but also social cohesion, communication, and organisational functioning.

Understanding why stigma develops in workplaces therefore requires looking beyond individual attitudes to the social environment in which those attitudes are formed. Employees often rely on peers, supervisors, and colleagues for information and emotional cues, particularly during uncertain periods (Ampon-Wireko et al., 2022; Schubert et al., 2021). Through repeated interaction, attitudes about infection risk, responsibility, and appropriate behaviour may be reinforced within workplace groups. Negative attitudes may spread through conversations, rumours, and informal communication, weakening social cohesion and discouraging disclosure, testing, or help-seeking (Brooks et al., 2020; Schubert et al., 2021). This suggests that workplace stigma is not only an individual experience, but also a relational process shaped by ongoing interaction.

Social Network Analysis (SNA) provides a useful framework for examining these processes because it focuses on how people are connected and how information, trust, and attitudes circulate within a network (Valente, 2010; Wasserman & Faust, 1994). During the COVID-19 pandemic, SNA was widely used to trace transmission chains and contact networks, demonstrating the value of relational data for understanding infection spread (Nagarajan et al., 2020; Ostovari et al., 2020; Saraswathi et al., 2020; Wickramasinghe & Muthukumarana, 2021). However, there remains limited research using SNA to examine how stigma and misinformation move through workplace settings (Baharuddin et al., 2025). Workplace network structure, including who interacts with whom, how frequently, and how groups are organised, may influence whether stigma is reinforced or reduced. Employees occupying central positions may help reduce stigma if they circulate accurate information and supportive attitudes, but may also amplify fear and blame if they share misinformation. Homophily, whereby individuals form ties with others who are similar to themselves, may further strengthen these processes by creating subgroups that reinforce shared beliefs and responses (McPherson et al., 2001; Takada et al., 2019). This highlights an important gap in the literature, namely the limited structural analysis of how workplace stigma may cluster, circulate, or persist through social relations.

Knowledge was included in this study because workplace stigma toward infectious disease is shaped not only by fear and prejudice, but also by misunderstanding, misinformation, and inaccurate beliefs about transmission and risk. In workplace settings, knowledge may function as a protective factor by reducing fear-based judgement and supporting more informed responses towards infected or recovered colleagues. At the same time, inadequate knowledge may leave workers more vulnerable to misinformation and socially reinforced stigma within their networks. For this reason, knowledge and stigma are treated as related but distinct components of workplace responses to COVID-19.

Accurate measurement is necessary because stigma is multidimensional and may include stereotypes, prejudice, fear, and discriminatory attitudes. Existing instruments developed for clinical or community settings may not adequately capture how these elements appear in industrial workplaces. The Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS) was therefore developed to address this gap by measuring both COVID-19 knowledge and stigma-related attitudes among factory workers. Its development followed recognised psychometric procedures, including expert review, face validation, factor analysis, and reliability testing, to ensure that the instrument was relevant, clear, and contextually appropriate for workplace populations (Baharuddin et al., 2024).

This study employs both egocentric and sociocentric network approaches to link individual perceptions with surrounding social structures. The egocentric approach focuses on each worker's personal network, which may include ties within and outside the workplace, to examine whether supportive or well-informed connections are associated with lower stigma. In contrast, the sociocentric approach examines the overall workplace network and how structural features such as centrality, density, and clustering relate to the distribution of stigma-related attitudes. By integrating a context-specific measure of knowledge and stigma with SNA, this study seeks to explain how workplace attitudes are formed, reinforced, and distributed within factory settings. The findings may inform practical strategies to reduce stigma, enhance wellbeing, and strengthen social cohesion in Malaysia's manufacturing sector and similar organisational environments.

1.2 Problem Statement

The COVID-19 pandemic has highlighted stigma as a complex challenge that extends beyond the direct health effects of the virus. Stigma is shaped not only by fear and misinformation, but also by the structure and dynamics of social interaction. Attitudes toward individuals who are infected, suspected of infection, or associated with infection may be influenced by social connections, which can shape behaviour more strongly than personal characteristics alone (Alkautsar, 2020; Grivel et al., 2021). In social settings, individuals naturally gravitate toward others with similar attributes, leading to homogenous groups that may resist new ideas or behaviours (McPherson et al., 2001). Within workplaces, where individuals spend a substantial portion of their time, peer influence may be particularly significant. This is especially relevant in factory settings, where close-contact work arrangements and shared experiences may amplify the social consequences of infection and recovery. The issue is urgent in the Malaysian context, where workplace clusters have been identified as major contributors to COVID-19 transmission (Solhi, 2021). This concern is especially relevant in manufacturing settings, where close-contact work arrangements and tightly structured interpersonal interactions may intensify the social consequences of infection and recovery.

As COVID-19 transitions to an endemic phase, it remains important to assess the presence and patterns of COVID-19 stigma within workplace social networks because of its implications for both individual and collective wellbeing. Residual stigma may continue to affect social acceptance, willingness to disclose illness, and workplace relationships even after the immediate public health crisis has subsided. Traditional approaches that focus primarily on individual attributes often overlook the broader social context and provide limited insight into how attitudes are shaped and reinforced through interpersonal ties and organisational structures. SNA is theoretically appropriate in this context because stigma is understood not only as an individual attitude, but also as a socially embedded process shaped through interaction, influence, and workplace relationships. Examining stigma through network structure may therefore help explain how stigma-related attitudes cluster, persist, or are reinforced within everyday social environments. Applying SNA to workplace settings can provide a more comprehensive understanding of how stigma is shaped and sustained within factory networks.

A major barrier to studying workplace COVID-19 stigma in Malaysia is the absence of a validated Malay-language instrument that measures both COVID-19 knowledge and workplace stigma. Existing scales are typically designed for clinical or general community settings and may not capture the ways in which stigma manifests in industrial workplaces. This gap is particularly important because misinformation and inadequate knowledge may contribute to fear-based judgement and stigma-related attitudes in workplace settings. Measuring both knowledge and stigma therefore allows the study to examine related but distinct components of workplace responses to COVID-19. Addressing this measurement gap is essential for advancing research and informing interventions. As a first step, this study develops and validates a reliable and contextually appropriate measurement tool, the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS), to assess knowledge and stigma among factory workers.

In this study, stigma dynamics refer to the ways in which stigma is formed, reinforced, and potentially distributed through workplace relationships and network structures. Understanding these dynamics is particularly important in Malaysian factory settings, where close interpersonal contact, shared work routines, and frequent peer interaction may shape how COVID-19-related attitudes are sustained or challenged. The validated instrument then forms the foundation for subsequent stages of the research, which apply egocentric and sociocentric SNA to examine how stigma operates within workplace networks. By integrating scale development with network analysis, the study addresses conceptual, methodological, and empirical gaps in the understanding of workplace COVID-19 stigma in Malaysian factory settings.

1.3 Research Question

1.3.1 Primary Research Question

To what extent do individual-level egocentric networks and workplace sociocentric network structures influence the distribution of COVID-19 stigma among factory workers?

1.3.2 Specific Research Questions

i) How valid and reliable is the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS) in measuring COVID-19 stigma in the workplace?
ii) What factors within egocentric networks influence workplace COVID-19 stigma among factory workers, and how do ego-level and alter-level characteristics shape the perceived influence of social contacts on stigma perceptions?
iii) How do network structure and interpersonal relationships within the workplace sociocentric network relate to the presence and distribution of COVID-19 stigma among employees?

1.4 Hypothesis

i) The Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS) will demonstrate strong content validity, face validity, construct validity, reliability, and appropriate item response characteristics.
ii) Egocentric network characteristics significantly predict workplace COVID-19 stigma among factory workers, and the perceived influence of alters on ego's stigma perceptions is significantly associated with both ego-level and alter-level attributes.
iii) Employees are more likely to be socially connected to others who share the similar COVID-19 stigma status, suggesting the presence of stigma-based homophily and clustering within the workplace social network.

1.5 Research Objectives

1.5.1 General Objective

To examine workplace COVID-19 stigma and its underlying dynamics among factory workers by developing and validating a measurement scale and utilising social network analysis to understand the role of social structures in shaping stigma patterns.

1.5.2 Specific Objectives

i) To develop and validate the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS) by assessing its content validity, face validity, construct validity, reliability, and item response characteristics.
ii) To investigate the influence of egocentric network characteristics on perceived COVID-19 stigma in the workplace by examining individual and relational factors among factory workers.
iii) To examine the influence of structural features of the workplace sociocentric network and individual relationships on the distribution of COVID-19 stigma among employees.

1.6 Significance of Study

This study makes several contributions to understanding COVID-19 stigma in the workplace, particularly within the factory manufacturing sector. First, it introduces and validates the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS), a Malay-language instrument specifically designed for industrial work environments. This addresses a critical limitation of existing measurement tools, which are often not tailored to workplace contexts or do not assess both knowledge and stigma-related attitudes.

Second, the study applies both egocentric and sociocentric social network analysis to examine COVID-19 stigma at multiple levels. This dual approach provides a more comprehensive understanding of how stigma develops and spreads by considering individual relationships as well as the broader structure of workplace networks. By linking individual attitudes to network position and relational patterns, the research contributes methodologically to the application of SNA in occupational health and stigma research.

From a practical perspective, the findings offer insights that can inform targeted interventions and workplace policies. These may include network-informed strategies that harness influential employees, strengthen supportive ties, and reduce sources of misinformation or blame. Such approaches can help reduce stigma, promote a more supportive work culture, and improve overall employee wellbeing and safety. The insights are also relevant for future outbreaks involving other infectious diseases where similar patterns of workplace stigma may emerge.

Although COVID-19 has transitioned into an endemic phase and become part of everyday life, the lessons from this study remain pertinent. In the event of new communicable disease threats, the findings can support early intervention strategies by highlighting the importance of workplace-level prevention, communication, and stigma reduction.

In summary, this research contributes to both academic and practical fields by integrating a context-specific measurement scale with social network analysis to explore the influence of individual and network factors on workplace stigma. The results support broader efforts to enhance health, resilience, and social cohesion in industrial settings.

1.7 Conceptual Framework

The conceptual framework for this study was developed to explain workplace COVID-19 stigma as a socially embedded phenomenon within factory settings (Figure 1.1). It integrates stigma theory and social network theory to show how stigma-related attitudes may be shaped not only by individual characteristics, but also by interpersonal relationships and the broader structure of workplace social networks.

From the perspective of stigma theory, workplace COVID-19 stigma is understood as a social process involving negative labelling, stereotyping, fear, prejudice, and social judgement directed towards individuals associated with COVID-19. Drawing on Goffman's concept of stigma (1963), Link and Phelan's emphasis on labelling and power (2001), and the Health Stigma and Discrimination Framework by Stangl et al. (2019) , the present study conceptualises stigma as more than an individual attitude. Instead, it is viewed as a relational and socially shaped process that develops within a wider interpersonal and organisational environment. In this study, workplace COVID-19 stigma is represented through three dimensions, namely stereotype, fear, and prejudice.

The framework also incorporates COVID-19 knowledge as an important construct. Knowledge is included because workers' understanding of COVID-19 may influence how they interpret infection risk, respond to misinformation, and form judgements towards others in the workplace. COVID-19 knowledge is therefore considered part of the broader context within which workplace stigma is formed and expressed.

To capture the relational nature of workplace stigma, the framework incorporates social network theory through two complementary perspectives, namely egocentric and sociocentric networks. The egocentric perspective focuses on the worker's immediate personal network and assumes that workplace stigma may be associated with individual and relational factors, including demographic characteristics, education, job position, COVID-19 infection history, COVID-19 knowledge, and the characteristics of nominated alters. This perspective reflects the view that workers do not form attitudes in isolation, but within their immediate circle of social influence.

The sociocentric perspective focuses on the wider workplace network as a whole. It assumes that workplace stigma may also be associated with structural features of the workplace network, including centrality measures, relational structure, positional structure, and group structure. These structural properties may influence whether stigma-related attitudes become concentrated, reinforced, or distributed across the workplace.

Within this framework, the WoCKSS plays a methodological role by operationalising the key study constructs of COVID-19 knowledge and workplace stigma. It provides the measurement basis for examining these constructs in a contextually appropriate manner among factory workers.

Overall, the framework assumes that workplace COVID-19 stigma is associated with both individual-level and network-level conditions. It further assumes that workplace social relationships may contribute to the shaping, reinforcement, or containment of stigma. As the study employed a cross-sectional design, the framework does not imply definitive causal direction. Rather, it proposes a relational interconnection between individual stigma and workplace social structure. The inclusion of both egocentric and sociocentric perspectives is therefore necessary to provide a fuller understanding of workplace COVID-19 stigma among factory workers.

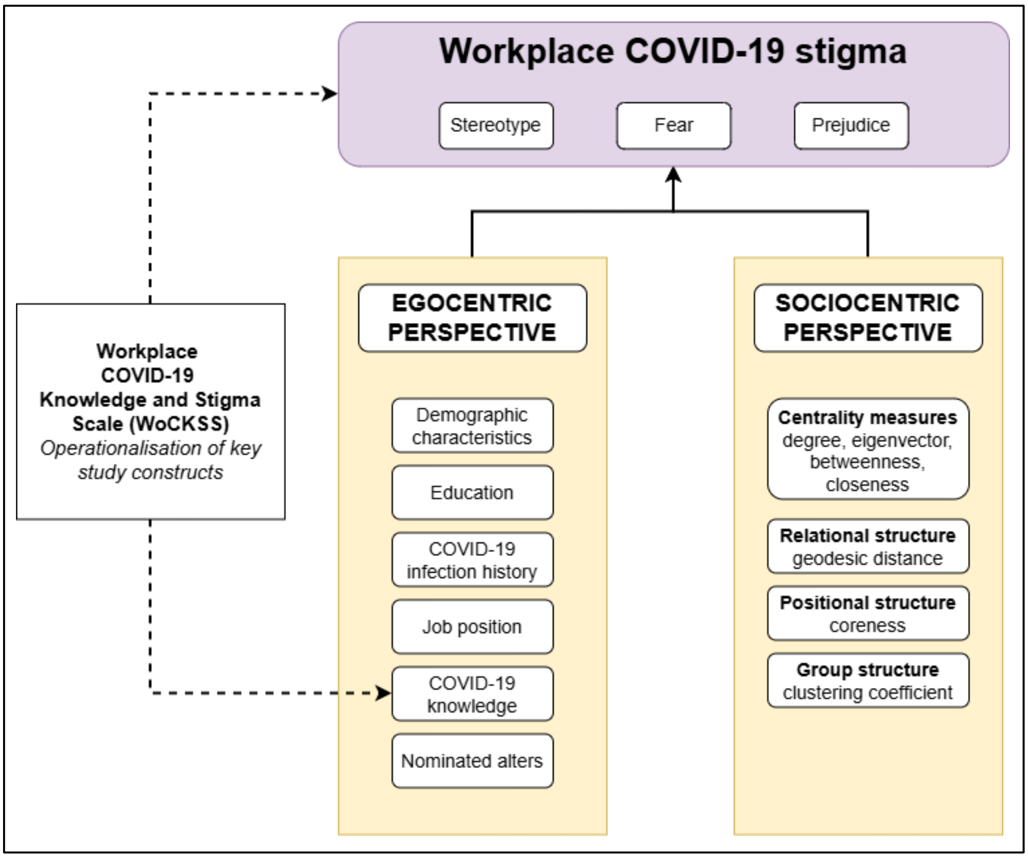

Figure 1.1 Conceptual Framework of Workplace COVID-19 Stigma among Factory Workers

CHAPTER 2
LITERATURE REVIEW

2.1 Overview of Stigma

2.1.1 Definition and Conceptualisation of Stigma

Stigma is a complex social phenomenon that influences how individuals and groups are perceived, valued, and treated within society. It is most often defined as a process in which certain attributes, behaviours, or conditions become socially discrediting, resulting in exclusion, blame, or discrimination. Goffman (1963) first described stigma as an attribute that is "deeply discrediting," transforming an individual "from a whole and usual person to a tainted, discounted one." He argued that stigma arises when society establishes expectations of normality and rejects those who deviate from them. The interaction between the "normal" and the "stigmatised" leads to the construction of social distance and prejudice.

Goffman identified three main types of stigma: physical deformities, blemishes of individual character, and tribal stigmas such as race, nationality, or religion. He also differentiated between discredited stigmas, which are visible or known, and discreditable stigmas, which are concealable and can be hidden to avoid social rejection. This distinction remains influential, as it explains why some individuals experience stigma continuously in public interactions, while others struggle internally with fear of exposure. Although Goffman focused primarily on face-to-face interaction and spoiled identity, his work offered limited explanation of how stigma is maintained through broader social structures, institutional forces, and power relations. This limitation was addressed more explicitly in later frameworks.

Later scholars expanded on Goffman's work to clarify stigma as a broader social process rather than merely an individual attribute. Link and Phelan (2001) proposed a comprehensive conceptualisation in which stigma occurs when several components operate together: (1) human differences are labelled, (2) negative stereotypes are attached to these labels, (3) labelled individuals are placed in distinct categories of "us" and "them," (4) they experience status loss, and (5) they face discrimination. For stigma to fully manifest, these components must occur in a context where power enables one group to control or marginalise another. The inclusion of power in this framework shifted the understanding of stigma from a personal or psychological problem to a structural mechanism that maintains social hierarchies and unequal access to resources. Compared with Goffman's interactional emphasis, Link and Phelan's framework provides a stronger explanation of how stigma is socially organised through labelling, stereotyping, separation, and discrimination within unequal power structures.

In public health research, stigma is now recognised as both a social and structural determinant of health. It contributes to disparities by limiting access to employment, healthcare, and social participation, while also causing psychological distress. The Health Stigma and Discrimination Framework (HSDF) developed by Stangl et al. (2019) integrated these perspectives into a model applicable across different diseases and populations (Figure 2.1). The framework describes stigma as a process driven by individual, social, and institutional factors that produce multiple manifestations, including enacted stigma (actual discrimination), perceived or anticipated stigma (expectation of rejection), and internalised stigma (self-blame or shame). This multi-level approach allows researchers to examine how stigma arises from social structures and how it affects individual wellbeing.

The Health Stigma and Discrimination Framework provides a broad theoretical basis for understanding stigma as a multi-level social process. Building on this perspective, the present study developed a study-specific conceptual framework, presented in Chapter 1, that integrates stigma theory with social network theory to examine workplace COVID-19 stigma among factory workers.

In relation to the present study, stigma is conceptualised primarily as public stigma, particularly stigma practices reflected in negative judgements towards others associated with COVID-19. The WoCKSS stigma domain measures stereotype, fear, and prejudice, which correspond more closely to public expressions of stigma than to internalised or enacted stigma. Within the Health Stigma and Discrimination Framework, these dimensions are most consistent with stigma practices and discriminatory attitudes that arise from social judgement and perceived infection risk. This study therefore focuses on how such attitudes are shaped within workplace relationships and social structure, rather than on internalised shame or direct experiences of discrimination among infected individuals

Overall, the conceptualisation of stigma has evolved from viewing it as a personal defect to recognising it as a socially constructed process embedded within power relations and social relationships. In health and workplace contexts, stigma can limit opportunities, distort social interactions, and undermine wellbeing. This perspective is particularly relevant to the present study, which examines workplace COVID-19 stigma not only as an individual attitude, but also as a phenomenon shaped by interpersonal ties and workplace social structure.

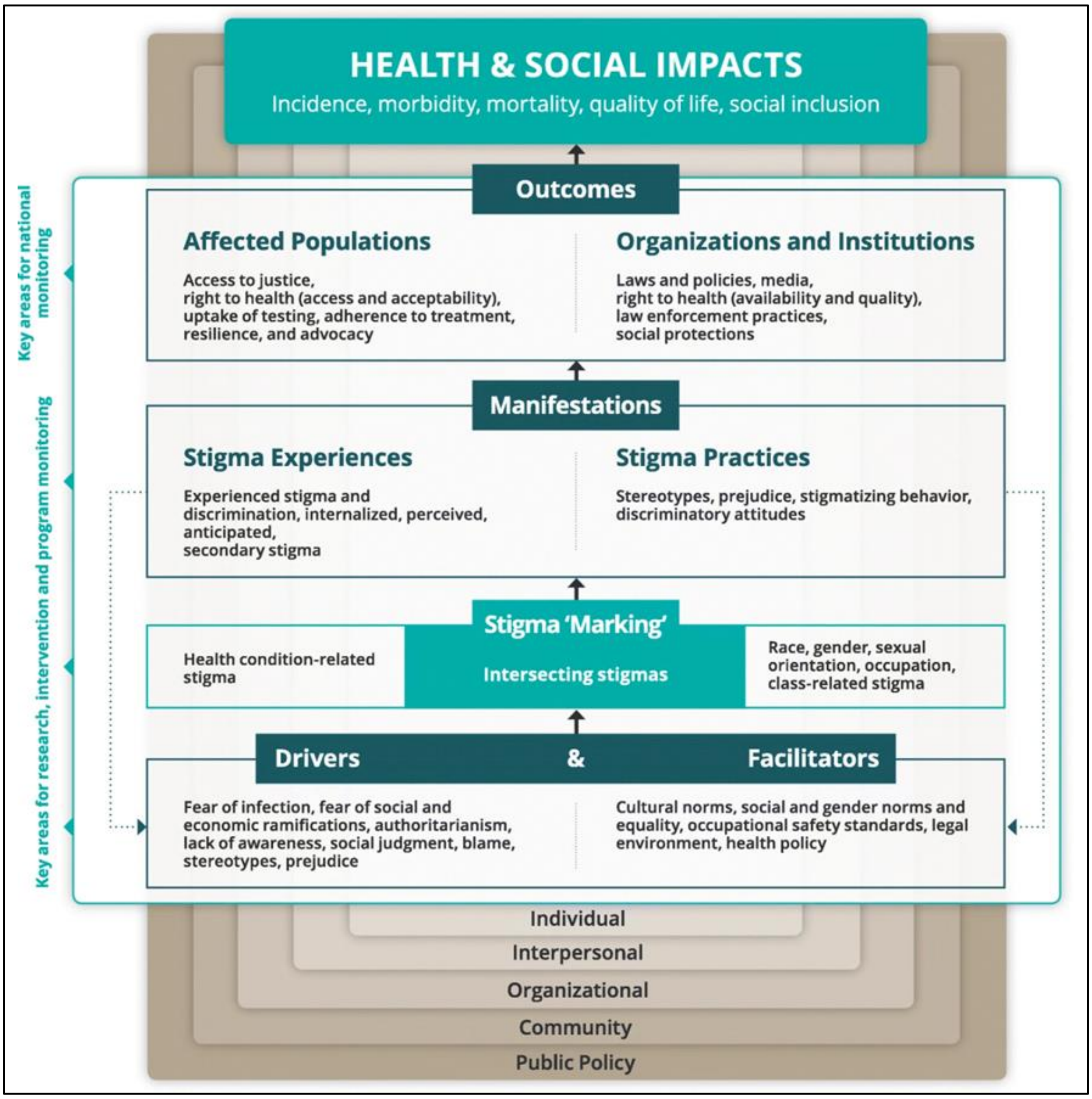

Figure 2.1 Theoretical Framework: Health stigma & discrimination by Stangl et al. (2019)

2.1.2 Stigma during Health Crises and Communicable Diseases

Stigma has been a recurring feature of major communicable disease outbreaks throughout history. Across different epidemics, it has consistently reflected a combination of fear, misinformation, and moral judgement, which together produce social exclusion and discrimination. The experience of stigma in these contexts reveals how societies respond not only to disease but also to deeper anxieties about morality, identity, and social order. Research on infectious diseases such as HIV/AIDS, tuberculosis, and leprosy provides valuable insight into the persistence of stigma and its consequences for individuals and communities. These examples demonstrate that stigma remains one of the main barriers to effective disease control, care engagement, and recovery. These disease contexts are theoretically relevant to COVID-19 not simply because they are infectious, but because they demonstrate how stigma emerges when fear of contagion, uncertainty, moral judgement, and socially visible or symbolically marked identities interact with existing social inequalities. Although these diseases differ in their modes of transmission, prognosis, and social meanings, they are theoretically relevant to COVID-19 because they demonstrate how fear of contagion, moral judgement, misinformation, and pre-existing social inequality can interact to produce stigma during health crises.

The global HIV/AIDS epidemic has been one of the most widely studied examples of health-related stigma. In the early years of the epidemic, people living with HIV and AIDS (PLWHA) experienced severe social rejection, discrimination, and violations of their human rights (Herek et al., 2002). Public reactions were often shaped by fear and misinformation about how HIV was transmitted, with many people avoiding contact with individuals living with the disease (Des Jarlais et al., 2006). During the 1990s, overtly punitive or coercive responses, such as support for quarantine and public identification of individuals with AIDS, showed a significant decline. By 1999, fewer than one in five American adults supported such measures (Herek et al., 2002). However, negative feelings and moral judgements remained widespread. Approximately one third of respondents in a 1999 national survey still reported feeling discomfort, fear, or disgust towards people with AIDS, and about one in four believed that those who contracted HIV through sex or drug use had "gotten what they deserve" (Herek et al., 2002). These attitudes reflected a persistence of symbolic prejudice rather than overt hostility, linking HIV stigma to broader social inequalities associated with sexual orientation, drug use, and race. Des Jarlais and colleagues (2006) further argued that stigma towards newly emerging infectious diseases often follows a similar trajectory, where early fear-driven reactions gradually evolve into subtler forms of moral and social distancing. Thus, although extreme expressions of prejudice declined over time, the underlying patterns of blame, fear, and discrimination remained embedded within the social response to HIV. This suggests that infectious disease stigma cannot be understood only as a reaction to biomedical risk, but also as a social response shaped by moral meanings, symbolic boundaries, and unequal power relations.

The conceptual expansion of stigma studies during the HIV epidemic further deepened understanding of how power and inequality shape social reactions to disease. Parker and Aggleton (2003) argued that stigma should be viewed not as a static attitude but as a dynamic social process rooted in existing hierarchies of class, gender, and sexuality. In the context of this thesis, stigma dynamics refer to the relational and social processes through which stigma is formed, reinforced, negotiated, and potentially propagated within a group over time. Rather than viewing stigma as a fixed individual attitude, this perspective emphasises that stigma develops through repeated interaction, shared meanings, group norms, and existing power relations. In workplace settings, these dynamics may be shaped by informal communication, peer influence, social proximity, and patterns of inclusion or exclusion, all of which affect how stigma-related attitudes are sustained, challenged, or transmitted. Parker and Aggleton (2003) contended that focusing only on information and behaviour change was inadequate, as such strategies overlook the broader social and institutional conditions that sustain exclusion. Mahajan and colleagues (2008) supported this position, emphasising that stigma functions simultaneously at multiple levels, from interpersonal prejudice to structural discrimination. They called for more comprehensive measurement tools to capture these dimensions and guide multi-level interventions. Later, Turan and colleagues (2017) provided quantitative evidence that stigma operates through interlinked psychological and social pathways. Their model showed that perceived community stigma increases both anticipated and internalised stigma, which in turn predict depression, low self-esteem, and poor adherence to treatment. Together, these studies established that HIV-related stigma is not merely an emotional reaction but a socially embedded process that undermines both wellbeing and public health outcomes.

Patterns similar to those seen in the HIV epidemic have also emerged in the context of tuberculosis (TB), particularly in low- and middle-income countries where infection is intertwined with poverty. People with TB are often regarded as "unclean" or personally responsible for their condition because of its association with poor living environments (Courtwright & Turner, 2010). Such perceptions create a complex form of social exclusion that extends beyond the patient to affect families and communities

(Baral et al., 2007; Somma et al., 2008). This stigma not only causes emotional distress but also leads to practical consequences such as job loss, reduced marriage prospects, and social isolation driven by fear of contagion (Dixit et al., 2024). Consequently, stigma becomes self-perpetuating, as fear and moral blame reinforce each other, prompting individuals to conceal symptoms or delay seeking care until the disease is advanced (Courtwright & Turner, 2010).

Evidence from South Asian and African settings highlights how TB stigma is shaped by cultural and gender dynamics. In Nepal, Baral and colleagues (2007) reported that fear of infection, caste hierarchy, poverty, and moral judgement jointly sustained discriminatory attitudes. Even after treatment began, many patients continued to experience shame and social withdrawal, suggesting that information alone cannot dismiss stigma. Somma and colleagues (2008) further demonstrated that gender plays a defining role in the expression of TB stigma. Across Bangladesh, India, Malawi, and Colombia, women faced stronger social and economic repercussions, including rejection by spouses, loss of financial support, and exclusion from social life. These findings reveal that stigma is not simply the result of ignorance but a socially organised process shaped by power, gender, and culture. Such evidence underscores the need for interventions that extend beyond education to address the socio-structural context in which stigma thrives.

Complementing these studies, Courtwright and Turner (2010) described fear of infection as the most common driver of TB stigma globally, while also identifying the disproportionate burden on women and marginalised groups. They highlighted the scarcity of validated tools to measure TB stigma and recommended standardised quantitative approaches to link stigma to treatment outcomes. More recently, Dixit and colleagues (2024) found that TB stigma in Nepal remained moderate but persistent over the treatment period, and that it was positively correlated with depression. The inclusion of psychosocial support was associated with improved wellbeing and quality of life, suggesting that integrating mental health care into TB programmes may mitigate the effects of stigma. Taken together, these studies reinforce the understanding that TB stigma, like HIV stigma, is a multidimensional phenomenon encompassing psychological, social, and structural dimensions.

Leprosy, historically known as Hansen's disease, provides an enduring historical example that illustrates the longevity of disease-related stigma. For centuries, leprosy was associated with divine punishment and moral failing, resulting in the segregation and exclusion of affected individuals (Santacroce et al., 2021). Historical accounts describe how people with visible deformities were confined to leper colonies and stripped of basic social rights, reflecting a deep societal fear of contagion. Despite major advances in treatment, these negative social meanings have remained entrenched in many cultures. Shin and Oh (2022) noted that in several countries, misconceptions about heredity and infection continue to generate stigma even where prevalence is low. They also found that the COVID-19 pandemic further disrupted leprosy services, reducing early detection and thereby reinforcing stigma through delayed care and visible deformity.

Efforts to counter leprosy stigma demonstrate the significance of both policy and language in changing social attitudes. Santacroce and colleagues (2021) documented international campaigns promoting the term “Hansen’s disease” to replace “leprosy” or “leper,” aiming to remove harsh connotations. Some countries, including Brazil and South Korea, implemented legal reforms to eliminate discriminatory laws and integrated leprosy management into general healthcare to normalise care access (Shin & Oh, 2022). However, these authors emphasised that legal and linguistic changes alone cannot fully dismantle stigma unless accompanied by community education and psychosocial support for patients and families. The persistence of stigma in leprosy, despite biomedical progress, demonstrates the depth of its cultural and symbolic roots and the challenges of achieving social reintegration. In this sense, COVID-19 stigma may be understood as sharing features with both TB-related stigma, particularly in its emphasis on contagion fear and avoidance, and HIV-related stigma, particularly where blame, perceived irresponsibility, or symbolic judgement become attached to infection.

The persistence of stigma across HIV, TB, and leprosy underscores that it is not limited to specific diseases but arises from broader social mechanisms. In each case, fear of contagion interacts with moral judgement and structural inequality to produce exclusion. Studies have shown that stigma is reinforced by social hierarchies and power dynamics, with gender and class often determining how individuals experience discrimination (Baral et al., 2007; Parker & Aggleton, 2003; Somma et al., 2008). Moreover, stigma is both external and internal: community-level prejudice translates into internalised shame, leading to depression, reduced self-esteem, and reluctance to seek medical help (Dixit et al., 2024; Turan, Budhwani, et al., 2017). These patterns illustrate how stigma operates simultaneously at the structural, social, and psychological levels, shaping both behaviour and wellbeing.

Collectively, these findings carry important implications for understanding stigma in contemporary health crises. Historical evidence demonstrates that stigma evolves alongside a disease's visibility and perceived threat. In the early phases of an outbreak, stigma often manifests as overt fear and blame, while in later stages it may become more implicit, expressed through avoidance and silent prejudice. Moreover, interventions that rely solely on public education have limited effectiveness unless they also address power relations, gender inequality, and institutional discrimination (Courtwright & Turner, 2010; Mahajan et al., 2008). Recognising stigma as a social process embedded in networks of communication and influence also highlights the value of social network analysis in examining how attitudes and information flow through groups, affecting perceptions of disease within workplaces and communities.

In summary, stigma during health crises represents both a social and structural phenomenon that transcends individual prejudice. Evidence from HIV/AIDS, TB, and leprosy shows that it restricts access to care, disrupts livelihoods, and erodes social cohesion. Despite advances in medicine and policy, stigma remains deeply entrenched in cultural and institutional systems. Understanding these recurring mechanisms provides a foundation for examining how similar processes of fear, blame, exclusion, and structural inequality may also shape COVID-19 stigma, particularly in workplace settings where social interaction, misinformation, and organisational hierarchy influence everyday responses to disease and recovery.

2.1.3 Stigma and Health Outcomes

Stigma is widely recognised as a major determinant of health that influences physical, psychological, and social outcomes across a wide range of conditions. It operates through multiple pathways that shape how individuals experience illness, interact with healthcare systems, and participate in society. The effects of stigma extend beyond individual attitudes to include systemic and institutional mechanisms that reproduce health inequalities. By fostering shame, fear, and social isolation, stigma creates barriers to care and undermines wellbeing. Its impact has been consistently observed in both infectious and chronic conditions, such as HIV/AIDS, tuberculosis, epilepsy, and mental illness, demonstrating that stigma is a pervasive force in shaping health outcomes.

The psychological consequences of stigma are among the most immediate and well-documented. Individuals who experience rejection, negative judgement, or discrimination frequently internalise these encounters, leading to emotional distress and diminished self-worth. Florom-Smith and De Santis (2012) reported that people living with HIV who faced stigmatisation from their families and communities described feeling devalued and disconnected from social life. These experiences produced guilt, sadness, and hopelessness, reflecting the cumulative stress associated with repeated social rejection. Turan, Budhwani and colleagues (2017) further demonstrated that perceived community stigma often transforms into internalised stigma, which predicts depression, low self-esteem, and reduced social support. Such findings confirm that stigma functions as a chronic psychosocial stressor that damages mental health over time. This pattern has also been observed beyond HIV, such as in epilepsy and mental illness, where stigma has been linked to anxiety, depressive symptoms, and impaired emotional regulation (Abi et al., 2025; Katz et al., 2013). Individuals who conceal their condition to avoid discrimination often lose access to social support, which worsens emotional distress and reinforces isolation.

The negative effects of stigma on mental health can also manifest indirectly through reduced coping capacity and poor stress management. Continuous exposure to stigma-related stress drains psychological resources and limits resilience. Over time, this can result in emotional exhaustion and diminished hope for recovery. Yuan and colleagues (2022) found that persistent experiences of discrimination reduce individuals' ability to regulate stress and maintain positive coping strategies. When stigma is internalised, it shapes self-perception and expectations, leading individuals to view themselves as undeserving of care or improvement. This pattern reinforces withdrawal from social interaction and further exacerbates psychological decline. In severe cases, long-term exposure to stigma-related stress has been associated with suicidal ideation and learned helplessness, illustrating how the psychological burden of stigma can accumulate and become self-sustaining if unaddressed.

Stigma also affects health outcomes through behavioural mechanisms that influence healthcare-seeking and treatment adherence. Anticipated discrimination frequently discourages individuals from accessing services, leading to diagnostic delays or non-adherence to treatment. Turan, Hatcher and colleagues (2017) found that women who feared HIV-related stigma were less likely to disclose their status to healthcare providers or attend prevention programmes, despite being aware of the benefits.

Similarly, Shubber and colleagues (2016) showed that stigma reduced adherence to antiretroviral therapy by around 15% across multiple contexts. Comparable behavioural effects have been observed in non-communicable diseases. Katz and colleagues (2013) reported that people with epilepsy who perceived high stigma avoided medical follow-ups and concealed their condition from employers, compromising consistent treatment. In mental illness, internalised stigma has been shown to reduce motivation for therapy and lead to premature discontinuation of care (Abi et al., 2025). These behavioural effects show how stigma creates a state of health-related avoidance, where individuals weigh the social cost of disclosure against the potential health benefits of care.

The impact of stigma on treatment adherence is further compounded by mistrust of healthcare institutions. Patients who perceive health systems as judgemental or discriminatory often withdraw from care even when services are available. Nawfal and colleagues (2024) found that in Middle Eastern healthcare settings, individuals who experienced condescending attitudes from healthcare providers were less likely to return for follow-up appointments or disclose sensitive information. This dynamic illustrates how stigma can erode the therapeutic relationship between patient and provider, transforming a place of healing into one of anxiety and avoidance. Dessie and colleagues (2024) similarly found that tuberculosis patients who feared negative reactions from health workers delayed seeking treatment and were more likely to default midway through therapy. Such delays not only endanger individual health but also compromise community control measures, illustrating how stigma has both personal and public health implications.

In addition to its psychological and behavioural dimensions, stigma operates at a structural level through institutional practices, cultural norms, and policies that perpetuate health inequities. Hatzenbuehler and colleagues (2013) described this as structural stigma and demonstrated that individuals living in high-stigma environments experienced higher rates of psychiatric disorders and premature mortality. Even in the absence of direct discrimination, exposure to social contexts that devalue certain groups has measurable health effects. Structural stigma is perpetuated through laws, institutional cultures, and policy gaps that normalise exclusion or moral judgement. In healthcare, these dynamics often manifest as biased decision-making, inadequate communication, and reduced empathy. Chime and colleagues (2022) observed that in several African countries, healthcare professionals with prejudicial attitudes were less likely to prioritise patients from marginalised backgrounds, reducing equitable access to testing and treatment. Nawfal and colleagues (2024) also highlighted how healthcare providers' implicit moral assumptions shaped patient experiences, often discouraging individuals from seeking care. These studies demonstrate that stigma is not confined to interpersonal exchanges but is embedded in the structures and systems that shape healthcare delivery.

The intersection between stigma and structural inequality extends into broader social and economic domains. Yuan and colleagues (2022) found that individuals who experience social exclusion and discrimination are more likely to face unemployment, financial hardship, and reduced social mobility, all of which are predictors of poor health. Phelan and colleagues (2023) described this as a stigma-inequality cycle, where social disadvantage and health-related stigma reinforce each other. People who are marginalised are more likely to develop health problems, and those health problems, in turn, become a source of further stigma and exclusion. Over time, these cumulative disadvantages create enduring patterns of inequality that persist across generations. This dynamic is particularly evident in contexts where access to education, employment, and housing is limited by social identity or health status. The resulting disparities are not only socioeconomic but also health-related, as limited opportunities contribute to chronic stress, poor nutrition, and restricted access to healthcare.

Another research also highlights the biological dimension of stigma's impact. Prolonged exposure to stigma-related stress activates the body's stress-response systems, leading to hormonal and immune dysregulation. Hatzenbuehler and colleagues (2013) reported that individuals exposed to discrimination and social devaluation had elevated cortisol levels and systemic inflammation, both of which contribute to cardiovascular disease and immune suppression. Chronic stress of this kind weakens the body's ability to resist infection and slows recovery from illness. Physiological research therefore supports the idea that stigma is not only a psychological or social phenomenon but a biological stressor with measurable physical consequences. The cumulative effects of psychological strain, behavioural avoidance, and biological dysregulation demonstrate how stigma can shorten lifespan and reduce quality of life.

The consequences of stigma for social functioning are equally significant. Katz and colleagues (2013) found that concealment of epilepsy to avoid prejudice led to social isolation and loss of community belonging. Abi and colleagues (2025) observed that people with mental illness who internalised stigma reported weaker family relationships and less participation in social activities, which worsened their mental health. Yuan and colleagues (2022) noted that social isolation reduces access to support networks that are crucial for coping with chronic illness. These findings underscore that stigma disrupts the social connections that are central to resilience and recovery. When individuals withdraw from social contact to avoid stigma, they lose access to emotional, informational, and practical support, creating a cycle in which isolation reinforces illness and illness reinforces isolation.

The health effects of stigma are further intensified when it intersects with other forms of inequality such as gender, class, and ethnicity. Dessie and colleagues (2024) found that tuberculosis patients who also experienced poverty or food insecurity reported higher levels of stigma and poorer adherence to treatment. Intersectional factors amplify vulnerability by combining the effects of social marginalisation with health-related discrimination. Abi and colleagues (2025) noted that women with mental illness faced greater stigma than men, as their condition was perceived as a failure to fulfil gendered expectations of emotional control and caregiving. The interaction of stigma with social hierarchies means that the same illness can have very different consequences depending on a person's social position. Understanding these layered vulnerabilities is essential for designing interventions that address both individual and structural determinants of health.

As described above, the pathways through which stigma affects health are interconnected and mutually reinforcing. Psychological distress leads to avoidance of healthcare, which contributes to disease progression and increases visibility of illness, reinforcing public prejudice. Structural discrimination limits access to resources, while physiological stress reduces the body's capacity to recover. Together, these mechanisms create a feedback loop in which stigma produces poor health, and poor health perpetuates stigma. This cyclical relationship underscores the need to view stigma not as an isolated social problem but as a fundamental cause of health inequities.

In summary, stigma operates as a multidimensional determinant of health that influences wellbeing through psychological, behavioural, structural, and biological mechanisms. It undermines mental health, reduces engagement with care, and reinforces social and economic exclusion, which together shape health outcomes across diverse conditions. These effects demonstrate that stigma cannot be understood solely as an issue of personal prejudice but as a systemic process embedded within social structures and health systems. Addressing its impact requires multi-level interventions that integrate mental health support, institutional reform, and social inclusion.

Understanding these pathways provides a necessary foundation for exploring how similar mechanisms operate in workplace environments, where social perceptions, peer influence, and patterns of connection may shape both health behaviour and wellbeing.

In workplace settings, these health consequences may also be shaped by employees' positions within the social structure. Individuals who are socially isolated may have less access to emotional, informational, and practical support, which can intensify distress and reduce help-seeking. Conversely, those embedded in more supportive or influential networks may experience protection against stigma-related harms through reassurance, information sharing, and social support. This suggests that the consequences of stigma are not only individual, but also relationally patterned, making social network analysis relevant for understanding how stigma affects wellbeing and behaviour within organisational environments.

2.1.4 Stigma at the Workplace

The workplace represents one of the most significant social environments where individuals define their identity, maintain livelihood, and develop social relationships (Ashforth & Mael, 1989). Although employment is generally associated with improved wellbeing, economic stability, and social inclusion, it can also be a source of inequality and stigma (Lightner et al., 2021; Mahajan et al., 2008). Within organisations, stigma emerges when certain employees are marked as different or deficient based on attributes that are undervalued or misunderstood, such as health conditions, disabilities, or perceived performance limitations (Fesko, 2001; Krupa et al., 2009; van Beukering et al., 2022). These processes are often shaped by hierarchical structures, organisational norms, and interpersonal interactions that reinforce exclusion or bias (Cunningham, 2024; Van Laar et al., 2019; Zhou et al., 2024). Research across various sectors shows that stigma at work is expressed through gossip, stereotyping, social isolation, and unequal treatment, which collectively weaken morale and psychological safety (Krupa et al., 2009; Song & Guo, 2022; van Beukering et al., 2022). Such experiences do not only affect the targeted individuals but can also damage team cohesion, productivity, and overall organisational climate (Cunningham, 2024). In this study, workplace stigma is understood as more than interpersonal prejudice occurring at the site of employment. It is conceptualised as a socially embedded phenomenon operating across interpersonal, organisational, and structural levels, where workplace roles, hierarchy, productivity expectations, and patterns of interaction shape how stigma is expressed and sustained.

Stigma in organisational settings has also been examined through sociolinguistic perspectives that analyse how workplace interactions and institutional practices reproduce forms of exclusion. Wu and colleagues (2024) conceptualised the workplace as a discursive space in which stigma is produced through dynamic processes operating across three interconnected layers: immediate interpersonal encounters, organisational practices, and wider societal ideologies. Their findings show that stigma is reinforced through discursive practices such as identity management, concealment, labelling, and the negotiation of competence and credibility, all of which influence access to resources, performance evaluations, and career opportunities. This model complements classical sociological theories by demonstrating that stigma is sustained not only by individual attitudes but also by cultural and structural features of professional environments, including expectations related to professionalism, productivity, and moral responsibility (Wu et al., 2024). These insights highlight the importance of considering workplace hierarchies, relational mechanisms, and broader organisational norms when examining health-related stigma in industrial contexts such as factory settings.

These issues may be especially pronounced in factory environments, where workers often operate in dense settings characterised by repeated face-to-face contact, limited opportunities for remote work, strong dependence on team-based coordination, and, in some cases, shared transport or accommodation. Compared with office-based settings, such conditions may intensify both fear of contagion and the social consequences of being identified as infected, quarantined, or suspected of exposing others to risk. Employment dependence and workplace hierarchy may further shape stigma dynamics, as workers in lower-status or less secure positions may be especially vulnerable to blame, exclusion, or silencing (Ang et al., 2023; Ranjit et al., 2023; Schubert et al., 2021; Solhi, 2021).

In the context of health-related stigma, employment carries unique challenges for individuals with chronic or stigmatised conditions. Fesko (2001) explored how people living with HIV manage disclosure in the workplace and found that decisions about revealing one’s diagnosis are influenced by personal, interpersonal, and organisational factors. Many employees weighed the benefits of disclosing their status, such as gaining access to reasonable accommodations or understanding from supervisors, against potential risks including job loss, social rejection, or gossip. Non-disclosure often led to psychological strain, secrecy, and social isolation, while disclosure could create opportunities for support but also expose employees to discrimination. This decision-making process illustrates how stigma operates through fear and uncertainty, compelling individuals to navigate between authenticity and protection. Similar patterns were observed by Pos, Hlongwane, and Madiba (2021), who studied HIV-positive domestic workers in South Africa. Their participants described how fear of job loss and anticipated stigma prevented them from disclosing their HIV status, particularly in live-in employment arrangements where privacy was limited. The emotional burden of concealment led to stress and mistrust in employer–employee relationships, demonstrating how power imbalances in workplaces can intensify stigma and its health effects.

The persistence of HIV-related stigma at work is not confined to a single country or occupational group. Utuk and colleagues (2017) conducted a survey of workplace attitudes in Nigeria and found high levels of stigmatising beliefs toward co-workers with HIV. Many respondents expressed reluctance to share workspaces or collaborate with HIV-positive colleagues, reflecting widespread misconceptions about transmission. Lower education and poor knowledge about HIV were associated with stronger discriminatory attitudes. Conversely, workplaces that had clear policies and education initiatives reported lower stigma levels. These findings show that organisational culture and information dissemination play pivotal roles in shaping workplace attitudes (Utuk et al., 2017). Similarly, Korkmaz and colleagues (2023) reported continuing workplace HIV stigma in Türkiye, highlighting the need for qualitative evidence to guide culturally appropriate interventions. Together, these studies illustrate that health-related stigma in employment persists globally, reinforced by misinformation, fear of contagion, and insufficient policy enforcement.

Employment outcomes are closely linked to health among people living with chronic conditions, making workplace stigma particularly consequential. Lightner and colleagues (2021) analysed data from over 1,400 people living with HIV and found that internalised and anticipated stigma were both associated with lower odds of employment or return to work. Stigma was a significant barrier to re-entry even after adjusting for health and demographic factors. These results confirm that the social context of work, not merely physical capability, determines employment opportunities for stigmatised groups. Maulsby and colleagues (2020) further demonstrated that employment promotes better health and survival among people living with HIV, yet stigma, health limitations, and fear of discrimination continue to deter re-engagement in work. They argued that employment services and HIV care should collaborate to address these barriers by improving workplace education, offering flexible accommodations, and safeguarding against benefit loss. Mahajan and colleagues (2008) also emphasised that tackling stigma requires action beyond the individual level, calling for legal, organisational, and labour-based reforms that protect workers from discrimination and support equitable participation. Collectively, these studies identify stigma as both a social and structural obstacle to sustainable employment and highlight employment itself as a pathway to improved health when stigma is effectively addressed.

Workplace stigma also affects employees with mental illness, where prejudicial attitudes often result in exclusion, limited career advancement, and emotional distress. Krupa and colleagues (2009) synthesised evidence on mental illness stigma in employment and found that stigma acts through processes of labelling, stereotyping, and separation. These mechanisms lead to discriminatory hiring and promotion practices, strained relationships with colleagues, and limited access to support. The authors emphasised that organisational culture and co-worker attitudes determine whether employees feel safe to disclose their mental health conditions or seek accommodations. The resulting concealment and fear reduce job control, social support, and self-efficacy, all of which are important determinants of work ability and mental health. Similarly, Hampson and colleagues (2020) found that stigma and discrimination against individuals with psychosis continue to undermine job-seeking and employment sustainability. In their qualitative study, participants described being rejected during recruitment, subjected to unequal pay, and monitored more closely than other employees. Many concealed their mental health status to avoid stigma, yet this secrecy prevented access to necessary workplace support and accommodations. The cumulative effect of these experiences was moral distress, anxiety, and fear of relapse, which in turn jeopardised employment stability. These studies show that even when legal protections exist, unspoken stigma within workplace culture can sustain unequal treatment and erode the psychological safety necessary for inclusion.

Stigma in the workplace is not limited to individual relationships but can also arise from organisational and structural dynamics. Cunningham and colleagues (2024) highlighted that structural stigma embedded in laws, policies, and institutional practices contributes to health disparities across multiple domains, including employment. Their review identified workplace policies as both potential sources and remedies for stigma-related inequities. When organisational norms tolerate exclusion or lack mechanisms to address discrimination, stigma becomes institutionalised. Conversely, proactive policy reforms, anti-discrimination enforcement, and workplace education can reduce stigma exposure and improve employee wellbeing. Van Beukering and colleagues (2022) conducted a systematic review of health-related stigma at work across conditions such as HIV, cancer, and mental illness. They identified several mechanisms linking stigma to diminished wellbeing, including fear of disclosure, reduced access to accommodations, and decreased job security. The review concluded that organisational culture change and empowerment-oriented practices, such as flexible work arrangements and supportive supervision, can mitigate these harms. These findings reinforce that workplace stigma is a systemic problem requiring structural responses rather than isolated awareness programmes.

Beyond health and policy dimensions, workplace stigma also manifests in subtle interpersonal forms that erode self-esteem and social cohesion. Song and Guo (2022) examined how negative workplace gossip undermines employees' organisational self-esteem. Their study found that gossip acts as a social-evaluative threat, producing feelings of exclusion and unfair hierarchy. These perceptions lower employees' sense of belonging and value, which diminishes motivation and performance. Similarly, Van Laar and colleagues (2019) synthesised research on stigma, identity threat, and coping strategies, proposing that employees from stigmatised groups experience chronic identity threats that affect wellbeing and performance. Supportive workplace climates and visible role models can buffer these effects, but coping efforts themselves may carry hidden costs such as emotional exhaustion and reduced engagement. The authors argued that effective interventions should create identity-safe environments that centre the experiences of stigmatised employees while avoiding overreliance on individual coping. This perspective underscores the dual nature of coping in the workplace: while resilience and adaptation can protect wellbeing, they can also drain emotional resources when systemic barriers remain unaddressed.

Stigma at work may also arise from perceptions of poor performance or organisational labelling. Kumar and colleagues (2021) found that employees whose performance fell below expectations experienced social stress similar to stigma, as negative evaluation threatened their status within teams. These employees were more likely to experience counterproductive behaviours such as withdrawal or reduced cooperation, particularly when workplace hierarchies were rigid. When status differences were more flexible, employees channelled pressure into innovation, suggesting that organisational context shapes whether performance-related stigma results in harm or growth. At a broader level, Zhou, Zheng, and Liu (2024) investigated organisational stigma, where a company's damaged external reputation transfers to its employees. They found that employees of blacklisted firms experienced emotional exhaustion and reduced innovative performance, mediated by the need to manage negative public perceptions. This demonstrates that stigma can occur not only at the individual level but also at the organisational level, affecting employees' emotional wellbeing and productivity through association with a stigmatised entity. Such findings highlight that stigma within work settings can originate from both internal and external social evaluations, influencing motivation, emotional regulation, and long-term engagement.

Across these studies, several consistent themes emerge. First, stigma in the workplace functions as a social-evaluative stressor that undermines psychological safety, belonging, and identity. It reduces employees' self-esteem and sense of control while increasing stress and emotional fatigue. Second, the consequences of stigma extend beyond emotional harm to tangible outcomes such as lower job satisfaction, absenteeism, and turnover. Stigmatised employees may face limited career advancement and reduced access to resources, perpetuating inequality. Third, organisational context and leadership play decisive roles in moderating these effects. Supportive managers, transparent policies, and positive diversity climates have been shown to reduce stigma and improve both wellbeing and performance (van Beukering et al., 2022; Van Laar et al., 2019). Conversely, cultures that tolerate gossip, silence, or exclusion sustain stigma even when formal policies prohibit it. Fourth, coping with workplace stigma can have hidden psychological costs. Employees who manage their identity or emotions to fit in may appear resilient but often experience exhaustion and reduced authenticity over time (Van Laar et al., 2019; Zhou et al., 2024). Addressing workplace stigma therefore requires not only supporting targets of stigma but also transforming the systems that perpetuate unequal treatment. Taken together, these findings suggest that workplace stigma is shaped not only by attitudes toward illness, but also by how organisational systems distribute power, visibility, responsibility, and dependence. This makes workplace stigma theoretically distinct from community stigma, as the employment setting introduces formal hierarchy, performance expectations, and institutional control that may intensify both the experience and consequences of exclusion.

The cumulative evidence shows that workplace stigma operates through interconnected psychological, social, and structural processes that affect health and organisational outcomes. It produces stress, isolation, and reduced performance, while also limiting access to supportive relationships and fair treatment. In health contexts, stigma at work intersects with discrimination, privacy concerns, and job insecurity, which amplify vulnerability for employees with chronic or stigmatised conditions. Structural reforms, such as policy enforcement, confidential reporting mechanisms, and education about rights and accommodations, are essential to protect workers and promote equity. Equally important are initiatives that foster supportive cultures, empower managers to act as allies, and normalise open discussion about health and difference. As van Beukering et al. (2022) and Cunningham (2024) emphasised, stigma reduction must move beyond awareness campaigns toward systemic change that integrates health, labour, and social policies. Employment has the potential to enhance wellbeing, but only when workplaces are inclusive, fair, and psychologically safe. Understanding the dynamics of workplace stigma thus provides an essential bridge between the general concept of stigma and its manifestations in specific settings such as health crises, where fear, misinformation, and social comparison can again influence how employees perceive and treat one another.

2.2 Overview of COVID-19

2.2.1 Epidemiology and Global Timeline of the COVID-19 Pandemic

Coronavirus disease 2019 (COVID-19) was first reported in Wuhan, Hubei Province, China, in December 2019, where a cluster of pneumonia cases of unknown cause was identified. Early investigations linked the outbreak to a seafood market that also sold live wild animals, suggesting possible zoonotic transmission (Eurosurveillance Editorial Team, 2020). On 7 January 2020, Chinese authorities identified a novel coronavirus as the causative agent, later named severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (Liu et al., 2020). The WHO designated the illness it caused as coronavirus disease 2019 (COVID-19) (Cucinotta &

Vanelli, 2020). From the outset, the emergence of COVID-19 was marked by uncertainty regarding its source, transmission dynamics, and severity, creating conditions that heightened fear and public anxiety.

Initial evidence indicated that the virus was transmitted through respiratory droplets and direct contact, with an incubation period averaging five to six days but extending up to fourteen days (Eurosurveillance Editorial Team, 2020). The occurrence of asymptomatic and pre-symptomatic transmission made the disease especially difficult to detect and control, and this uncertainty increased social concern about who might be infectious even in the absence of visible symptoms. By March 2020, widespread community transmission was evident in multiple regions, and WHO officially characterised COVID-19 as a pandemic on 11 March 2020, acknowledging the need for coordinated international response (World Health Organization, 2020d). Epidemiological models estimated the basic reproduction number (R_0) between 2 and 3, indicating high transmissibility in the absence of intervention (Eurosurveillance Editorial Team, 2020). This combination of rapid spread, asymptomatic transmission, and evolving scientific knowledge intensified public uncertainty and fear, both of which are highly relevant to stigma formation.

As the pandemic progressed, repeated waves of infection, changing public health guidance, and the emergence of new variants reinforced the unpredictability of the disease. Variants of concern such as Alpha, Delta, and Omicron demonstrated increased transmissibility, altered virulence, or immune escape, contributing to renewed global surges and sustained public concern (Liu et al., 2024; Siddiqui et al., 2022; Yang & Shaman, 2022). Although large-scale vaccination programmes substantially reduced severe disease, hospitalisation, and mortality, breakthrough infections and continued viral evolution meant that COVID-19 remained socially disruptive even as clinical management improved.

Another defining feature of the pandemic was the infodemic, characterised by the rapid circulation of misinformation and conflicting information through digital and social media (World Health Organization, 2020a; Zarocostas, 2020). This environment intensified confusion about transmission, risk, and appropriate behaviour, and often fuelled blame, suspicion, and stigma toward infected or exposed individuals. Public health responses such as quarantine, contact tracing, isolation, and movement restrictions were essential for infection control, but they also increased the social visibility of disease status and could reinforce fear-based judgement or exclusion.

By 2023 and 2024, many countries had transitioned from emergency pandemic response to endemic management. This shift reflected growing population immunity, improved treatment, and reduced severity at the population level, but it did not signify the disappearance of the virus or its social consequences (Liu et al., 2024; Meijers et al., 2023). Endemicity instead marked a transition to long-term coexistence with continued surveillance, periodic outbreaks, and ongoing adaptation of public health strategies. In this context, residual fear, misinformation, and stigma may persist even as the biomedical threat becomes more manageable.

The epidemiology of COVID-19 is therefore relevant to the present study not simply as historical background, but because several of its defining characteristics created conditions conducive to stigma. High transmissibility, uncertainty during the early pandemic period, asymptomatic spread, repeated variant-driven surges, and the infodemic all contributed to heightened social anxiety and the tendency to distinguish between those perceived as safe and unsafe. These dynamics are especially important in workplace settings, where infection may affect not only health, but also productivity, attendance, trust, and organisational functioning.

In summary, the global course of COVID-19 reflects more than a sequence of epidemiological events. It also illustrates how fear, uncertainty, misinformation, and public health control measures can shape social responses to disease. Understanding these features is important for examining how stigma emerged and persisted during the pandemic, particularly in workplace environments where repeated interaction and perceived exposure could intensify social judgement and exclusion.

2.2.2 Economic and Psychosocial Consequences of the Pandemic

The COVID-19 pandemic generated a global crisis that was both economic and social, disrupting livelihoods, weakening financial stability, and intensifying psychological distress across all population groups. The scale and duration of the pandemic made its consequences uniquely complex, as economic losses and psychosocial strain reinforced one another. Evidence from multiple regions demonstrates that declining income, job insecurity, and restricted mobility not only reduced household spending but also fuelled anxiety, depression, and loss of social wellbeing (Efriyani Sumastuti, 2024; Lu & Lin, 2021). These consequences are particularly relevant to stigma research because economic insecurity, uncertainty, and psychosocial strain may increase fear, blame, and social tension within workplaces and communities.

Lockdowns and international trade interruptions caused unprecedented declines in output and employment. In China, gross domestic product fell by 6.8% in the first quarter of 2020, and urban unemployment rose to more than 6% (Lu & Lin, 2021). Similar downturns were observed across emerging economies where limited fiscal capacity constrained recovery efforts. The contraction spread rapidly through supply chains, creating income shocks that affected small enterprises and informal workers more severely than large firms. In Indonesia, for instance, Efriyani Sumastuti (2024) found that lower income households experienced a marked reduction in expenditure ($B = -0.26$) and savings ($B = -0.14$) as a direct result of pandemic restrictions. These findings illustrate how financial vulnerability intensified during the pandemic, especially among groups with limited economic protection.

This financial disruption also revealed deeper structural inequalities within labour markets. Lu and Lin (2021) observed that workers in the service, hospitality, and manufacturing sectors faced higher rates of redundancy and wage loss, while employees in public or technology-based roles remained relatively protected. Many lost not only income but also access to health insurance and other benefits tied to formal work. The resulting insecurity increased reliance on short-term loans and informal borrowing, deepening household debt burdens. Tomlinson and Tholen (2023) referred to this process as labour-market scarring, describing how early-career disruption among young people produced persistent disadvantages in earnings, confidence, and wellbeing long after initial recovery. This uneven distribution of economic risk is important in workplace stigma research because insecurity may heighten sensitivity to illness, reduce tolerance toward infected colleagues, and intensify the social consequences of perceived risk.

At the household level, economic contraction quickly translated into reduced consumption and increased financial anxiety. Data from Efriyani Sumastuti (2024) showed that Indonesian households responded by cutting non-essential spending and using their limited savings to meet daily necessities, an adaptive strategy that further reduced resilience to prolonged shocks. Lu and Lin (2021) explained that pandemic-related economic uncertainty disproportionately affected disadvantaged groups, with lower-income populations experiencing heightened psychological distress due to unstable employment and reduced financial security. These economic consequences were not merely short-term adjustments but sources of psychological strain, as uncertainty about employment and debt repayments became chronic stressors.

The pandemic also widened existing inequalities between social classes and regions. Liu and colleagues (2021) found that individuals with lower income experienced significantly higher psychological distress and loneliness, reflecting how financial hardship and limited resources intensified vulnerability during periods of restricted mobility. Younger adults were particularly affected, reporting greater distress and social isolation than older groups. These disparities contributed to broader feelings of exclusion and perceived inequity, especially among economically disadvantaged populations. For many households, financial insecurity was accompanied by feelings of helplessness and reduced self-efficacy, factors known to predict depression and anxiety (Oviedo et al., 2023). Such conditions may also create a social climate in which fear, frustration, and uncertainty become projected onto others, increasing the likelihood of stigma-related judgement or exclusion.

Psychological consequences of the pandemic were profound and global. A systematic review by Xiong and colleagues (2020) synthesised 19 cross-sectional studies comprising about 93,569 participants and found that anxiety symptoms affected between 6.3% and 50.9% of respondents, while depressive symptoms ranged from 14.6% to 48.3% during the early phase of the outbreak. Post-traumatic stress symptoms were around 7% in some samples, while stress and general psychological distress varied widely across studies. Women, younger adults (≤ 40 years), students, and those with chronic or psychiatric conditions were consistently more affected. Frequently cited stressors included fear of infection, quarantine and social isolation, heavy exposure to COVID-19 news, academic disruption, and financial insecurity. Fatahi and colleagues (2021) reported similar global patterns in their qualitative study across Sweden, Norway, and Iraq. Participants described heightened anxiety, worry about loved ones, financial strain, and emotional distress arising from mobility restrictions and disruptions to normal life. Their findings reinforced that the psychological impact of the pandemic extended beyond the risk of infection, affecting daily functioning, interpersonal relationships, and overall wellbeing.

Healthcare workers were among the most psychologically affected groups during the pandemic because of their heightened exposure to risk, demanding workloads, and disruptions to normal clinical routines. In Fatahi and colleagues' (2021) cross-country qualitative study, healthcare personnel in Sweden, Norway, and Iraq described persistent fear of infection, concerns about transmitting the virus to family members, and significant emotional strain arising from rapidly changing work conditions and shortages of protective equipment. Participants also reported exhaustion, feelings of uncertainty, and a constant need to adapt to new clinical guidelines. Evidence summarised in Pasha and colleagues' (2025) review similarly highlighted that frontline staff experienced substantial stress, driven by workload pressures, infection risk, and challenges in balancing professional duties with personal wellbeing. These findings are relevant because emotionally strained environments may contribute not only to psychological burden but also to distancing, suspicion, and stigma toward those perceived as sources of risk.

Economic stress interacted closely with mental-health outcomes. Villatoro and colleagues (2022) studied Latinx young adults in Texas and found that psychosocial disruptions, such as loss of relationships and social support, had stronger associations with mental-health symptoms than economic strain itself. Nevertheless, financial hardship remained a significant predictor of clinical outcomes. Oviedo and colleagues (2023) provided further evidence from Panama, where economic difficulties were directly related to higher depression, anxiety, and stress scores. Their study showed that social support and resilience moderated these effects, with women displaying greater vulnerability. These results illustrate the bidirectional link between material insecurity and psychological wellbeing. Individuals facing prolonged financial difficulties reported higher levels of stress and emotional exhaustion, which are commonly accompanied by sleep disturbance, irritability, and difficulties concentrating (Xiong et al., 2020). In workplace settings, such psychosocial strain may influence how employees perceive one another, respond to illness, and manage fear-related interactions.

While the pandemic affected many social groups, its consequences were especially salient in employment settings, where fear of infection, job insecurity, disrupted routines, and strained interpersonal relations occurred simultaneously. The pandemic also affected family and community dynamics. Ivbijaro and colleagues (2020) observed that extended confinement, caregiving responsibilities, and bereavement contributed to domestic conflict and emotional exhaustion. Women, particularly mothers, bore a disproportionate share of unpaid care work, amplifying gendered stress differentials. Evidence from other studies shows that women reported higher anxiety, emotional strain, and difficulties balancing work, family responsibilities, and pandemic-related disruptions (Fatahi et al., 2021; Xiong et al., 2020). In low-income households, these psychosocial burdens were intensified by food insecurity, limited access to support, and inadequate digital resources, exacerbating feelings of stress and vulnerability.

Resilience and coping mechanisms played a crucial role in moderating the psychological impact of the pandemic. Oviedo and colleagues (2023) found that individuals with higher resilience and stronger social support networks reported lower levels of depression, anxiety, and stress, indicating that social connectedness acted as an important buffer against psychological distress. Pasha and colleagues (2025) further demonstrated that transparent government communication, access to protective equipment, and confidence in vaccination programmes were associated with reduced anxiety among healthcare workers. Fatahi and colleagues (2021) similarly highlighted that clear organisational communication and supportive leadership helped alleviate fear and emotional strain. At a broader population level, Liu and colleagues (2021) emphasised that socioeconomic disadvantage intensified stress and loneliness, demonstrating that coping capacity is also influenced by structural conditions that determine access to resources and support. These findings are also relevant to stigma because supportive communication, trustworthy information, and strong social ties may buffer against fear-based judgement and exclusion.

The intersection of economic and psychological effects underscores that crises of this magnitude cannot be addressed by fiscal policy alone. Economic uncertainty and social isolation operate through similar stress pathways, producing cumulative strain on individuals and communities. As shown by Fatahi and colleagues (2021) and Xiong and colleagues (2020), widespread anxiety and depression were not confined to infected individuals but spread across populations through shared experiences of fear and loss. Sustained monitoring of mental-health indicators, alongside economic recovery metrics, is therefore essential.

In sum, the COVID-19 pandemic revealed the deep interdependence of economic security and psychosocial wellbeing. Sudden income loss, unemployment, and financial instability intensified psychological distress, while fear, isolation, and uncertainty further undermined productivity and social cohesion. These mutually reinforcing processes widened existing inequalities and generated long-term risks to both economic and mental health. For the present study, these consequences are important because they help explain why workplace environments during the pandemic could become fertile ground for fear, blame, misinformation, and stigma, particularly where insecurity and close social interaction coexisted.

2.2.3 COVID-19 in Malaysia

Malaysia experienced the progression of COVID-19 in a pattern that broadly paralleled the global epidemiological timeline described in Section 2.2.1. The country recorded its first confirmed cases on 24 January 2020 among travellers arriving from China via Singapore, marking the start of the national pandemic period (Ghazali et al., 2022). The early phase was characterised by imported cases and limited local transmission, but the situation changed rapidly as larger clusters began to emerge.

A major shift occurred at the end of February 2020 with the emergence of the second wave. This period was dominated by the Sri Petaling Tabligh cluster, a large religious gathering that generated widespread transmission and quickly became the largest cluster in the country (Hashim et al., 2021). By May 2020, it accounted for 47% of all recorded cases in Malaysia and produced multiple subclusters across several states and international locations. The government responded by implementing a nationwide Movement Control Order (MCO) beginning on 18 March 2020, which served as a central non-pharmaceutical intervention to curb transmission (Gill et al., 2020). This early phase of the Malaysian epidemic highlighted how cluster-based transmission could rapidly amplify public concern, visibility of infection, and social scrutiny.

Following the containment of the Sri Petaling cluster in July 2020, daily case numbers declined for several months. However, a resurgence was observed in early October 2020 with the start of the third wave (Hashim et al., 2021). This wave produced an exponential increase in cases, driven by widespread community transmission and several new clusters, particularly in Sabah, Selangor, Kuala Lumpur, and Kedah. Subsequent waves were influenced by variant emergence, increased community spread, and differences in local transmission contexts, reflecting the evolving and uneven nature of the epidemic within the country (Md Nadzri et al., 2024).

The national vaccination rollout began on February 2021 under the National COVID-19 Immunisation Programme, initially prioritising healthcare workers and other frontline groups (Hamdan et al., 2022). By September 2021, 76.2% of the adult population was fully vaccinated, although the emergence of the Delta variant produced a significant surge in cases nationwide. The Delta and later Omicron waves reinforced the continuing social and organisational disruption caused by COVID-19, even as vaccination reduced the severity of illness at the population level (Md Nadzri et al., 2024). By 1 April 2022, Malaysia declared the transition to the endemic phase, closing a two-year period of intense public health management and pandemic response (Md Nadzri et al., 2024; Ministry of Health Malaysia, 2024).

By February 2023, Malaysia recorded a cumulative total of 5,037,995 confirmed cases and 36,943 deaths, corresponding to an overall case fatality rate of 0.7% (World Health Organization Team Malaysia, 2023). During the course of the pandemic, specific demographic groups were disproportionately affected. Individuals aged 55 to 64 years had the highest incidence rate, while 63% of total deaths occurred among those aged above 60 years, with a substantial proportion of deaths occurring among individuals with comorbidities, particularly diabetes, hypertension, and heart disease, which collectively accounted for 81% of all fatalities (Hashim et al., 2021). These patterns indicate that the burden of COVID-19 in Malaysia was shaped not only by viral transmission, but also by pre-existing health and social vulnerabilities.

Workplace transmission emerged as a central feature of the Malaysian epidemic landscape. Epidemic reports identified workplace clusters as a substantial contributor to national case numbers, with the manufacturing sector disproportionately affected (Hashim et al., 2021; Solhi, 2021). Migrant workers were particularly vulnerable, frequently living in overcrowded dormitories and working in environments with limited capacity for distancing. This group accounted for 68% of confirmed cases arising from workplace clusters, highlighting structural conditions that placed foreign workers at significant epidemiological risk and complicated national containment efforts (Nungsari et al., 2022). These conditions are particularly relevant to the present study because they show that workplace outbreaks in Malaysia were not simply biomedical events, but were embedded in labour conditions, housing arrangements, and organisational structures that could also shape fear, blame, and social exclusion. In factory environments, where employees work in close proximity and where infection may disrupt operations, the social consequences of COVID-19 may be especially pronounced.

Overall, the Malaysian experience reflects a pattern shaped by early government intervention, cluster-driven outbreaks, the emergence of more transmissible variants, and the eventual stabilisation of transmission following widespread vaccination coverage. For the present study, the Malaysian context is especially important because it demonstrates how COVID-19 intersected with workplace structure, labour inequality, and cluster-based transmission in ways that made the manufacturing sector a particularly relevant setting for examining workplace stigma. The progression through successive waves provides not only epidemiological context, but also a basis for understanding how fear, risk perception, and social responses to infection may have developed within Malaysian workplaces.

2.3 COVID-19 Stigma

The COVID-19 pandemic generated extensive social stigma across many societies, shaped by fear, uncertainty, and widespread misinformation during the early stages of the outbreak. In this context, stigma refers to the negative labelling, stereotyping, and discriminatory treatment of individuals associated with COVID-19, including confirmed patients, survivors, healthcare workers, family members, and residents of areas with high infection rates (Bagcchi, 2020; Chew et al., 2021; Di et al., 2021; Jayakody et al., 2021; Negarandeh et al., 2024; Yuan et al., 2021). These reactions reflect broader social processes that occur when infectious diseases are perceived as threatening, and when communities attempt to identify, avoid, or blame those deemed risky or responsible.

A key mechanism underlying COVID-19 stigma is the public's fear of contagion, particularly during periods when scientific understanding of transmission was limited. Uncertainty about asymptomatic spread and the potential long-term effects of infection contributed to heightened anxiety, prompting individuals to distance themselves from those suspected of exposure or contact with the virus. Misinformation circulated on digital and social media further reinforced stereotypes, portraying certain communities, occupations, or geographic groups as sources of infection and thereby framing COVID-19 risk as a moral or behavioural failing (Bagcchi, 2020; Di et al., 2021). These dynamics mirror long-standing patterns observed in other infectious disease outbreaks, where fear and social blame amplify exclusion and discrimination.

COVID-19 stigma has affected a broad range of groups. Patients and survivors are often treated as continuing risks even after recovery, while their family members may experience courtesy stigma through association (Chew et al., 2021; Jayakody et al., 2021). Healthcare workers have been particularly vulnerable because of their occupational exposure, frequently perceived as potential carriers despite adherence to safety measures (Bagcchi, 2020; Negarandeh et al., 2024). Residents of outbreak epicentres have also faced prejudice, illustrating how geographic identity can become a basis for social judgement during epidemics (Di et al., 2021).

The consequences of COVID-19 stigma extend beyond interpersonal discomfort to affect mental health, social cohesion, and health-seeking behaviour. Studies report that stigma heightens anxiety, distress, and social withdrawal among affected individuals, while persistent suspicion from others can delay reintegration into work and community life (Chew et al., 2021; Yuan et al., 2021). At the community level, stigma reduces willingness to disclose symptoms, discourages engagement with testing or contact tracing, and undermines public health measures that rely on cooperation (Jayakody et al., 2021). These effects illustrate how stigma operates at individual, interpersonal, and societal levels, shaping behavioural responses in ways that impede effective disease control.

2.3.1 Experience of COVID-19 Stigma

The lived experiences of individuals affected by COVID-19 reveal the pervasive and multifaceted nature of stigma during the pandemic. Across different settings, those infected with the virus, their families, survivors, and even individuals merely perceived to be associated with COVID-19 have reported varying forms of enacted, perceived, and internalised stigma. In China, an analysis of Weibo posts during the early phase of the outbreak showed that stigmatising attitudes toward Wuhan residents emerged quickly, including portrayals of them as ‘infectious’, ‘irresponsible’ or ‘stupid’, and characterisations that framed them as a source of danger to others (Di et al., 2021). Yuan and colleagues (2021) reported that, even after the outbreak was well contained, COVID-19 survivors experienced higher levels of perceived social rejection and isolation than healthy controls, consistent with reports that they were treated as continuing sources of risk and faced difficulties re-entering work and community life (Yuan et al., 2021). These accounts demonstrate how community fear and uncertainty can evolve into persistent discriminatory practices that extend beyond the infectious period.

Across these accounts, COVID-19 stigma may be understood in several overlapping forms. Public stigma refers to negative stereotyping, blame, and discriminatory reactions directed toward infected or associated individuals by others.

Perceived stigma refers to the expectation or awareness of being judged, avoided, or rejected. Internalised stigma refers to the emotional incorporation of these negative perceptions, such as shame, distress, or self-withdrawal. In addition, institutional discrimination may occur when organisational or administrative practices, whether formal or informal, disadvantage individuals because of their association with COVID-19.

Qualitative studies in Malaysia provide additional insight into the social consequences of stigma during COVID-19. Chew and colleagues (2021) found that recovered patients and their family members experienced a range of stigmatic responses, including isolation, labelling, and blame. Participants noted that healthcare providers maintained deliberate physical distance, limited face-to-face interaction, and communicated through barriers or telecommunication devices despite being in clinical proximity. Although these practices were grounded in infection-prevention measures, they were interpreted by patients as signs that they were viewed as hazardous or undesirable. This illustrates how institutional or procedural responses, even when introduced for infection control, may also be experienced as stigmatising when they reinforce social distance and symbolic exclusion. At the community level, participants described neighbours instructing children to avoid them, monitoring their homes, and referring to them using labels such as "COVID-19 people." In several cases, suspicion persisted despite repeated negative tests, indicating that social perceptions of risk may remain disconnected from clinical outcomes.

Evidence from Sri Lanka further illustrates how stigma may be reinforced through community dynamics and public discourse. Jayakody and colleagues (2021) documented the role of rumours, defamatory social media posts, and blame narratives that questioned individuals' behaviour and responsibility for infection. Participants recounted experiencing insults, public shaming, and differential treatment by neighbours, employers, and local authorities. Some individuals faced employment consequences, including job loss or delayed return to work, despite completing all required isolation protocols. In several households, stigma persisted for extended periods, indicating how associations between infection and blame can become embedded within local social structures.

Healthcare workers represent another group disproportionately affected by stigma. In Iran, Negarandeh and colleagues (2024) reported that nurses and physicians caring for COVID-19 patients encountered avoidance, verbal harassment, and discriminatory behaviour in both public and private settings. Some healthcare workers noted that neighbours avoided sharing lifts or physical proximity in common areas, while others observed a reduction in social contact from friends and extended family members. Within the household, some experienced precautionary distancing driven by fear of transmission. These experiences contributed to considerable emotional strain, including anxiety, sadness, and feelings of being undervalued despite their professional responsibilities. Additional reports from global settings describe healthcare workers being evicted from rental housing, denied access to public transport, or subjected to harassment due to their perceived high exposure to the virus (Bagcchi, 2020). Together, these accounts illustrate how occupational proximity to COVID-19 can become a basis for discrimination.

Stigma also affected individuals indirectly linked to COVID-19, demonstrating how courtesy stigma extends beyond the infected person. In Malaysia, family members of COVID-19 patients experienced social avoidance and suspicion from employers, colleagues, and neighbours, even when asymptomatic and tested negative (Chew et al., 2021). Children of infected parents encountered avoidance at school, highlighting the intergenerational dimensions of stigma. In Sri Lanka, households affected by COVID-19 were sometimes perceived as irresponsible or morally culpable, and in certain cases reported reduced access to community support during emergencies (Jayakody et al., 2021). In India, severe forms of enacted stigma were also documented, including a case in which a woman who tested positive during pregnancy was subsequently abandoned by her family after childbirth (Bagcchi, 2020). These examples show that stigma can extend through familial, workplace, and neighbourhood ties, reinforcing exclusion within broader social networks.

The emotional and psychological effects of stigma were substantial. Across multiple studies, individuals exposed to stigma reported elevated levels of anxiety, fear, sadness, distress, and irritability (Chew et al., 2021; Jayakody et al., 2021; Negarandeh et al., 2024; Yuan et al., 2021). Among survivors in China, perceived and enacted stigma were associated with higher levels of depression, psychological distress, and sustained feelings of social rejection (Yuan et al., 2021). In Sri Lanka, rumour-driven harassment and community surveillance heightened individuals' sense of vulnerability and shame (Jayakody et al., 2021). Among healthcare workers, emotional exhaustion was compounded by demanding work conditions and discriminatory behaviour from the public and their communities (Negarandeh et al., 2024). These findings demonstrate that the psychological burden of stigma compounds the broader stressors associated with the pandemic.

Experiences of stigma also influenced decisions regarding illness disclosure. In Malaysia, Chew and colleagues (2021) found that some individuals disclosed their previous COVID-19 status selectively, often limiting disclosure to administrative or official contexts. Concerns about negative reactions, restricted access to services, or workplace discrimination discouraged open communication. Conversely, some individuals felt a responsibility to disclose their experiences to support community understanding and public health efforts. In Sri Lanka, stigma contributed to concealment of symptoms, reluctance to seek testing, and avoidance of contact-tracing activities due to concerns about being blamed or labelled (Jayakody et al., 2021). These behaviours have important public health implications, as nondisclosure may delay diagnosis, reduce adherence to control measures, and undermine surveillance accuracy.

Taken together, these experiences across China, Malaysia, Sri Lanka, Iran, and India indicate that COVID-19 stigma is a pervasive and persistent social phenomenon shaped by fear, uncertainty, misinformation, and moral judgement. Stigma manifested in various forms, including public stigma, courtesy stigma, institutional disadvantage, social avoidance, harassment, blame, employment consequences, diminished community support, and disruptions to family relationships. The extension of courtesy stigma to family members, the marginalisation of healthcare workers, and the substantial psychological effects observed among survivors and their families underscore the importance of addressing stigma as part of the broader pandemic response. These narratives show that COVID-19 stigma extends beyond the period of active infection and continues to influence social relationships, mental health, and health-seeking behaviour well after clinical recovery.

2.3.2 Factors Contributing to COVID-19 Stigma

COVID-19 stigma was shaped by multiple interrelated influences rather than by any single cause. As summarised in Table 2.1, the contributing factors identified in the literature can be grouped broadly into psychological and informational drivers, wider social and cultural influences, and structural conditions surrounding the pandemic response. This pattern suggests that stigma emerged not only from fear of disease, but also from how COVID-19 was understood, communicated, judged, and managed within society.

Table 2.1
Summary of Evidence on Factors Contributing to COVID-19 Stigma

Factor	**Supporting studies**	**Summary of evidence**	**Relevance to workplace COVID-19 stigma**
Fear of infection	Jiang et al. (2021), Bagcchi (2020), Negarandeh et al. (2024)	Fear of becoming infected, especially during the early phase of the pandemic, led people to view those associated with COVID-19 as dangerous. Avoidance, harassment, and even eviction were reported among healthcare workers, family members, and survivors.	Fear may lead workers to avoid or negatively judge colleagues associated with infection, even after recovery.
Limited knowledge and low health literacy	Jiang et al. (Mashinini et al. (2024), Bagcchi (2020)	Poor understanding of COVID-19 transmission and disease processes was associated with stronger stigmatising attitudes, anticipated stigma, and concealment of infection status.	In workplace settings, low health literacy may increase misconceptions about contagion and reinforce blame or avoidance of infected coworkers.
Misinformation and rumours	Caceres et al. (2022), Al-Ghuraibi & Aldossry (2022), Bagcchi (2020), Negarandeh et al. (2024), Lohiniva et al. (2021)	False claims circulating through social media and informal networks intensified fear, suspicion, blame, and self-stigma. Misinformation had harmful behavioural consequences, contributed to social rejection, and may become normalised when repeatedly circulated and socially validated within trusted networks.	Workplace stigma may be reinforced when unverified information about infection, risk, or responsibility circulates among workers. In close workplace networks, repeated interaction and interpersonal trust may further amplify shared stigma beliefs.
Sociodemographic and socio-economic factors	Jiang et al. (2021), Teksin (2020), Mashinini et al. (2024), Shah et al. (2024), Lohiniva et al. (2021)	Higher stigma was associated with lower education, lower income, and older age. Essential workers, migrants, and lower-income groups were more likely to face discrimination.	Workers' social position, education, and occupational role may shape both the experience and expression of stigma in the workplace.

Table 2.1
(Continued…)

Factor	**Supporting studies**	**Summary of evidence**	**Relevance to workplace COVID-19 stigma**
Cultural values and moral beliefs	Alchawa et al. (2023), Al-Ghuraibi & Aldossry (2022), Lohiniva et al. (2021), Mashinini et al. (2024)	COVID-19 was sometimes interpreted as a sign of irresponsibility or moral failure. Concerns about honour, reputation, and blame encouraged concealment and reinforced stigma.	In workplaces, infection may be judged as personal failure or carelessness, contributing to negative labelling of affected workers.
Racialisation and blame of specific groups	Gardner et al. (2022), Shah et al. (2024), Lohiniva et al. (2021)	COVID-19 stigma in some settings was shaped by xenophobia, racialised blame, and ethnic stereotyping, including workplace discrimination against Asian and Asian American individuals.	Demonstrates how stigma may be reinforced when infection becomes associated with particular ethnic or social groups within organisational settings.
Structural and policy-related factors	Lohiniva et al. (2021), Park et al. (2024), Teksin (2020), Negarandeh et al. (2024)	Public disclosure of case details, quarantine requirements, punitive measures, weak institutional support, and inadequate workplace protection sometimes increased labelling, suspicion, and psychological strain.	Organisational responses and workplace policies may unintentionally intensify stigma if they isolate, expose, or inadequately support infected workers.

At the psychological and informational level, fear, limited knowledge, and misinformation appear to have acted as immediate drivers of stigma. Uncertainty about infection risk encouraged people to perceive those associated with COVID-19 as dangerous, while poor understanding of transmission and prevention increased the likelihood of negative judgement, fear of disclosure, and social avoidance. These reactions were further intensified by misinformation circulated through social media and informal communication networks. False or sensational claims did not merely distort knowledge but also amplified suspicion and blame, particularly when repeated within trusted social circles. This suggests that stigma was reinforced through both misunderstanding and the social circulation of fear-based narratives (Caceres et al., 2022; Jiang et al., 2021; Lohiniva et al., 2021; Mashinini et al., 2024).

Although the above studies did not directly examine COVID-19 stigma using formal social network methods, many of their findings point to processes that are inherently relational. Misinformation is not typically encountered in isolation, but is circulated, repeated, and socially validated through digital and interpersonal ties. From a network perspective, this suggests that COVID-19 stigma may be especially susceptible to amplification within digital misinformation ecosystems and dense interpersonal networks, where repeated exposure, homophily, clustering, and peer influence may reinforce shared beliefs about who is dangerous, irresponsible, or socially undesirable. This theoretical implication is important because it indicates that stigma may spread not only through individual fear or misunderstanding, but also through patterns of social connection and communication. Taken together, these findings suggest that, although prior COVID-19 stigma studies have identified misinformation as a driver, they have rarely examined how such misinformation may be amplified, normalised, or contained through network structures (Caceres et al., 2022; Lohiniva et al., 2021; Negarandeh et al., 2024).

The literature also indicates that stigma was shaped by broader social and cultural influences. Sociodemographic disadvantage, lower educational attainment, and economic vulnerability were associated with stronger stigma or greater exposure to discrimination in several settings. At the same time, cultural values concerning responsibility, honour, and family reputation contributed to moral judgement of infected individuals, leading some people to conceal their diagnosis or fear being blamed for bringing illness into the household or community. In some contexts, these reactions also intersected with racialised or xenophobic narratives, showing that stigma was not confined to infection status alone but could become attached to ethnicity, nationality, occupation, or other socially marked identities. These findings indicate that COVID-19 stigma was shaped by existing social inequalities and cultural norms as much as by the disease itself (Alchawa et al., 2023; Jiang et al., 2021; Mashinini et al., 2024; Shah et al., 2024; Teksin, 2020).

Structural features of the pandemic response further influenced the development of stigma. Measures such as public disclosure of case details, quarantine requirements, punitive responses to non-compliance, and inadequate institutional support sometimes had unintended social consequences, including labelling, suspicion, and psychological distress. This is especially relevant in workplace settings, where organisational communication, infection-control practices, and the degree of support provided to affected workers may influence whether stigma is reduced or reinforced. Overall, the evidence suggests that COVID-19 stigma was produced through the interaction of individual fear, social judgement, and structural conditions, making it a complex social process rather than a simple reaction to infection alone (Lohiniva et al., 2021; Negarandeh et al., 2024; Park et al., 2024; Teksin, 2020).

2.3.3 Workplace Stigma during COVID-19

In this study, workplace stigma refers to stigma that emerges, or is expressed within the social and organisational environment of work, including through peer interactions, supervisory relations, informal labelling, exclusion, and workplace norms. Stigma in workplace settings emerged as a critical challenge during the COVID-19 pandemic, particularly for employees whose professional roles involved direct or perceived contact with infected individuals. Evidence from occupational and healthcare studies consistently shows that workers associated with COVID-19 exposure were vulnerable to discrimination, avoidance, and negative social labelling (Ranjit et al., 2023; Schubert et al., 2021). Several studies have demonstrated that discriminatory behaviour within workplaces often arose from uncertainty and fear among colleagues, which contributed to strained interpersonal interactions and erosion of trust. In India, for example, healthcare workers reported being treated with suspicion and hostility because their roles brought them into contact with COVID-19 patients, with almost half of respondents in one study indicating that they had experienced discrimination linked to their professional duties (Ranjit et al., 2023). This pattern reflects courtesy stigma, where individuals are targeted not because they are infected but because of their association with a stigmatised condition. Such labelling processes within workplaces can result in employees being characterised as potential carriers of infection, thereby triggering avoidance and social distancing that extend beyond accepted infection-control practices. In workplace settings, such responses are unlikely to be distributed randomly, but may instead be shaped by patterns of proximity, repeated interaction, informal group boundaries, and hierarchical role relations.

Accounts from media and institutional reports further illustrate how workplace stigma spilled over into workers' everyday lives. Bagcchi (2020) described cases in Mexico, Malawi, India, and other countries where healthcare staff were denied access to public transport, subjected to verbal or physical harassment, and evicted from rented homes as a result of public misconceptions about disease transmission. Although these incidents occurred outside formal workplaces, they originated from occupational exposure and highlight how professional identity became tightly linked to stigma during the pandemic. Such experiences blurred the boundaries between work and personal life, reinforcing the social vulnerability of frontline employees and compounding the burdens they faced within their work environments.

The psychological implications of workplace stigma were substantial. Empirical evidence shows that stigmatised workers experienced heightened levels of stress, anxiety, and depressive symptoms, influenced by a combination of discriminatory treatment and fear of societal judgement (Ranjit et al., 2023; Sachdeva et al., 2022). In one northern Indian study, more than half of healthcare providers reported moderate to severe mental health symptoms, with the highest distress levels observed among those working in COVID-19 wards (Sachdeva et al., 2022). These findings suggest that workplace stigma contributed not only to emotional exhaustion but also to reduced coping capacity, particularly among employees who worried about infecting their families or felt blamed for their occupational risks. The interplay between professional expectations, social perceptions, and internalised fear created a complex mental health burden that extended beyond routine occupational stress.

Workplace stigma during COVID-19 was not confined to a single profession but emerged across diverse occupational settings. Evidence from a systematic review by Schubert and colleagues (2021) demonstrates that employees who were perceived to have direct or indirect contact with COVID-19 frequently encountered multiple forms of stigma, including public stigma, internalised stigma, and associative stigma. These manifestations reflected broader social anxieties surrounding contagion and were directed at workers irrespective of their actual infection status. The review also highlighted consistent associations between work-related stigma and adverse mental health outcomes, with stigma exposure significantly increasing the risk of depression and anxiety. Although the methodological quality of the included studies varied, the convergence of findings across countries and occupational groups underscores that stigma linked to occupational exposure represented a widespread and persistent phenomenon. These patterns illustrate how societal fear, misinformation, and risk attribution permeated organisational environments, shaping employee interactions and contributing to psychological strain during the pandemic.

Evidence suggested that the consequences of workplace stigma extended beyond individual psychological distress to influence broader organisational functioning. Schubert and colleagues (2021) highlighted that stigma can disrupt collegial relationships, reduce morale, and undermine the sense of safety required for effective teamwork. In settings where workers feared judgement or negative labelling, the willingness to seek support, communicate openly, or disclose health concerns was diminished. These behavioural responses mirror findings from healthcare contexts in India, where fear of social backlash contributed to heightened stress and emotional withdrawal among frontline staff (Ranjit et al., 2023; Sachdeva et al., 2022). Such patterns indicate that stigma operates not only at the interpersonal level but also as a structural constraint that hampers cooperation and weakens organisational resilience during periods of crisis.

These patterns suggest that workplace stigma during COVID-19 was shaped not only by fear of contagion, but also by organisational and relational mechanisms. In workplaces characterised by close physical proximity, repeated interaction, and dependence on teamwork, employees who were infected, quarantined, or perceived as exposed could become highly visible and symbolically associated with disruption or risk. Hierarchical relationships may further influence these dynamics, as supervisors, managers, and peers may differ in how they interpret responsibility, enforce norms, or respond to perceived threats. At the same time, managerial communication, organisational culture, and informal group norms may either reinforce stigma through silence and blame or reduce it through clarity, support, and trust. These mechanisms are especially relevant to network-based analysis because they suggest that workplace stigma may be shaped through both influence processes and patterns of selective interaction. These dynamics also suggest that stigma may cluster within particular departments or work units, vary according to physical or social proximity, and differ between vertical relationships, such as manager-to-worker interactions, and horizontal relationships between peers.

Taken together, the literature shows that workplace stigma during COVID-19 emerged through interacting processes of risk perception, social labelling, and misinformation, which collectively shaped how employees interpreted and responded to one another. Stigma linked to occupational exposure, whether direct, indirect, or presumed, produced adverse mental health outcomes, strained professional relationships, and contributed to environments characterised by fear and mistrust

(Bagcchi, 2020; Ranjit et al., 2023; Schubert et al., 2021). These dynamics are particularly relevant for studies examining workplace networks because patterns of avoidance, exclusion, and selective interaction have the potential to influence relational structures within organisations. Although prior studies have highlighted these relational and organisational mechanisms, they have rarely examined workplace COVID-19 stigma using formal network approaches, leaving important questions about clustering, diffusion, and the role of influential actors within organisational systems insufficiently explored. Understanding how stigma manifests and circulates in workplace settings therefore provides a critical foundation for analysing its transmission through social networks and for identifying network features that may either amplify or mitigate stigma within organisational systems.

2.4 Measurement Tools for COVID-19 Knowledge and Stigma

A considerable number of instruments were developed during the COVID-19 pandemic to assess knowledge and stigma across different populations. These tools were useful in documenting public understanding, behavioural responses, and stigma-related experiences during a rapidly evolving health crisis. However, the existing literature also shows that most instruments were developed for general population surveillance, healthcare settings, educational environments, or patient groups rather than occupational settings. This distinction is important because workplace contexts, particularly factory settings, are shaped by different organisational structures, patterns of interaction, levels of education, and communication needs. Therefore, the suitability of existing COVID-19 instruments for Malaysian factory workers cannot be assumed and requires critical evaluation.

2.4.1 Existing Scales for Measuring COVID-19 Knowledge

Numerous instruments were developed during the COVID-19 pandemic to assess COVID-19 knowledge, frequently as part of broader knowledge, attitude, and practice surveys. These instruments commonly covered core areas such as symptoms, transmission, prevention, and public health control measures. Some also included items on risk groups, vaccination, or misconceptions surrounding infection. Although these domains overlap substantially with the broad content typically required to assess

COVID-19 knowledge, the instruments differed considerably in their target populations, language, depth of psychometric evaluation, and contextual framing. The main characteristics of the identified COVID-19 knowledge instruments are summarised in Table 2.2.

Table 2.2
Summary of Existing Instruments for Measuring COVID-19 Knowledge

Study	Population / Setting	Instrument focus	Psychometric evaluation	Main findings / strengths	Relevance and limitation for the present study
Zhong et al. (2020)	General population, China	General COVID-19 knowledge, attitudes, and practices	Cronbach's alpha reported for knowledge domain (0.71); no further psychometric testing	Brief and widely used early pandemic instrument covering symptoms, transmission, and prevention	Useful for general surveillance but lacks detailed validation and was not designed for workplace or factory settings. It was not developed in Malay, which may limit understandability among Malaysian factory workers, many of whom have lower educational backgrounds, often up to secondary school level only.
Azlan et al. (2020)	General population, Malaysia	General COVID-19 knowledge and practices	Forward and backward translation; no content validation or advanced psychometric analysis	Locally adapted for Malaysian use and suitable for national survey work	Relevant to the Malaysian public context, but still general in nature and not tailored to industrial workers. Although available in Malay, it was developed for the general population rather than factory workers, whose educational background, work demands, and informational needs may differ substantially.
A Rahman et al. (2021)	General population, Malaysia	COVID-19 knowledge, attitudes, and practices	Content validation, face validation, KR-20 for knowledge, Cronbach's alpha for attitude and practice, item difficulty analysis, EFA for attitude and practice	More comprehensive validation than many KAP tools; strong internal consistency	Stronger methodological basis but focused on general preventive behaviour and MCO-related practices rather than workplace-specific knowledge. Although developed in the Malaysian context, it was not specifically designed for factory workers with potentially lower educational attainment.

EFA = exploratory factor analysis, KR-20 = Kuder–Richardson Formula 20, MCO = movement control order

Table 2.2
(Continued…)

Study	Population / Setting	Instrument focus	Psychometric evaluation	Main findings / strengths	Relevance and limitation for the present study
Kumari et al. (2021)	General population, India	COVID-19 vaccination knowledge, attitudes, practices, and concerns	EFA and reliability testing	Methodologically rigorous and grounded in local perceptions	Focused on vaccination rather than broader workplace COVID-19 knowledge, and not directly transferable to Malaysian factory workers. It was also not developed in Malay, which may reduce clarity and accessibility for workers with lower education levels.
Bhagavathula et al. (2020)	Healthcare workers, global sample	COVID-19 knowledge and perceptions	Content validation, face validity, pilot testing	Suitable for assessing clinically relevant knowledge gaps among healthcare workers	Uses medical terminology and clinically oriented content, limiting relevance to factory workers. It was not developed in Malay, and the language and technical complexity may reduce understandability among Malaysian factory workers with secondary-level education.
Richardson & Bélanger (2020)	Health education students	COVID-19 knowledge	Rasch analysis including item difficulty, fit, and person reliability	Strong psychometric refinement and unidimensional measurement	Designed for learners with biomedical backgrounds, so content complexity may not suit industrial workers. It was also not developed in Malay, limiting direct comprehensibility and suitability for the Malaysian factory context.
Patelarou et al. (2020)	Nursing students, Greece	COVID-19 knowledge, attitudes, and behavioural practices	Content validation, pilot testing, EFA, reliability testing	Robust for examining disease-specific knowledge in nursing students	Healthcare-focused and built around educational assumptions not suitable for factory workers. In addition, it was not developed in Malay, which may further limit understanding among workers with lower formal education.

EFA = exploratory factor analysis

Table 2.2
(Continued…)

Study	Population / Setting	Instrument focus	Psychometric evaluation	Main findings / strengths	Relevance and limitation for the present study
Park (2021)	Nursing students, Korea	COVID-19 knowledge, attitudes, and practices	Content validity, pilot testing, EFA, KR-20, Cronbach's alpha	Structured multi-phase development with acceptable reliability for most domains	Clinically oriented and designed for nursing students rather than non-clinical occupational groups. It was not developed in Malay, and this linguistic and contextual mismatch may reduce understandability for Malaysian factory workers.
Saefi et al. (2020)	Undergraduate students, Indonesia	COVID-19 knowledge, attitudes, and practices	Content validity, face validity, CFA, Rasch modelling	Strong methodological rigour with both CFA and Rasch analysis	Developed for university students and assumes higher educational background than factory workers. It was not developed in Malay, which may restrict comprehension among Malaysian factory workers with lower educational attainment.
Sazali et al. (2021)	University students, Malaysia	COVID-19 knowledge, attitudes, and practices	Content validation and pre-testing only	Identified useful educational differences among students	Limited psychometric assessment and academic context reduce applicability to occupational settings. Although conducted in Malaysia, it was designed for university students and may not be sufficiently accessible or relevant to factory workers with lower education levels.
Wesonga et al. (2024)	University students, Oman	COVID-19 knowledge and attitudes	IRT using Rasch and 2-PL models	Demonstrated usefulness of IRT for item discrimination and difficulty	Developed for student populations and included several very easy items, reducing suitability for industrial workers. It was not developed in Malay, which may further limit its understandability and appropriateness for Malaysian factory workers.

EFA = exploratory factor analysis, KR-20 = Kuder–Richardson Formula 20, IRT = item response theory, 2-PL = 2-parameter logistic

As shown in Table 2.2, early COVID-19 knowledge instruments were largely developed to support rapid public health surveillance. General-population tools, such as those reported by Zhong et al. (2020) and Azlan et al. (2020), focused mainly on symptoms, routes of transmission, and preventive practices. These instruments were useful in capturing broad public understanding during the early phase of the pandemic, but their psychometric evaluation was generally limited. In most cases, knowledge was treated as a practical public health construct to be described rather than as a measurement domain requiring detailed validation. As a result, while these tools were informative for monitoring awareness at population level, they were less suitable for determining whether items functioned appropriately in more specific groups.

Later studies introduced more rigorous methods. For instance, A Rahman et al. (2021) incorporated content and face validation, whereas other researchers, such as Richardson & Bélanger (2020) and Wesonga et al. (2024), applied Rasch analysis or item response theory to examine item performance in greater depth. These studies showed that COVID-19 knowledge can be evaluated psychometrically rather than only descriptively. However, the populations involved remained important. Instruments developed for healthcare workers or students were shaped by the language, educational background, and information environments of those groups. Consequently, although their methods were stronger, their content presentation and assumptions about comprehension may not translate well to factory workers.

A further pattern emerging from the literature is that many instruments assessed knowledge in relatively general terms. Common domains included recognition of symptoms, understanding of transmission, and knowledge of preventive behaviours. These areas are also relevant in workplace settings. However, the way knowledge is framed matters. In factory environments, knowledge is not only about recognising disease characteristics, but also about understanding how infection may spread through everyday interactions at work, how workplace preventive measures operate, and how misconceptions about asymptomatic infection, vaccination, and reinfection may influence behaviour toward colleagues. Instruments developed for community or academic settings may cover similar topics, yet still fail to reflect the practical and interpersonal realities through which such knowledge is interpreted in workplaces.

Language and educational suitability also represent important concerns. Many of the reviewed instruments were developed in non-Malay languages, while several others were designed for populations with relatively high literacy or formal education, such as university students, nursing students, or healthcare personnel. This is relevant because many factory workers in Malaysia may have educational attainment up to secondary school level only. Even where a tool has acceptable content coverage, its wording and response demands may not be equally understandable across populations. Therefore, contextual and linguistic appropriateness are critical considerations alongside content relevance.

Knowledge is also conceptually relevant to stigma, even though the two constructs are distinct. In the COVID-19 context, inaccurate or incomplete knowledge may contribute to fear, blame, and avoidance, while clearer understanding of transmission, prevention, and recovery may help reduce unwarranted judgement towards affected individuals. At the same time, knowledge is not always purely factual, as beliefs about infection risk and responsibility may also be shaped by social communication, public narratives, and misinformation. Thus, reviewing knowledge instruments alongside stigma measures is theoretically justified, provided that knowledge is treated as a related but separate domain rather than as part of the stigma construct itself.

Overall, the literature indicates that existing COVID-19 knowledge instruments were useful in establishing the main domains of knowledge relevant to the pandemic, particularly symptoms, transmission, prevention, and selected misconceptions. However, important limitations remain in relation to population specificity, language, literacy demands, and workplace relevance. Thus, the gap in the literature is not the absence of COVID-19 knowledge measures per se, but the limited availability of instruments that are linguistically appropriate, educationally accessible, and contextually suitable for factory workers in Malaysia.

2.4.2 Existing Scales for Measuring COVID-19 Stigma

COVID-19 stigma was measured using a range of instruments developed across different settings during the pandemic. These instruments reflected the broad social consequences of COVID-19 and were used to assess stigma among the general public, individuals who had experienced infection, survivors with long-term consequences, and healthcare workers. The main characteristics of the identified COVID-19 stigma instruments are summarised in Table 2.3.

Table 2.3
Summary of Existing Instruments for Measuring COVID-19 Stigma

Study	Questionnaire / Instrument name	Population / Setting	Instrument focus	Psychometric evaluation	Main findings / strengths	Relevance and limitation for the present study
Nochaiwong et al. (2021)	COVID-19 Public Stigma Scale (COVID-PSS)	General population, Thailand	Public stigma toward COVID-19	Literature review, interviews, expert review, pilot testing, EFA, CFA, Cronbach's alpha, ICC, convergent and discriminant validity, IRT	One of the most rigorous COVID-19 stigma scales; identified stereotype, prejudice, and fear domains	Strong conceptual and psychometric basis but developed for the general population and not for workplace-specific stigma processes. It was not developed in Malay, which may limit understandability among Malaysian factory workers with lower educational backgrounds.
Pallavi et al. (2023)	COVID-19 Stigma Scale-Modified (CSS-M)	General population, India	Adapted COVID-19 stigma based on HIV stigma scale	Correlation analysis, Cronbach's alpha, EFA, parallel analysis, convergent and discriminant validity	Acceptable reliability and useful for measuring public stigma	Adapted from HIV stigma, with conceptual mismatch for COVID-19, and not designed for occupational or organisational settings. It was also not developed in Malay, which may reduce accessibility and understanding among Malaysian factory workers.
Geniş & Yıldız (2024)	COVID-19 Stigma Scale (CSS)	General population, Türkiye	Attitudes toward people who had COVID-19	Expert review, pilot testing, EFA, internal consistency testing	Strong reliability and coherent three-factor structure	Focuses on general public attitudes and does not assess stigma within workplace relational structures. It was not developed in Malay, which may further limit its use among Malaysian factory workers with lower educational attainment.

EFA = exploratory factor analysis, CFA = confirmatory factor analysis, ICC = intraclass correlation, IRT = item response theory

Table 2.3
(Continued…)

Study	Questionnaire / Instrument name	Population / Setting	Instrument focus	Psychometric evaluation	Main findings / strengths	Relevance and limitation for the present study
Bonetto et al. (2022)	COVID-19 Experienced Discrimination Scale (CEDISC) and COVID-19 Internalised Stigma Scale (COINS)	COVID-19 patients and survivors, Italy	Experienced discrimination and internalised stigma	Qualitative development, expert consultation, pilot testing, EFA, Cronbach's alpha, ICC	Psychometrically robust patient-centred tools with strong reliability	Focuses on illness experiences in family and social contexts rather than workplace networks or organisational dynamics. It was not developed in Malay and may not be easily understood by general factory workers in Malaysia.
Elgohari et al. (2021)	COVID-19 Infection Stigma Scale (CISS)	Recovered COVID-19 patients, Egypt	Perceived COVID-19 infection stigma	Theory-based item generation, expert review, pilot testing, Cronbach's alpha, ICC	Captured culturally relevant stigma dimensions such as disclosure fear and social rejection	Measures patient-perceived stigma rather than relational stigma processes in workplaces. It was not developed in Malay, limiting direct applicability and understandability in the Malaysian factory setting.
Mlouki et al. (2022)	Modified HIV Stigma Scale for COVID-19	Recovered COVID-19 patients, Tunisia	Modified HIV stigma scale for COVID-19	Translation and cultural adaptation, expert review, patient interviews, EFA, Cronbach's alpha	Excellent reliability and strong adaptation process	Based on HIV stigma framework and focused on personal experiences, not peer influence or organisational structures. It was not developed in Malay, which may limit comprehension among factory workers with lower education levels.

EFA = exploratory factor analysis, ICC = intraclass correlation, IRT = item response theory

Table 2.3
(Continued…)

Study	Questionnaire / Instrument name	Population / Setting	Instrument focus	Psychometric evaluation	Main findings / strengths	Relevance and limitation for the present study
Damant et al. (2023)	Post COVID-19 Condition Stigma Questionnaire (PCCSQ)	Long COVID patients, Canada	Stigma related to post COVID-19 condition	Patient-informed development, expert review, preliminary testing, factor validation, Cronbach's alpha, ICC	Comprehensive multidimensional instrument with excellent reliability	Focused on long COVID experiences rather than workplace stigma among active workers. It was not developed in Malay and may not be sufficiently understandable or culturally appropriate for Malaysian factory workers.
Rahmani et al. (2023)	COVID-19 Stigma Scale	Nurses, Iran	COVID-19 stigma in nursing staff	Qualitative interviews, face and content validation, EFA, Cronbach's alpha	Contextually grounded in nurses' experiences	Specific to clinical roles and hospital environment, limiting industrial applicability. It was also not developed in Malay, and the language and context may not suit factory workers in Malaysia.
Mostafa et al. (2021)	E16-COVID19-S	Physicians / HCWs, Egypt	COVID-19 stigma among healthcare workers	EFA, CFA, Cronbach's alpha, model fit indices	Strong model fit and high reliability	Focused on stigma linked to healthcare roles, not workplace stigma in factories. It was not developed in Malay, which may further reduce its understandability for Malaysian factory workers.

EFA = exploratory factor analysis, CFA = confirmatory factor analysis, ICC = intraclass correlation, IRT = item response theory

Table 2.3
(Continued…)

Study	Questionnaire / Instrument name	Population / Setting	Instrument focus	Psychometric evaluation	Main findings / strengths	Relevance and limitation for the present study
Al Houri et al. (2022)	COVISS-HCWs Scale	Healthcare workers, Syria	COVID-19 stigma experienced by HCWs	Expert review, EFA, CFA, Cronbach's alpha	Strong psychometric support for HCW setting	Assesses being stigmatised as HCWs rather than stigma attitudes and dynamics among factory workers. It was not developed in Malay and is not readily suitable for workers with lower educational backgrounds in Malaysia.
Nashwan et al. (2021)	S19-HCPs Scale	Healthcare providers	Stigma toward healthcare providers caring for COVID-19 patients	Internal consistency and test-retest reliability in English and Arabic versions	Useful bilingual tool with stable measurement	Specific to frontline healthcare experience and not designed for non-clinical workplace environments. It was not available in Malay, which may limit understandability among Malaysian factory workers.

EFA = exploratory factor analysis, CFA = confirmatory factor analysis

As shown in Table 2.3, one important group of instruments focused on public stigma, particularly negative attitudes toward individuals associated with COVID-19. Within this group, the COVID-19 Public Stigma Scale (COVID-PSS) developed by Nochaiwong et al. (2021) is especially important because it demonstrated strong psychometric development and identified stereotype, prejudice, and fear as key dimensions of COVID-19 stigma. These domains are useful in understanding stigma as a multidimensional construct and provide an important conceptual basis for subsequent stigma research. Other general-population scales, such as those by Pallavi et al. (2023) and Geniş & Yıldız (2024), similarly examined negative public responses toward infected or recovered individuals. However, these instruments were primarily designed to assess stigma at community level rather than within workplace relationships. Their focus was largely on public attitudes, discomfort, discrimination, or anticipated stigma, rather than on how stigma may be expressed through everyday coworker judgements and organisational interactions.

A second group of instruments examined stigma among patients, survivors, and individuals with long COVID. These scales made an important contribution by showing that COVID-19 stigma can involve experienced discrimination, internalised stigma, fear of disclosure, and altered social identity. Such findings are valuable for understanding the psychosocial consequences of infection. However, these instruments addressed stigma mainly as something experienced by affected individuals in family, community, or healthcare settings. They were therefore conceptually different from instruments intended to assess stigma attitudes held by others in a workplace. In addition, several of these tools were adapted from HIV stigma frameworks. Although such adaptation provided a useful starting point, some inherited domains may not fully reflect the social meanings of COVID-19 stigma, particularly in occupational contexts where judgements may centre more on perceived carelessness, non-compliance, or burden to others than on disclosure or identity-based stigma (Bonetto et al., 2022; Damant et al., 2023; Elgohari et al., 2021; Mlouki et al., 2022).

A third group of instruments focused on healthcare workers, who were often stigmatised because of their perceived exposure to COVID-19. These scales captured rejection, blame, anxiety, and negative treatment directed at frontline staff. Several also demonstrated acceptable to strong psychometric properties. Nevertheless, their relevance to industrial settings is limited because they were developed in clinical environments where stigma was closely linked to patient care, infection risk, and professional roles in health services. In contrast, workplace stigma in factory settings is more likely to arise through peer judgement, assumptions about responsibility, concerns about disruption to work, and perceptions that infected workers place burdens on colleagues or the organisation. These dynamics are not fully captured by instruments developed for healthcare settings (Al Houri et al., 2022; Mostafa et al., 2021; Nashwan et al., 2021; Rahmani et al., 2023).

Another important issue concerns language and contextual suitability. Most of the reviewed stigma instruments were developed in non-Malay languages and in cultural settings that differ from the Malaysian industrial context. This is particularly relevant when measuring workplace attitudes among factory workers, many of whom may have educational attainment up to secondary school level only. In such populations, clarity of wording and contextual familiarity are important not only for comprehension, but also for ensuring that items accurately reflect how stigma is understood and expressed in everyday workplace life. Thus, even where existing scales demonstrate good psychometric performance, they may not be directly suitable without cultural adaptation, linguistic revision, and contextual re-evaluation (Damant et al., 2023; Elgohari et al., 2021; Nochaiwong et al., 2021; Rahmani et al., 2023).

More specifically, the limitations of existing COVID-19 stigma scales appear to operate at three levels. First, there is a contextual limitation, as most instruments were developed for community, clinical, or survivor settings rather than workplace environments. Second, there is a conceptual limitation, because many scales assess either public stigma or experienced stigma, but do not focus on workplace-based attitudinal stigma directed towards coworkers. Third, there is a relational limitation, as existing tools are largely designed for individual-level assessment and do not incorporate structural or network-oriented features through which stigma may be reinforced within organisational settings. These limitations are important in understanding why workplace stigma may not be adequately captured by existing measures alone (Bonetto et al., 2022; Mostafa et al., 2021; Nochaiwong et al., 2021; Pallavi et al., 2023).

Overall, the literature shows that COVID-19 stigma has been measured in multiple ways and across diverse populations. Existing instruments have been especially useful in identifying stigma as a multidimensional construct involving stereotype, prejudice, fear, discrimination, and internalised stigma. However, relatively limited attention has been given to stigma as a workplace-based attitudinal process, particularly one shaped by coworker judgement, perceived rule-breaking, and beliefs that infected individuals create burdens for colleagues or the company. Therefore, the main gap in the literature is not the absence of stigma measures, but the limited availability of instruments that are linguistically appropriate, contextually grounded, and specifically suited to assessing workplace COVID-19 stigma among Malaysian industrial workers.

2.5 Social Network Analysis (SNA) and Stigma Studies

SNA is increasingly utilised in public health research to explore the ways in which social structures influence health behaviours, disease patterns, and psychosocial outcomes. In stigma research, SNA aligns closely with established sociological theories by emphasising that stigma emerges and operates through social interactions rather than through individual attributes alone. Goffman (1963) conceptualised stigma as a socially constructed process rooted in everyday interactions that define who is discredited or discreditable. Similarly, Link and Phelan (2001) highlighted the role of labelling, separation, and power within networks of relationships. Parker and Aggleton (2003) further argued that stigma is embedded within broader social structures and reproduced through patterned social relations. SNA provides methodological tools to examine these relational mechanisms by identifying influential actors, mapping communication pathways, and assessing structural features that facilitate or constrain stigma. In the context of communicable diseases, including COVID-19, SNA extends beyond tracing transmission to uncover how social ties can reinforce or reduce stigma, making it a valuable approach for understanding workplace dynamics and informing targeted interventions.

2.5.1 Overview of Social Network Analysis (SNA)

SNA is based on the idea that understanding social phenomena requires examining how individuals are connected to one another rather than focusing solely on their personal characteristics. Originating from the sociometric work of Moreno (1934), SNA conceptualises social life as a system of interconnected actors whose ties form identifiable structures. These structures influence how resources, information, and behaviours flow within a community, and they shape the positions individuals occupy relative to one another. The analytical foundations of SNA were formalised through the mathematical and graph theoretic contributions of Wasserman and Faust (1994), whose work established the conceptual and statistical tools for analysing relational data. In the context of this thesis, SNA is not used only as a descriptive mapping tool, but as a theoretical framework for examining how stigma may be shaped by patterns of social connection, influence, and structural position. This study draws particularly on the structural view that individuals' attitudes and behaviours are partly conditioned by their embeddedness within networks, and on the diffusion perspective that information, norms, and stigma-related perceptions may circulate through repeated interaction. From this perspective, centrality is relevant not merely as a positional feature, but as a potential indicator of visibility, connectedness, and influence within the workplace. Similarly, density, clustering, and homophily are important because they may shape the extent to which stigma-related attitudes are reinforced, shared, or contained within particular groups.

The strength of SNA lies in its capacity to quantify structural characteristics of a network. Metrics such as degree, betweenness, closeness, and eigenvector centrality capture different dimensions of connectivity and potential influence within a network (Borgatti et al., 2009). Degree reflects the number of direct ties an actor holds, whereas betweenness identifies actors who bridge otherwise disconnected groups and therefore exert control over information flow. Closeness centrality reflects how quickly an actor can access others in the network, and eigenvector centrality highlights actors who are connected to others who are themselves influential. Network-level measures such as density, clustering coefficients, modularity, and average path length describe overall cohesion, subgroup formation, and the efficiency of communication within the network (Borgatti et al., 2009). These metrics allow researchers to detect structural vulnerabilities, cohesive clusters, or positions of strategic importance.

SNA also distinguishes between two major analytical perspectives: the sociocentric and the egocentric approach. Sociocentric (whole network) analysis examines all relational ties within a defined boundary, enabling the identification of structures, influential actors, hierarchical patterns, and cohesive subgroups (Wasserman & Faust, 1994). This approach is particularly useful in formal organisations or geographically bounded communities where complete network data can be obtained. Egocentric network (personal network) analysis focuses on an individual (ego) and the individuals to whom they are directly connected (alters), capturing the composition, diversity, and influence of personal social environments. Egocentric data are typically collected through name generator and name interpreter questions, where respondents identify individuals with whom they have meaningful interactions and provide information on the characteristics of these alters (Valente, 2010). Rice and colleagues (2012) highlight that egocentric designs are particularly valuable in public health research because they reveal how relational contexts shape behaviour, perceptions, and social norms. Takada and colleagues (2019) further demonstrate that egos' attitudes and beliefs often correspond with those of their alters, underscoring the importance of immediate social surroundings even in the absence of complete network data.

Another important component of SNA is the analysis of tie characteristics. Ties may represent different forms of relationships, such as communication, friendship, advice, kinship, or workplace collaboration. Granovetter's seminal work on the strength of weak ties (1973) demonstrated that ties vary in their capacity to transmit information or influence, with weak ties serving as crucial bridges across social groups and strong ties providing emotional support and cohesion. SNA allows these relational differences to be operationalised, quantified, and linked to behavioural outcomes. This flexibility makes SNA suitable for studying diverse social settings, ranging from informal personal networks to highly structured organisational environments.

Beyond descriptive metrics, SNA incorporates inferential analytical techniques designed to account for interdependence in relational data. Methods such as the Exponential Random Graph Model (ERGM) estimate the probability of network configurations based on structural tendencies or attribute-based homophily (Robins et al., 2007). The Quadratic Assignment Procedure (QAP) and Multiple Regression QAP (MR-QAP) address autocorrelation in network data by permuting relational matrices, enabling robust assessment of associations between network structures and covariates (Krackhardt, 1988). In addition to these network-specific approaches, traditional statistical methods can be adapted for network data. Multiple logistic regression (MLogR) can be applied to examine individual-level outcomes while incorporating network-derived predictors, such as centrality or alter characteristics, allowing researchers to quantify how positional attributes or local neighbourhoods influence behavioural or psychosocial phenomena (Valente, 2010). Multilevel modelling (MLM) is also increasingly used in network research to account for hierarchical or nested structures, such as alters nested within egos or employees nested within workplace networks. MLM accommodates clustering and non-independence, enabling simultaneous estimation of individual, relational, and structural effects within social networks (Snijders & Bosker, 2012).

Taken together, SNA provides a framework for examining how relational structures shape behavioural and social processes. By mapping the distribution of ties, identifying influential actors, and analysing structural configurations, SNA offers a systematic way to understand how social environments operate. The integration of sociocentric and egocentric perspectives, combined with descriptive and inferential techniques such as ERGM, MR-QAP, MLogR, and MLM, enables a comprehensive analysis of social systems. This analytical versatility makes SNA suitable for examining relational processes in various settings, including structured environments such as workplaces, where network configurations can meaningfully influence attitudes, behaviours, stigma-related perceptions, and collective outcomes.

2.5.2 SNA in Communicable Diseases: From Spread to Stigma

SNA has been used in several communicable disease studies to map how infections move through social contacts. The same relational approach has also been applied to examine how stigma develops and spreads within affected groups. Although SNA has often been used to trace the spread of infectious disease, its value in stigma research lies in its ability to map the relational context in which attitudes are shared and reinforced. Stigma does not spread biologically, but socially, through interaction, communication, observation, and norm formation. Employees may adopt or resist stigma-related attitudes based on whom they interact with, whose opinions carry influence, and how tightly connected particular groups are. In this way, SNA provides a framework for examining whether stigma clusters among socially connected individuals, whether influential actors reinforce or reduce stigma, and whether homophily and network position contribute to the maintenance of stigmatising beliefs. These insights are relevant for targeted intervention because they help identify which groups, ties, or actors may be most important in disrupting stigma within workplace settings. This perspective draws particularly on the ideas of homophily, social influence, and norm reinforcement, which help explain why stigma-related attitudes may become concentrated within some parts of a network while being challenged or reduced in others.

During the COVID-19 pandemic, several studies used SNA to identify individuals or locations that played a major role in sustaining transmission. Although the spread of infection differs from the spread of stigma, both processes are shaped by patterns of contact, centrality, and relational structure. In Karnataka, India, Saraswathi and colleagues (2020) analysed contact tracing data and showed that a small number of cases acted as superspreaders because they held highly central positions in the network. These individuals had many direct contacts and served as bridges between different groups, which allowed the virus to spread more widely. Similarly, Nagarajan and colleagues (2020) applied SNA to visualise transmission patterns and identify important clusters and key nodes. Their findings demonstrated that SNA could uncover connections that may not be visible in standard epidemiological data. These studies illustrate how patterns of contact, rather than individual characteristics alone, shape the spread of infection.

Beyond disease transmission, SNA has also been useful in understanding stigma in communicable disease settings. Studies of HIV, for example, show how stigma affects network position and patterns of interaction. In Namibia, Smith and Baker (2012) examined community group participation among rural residents and found that perceptions of stigma were closely related to individuals' structural positions in the community network. Individuals who perceived high levels of HIV stigma, especially when combined with higher perceived personal risk, tended to occupy more peripheral positions. Linear regression analyses showed that the interaction between perceived risk and perceived stigma was strongly associated with reduced centrality across several measures, including degree ($B = -0.21$, $p < 0.05$), betweenness ($B = -0.20$, $p < 0.05$), and eigenvector centrality ($B = -0.19$, $p < 0.05$). These individuals also participated in fewer community groups, reflected by a significant negative association with group involvement ($B = -0.26$, $p < 0.01$). In contrast, people who perceived higher HIV risk but lower stigma were more active in their networks and held more central roles, giving them greater influence and access to support. These findings indicate that stigma can shape both network structure and individual participation in community life, with higher stigma leading to social withdrawal and reduced integration.

Egocentric and sociocentric research both show that stigma is influenced by social relationships. In rural Uganda, Takada and colleagues (2019) conducted a population-based sociocentric network study and found that an individual's HIV stigma was strongly associated with the stigma levels of their social contacts. Linear network autocorrelation models (LNAM) showed that egos' stigma scores increased when their alters' average stigma score was higher (B = 0.53, 95% CI = 0.42, 0.63). The study also found that egos who had one or more HIV-positive alters reported slightly lower levels of stigma (B = -0.05, 95% CI = -0.10, -0.003). This pattern is consistent with the contact hypothesis, where interpersonal contact with people living with HIV may reduce negative attitudes. These findings indicate that stigma is shaped by the attitudes and characteristics of people within one's social environment, showing that stigma operates as a relational and shared social process rather than an isolated individual belief.

Taken together, these studies demonstrate that SNA offers important insights into how communicable diseases and related forms of stigma emerge within social structures. Evidence from COVID-19 and HIV research shows that patterns of connection influence who becomes central, who becomes marginalised, and how negative attitudes circulate through social ties. These findings highlight that stigma is shaped not only by individual beliefs but also by the relational environment in which people are embedded. Egocentric network analysis is particularly useful when the aim is to examine how an individual's immediate social environment relates to attitudes or behaviours. It allows the researcher to assess the composition and influence of nominated social ties, even when a full network cannot be directly observed. In stigma research, this approach is especially relevant because perceptions may be shaped by the characteristics of alters and the nature of their relationship to the ego. Logistic regression is appropriate when the outcome is binary, while multilevel logistic regression is particularly suitable when alter-level observations are nested within egos. Nevertheless, egocentric analysis has recognised limitations, including dependence on respondent recall, nomination boundaries, and a limited ability to capture the broader sociocentric structure in which individuals are embedded.

2.5.3 Communication, Influencers, and the Role of Centrality

Communication processes within social networks play an important role in shaping how stigma emerges and circulates during public health crises. Social media platforms such as Twitter act as highly interactive environments where users generate, share, and amplify messages that may contain stigma cues. In their analysis of COVID-19 related Twitter (now known as X) content, Kumble and Diddi (2021) found that 37.6% of tweets in their dataset included at least one stigma cue. Their network analysis showed that stigma-related messages were not evenly distributed. Instead, they were circulated through identifiable network structures involving both influential and ordinary users. Influencers and laypersons posted a considerable share of tweets containing stigma cues, while media organisations and health agencies, despite being structurally central in the network, mainly disseminated informational content rather than stigma-related messages.

Centrality measures from Kumble and Diddi's analysis help explain how certain actors shape the flow of stigma online. Accounts such as major media outlets and the World Health Organization (WHO) held strong in-degree and betweenness centrality positions, allowing them to function as hubs for receiving information and as bridges between otherwise disconnected groups. Although influencers produced fewer original tweets compared to organisational accounts, their messages often gained high visibility because of their large follower networks and high engagement levels. This structural prominence gives influencers substantial capacity to amplify stigma cues or, conversely, to challenge them if they choose to communicate corrective or empathetic messages. Importantly, centrality should not be interpreted as automatically equivalent to positive or negative influence. Rather, central actors occupy positions that give them greater visibility, reach, and potential to shape communication flows. Whether such actors reinforce stigma or reduce it depends on the content they share, the credibility they hold within the network, and the extent to which their messages are repeated and endorsed by others. In this sense, centrality is best understood as a structural condition that may facilitate influence, rather than as influence itself.

Emotional expression also plays a role in how messages spread across online networks. Tsao and colleagues (2021) reported that COVID-19 discussions on social media commonly contained emotions such as fear, anxiety, and anger, and that posts eliciting strong emotional responses tended to receive greater engagement. This dynamic increases the likelihood that stigma-related content will circulate widely, especially when shared by central actors with large audiences. At the same time, central accounts that actively promote accurate, supportive, or inclusive messaging can use their structural advantages to counteract harmful narratives.

Health organisations occupy a particularly important position in this communication landscape. Kumble and Diddi (2021) observed that WHO and its leadership were among the most central nodes in the COVID-19 information network, regularly posting content aimed at reducing misinformation and discouraging discriminatory attitudes. Bavel and colleagues (2020) similarly emphasised that effective communication during pandemics relies on timely, credible, and clear messaging to reduce fear and uncertainty, both of which can fuel stigma.

Although much of this evidence comes from digital communication networks, similar principles are relevant to organisational settings, where highly connected or respected actors may shape local norms, reinforce blame, or help reduce fear through everyday interaction.

Overall, these studies show that the spread of stigma in online environments is shaped not only by message content but also by the network positions of the individuals and organisations disseminating those messages. Central actors, including influencers and public health agencies, act as key gatekeepers whose communication may either reinforce stigma or promote more accurate, supportive, and stigma-reducing narratives.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

This section is presented according to the research phases. The study is divided into two phases. Phase 1 involved the development and validation of the research instrument, which was to be used in Phase 2. Figure 3.1 provides a summary of the phases involved.

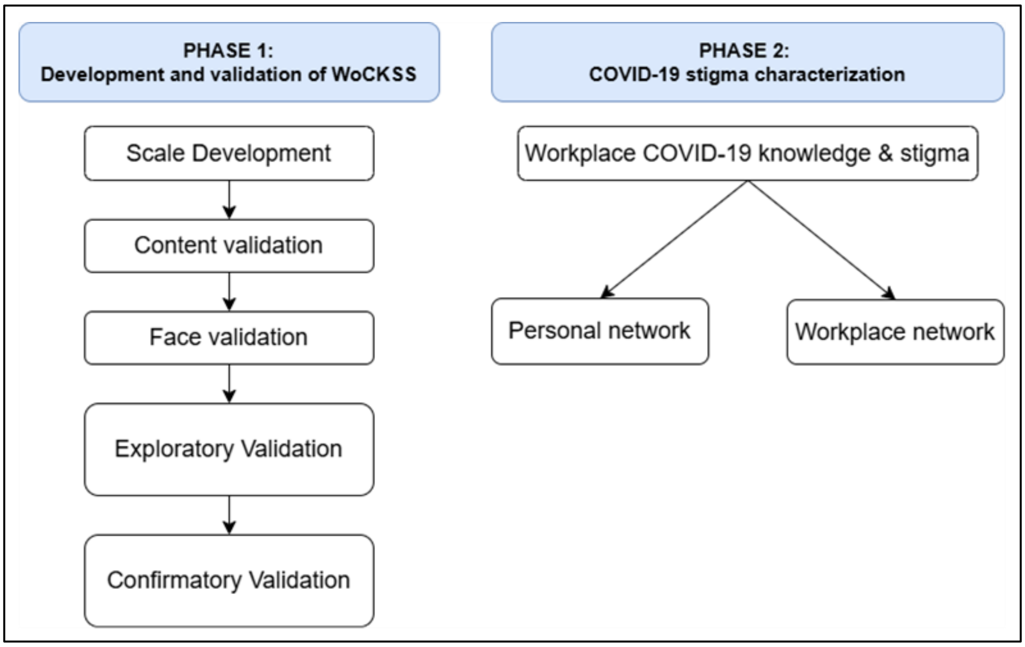

Figure 3.1 Summary of Phases Involved

In Phase 1, the study began with the development of the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS). Phase 1 aimed to address Objective 1 of the study. Following the scale development, data collection for validation testing was conducted in several cycles:

1. Content validation by experts.
2. Face validation with target respondents.
3. Exploratory validation: Item response theory (IRT) analysis of the knowledge domain and construct validation and reliability testing for the stigma domain.

4. Confirmatory validation: IRT analysis of the knowledge domain and construct validation and reliability testing for the stigma domain.

Upon completion of Phase 1, the research proceeded to Phase 2, which aimed to answer objective 2 and objective 3 of the study. This phase characterises workplace COVID-19 stigma among factory workers and the role of social networks, including workers' personal network (egocentric) and workplace networks (sociocentric). Phase 2 utilised the instrument validated during Phase 1. Although the study was guided by an integrated conceptual framework, the analyses were conducted in separate but complementary stages because the egocentric and sociocentric perspectives addressed different levels of inquiry and required different statistical approaches.

3.2 Phase 1: Development and Validation of Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS)

The WoCKSS was developed in two (2) domains: knowledge, and stigma; with 20 and 31 items, respectively. The items were developed in the Malay language after conducting a qualitative review of the literature on COVID-19 knowledge and stigma. The literature search included sources from Scopus, Web of Science (WOS), and Google Scholar, aimed at exploring relevant literature. The search terms included "COVID-19", “knowledge”, "stigma", "questionnaire", "development", and "validation". No specific inclusion and exclusion criteria were applied as the intent was to explore the availability of questionnaires related to COVID-19 knowledge and stigma in the workplace, with a particular focus on the manufacturing industry.

The stigma domain was developed based on three constructs, namely ‘stereotype’, ‘prejudice’, and ‘fear’ referring to COVID-PSS by Nochaiwong et al. (2021). These constructs were selected because they represented attitudinal dimensions of stigma considered most relevant to workplace COVID-19 stigma, particularly negative beliefs, prejudicial judgements, and fear-based responses towards workers associated with infection. The scale was designed to be self-administered, allowing respondents to complete it independently without the need for assistance. Item wording was framed to reflect workplace-related situations and worker interactions in order to improve contextual relevance for manufacturing employees.

In this thesis, the terms exploratory and confirmatory refer to two stages of psychometric evaluation rather than distinct forms of validity in themselves. The exploratory stage was used to assess the initial performance and structure of the items, including item behaviour and dimensionality, while the confirmatory stage was used to reassess the retained items and evaluate the stability of the measurement structure in an independent sample. This two-stage approach was applied differently across the two domains according to item format and analytical suitability. Specifically, the knowledge domain consisted of dichotomous right-or-wrong items, making it suitable for 2-PL IRT analysis of item difficulty and discrimination, whereas the stigma domain comprised Likert-type attitudinal items more appropriately analysed using factor-analytic methods.

3.2.1 Content Validation

To ensure the validity of the WoCKSS, a content validity process was first conducted. Content validity refers to the degree to which the elements of an assessment instrument are relevant to and representative of the targeted construct for a specific assessment purpose (Haynes et al., 1995; Yusoff, 2017). Establishing content validity is crucial for supporting the overall validity of the assessment tool. In this study, content validity was quantified using the Content Validity Index (CVI).

3.2.1.1 The Experts

To ensure the content validity of the workplace COVID-19 knowledge and stigma scale, a thorough content validation process was conducted. The selection of experts for this process was carried out with careful consideration. A panel of four experts was carefully selected based on their diverse qualifications and expertise in relevant domains. The panel comprised experts with backgrounds in public health, including epidemiology and biostatistics, and family and community health. Additionally, a microbiologist and a primary care medicine expert enriched the multidisciplinary composition of the panel. The number of experts involved in content validation was based on published methodological recommendations for CVI assessment rather than statistical power calculation (Yusoff, 2019a).

3.2.1.2 Data Collection

Prior to conducting the content validation, a content validation form was prepared, which consisted of a list of items and a rating scale. The form was designed to assess the relevancy of each item in the scale to the intended construct, namely workplace COVID-19 knowledge and stigma. The rating scale ranged from 1 to 4, with 1 being not relevant and 4 being highly relevant. The experts were informed about the purpose of the scale and the content validation process. They were asked to review the domain and items and provide comments on their relevance, clarity, simplicity, and ambiguity. Each expert provided a score on each item based on their relevancy to the intended construct.

3.2.1.3 Analysis

The Content Validity Index (CVI) was calculated for each item using Microsoft Excel. The CVI is a widely used method to assess the content validity of a scale (Yusoff, 2019a). Item Content Validity Index (I-CVI) was calculated by dividing the number of experts who rated an item as 3 or 4 by the total number of experts. For Universal Agreement (UA), a score of '1' is assigned to the item that achieved 100% agreement among experts, while '0' is assigned to items that did not achieve 100% expert agreement. The mean I-CVI was also calculated by taking the sum of the Item Content Validity Index (I-CVI) scores for all items and dividing by the total number of items. The I-CVI is the proportion of experts who rated an item as relevant.

The Scale-level Content Validity Index/Unweighted Average (S-CVI/UA) and Scale-level Content Validity Index/Average (S-CVI/AVE) were also calculated for both domains. The S-CVI/UA represents the proportion of items that achieved a CVI of 1.0, while the S-CVI/AVE represents the average CVI across all items. The S-CVI/UA was calculated by dividing the number of items rated as "relevant" by all experts by the total number of items. The S-CVI/AVE was calculated by summing all the I-CVIs of the items that were rated as "relevant" and dividing by the total number of items. Finally, the Proportion Relevance was calculated for each expert as the proportion of items rated as relevant out of the total number of items. This provides an indication of the proportion of items in the scale that are relevant to the construct being measured. These calculations were performed to ensure that the scale had adequate content validity. Items with a CVI

< 1 were considered problematic and were discarded (Polit et al., 2007; Polit & Beck, 2006; Yusoff, 2019a). Calculations involved for face validity are summarised in Table 3.1.

Table 3.1
Calculations for Content Validity

Analysis	Calculation
I-CVI	$\frac{Number\ of\ experts\ rating\ item\ 3\ or\ 4}{Total\ number\ of\ experts}$
Mean I-CVI	$\frac{Sum\ of\ all\ I-CVI\ scores}{Total\ number\ of\ items}$
S-CVI/UA	$\frac{Number\ of\ items\ with\ I-CVI\ =\ 1}{Total\ number\ of\ items}$
S-CVI/AVE	$\frac{Sum\ of\ I-CVIs\ for\ all\ items}{Total\ number\ of\ items}$
Proportion Relevance	$\frac{Number\ of\ items\ rated\ relevant\ by\ expert}{Total\ number\ of\ items}$

3.2.2 Face Validation

To further ensure the validity of the workplace COVID-19 knowledge and stigma scale, a face validation process was conducted. This process aimed to assess the clarity and comprehension of the scale items, ensuring that respondents interpreted them consistently with the developers' intentions (Streiner et al., 2015).

3.2.2.1 Study Design, Sampling Method & Sample Size

A cross-sectional study design was employed. Due to logistical constraints, a multistage random sampling technique was used to select one company (a paper manufacturer) from a list provided by the Selangor Task Force for COVID-19 (STFC) based on those registered under the Preventing Outbreak at Ignition Site (POIS). Then, 10 workers from the selected company were randomly invited to participate in the study. The face-validation sample size was based on methodological recommendations for clarity and comprehensibility assessment rather than inferential sample size estimation (Yusoff, 2019b).

3.2.2.2 Inclusion and Exclusion Criteria

The inclusion criteria for this study were defined as follows:

- The selected company had to be a manufacturing factory.
- Participants needed to be Malaysian workers employed by this company.
- Capable of understanding the Malay language.

The exclusion criteria for this study were defined as follows:

- Workers who were illiterate or unable to read Malay.

Eligibility in relation to Malay literacy was assessed through self-report at the point of participation, as respondents were required to read the study information sheet and complete the questionnaire in Malay.

3.2.2.3 Data Collection

Prior to conducting the face validation, a face validation form was prepared containing only the items retained after content validation. The form was designed for the respondents to rate the clarity and comprehension of each question on a 4-point Likert scale, ranging from 1 (not clear/ comprehensible) to 4 (very clear/ comprehensible). The face validation process was conducted by distributing the face validation form to the selected respondents through their management office. Written consent was obtained from the respondents prior to data collection. The respondents were asked to read each question and rate its clarity and comprehension based on their interpretation. They were also asked to provide comments on any unclear or ambiguous items. After the face validation process was completed, the items were analysed for clarity and comprehension.

3.2.2.4 Analysis

Demographic characteristics were analysed descriptively using IBM SPSS Statistics version 29. Calculations for face validity were executed in Microsoft Excel.

For Universal Agreement (UA), a score of '1' is assigned to the item that achieved 100% agreement among respondents, while '0' is assigned to items that did not achieve 100% agreement. The proportion of respondents who rated each question as clear and comprehensible (scores of 3 or 4) were calculated to determine the Item Face Validity Index (I-FVI) for each question. The I-FVI was calculated by dividing the number of respondents who rated the question as clear and comprehensible by the total number of respondents. The Mean I-FVI was then calculated by taking the average of the I-FVI values for all items (Yusoff, 2019b). The Scale Face Validity Index (S-FVI/UA) was calculated by dividing the number of items that achieved an I-FVI value of 3 or 4 by the total number of items. The S-FVI/UA provides an overall measure of the scale's face validity. Additionally, the Scale-level Face Validity Index/Average (S-FVI/AVE) was calculated by taking the average of the I-FVI values for all items. This provides a more conservative estimate of the scale's face validity since it considers the possibility of chance agreement among respondents.

Finally, the Proportion Relevance was calculated for each respondent as the proportion of items rated as relevant out of the total number of items. This provides an indication of the proportion of items in the scale that are relevant to the construct being measured. The FVI value ranged from 0 to 1, with a score of 1 indicating perfect clarity and comprehensibility. Items with an FVI < 0.83 were discarded, as they were not considered clear and comprehensible (Mohamad Marzuki et al., 2018; Yusoff, 2019b). Item-level decisions during content and face validation were based primarily on the predefined CVI and FVI thresholds, with optional qualitative comments used only as supplementary feedback where available. The final retained items are reported in the Results section. Calculations involved for face validity are summarised in Table 3.2.

Table 3.2
Calculations for Face Validity

Analysis	Calculation
I-FVI	$\frac{Number\ of\ respondents\ rating\ item\ 3\ or\ 4}{Total\ number\ of\ respondents}$
Mean I-FVI	$\frac{Sum\ of\ all\ I-CVI\ scores}{Total\ number\ of\ items}$
S-FVI/UA	$\frac{Number\ of\ items\ with\ I-FVI=1}{Total\ number\ of\ items}$
S-FVI/AVE	$\frac{Sum\ of\ I-FVIs\ for\ all\ items}{Total\ number\ of\ items}$
Proportion Relevance	$\frac{Number\ of\ items\ rated\ relevant\ by\ respondents}{Total\ number\ of\ items}$

3.2.3 Validation Part 1: Exploratory

To further evaluate the validity of the Workplace COVID-19 Knowledge and Stigma Scale, an exploratory validation stage was conducted. This stage aimed to assess the difficulty and discriminative ability of the knowledge domain, as well as the construct validity of the stigma domain. Item Response Theory (IRT) and Exploratory Factor Analysis (EFA) and internal consistency via Cronbach's alpha were utilised at this exploratory validation stage.

IRT was employed to analyse the difficulty and discriminative ability of the knowledge items, item characteristic curves, and test response function, in addition to assessing the fundamental assumption of unidimensionality (Baker, 2001; Bartholomew et al., 2008; Streiner et al., 2015).

Following the IRT analysis, EFA was conducted to explore the dimensionality of the stigma domain by identifying the smallest number of interpretable factors necessary to explain the correlations among the items (Brown, 2014). During EFA, no prior restrictions were placed on the relationships between observed measures and latent variables. Items were freely loaded onto all factors, and the solution was rotated to maximise primary loadings while minimising cross-loadings (Brown, 2015; Hair et al., 2019).

3.2.3.1 Study Design and Sampling Method

A cross-sectional validation study design was employed. A multistage sampling method was used for data collection, which was conducted via Google Forms. Initially, six companies registered under the POIS initiative were randomly selected, excluding the company involved in the face validation stage. The Google Form link was then distributed to all employees via the selected companies' representatives, and responses were collected using convenience sampling.

3.2.3.2 Inclusion and Exclusion Criteria

The inclusion criteria for this study were defined as follows:

- The selected company had to be a manufacturing factory.
- Participants needed to be Malaysian workers employed by this company.
- Capable of understanding the Malay language.

The exclusion criteria for this study were defined as follows:

- Companies that were involved in the face validation stage of the research.
- Individuals who had already participated in the face validation stage.
- Workers who were illiterate or unable to read Malay.

3.2.3.3 Sample Size

The sample size for EFA was determined based on the recommendation by Stevens & Pituch (2016), who suggested a minimum of 5 subjects per item. With 22 items in the stigma domain carried forward from the face validation stage, the minimum required sample size was 110. However, to increase robustness, the sample size was inflated with the goal of achieving 150 respondents, as recommended by Tabachnick & Fidell (2013), Guadagnoli & Velicer (1988), and Kyriazos (2018).

For reliability assessment via internal consistency (Cronbach's alpha), the sample size was calculated based on the following parameters: $\alpha = 0.05$, power = 0.8, number of items = 22, required Cronbach's alpha = 0.7, and reference Cronbach's alpha = 0.5. The minimum sample size required was 66 respondents (Statstodo.com, 2020).

The sample size required for IRT was based on the sample size determined for EFA, as there are no definitive guidelines for IRT sample sizes. However, the general recommendation is to have between 100 and 500 respondents, which is still being fulfilled in this exploratory validation stage (Edelen & Reeve, 2007).

3.2.3.4 Data Collection

The exploratory validation process was conducted by distributing a research poster and the link to the Google Form to the companies' representatives, who then disseminated them among their employees. Upon clicking the link, respondents were first presented with the research information and consent page. If the respondents agreed to participate, they could proceed to the next page to complete the survey. If they did not agree, they could terminate the session. After data collection was completed, the items were analysed for difficulty, discrimination, construct validity, and internal consistency.

3.2.3.5 Analysis

Data analysis was conducted using R (version 4.4.2) within RStudio (version 2024.09). Descriptive analyses were performed for the demographic data.

For the Item Response Theory (IRT) analysis, the '*psych*', '*ltm*', and '*irtoys*' packages were used to run the two-parameter logistic IRT (2-PL IRT) model (Partchev & Maris, 2022; Revelle, 2026; Rizopoulos, 2006). Respondents' answers for the knowledge domain were first classified as correct or incorrect, with correct answers coded as 1 and incorrect answers coded as 0. The difficulty and discrimination parameters were then estimated. Item characteristic curves (ICCs) and the test response function (TRF) were plotted to visualise the data. Additionally, the amount of information provided by the test across the ability range of -3 to +3 was calculated. Item-fit statistics and their associated p-values were calculated, and the goodness-of-fit for two-way margins was assessed, with chi-square residuals greater than 4 indicating poor fit. Items were removed based on their discrimination (acceptable > 0.35), difficulty (acceptable range -3 to +3), and item-fit based on recommendation by Arifin

& Yusoff (2017) and Baker (2001). The assumption of unidimensionality was evaluated via modified parallel analysis to assess whether the observed second eigenvalue is substantially larger than that expected under the fitted IRT model. The purpose of the IRT analysis in Phase 1 was to evaluate item performance and refine the knowledge domain prior to subsequent use of the validated instrument in Phase 2, rather than to derive latent IRT scores for direct integration into the network models.

EFA was conducted using RStudio with the '*psych*', '*GPArotation*', '*ggplot2*', '*tidyverse*', and '*haven*' packages (Bernaards & Jennrich, 2005; Revelle, 2026; Wickham, 2016; Wickham et al., 2019, 2025). The '*haven*' package facilitated the import of the dataset in SPSS format, while the '*tidyverse*' and '*ggplot2*' packages were used for data wrangling and visualising univariate normality. The '*psych*' package was employed for factor analysis and reliability testing, and the '*GPArotation*' package supported oblique rotation. EFA aimed to explore the underlying factor structure of the stigma domain within the WoCKSS.

Prior to conducting EFA, assumptions of univariate and multivariate normality were evaluated. Univariate normality was examined visually using histograms and statistically using the Shapiro-Wilk test. Multivariate normality was tested using Mardia's multivariate skewness and kurtosis tests. The factorability of the dataset was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity.

The initial item pool for the stigma domain was informed by the conceptual dimensions of stereotype, fear, and prejudice, but the EFA was conducted without constraining the factor structure to these domains. The number of factors to extract was determined using multiple criteria, including Kaiser's eigenvalue > 1 rule, Cattell's scree test, parallel analysis, Very Simple Structure (VSS) criterion, and Velicer's Minimum Average Partial (MAP) test. The retained factor solution was subsequently evaluated for conceptual interpretability in relation to the intended stigma constructs. EFA was performed using Principal Axis Factoring (PAF) as the extraction method, which is robust to deviations from normality. Oblique rotation (promax) was applied to allow for correlations among the factors. Items were iteratively removed based on predefined criteria, including low factor loadings (< 0.5), low communalities (< 0.3), cross-loadings, or high factor correlations ($r > 0.85$). Cross-loading items were treated as potentially ambiguous indicators and were removed when they did not contribute clearly to a distinct and interpretable factor.

The internal consistency reliability of the identified factors was evaluated using Cronbach's alpha, based on the retained items. Corrected item-total correlations and Cronbach's alpha if an item was deleted were also examined. The interpretation of Cronbach's alpha follows the guidelines presented in Table 3.3 (DeVellis & Carolyn T. Thorpe, 2021).

Table 3.3
Cronbach's Alpha Interpretation

Value	Interpretation
< 0.6	Unacceptable
0.60 to 0.65	Undesirable
0.65 to 0.70	Minimally acceptable
0.70 to 0.80	Respectable
0.80 to 0.90	Very good
> 0.90	Consider shortening the scale (i.e multicollinearity)

3.2.4 Validation Part 2: Confirmatory

To further validate the Workplace COVID-19 Knowledge and Stigma Scale, a confirmatory validation stage was conducted. This stage aimed to reassess the difficulty and discriminative ability of the knowledge domain, as well as to confirm the construct validity of the stigma domain, specifically validating the constructs found during the EFA. New samples were collected for this stage to confirm the factor structure and ensure that the findings were generalisable. IRT and Confirmatory Factor Analysis (CFA), along with internal consistency via McDonald's omega, were utilised to achieve these objectives.

For the knowledge domain, IRT was applied in both the exploratory and confirmatory stages. In the exploratory stage, it was used to assess item difficulty, discrimination, and unidimensionality. In the confirmatory stage, IRT was applied again to re-evaluate the retained knowledge items in an independent sample, including their difficulty and discriminative ability, item characteristic curves, test response function, and the continued suitability of the unidimensional measurement model (Baker, 2001; Bartholomew et al., 2008; Streiner et al., 2015). The resulting parameters were then compared with those obtained during the exploratory stage to assess the stability and consistency of item performance and to identify any potential discrepancies. This comparison was intended as a reassessment of item performance in an independent sample rather than as a formal test of item-parameter invariance across validation phases.

Following the IRT analysis, CFA was conducted to confirm the factor structure of the stigma domain identified during the exploratory validation stage. The CFA aimed to test the hypothesised model by evaluating the fit between the observed data and the proposed factor structure (Brown, 2015).

3.2.4.1 Study Design and Sampling Method

A cross-sectional validation study design was employed. Sampling was conducted in multiple stages. First, one company was randomly selected, excluding the company involved in previous validation stages. Following discussions with management, the sample was extended to include all companies under their subsidiaries that met the inclusion and exclusion criteria, encompassing various manufacturing categories. Research posters and Google Form links were distributed to the main company, which further disseminated them to employees across its subsidiaries. While the initial company selection was randomised, responses were collected through convenience sampling.

3.2.4.2 Inclusion and Exclusion Criteria

The inclusion criteria for this study were defined as follows:

- The selected company had to be a manufacturing factory.
- Participants needed to be Malaysian workers employed by this company.
- Capable of understanding the Malay language.

The exclusion criteria for this study were defined as follows:

- Companies that were involved in the previous validation stage of the research.
- Individuals who had already participated in the previous validation stage.
- Workers who were illiterate or unable to read Malay.

3.2.4.3 Sample Size

The sample size for this stage was calculated using a 10:1 ratio of respondents (N) to freely estimated parameters (*q*). For a 3-factor model with 12 freely estimated parameters (Figure 3.2), the minimum required sample size would be 10 x 12 = 120 respondents. However, based on the recommendation by Tabachnick & Fidell (2013) and Kyriazos (2018), a sample size of at least 300 respondents was targeted to ensure reliable and stable results for CFA, particularly given the complexity of the model and the potential for imperfect data. This rule of thumb is followed as it widely used in the social sciences to enhance the robustness of the analysis.

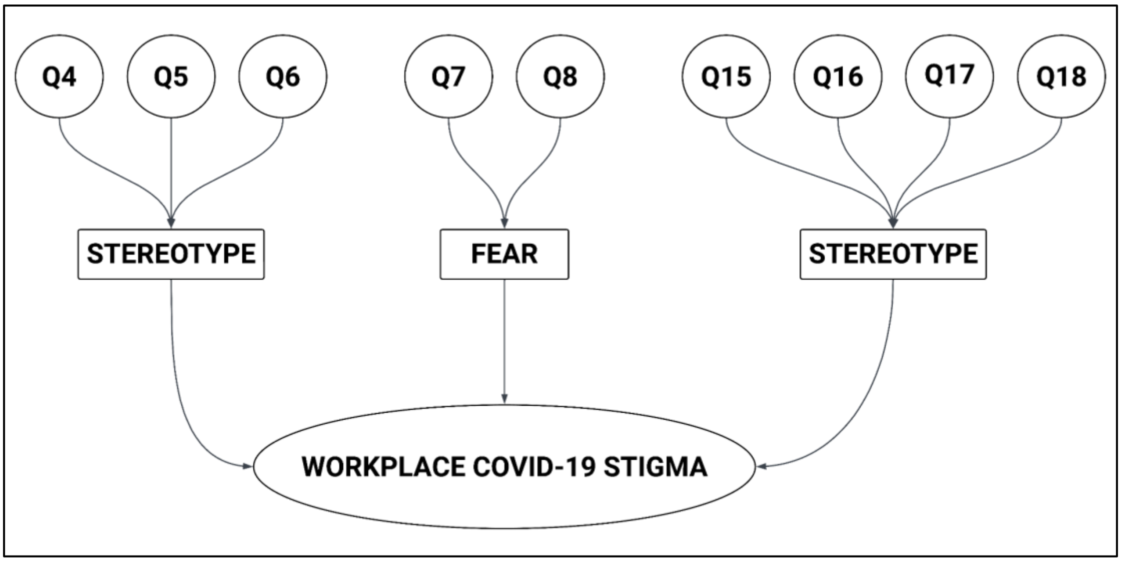

Figure 3.2 Proposed CFA Model

The sample size required for IRT was based on the sample size determined for CFA, as there are no definitive guidelines for IRT sample sizes. However, the general recommendation is to have between 100 and 500 respondents, which is still being fulfilled in this confirmatory validation stage (Edelen & Reeve, 2007).

3.2.4.4 Data Collection

A research poster and a Google Form link were distributed to the main company, which subsequently shared them with all employees across its subsidiaries. Upon accessing the link, respondents were first presented with the research information and consent page. Those who agreed to participate proceeded to complete the survey, while those who declined were able to exit the form. After data collection was completed, the items were analysed for difficulty, discrimination, confirmatory construct validity, and internal consistency.

3.2.4.5 Analysis

Data analysis was conducted using R (version 4.4.2) within RStudio (version 2024.09). Descriptive analyses were performed for the demographic data.

The same IRT methods used during the exploratory validation were applied in the confirmatory validation stage. This time, the analysis began with the 14 items of the knowledge domain that were retained from the exploratory validation phase. The 2-PL IRT model was employed to evaluate the items' discrimination, difficulty, and item fit. Each item was reassessed, with decisions regarding retention based on their statistical properties and relevance to the construct. Items with significant misfit ($p < 0.05$) were carefully reviewed, and final decisions on inclusion were made to ensure the robustness of the scale. The assumption of unidimensionality was also evaluated to ensure the validity of the analysis.

CFA was conducted using RStudio with the '*lavaan*', '*semTools*', '*semPlot*', and '*psych*' packages (Epskamp, 2026; Jorgensen et al., 2026; Revelle, 2026; Rosseel, 2012; Rosseel et al., 2025). The '*lavaan*' package was employed for specifying and estimating the CFA model, '*semTools*' for calculating composite reliability (McDonald's omega), '*semPlot*' for generating path diagrams, and '*psych*' for conducting preliminary psychometric analyses. CFA was performed to validate the factor structure identified during the Exploratory Factor Analysis (EFA) of the stigma domain within the WoCKSS.

Prior to performing CFA, the assumptions of univariate and multivariate normality were evaluated. Univariate normality was assessed visually using histograms with overlaid normal density curves for each item, while multivariate normality was tested using Mardia's multivariate skewness and kurtosis tests. Significant deviations from normality were observed, prompting the use of the Maximum Likelihood Robust (MLR) estimation method. MLR was selected because it provides standard errors and fit statistics that are robust to non-normality, making it suitable when multivariate normality assumptions are not fully satisfied.

The CFA model was specified using '*lavaan*' package, with latent factors representing the constructs identified in the EFA. Model fit was assessed using absolute, parsimony-adjusted, and comparative fit indices, as outlined in Table 3.4. Items contributing to model misfit were iteratively refined to improve model fit while ensuring the theoretical validity of the constructs.

Composite reliability for the identified factors: Fear, Stereotype, and Prejudice were calculated using McDonald's omega via the '*semTools*' package. Omega values exceeding 0.7 were considered indicative of acceptable internal consistency (Hair et al., 2019). The final model's path diagram, generated with the '*semPlot*' package illustrated the relationships between the observed variables and latent factors, confirming the robustness and validity of the scale.

Table 3.4
CFA Fit Indices

Category	Fit index	Cut-off
Absolute fit	χ^2	$P > 0.05$
	SRMR	≤ 0.08
Parsimony correction	RMSEA	≤ 0.08 at 90% CI, CFit $P > 0.05$
Comparative fit	CFI	≥ 0.95
	TLI	≥ 0.95

3.2.5 Study Flowchart for Phase 1

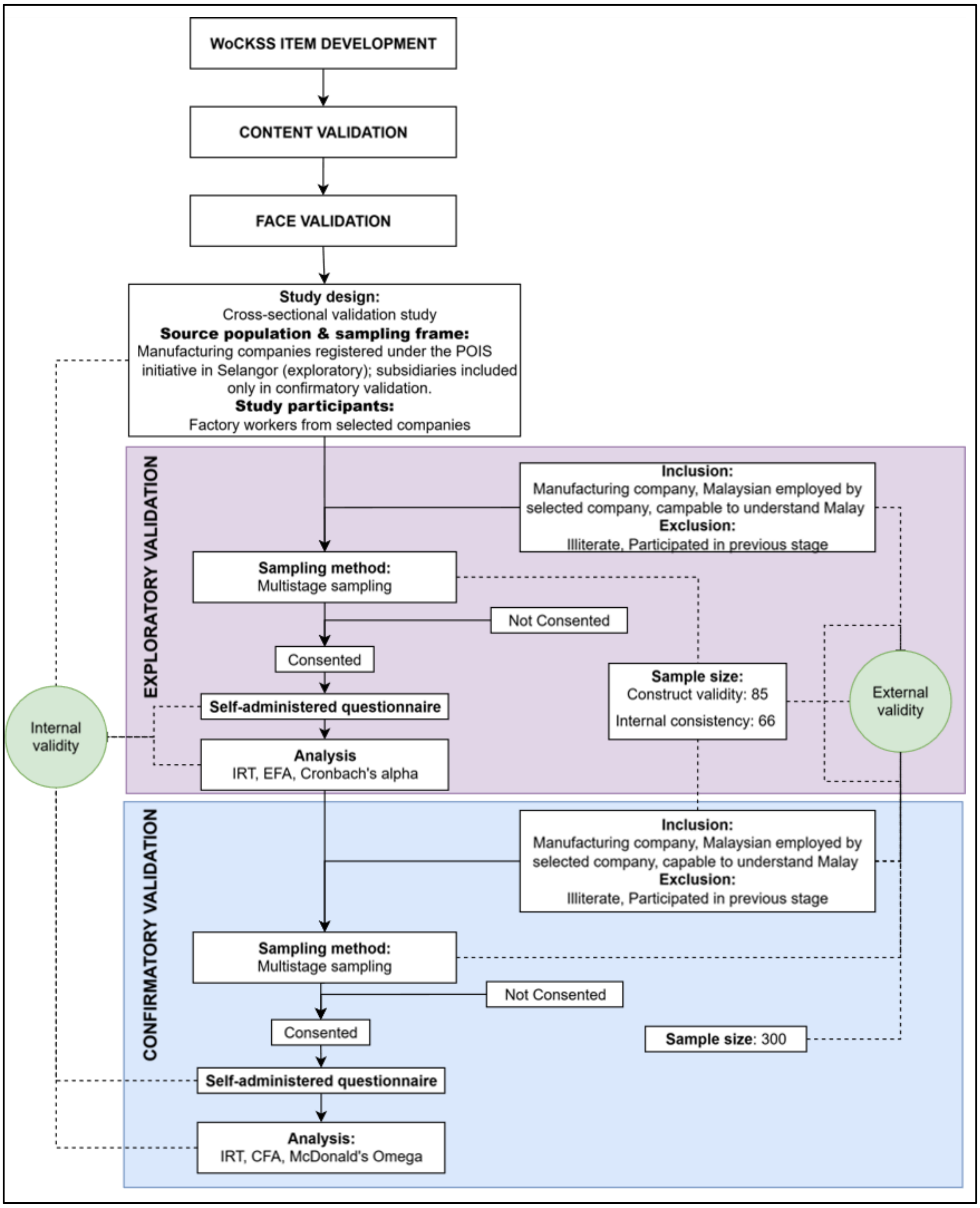

Figure 3.3 Study Flowchart for Phase 1

3.2.6 Statistical flowchart for Phase 1

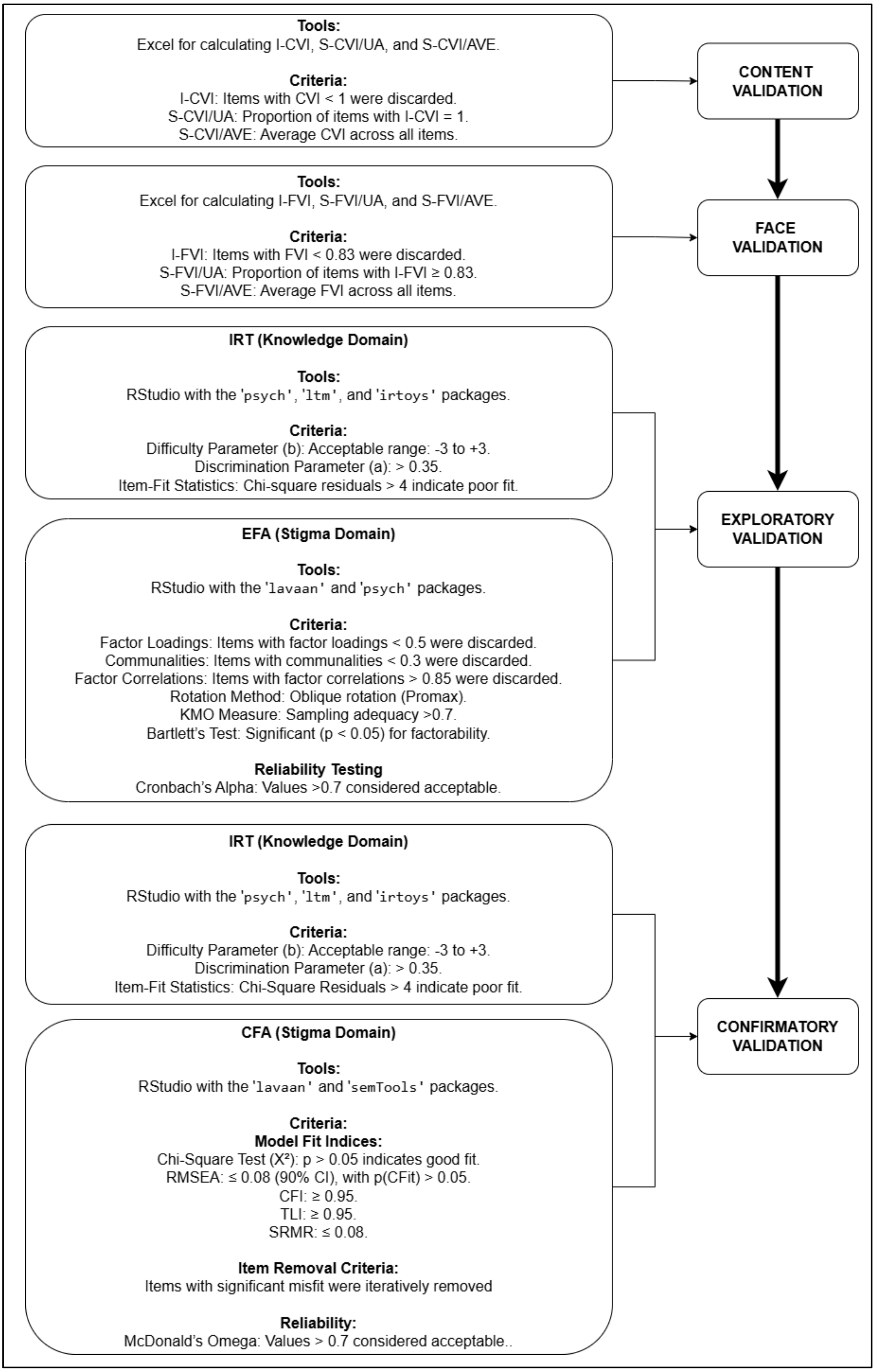

Figure 3.4 Statistical Flowchart for Phase 1

3.3 Phase 2: COVID-19 Stigma Characterisation through Social Network Analysis

Phase 2 of the research utilises the WoCKSS validated in Phase 1. The primary objective of this phase is to investigate and characterise the dynamics of COVID-19 stigma among factory workers, focusing on network perspectives. This phase explores stigma through two complementary approaches: egocentric and sociocentric network analysis.

The egocentric approach examines the stigma-related experiences of individual workers by focusing on their personal networks, including key contacts both within and outside the workplace. This approach allows for an understanding of how individual perceptions and behaviours are influenced by their immediate social environment.

The sociocentric approach, on the other hand, examines the structure of workplace networks, analysing how the collective interactions and relationships among workers influence stigma dynamics at the organisational level. This perspective provides insights into how stigma is propagated or mitigated across the entire workplace.

Together, these approaches offer a comprehensive view of the stigma dynamics within the manufacturing setting, addressing both individual and collective influences.

3.3.1 Study Design

This phase employed a cross-sectional case study design to investigate workplace COVID-19 stigma and its underlying dynamics within a selected manufacturing company. A sociocentric approach was applied, studying the entire network of the selected company to map and analyse the relationships and interactions among employees. The study leveraged the validated WoCKSS to evaluate COVID-19 stigma among employees and explored the role of both egocentric and sociocentric networks in shaping workers' perceptions and experiences of workplace COVID-19 stigma.

3.3.2 Sampling and Participants

A purposive sampling approach was employed to select a food manufacturing company located in Negeri Sembilan, whose parent company was registered under the Preventing Outbreak at Ignition Site (POIS) initiative. The selection was guided by logistical considerations and the practical challenges associated with obtaining permission to collect sociocentric network data from other companies. The selected company, comprising entirely of local workers at its factory site, agreed to participate in the study. All eligible employees were invited to take part, with the management allocating a full day for data collection, which was conducted in the company's canteen.

3.3.3 Inclusion and exclusion criteria

The inclusion criteria for this study were as follows: The selected company had to be a manufacturing company. Respondents needed to be Malaysian employees working at the selected company and able to understand the Malay language. Eligibility extended to all factory site employees, regardless of their role, tenure, or contract status, due to their potential interactions within the workplace.

Workers who were illiterate, unable to read Malay, or had participated in Phase 1 were excluded. Higher management was excluded from the study as per company restrictions. Additionally, workers who declined participation or did not provide informed consent were also excluded from the analysis.

3.3.4 Sample size

Given the nature of the sociocentric study, the entire workforce at the factory sites was targeted for inclusion. This approach was essential to ensure comprehensive data collection, particularly for the network analysis. Although higher management did not participate due to company restrictions, all other employees were invited to partake in the study. The company has approximately 250 employees at the factory sites. To achieve robust results, a minimum target response rate of 70% was set (Borgatti et al., 2006), which corresponds to at least 175 respondents.

3.3.5 Instrument and Variables

The primary instrument for data collection was the validated WoCKSS, which measures both workplace COVID-19 knowledge and stigma among employees. The survey also included sections that collected demographic information, egocentric network data (focusing on key contacts both inside and outside the workplace), and sociocentric network data (centred on workplace contacts). As requested by the company, data on income was excluded from collection due to the sensitive nature of the research and the potential for respondent identification.

Table 3.5 provides a comprehensive listing of the items in the knowledge domain included in Phase 2, with the numbers reassigned following the deletion of certain items in Phase 1.

Table 3.5
List of Items in the Knowledge Domain for Phase 2

Item	Question
K1	Gejala utama COVID-19 ialah demam, batuk dan sukar bernafas. *The main symptoms of COVID-19 are fever, cough, and breathing difficulty.*
K2	Tidak semua individu dijangkiti COVID-19 akan mengalami gejala teruk. *Not all individuals infected with COVID-19 will develop severe symptoms.*
K3	Mereka yang berumur lebih daripada 65 tahun dan mempunyai penyakit kronik mempunyai kebarangkalian lebih tinggi untuk mengalami gejala COVID-19 yang teruk. *People aged 65 and above and with chronic illnesses are more likely to develop severe symptoms.*
K4	Virus COVID-19 merebak melalui titisan air yang terbentuk di saluran pernafasan pesakit semasa mereka bercakap, bersin, atau batuk. *COVID-19 spreads through droplets from the respiratory tract of infected individuals when they talk, sneeze, or cough.*
K5	Individu yang dijangkiti COVID-19 tidak akan menjangkiti orang lain sekiranya dia tidak mempunyai gejala.* *Individuals infected with COVID-19 cannot transmit the virus if they do not have symptoms.* *
K6	Untuk mengelakkan jangkitan COVID-19, seseorang individu harus mengelak pergi ke tempat yang sesak. *To avoid COVID-19 infection, one should avoid crowded places.*
K7	Pemakaian pelitup muka boleh mengelakkan penularan COVID-19 di tempat kerja. *Wearing face masks can prevent the spread of COVID-19 in the workplace.*
K8	Penggunaan pensanitasi tangan (hand sanitizer) membantu mengelakkan penularan wabak COVID-19 di tempat kerja. *Using hand sanitiser helps prevent the spread of COVID-19 in the workplace.*
K9	Pengasingan individu yang dijangkiti virus COVID-19 adalah cara yang berkesan untuk mengurangkan penyebaran virus. *Isolating individuals infected with COVID-19 is an effective way to reduce transmission.*

Table 3.5
(Continued…)

K10	Vaksinasi COVID-19 mengurangkan risiko menghadapi jangkitan COVID-19 yang teruk. *COVID-19 vaccination reduces the risk of severe infection.*
K11	Individu yang telah menerima vaksinasi COVID-19 tidak akan mendapat jangkitan COVID-19.* *A vaccinated individual cannot get infected with COVID-19.**
K12	Kontak rapat yang tidak mempunyai gejala COVID-19 tidak akan menjangkiti orang lain.* *Asymptomatic close contacts cannot transmit COVID-19.**
K13	Proses sanitasi dan disinfeksi secara rutin dan berkala di tempat kerja boleh membendung penularan COVID-19. *Routine and regular sanitation and disinfection at the workplace can contain the spread of COVID-19.*
K14	Individu yang telah dijangkiti COVID-19 tidak akan mendapat jangkitan buat kali kedua. *A person who has been infected with COVID-19 will not get it again.*

*respondents receive marks if they correctly identify the statement as incorrect. Items were originally developed in Malay; English translations are provided for clarity.

Table 3.6 provides a comprehensive listing of the items in the stigma domain included in Phase 2, with the numbers reassigned following the deletion of certain items in Phase 1.

Table 3.6
List of Items in the Stigma Domain for Phase 2

Factor	Item	Question
F1 (Fear)	S4	Tiada sesiapa yang ingin dirinya dijangkiti COVID-19.* *No one wants to be infected with COVID-19.**
	S5	Tiada sesiapa yang dengan sengaja ingin menyebarkan virus COVID-19 di tempat kerja* *No one intentionally wants to spread COVID-19 at the workplace.**
F2 (Stereotype)	S1	Kebanyakkan individu yang dijangkti COVId-19 tidak menjaga kebersihan. *Most individuals infected with COVID-19 do not maintain personal hygiene.*
	S2	Kebanyakkan individu yand dijangkiti COVID-19 tidak menjaga Kesihatan mereka. *Most individuals infected with COVID-19 do not take care of their health.*
	S3	Kebanyakkan individu yang dijangkti COVId-19 tidak mematuhi SOP yang telah ditetapkan. *Most individuals infected with COVID-19 do not comply with established SOPs.*

Table 3.6
(Continued…)

F3 (Prejudice)	S6	Individu yang dijangkiti COVID-19 adalah beban kepada rakan sekerja. *People infected with COVID-19 are a burden to colleagues.*
	S7	Individu yang dijangkiti COVID-19 adalah beban kepada syarikat. *People infected with COVID-19 are a burden to the company*

*Negative question, scores are reversed. Items were originally developed in Malay; English translations are provided for clarity.

3.3.5.1 Demographic Variables

The following demographic information of the respondents, or egos, was collected to provide a comprehensive understanding of their background and characteristics:

- Age (open-ended)
- Gender (Male / Female)
- Education level (SPM or lower / Pre-University / Tertiary)
- Job position (Open-ended)
- Presence of chronic illness (No / Yes)
- Smoking status (No / Yes)
- History of COVID-19 infection (No / Yes)
- History of family members who died due to COVID-19 (No / Yes)

3.3.5.2 COVID-19 Knowledge and Stigma Scores

- **Total COVID-19 Knowledge Score:** Calculated by summing the correct responses to the knowledge items and converting the total into a percentage.
- **Total COVID-19 Stigma Score:** Calculated by summing the responses to the seven stigma items and converting the total into a percentage. The items were scored on a 5-point Likert scale, where a rating of 3 (*agak setuju* / somewhat agree) aligned with the presence of stigma. Based on this scoring, a total stigma score above 40% was classified as "having stigma", and scores of 40% or below were classified as "not having stigma".

3.3.5.3 Egocentric Network Variables

Egocentric network data related to the respondents' personal networks concerning COVID-19 stigma included the following variables:

- Identification of five key contacts (alters)
- Nature of the relationship with each alter (family, friends, superiors or employers / others)
- Gender of each alter (Male / Female)
- Duration of acquaintance with each alter (Open-ended)
- Perceived influence of each alter on the ego's COVID-19 stigma (No / Yes)

3.3.5.4 Sociocentric Network Variables

For the sociocentric network analysis, each respondent was asked to identify up to five individuals within the company with whom they had the most frequent contact. Specifically, respondents were presented the question: *Siapakah rakan sekerja anda yang anda rasa paling rapat dan kerap berkomunikasi dengan anda?* ("Who are your work colleagues you feel closest to and frequently communicate with?"). For this, respondents were asked to provide:

- Their own name and department
- The names and departments of each nominated individual (alter)
  - This information was used for data matching during the cleaning process to address potential misspellings or inconsistencies resulting from the name generator method.

3.3.6 Data collection

Data collection was conducted over a half-day period in the company's canteen, as arranged by the management. All eligible employees were invited to participate. After providing informed consent, respondents, referred to as "egos", completed a paper-based, self-administered survey which took approximately 15 minutes.

The survey captured multiple domains relevant to the study, including demographic information, COVID-19 knowledge and stigma, as well as egocentric and sociocentric network data. Egocentric data were gathered using name generator and name interpreter questions, where respondents were asked to nominate up to five individuals (alters) from within or outside the workplace who were considered influential in their daily interactions or personal decisions.

For sociocentric data, respondents identified up to five individuals within the company with whom they frequently communicated. To support accurate social network mapping and minimise data entry errors, participants were required to record both their own and their alters' names and departments.

As a token of appreciation, respondents were given RM 10 in cash upon returning the completed questionnaire.

3.3.7 Data cleaning and preparation for analysis

Data were initially recorded in Microsoft Excel and subsequently cleaned and prepared for analysis using RStudio, with the '*dplyr*' and '*tidyr*' packages employed for data cleaning, transformation, and reformatting (Wickham et al., 2023, 2024).

Demographic data were recorded as follows: Education was categorised into "SPM," "Pre-University/Diploma," "University (Bachelor's/Master's/PhD)," and "Not complete high school." For inferential statistics, these categories were further collapsed into "Up to SPM" and "Higher Education" to better accommodate the data distribution.

Job positions were categorised based on job type rather than hierarchical level. This approach was necessary due to the nature of the factory setting, where most employees occupy lower-level roles, thus enhancing the suitability of the data for inferential statistics. The classifications were as follows:

- **Productions:** Roles directly related to production processes.
- **Technical & Engineering:** Technical maintenance and specialised engineering roles.
- **Logistics and Material Handling:** Roles focused on the movement and storage of materials.
- **Administration:** Roles involved in administrative functions or management.

The total COVID-19 Knowledge Score and the total COVID-19 Stigma Score were calculated and expressed as percentages. The categorisation of stigma status based on the 40% threshold is detailed in Section 3.3.5.2.

For the egocentric data, a wide-format dataset was created for multiple logistic regression analysis (MLogR), with each row representing an individual ego. For multilevel modelling (MLM), the data were reshaped into a long format, where each row represented a dyadic connection between an ego and an alter.

For the sociocentric data, respondents were asked to nominate five individuals with whom they have the most contact at their current workplace. Nominated alters who did not participate in the survey were dropped, as no data beyond their names and department were available. In addition, one ego was excluded from the sociocentric network analysis, as none of their nominated alters responded, resulting in no observable ties. The data were prepared in two files: an edgelist (dyadic, long format) and a node attribute (wide format).

3.3.8 Analysis

Several analytical approaches were employed in Phase 2 to address Research Objectives 2 and 3, which aimed to examine the influence of individual and structural network factors on workplace COVID-19 stigma. Two distinct but complementary types of social network data were analysed: egocentric and sociocentric.

Egocentric data, which focused on the individual respondent (ego) and their nominated contacts (alters), were analysed using MLogR and binary logistic multilevel modelling (MLM). These techniques enabled the identification of factors associated with stigma perceptions and the perceived influence of social ties.

Meanwhile, sociocentric data, capturing the full network of interconnections among employees within the workplace, were analysed using Exponential Random Graph Modelling (ERGM) and Quadratic Assignment Procedure (QAP). These methods facilitated the examination of how relational structures and positional attributes within the organisational network influenced the presence and spread of stigma across the workforce.

3.3.8.1 Egocentric Network Analysis of Workplace COVID-19 Stigma

a. Multiple Logistic Regression (MLogR)

To explore the factors contributing to workplace COVID-19 stigma among employees, a Multiple Logistic Regression (MLogR) analysis was conducted with stigma status as the dependent variable. This variable was dichotomised as described in Section 3.3.5.2.

A block-wise (hierarchical) modelling approach was employed to examine how different groups of variables contributed to the prediction of stigma. The models were built incrementally:

- **Model 1 (Demographic variables):** Included age group, gender, education level, and job position.
- **Model 2 (Health-related variables):** Included all variables from Model 1 plus history of COVID-19 infection and COVID-19 knowledge.
- **Model 3 (Network variables):** Included all variables from Model 2, with the addition of compositional social network variables derived from egocentric network data. Gender homophily was calculated as the proportion of alters sharing the same gender as the ego. Alters' gender composition was calculated as the proportion of alters' gender within each egocentric network. Relationship type composition was calculated by determining the proportion of alters in each relationship category (family, friends, superiors/ employers, and others). For relationship duration, the total number of years known for each alter was averaged to produce an overall network-level score.

All categorical variables were appropriately recoded and factorised to ensure correct specification in the model. Model performance was evaluated using several criteria. The Akaike Information Criterion (AIC) was used to compare model fit, with lower AIC values indicating better fit. Classification accuracy and Area Under the Curve (AUC) were calculated to assess predictive performance. The Hosmer-Lemeshow test (HLM) was used to evaluate goodness-of-fit, and Variance Inflation Factor (VIF) was calculated to assess multicollinearity among predictors, with values below 5 considered acceptable. The analyses were performed using R, employing the following packages:

- *'lessR'*: for fitting logistic regression models and summarising results (Gerbing, 2021).
- *'pROC'*: for ROC analysis and AUC calculations (Robin et al., 2011).
- *'fmsb'*: to calculate VIF for multicollinearity checks (Nakazawa, 2024).
- *'ResourceSelection'*: to conduct the Hosmer-Lemeshow goodness-of-fit test (Lele et al., 2023).
- *'tidyverse'*: for data manipulating and cleaning (Wickham et al., 2019).

This hierarchical block-wise strategy allowed for the assessment of how demographic, health-related, and network structural factors contribute to the likelihood of stigma within the workplace, while controlling for potential confounding variables. The multiple logistic regression analysis was conducted at a single level, with the ego as the unit of analysis and binary workplace COVID-19 stigma status as the outcome variable.

b. Binary Logistic Multilevel Modelling (MLM)

In addition to the MLogR analysis, a binary logistic multilevel modelling (MLM) approach was employed to investigate the factors associated with the perceived influence of nominated alters on respondents' COVID-19 stigma, as assessed through the name interpreter question: *Adakah individu ini mempengaruhi penilaian anda terhadap rakan sekerja yang dijangkiti COVID-19? /* Does this person influence your judgment of colleagues who were infected with COVID-19? (response options: "Never" or "Yes"). The binary outcome variable was therefore defined at the alter level, indicating whether a nominated alter was perceived to influence the ego's judgement of colleagues infected with COVID-19. The random effect was specified at the ego level to account for clustering of alter observations within the same respondent.

MLM is particularly appropriate for this context due to the hierarchical nature of the data, where multiple alters (nominated social contacts) are nested within individual respondents (egos). This nested structure violates the assumption of independence among observations, thereby necessitating the use of MLM, which accounts for within-group (ego-level) clustering (Vacca, 2018). This constituted a two-level random-intercept model, with alters at Level 1 nested within egos at Level 2.

The analysis was conducted using the *'lme4'* package in R for model estimation, with model performance evaluated using the *'performance'* package (Bates et al., 2015; Lüdecke et al., 2021). A block-wise model-building strategy was applied to assess the incremental contribution of variable sets. Three nested models were fitted sequentially:

- **Model 0 (Null Model):** Included only the random intercept to estimate baseline variance across egos.
- **Model 1:** Introduced ego-level predictors, namely workplace COVID-19 knowledge and the ego's own stigma status.
- **Model 2:** Extended Model 1 by incorporating alter-level predictors, specifically the gender of the alter, type of relationship (family, friends, colleagues, and superiors), and the duration of acquaintance with the alter.

All categorical variables were appropriately recoded and factorised to ensure correct specification in the model. The models were estimated using maximum likelihood estimation via the 'bobyqa' optimiser with adaptive Gauss-Hermite quadrature (nAGQ = 5), suitable for binary outcomes with random effects.

Model assumptions were checked as follows. Pearson residual plots were used to assess the presence of heteroscedasticity and general model misspecification. Linearity in the logit for both continuous predictors, namely workplace COVID-19 knowledge and the duration of acquaintance with the alter, was examined using generalised additive models fitted with the 'mgcv' package (Wood, 2011), where models with linear terms were compared against models including smooth terms while accounting for random intercepts at the ego level. Multicollinearity among fixed effects was evaluated using Variance Inflation Factor (VIF), with values below 5 indicating an acceptable level of multicollinearity. The distribution of the binary outcome was examined to ensure suitability for logistic regression. In addition, the potential influence of individual egos was assessed by inspecting the distribution of random intercepts across ego clusters to identify any extreme or potentially influential values.

To evaluate model performance and improvement, several diagnostic statistics were reported: the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to compare model fit, with lower values indicating better performance; likelihood ratio tests were conducted to assess the significance of adding additional predictors between models. The Intraclass Correlation Coefficient (ICC) was computed to quantify the proportion of total variance attributable to between-ego variability. Additionally, marginal and conditional R^2 values were calculated to assess the proportion of variance explained by the fixed effects alone and by the full model (fixed and random effects combined), respectively.

3.3.8.2 Sociocentric Network Analysis of Workplace COVID-19 Stigma

To complement the egocentric approach, sociocentric network analysis was conducted to investigate the broader structural patterns and interrelationships within the workplace social network and their association with COVID-19 stigma. This analysis satisfies Objective 3. Two network-based analyses were employed: Exponential Random Graph Modelling (ERGM), and Quadratic Assignment Procedure (QAP). Prior to these inferential analyses, descriptive network analysis and network visualisation were conducted to characterise the overall structural properties of the workplace network.

a. Descriptive Network Analysis and Visualisation Procedures

An initial descriptive analysis was performed to examine the fundamental structure of the sociocentric workplace network. The edgelist and node attribute datasets were cleaned to ensure alignment between reported ties and respondent characteristics. A directed network object was created using the *'network'* package in R (Butts, 2015), with demographic and stigma-related attributes (gender, education level, smoking status, history of COVID-19 infection, and stigma status) assigned to each vertex.

Centrality measures, including degree, eigenvector centrality, betweenness centrality, and closeness centrality, were computed using the '*igraph'* package to evaluate the prominence of individuals within the network (Csárdi et al., 2026; Csárdi & Nepusz, 2006). Additional network-level metrics, such as density, reciprocity, number of components, size of the largest component, coreness, clustering coefficient, and average geodesic distance, were also calculated to describe the global structural characteristics of the network.

The network was visualised using the Kamada-Kawai layout algorithm, which optimises node placement to minimise edge crossings and highlight relational proximity (Kamada & Kawai, 1989). Nodes were coloured according to stigma status, and central actors were defined as individuals whose degree centrality values were within the top 5% of the network distribution. The top 5% threshold for identifying central actors by degree centrality was selected to focus on the most structurally influential individuals. A Louvain community detection algorithm was applied to detect potential modular structures within the network (Blondel et al., 2008). These descriptive and visual analyses provided structural context to guide the subsequent inferential modelling.

b. Exponential Random Graph Modelling (ERGM)

A series of Exponential Random Graph Models (ERGMs) were applied to the sociocentric network data. ERGM is a class of statistical models used to analyse the formation of ties in social networks by estimating the probability of an observed network structure as a function of endogenous structural dependencies and exogenous covariates (Hunter et al., 2008).

A directed network object was created using the network function from the '*network*' package within the statnet suite, ensuring that participating employees were retained as nodes (Butts, 2008). Node-level attributes, including stigma status, gender, age group, job position, smoking status, and COVID-19 knowledge score, were assigned to the network using attribute matching. Three nested ERGM models were specified to incrementally assess structural, homophily, and individual attribute effects:

- **Model 0 (Baseline)** included the edges term to model the baseline probability of tie formation.
- **Model 1 (Structural and Homophily model)** included reciprocity and examined homophily based on gender, job position, age group, smoking status, and stigma status.
- **Model 2 (Full model)** extended Model 1 by including node-level covariates: gender, age group, stigma status, smoking status, and COVID-19 knowledge score.

All models were estimated using the *'ergm'* package in R (Hunter et al., 2008). Model convergence was assessed using Markov Chain Monte Carlo (MCMC) diagnostics, including trace plots, autocorrelation, and distribution checks to ensure stability. Goodness-of-fit was evaluated by comparing observed and simulated network statistics. Model performance was compared using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to determine the best-fitting model.

c. Quadratic Assignment Procedures (QAP)

To investigate the association between dyadic structural characteristics and stigma homophily within the workplace network, the Quadratic Assignment Procedure (QAP) was employed. QAP is a permutation-based technique that enables hypothesis testing in relational data while preserving the interdependence inherent in network structures (Krackardt, 1987). This method compares the observed association between matrices to a reference distribution generated through repeated random permutations. This allows valid inference even when dyadic observations are not independent. In the present study, QAP was used to assess dyadic association and structural similarity rather than temporal diffusion or causal influence.

All variables of interest were transformed into dyadic matrices. For the binary attribute of stigma status, a homophily matrix was constructed. A value of 1 indicated that two actors shared the same stigma status, and a value of 0 indicated otherwise. For continuous node-level structural metrics, including degree centrality, eigenvector centrality, betweenness centrality, closeness centrality, coreness, clustering coefficient, and geodesic distance, dyadic matrices were generated by computing the absolute differences between each pair of actors. These matrices reflected structural similarity or dissimilarity in network positioning.

The dependent matrix for QAP analysis was the stigma homophily matrix, where each dyad was coded as 1 if both actors shared the same stigma status and 0 if they differed. Independent matrices were constructed from the absolute differences in node-level structural metrics, including degree centrality, eigenvector centrality, betweenness centrality, closeness centrality, coreness, clustering coefficient, and geodesic distance. Each independent matrix was regressed separately against the stigma homophily matrix using the '*netlm*' function from the '*asnipe*' package in R (Farine, 2013). A total of 5,000 permutations were performed for each test to obtain empirical p-values.

To verify the assumptions of the QAP analysis, several diagnostic procedures were conducted. Structural preservation was assessed by visually comparing the observed stigma similarity matrix with a randomly permuted version. Monotonicity and linear trends were evaluated using scatterplots for each network metric against stigma similarity, alongside Spearman's rank correlation coefficients. Finally, the distribution of stigma status across the network was checked to ensure sufficient group variability, which is essential for valid permutation-based inference.

In interpreting QAP estimate, a negative value ($r < 0$) indicates that actors with more similar network structures are more likely to share the same stigma status. This supports the presence of homophily. A positive value ($r > 0$) implies that actors who differ in network structure are more likely to share the same stigma status. Values near zero ($r \approx 0$) indicate no meaningful association between the structural metric and stigma similarity. While ERGM was used to model tie formation and structural dependence within the network, QAP was used to examine whether similarity in node-level structural positions was associated with similarity in stigma status across dyads.

3.3.9 Study Flowchart for Phase 2

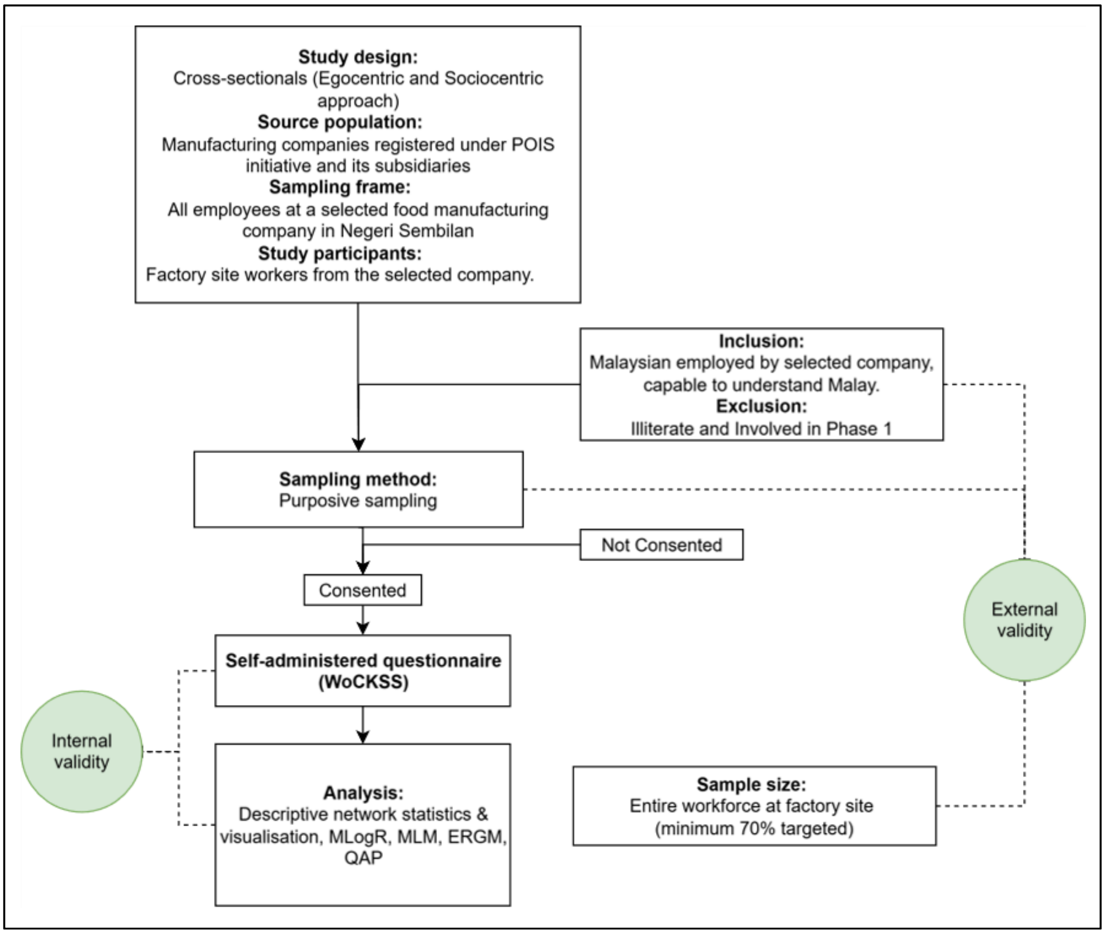

Figure 3.5 Study Flowchart for Phase 2

3.3.10 Statistical flowchart for Phase 2

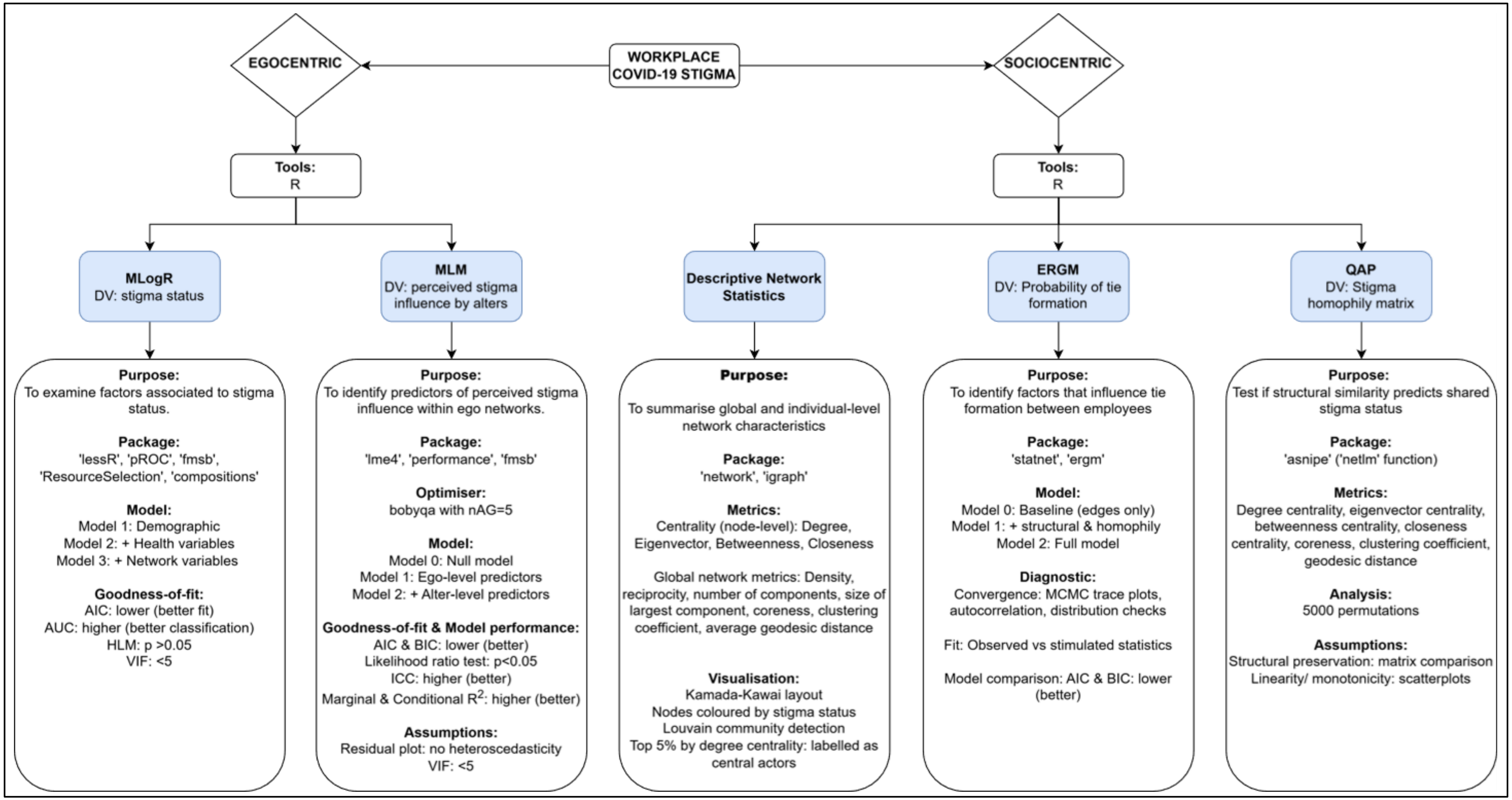

Figure 3.6 Statistical Flowchart for Phase 2

CHAPTER 4
RESULTS

4.1 Introduction

This results section is presented according to the objectives of the study and follows the phases outlined in the research methodology. The study was divided into two phases. Phase 1 focused on the development and validation of the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS), which was then utilised in Phase 2 to characterise workplace COVID-19 stigma among factory workers through SNA approach.

The results for Phase 1 are presented following the sequence of the validation processes: content validation, face validation, exploratory Item Response Theory (IRT) analysis, exploratory factor analysis (EFA), confirmatory Item Response Theory (IRT) analysis, and confirmatory factor analysis (CFA).

The results for Phase 2 comprise analyses designed to address Research Objectives 2 and 3. This phase integrates social network methodologies to explore the influence of individual, relational, and structural network characteristics on COVID-19 stigma in the workplace. The Phase 2 analyses were conducted in two parts: egocentric and sociocentric analyses.

Egocentric network data were first analysed using multiple logistic regression (MLogR) to determine factors associated with stigma status. This was followed by a binary logistic multilevel modelling (MLM) to investigate how alter-level attributes relate to the perceived influence of nominated contacts (alters) on the ego's stigma perception.

The sociocentric network data were then analysed to examine broader network-level patterns and clustering of stigma using Exponential Random Graph Models (ERGM) and Quadratic Assignment Procedure (QAP). These methods provided insight into the structural dependencies and homophily patterns present within the workplace network and how they relate to the distribution of COVID-19 stigma.

4.2 Phase 1: Development and Validation of Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS).

4.2.1 Content Validation

The content validity results for the WoCKSS are presented in Table 4.1 for the knowledge domain and Table 4.2 for the stigma domain. The experts evaluated each item on a four-point scale, ranging from 1 (not relevant) to 4 (highly relevant). The number of experts who rated each item as a 3 or 4, indicating relevance, is shown in the "Number in agreement" column. Of the initial 20 items in the knowledge domain and 31 items in the stigma domain, 19 knowledge items and 24 stigma items were retained after the CVI analysis.

As shown in both Table 4.1 and Table 4.2, all retained items in the knowledge and stigma domains of the WoCKSS received a CVI score of 1.00 from all four experts, demonstrating unanimous agreement among the panel. The CVI score reflects the proportion of experts who rated an item as relevant and serves as an indicator of the scale's content validity. The maximum CVI score of 1.00 indicates that all experts rated each retained item as highly relevant. The mean I-CVI score, which represents the average of the I-CVI scores across all items, was also found to be 1.00, indicating excellent agreement among the experts regarding the relevance of the items in the knowledge domain. The UA score represents the proportion of items that achieved a perfect CVI score of 1.00, while the S-CVI/AVE score represents the average CVI scores across all items. As shown in Table 4.1, all 19 items achieved a perfect CVI score of 1.00, resulting in a UA score of 1.00, indicating perfect agreement among the panel of experts regarding the relevance of the items in the knowledge domain. The S-CVI/AVE score was also found to be 1.00, indicating excellent content validity for the knowledge domain of the WoCKSS.

Table 4.1
Content Validation of Knowledge Domain

Item	Experts 1	Experts 2	Experts 3	Experts 4	Number in agreement	I-CVI	UA	Mean I-CVI	S-CVI/ UA	S-CVI/ AVE
1	X	X	X	X	4	1.00	1			
2	X	X	X	X	4	1.00	1			
3	X	X	X	X	4	1.00	1			
4	X	X	X	X	4	1.00	1			
5	X	X	X	X	4	1.00	1			
6	X	X	X	X	4	1.00	1			
7	X	X	X	X	4	1.00	1			
8	X	X	X	X	4	1.00	1			
9	X	X	X	X	4	1.00	1			
10	X	X	X	X	4	1.00	1	1.00	1.00	1.00
11	X	X	X	X	4	1.00	1			
12	X	X	X	X	4	1.00	1			
13	X	X	X	X	4	1.00	1			
14	X	X	X	X	4	1.00	1			
15	X	X	X	X	4	1.00	1			
16	X	X	X	X	4	1.00	1			
17	X	X	X	X	4	1.00	1			
18	X	X	X	X	4	1.00	1			
19	X	X	X	X	4	1.00	1			
Proportion relevance	1.0	1.0	1.0	1.0						

In Table 4.2, all 24 retained items in the stigma domain of the WoCKSS received an I-CVI score of 1.00, reflecting unanimous agreement among the experts regarding their relevance. This perfect agreement is further supported by a UA score of 1.00, indicating that every item achieved complete consensus among the panel. The mean I-CVI score for the stigma domain was also calculated as 1.00, underscoring the consistency of expert ratings across all items. The S-CVI/UA and S-CVI/AVE scores, both at 1.00, confirm the high content validity of the stigma domain, demonstrating that the retained items are not only relevant but also consistently aligned with the intended constructs of the WoCKSS. These findings support the conceptual adequacy of the retained stigma items for representing workplace-related COVID-19 stigma, particularly as an attitudinal construct comprising stereotype, fear, and prejudice within the context of worker interactions.

Table 4.2
Content Validation of Stigma Domain

Item	Experts 1	Experts 2	Experts 3	Experts 4	Number in agreement	I-CVI	UA	Mean I-CVI	S-CVI/ UA	S-CVI/ AVE
1	X	X	X	X	4	1.00	1	1.00	1.00	1.00
2	X	X	X	X	4	1.00	1			
3	X	X	X	X	4	1.00	1			
4	X	X	X	X	4	1.00	1			
5	X	X	X	X	4	1.00	1			
6	X	X	X	X	4	1.00	1			
7	X	X	X	X	4	1.00	1			
8	X	X	X	X	4	1.00	1			
9	X	X	X	X	4	1.00	1			
10	X	X	X	X	4	1.00	1			
11	X	X	X	X	4	1.00	1			
12	X	X	X	X	4	1.00	1			
13	X	X	X	X	4	1.00	1			
14	X	X	X	X	4	1.00	1			
15	X	X	X	X	4	1.00	1			
16	X	X	X	X	4	1.00	1			
17	X	X	X	X	4	1.00	1			
18	X	X	X	X	4	1.00	1			
19	X	X	X	X	4	1.00	1			
20	X	X	X	X	4	1.00	1			
21	X	X	X	X	4	1.00	1			
22	X	X	X	X	4	1.00	1			
23	X	X	X	X	4	1.00	1			
24	X	X	X	X	4	1.00	1			
Proportion relevance	1.0	1.0	1.0	1.0						

4.2.2 Face Validation

Table 4.3 presents the characteristics of the 10 respondents involved in the face validity assessment. The mean age of the respondents was 28.44 years. Most of the respondents were female, comprising 80% of the sample, while 20% were male. In terms of education, 60% of the respondents had an SPM or lower qualification, 20% had pre-university education, and 20% had tertiary education. The job positions of the respondents were varied. Most respondents had a monthly income of less than RM 2,500, while 30% had a monthly income between RM 2,501 and RM 4,850. Regarding COVID-19 infection history, 90% of the respondents had been infected with COVID-19, while 10% had not. Additionally, 10% of the respondents reported having a family member who had died due to COVID-19, while 90% did not.

Table 4.3
Characteristics of Respondents Involved in Face Validity, (n = 10)

Variables	Mean (SD)	n (%)
Age	28.44 (8.11)	
Gender		
Female		8 (80.0)
Male		2 (20.0)
Education		
SPM or lower		6 (60.0)
Pre-University		2 (20.0)
Tertiary		2 (20.0)
Job Position		
Executive		1 (10.0)
Supervisor		2 (20.0)
Operator		3 (30.0)
Others		3 (30.0)
Monthly income		
< RM 2500		7 (70.0)
RM 2501 - RM 4850		3 (30.0)
COVID-19 infection history		
No		1 (10.0)
Yes		9 (90.0)
History of family members died due to COVID-19		
No		9 (90.0)
Yes		1 (10.0)

The face validity results for the WoCKSS are presented in Table 4.4 for the knowledge domain and Table 4.5 for the stigma domain. Respondents rated the clarity and comprehensibility of each item on a four-point scale, ranging from 1 (not clear/comprehensible) to 4 (very clear/comprehensible). The number of respondents who rated each item as a 3 or 4, indicating clarity and comprehensibility, is shown in the "Number in Agreement" column. From the initial set of 19 items in the knowledge domain and 24 items in the stigma domain, 17 knowledge items and 22 stigma items were retained after the Face Validity Index (FVI) analysis.

As shown in both Table 4.4 and Table 4.5, the retained items in the knowledge and stigma domains received high levels of agreement on their clarity and comprehensibility. In the knowledge domain, 15 out of 17 items achieved a UA index of 1.00, indicating unanimous agreement among respondents. The mean I-FVI for the knowledge domain was 0.99, reflecting the overall clarity of the items. The S-FVI/UA score of 0.88 suggests a strong consensus among respondents, while the S-FVI/AVE score of 0.99 indicates that the items are generally well-understood and clearly presented.

For the stigma domain, the results indicate that 19 of the 22 retained items achieved a UA index of 1.00, demonstrating unanimous agreement on their clarity and comprehensibility. The mean I-FVI for the stigma domain was calculated at 0.99, further emphasizing the consistency of the respondents' ratings. The S-FVI/UA score of 0.86 and the S-FVI/AVE score of 0.99 highlight the strong face validity of the stigma domain, confirming that the items are both clear and comprehensible to the target population. Although face validation in this study was quantitative rather than interview-based, the high FVI results support the clarity and comprehensibility of the retained items among the target factory-worker population.

Table 4.4
Face Validation of Knowledge Domain

Item	Respondents										Number in agreement	UA	I-FVI	Mean I-FVI	S-FVI/UA	S-FVI/AVE
	1	2	3	4	5	6	7	8	9	10						
1	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
2	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
3	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
4	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
5	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
6	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
7	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
8	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
9	X	X	X	X	X	X	X	X	X	X	10	1	1.00	0.99	0.88	0.99
10	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
11	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
12	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
13	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
14	X	X		X	X	X	X	X	X	X	9	0	0.90			
15	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
16	X	X	X	X	X		X	X	X	X	9	0	0.90			
17	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
Proportion relevance	1.00	1.00	0.94	1.00	1.00	0.94	1.00	1.00	1.00	1.00						

Table 4.5
Face Validation of Stigma Domain

Item	Respondents										Number in agreement	UA	I-FVI	Mean I-FVI	S-FVI/UA	S-FVI/AVE
	1	2	3	4	5	6	7	8	9	10						
1	X	X	X	X	X	X	X	X	X	X	10	1	1.00	0.99	0.86	0.99
2	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
3	X		X	X	X	X	X	X	X	X	9	0	0.90			
4	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
5	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
6	X		X	X	X	X	X	X	X	X	9	0	0.90			
7	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
8	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
9	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
10	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
11	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
12	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
13	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
14	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
15	X		X	X	X	X	X	X	X	X	9	0	0.90			
16	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
17	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
18	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
19	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
20	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
21	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
22	X	X	X	X	X	X	X	X	X	X	10	1	1.00			
Proportion relevance	1.00	0.86	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00						

4.2.3 Validation Part 1: Exploratory

4.2.3.1 Demographic Characteristics of the Respondents

Table 4.6 gives the profile of the 137 respondents in validation part 1. Most of them are males, accounting for 65.7% of the entire sample, while the rest are female at 34.3%. The average age of the respondents is 31.64 years. Of the sample, 19.7% of the respondents attained SPM, 35.0% attended pre-university or diplomas, 39.4% were bachelor's, and 5.8% had postgraduate degree. In monthly income, 38.0% of respondents had an income less than RM 2,500 while 39.4% an income between RM 2,501 and RM 4,849 and another 20.4% had income more than RM 4,850. Among the respondents, 64.2% had been infected with the disease, 35.8% had not. 8.8% of the respondents reported a family member dead due to COVID-19 while another 89.8% did not have such a case history. A total of 81.8% reported being non-smokers, whereas 18.2% were smokers.

Table 4.6
Characteristics of Respondents Involved in Validation Part 1, (n = 137)

Variables	Mean (SD)	n (%)
Age	31.64 (9.0)	
Gender		
Female		47 (34.3)
Male		90 (65.7)
Education		
SPM		27 (19.7)
Pre-University / Diploma		48 (35.0)
Bachelor's degree		54 (39.4)
Postgraduate (Master / Degree)		8 (5.8)
Monthly income		
< RM 2500		52 (38.0)
RM 2501 - RM 4849		54 (39.4)
≥ RM 4850		28 (20.4)
COVID-19 infection history		
No		49 (35.8)
Yes		88 (64.2)
History of family members died due to COVID-19		
No		123 (89.8)
Yes		12 (8.8)
Smoking status		
Not smoking		112 (81.8)
Smoking		25 (18.2)

4.2.3.2 Item Response Theory (IRT) for the Knowledge domain

The results of the IRT analysis for the Knowledge domain, as part of Validation Part 1, are summarised in Table 4.7. A two-parameter logistic (2-PL) model was used because the dichotomous knowledge items were expected to vary in both discrimination and difficulty, allowing more flexible item evaluation than a one-parameter model. Initially, there were 17 items (K1 to K17) included in the analysis. Items were removed based on their discrimination, difficulty, and item fit parameters, with consideration also given to their overall interpretability within the knowledge domain. Specifically, items K5, K11, and K15 were removed after the pre-testing phase due to poor performance: K15 was excluded for having negative discrimination (-0.30), K11 for significant item misfit ($p = 0.004$) and very low difficulty (-5.06), and K5 due to significant item misfit ($p = 0.022$) and high difficulty (3.81).

The remaining items show that K1, K2, K3, K9, K10, K12, K16, and K17 fit well with the 2-PL IRT model, as indicated by p-values higher than 0.05. However, items K4, K6, K7, K8, K13, and K14 had p-values less than 0.05, suggesting a poor fit. Despite this, these items were retained due to their supportive discrimination and difficulty values.

Across the retained items, discrimination (a) parameters ranged from 0.41 to 18.63, although the very high estimate for K17 should be interpreted cautiously because it may reflect unusually sharp separation between respondents at that item. Difficulty (b) parameters ranged from -5.40 to 0.46. Most items demonstrated low to moderate difficulty, indicating that they were relatively easy for respondents, although a small number of items required higher ability levels. Discrimination values varied considerably across items, suggesting differences in how effectively each item distinguished between respondents with different knowledge levels.

The Item Characteristic Curves (ICCs) indicate that approximately 84.82% of the test information is concentrated within the ability range of -3 to +3, supporting the test's effectiveness across a broad spectrum of respondent abilities. Figure 4.1 illustrates the ICCs for the knowledge domain of the WoCKSS. These curves show the probability of a correct response across varying levels of ability, allowing visual inspection of item difficulty and discrimination. Items such as K1, K2, K3, K7, and K10 have flatter and left-shifted curves, suggesting these are easier items that require lower ability levels to achieve a high probability of a correct response. Conversely, items like K4, K14, and

K17 are positioned further to the right, indicating higher levels of difficulty. Regarding discrimination, items K6, K7, K13, K14, and K17 show steeper slopes, indicating stronger capacity to distinguish between respondents with differing abilities.

The Test Response Function (TRF), shown in Figure 4.2, presents a clear positive relationship between respondent ability and expected score, indicating that higher ability levels were associated with higher expected total scores. The curve suggests that the scale functioned most informatively around the mid-range of the ability spectrum, with less differentiation at the extremes. Although the scale appeared to perform reasonably across a broad range of abilities, the assumption of unidimensionality was not supported in Validation Part 1, as indicated by the modified parallel analysis ($p < 0.001$). This suggests that the knowledge domain may not have functioned as a strictly single latent construct at the exploratory stage.

Table 4.7
IRT Analysis for the Knowledge Domain in Validation Part 1

Item	Question	*a*	*b*	χ^2 (df = 8)	P-values
K1	Gejala utama COVID-19 ialah demam, batuk dan sukar bernafas.	0.75	-5.40	8.17	0.417
K2	Tidak semua individu dijangkiti COVID-19 akan mengalami gejala teruk.	0.79	-2.93	13.76	0.088
K3	Mereka yang berumur lebih daripada 65 tahun dan mempunyai penyakit kronik mempunyai kebarangkalian lebih tinggi untuk mengalami gejala COVID-19 yang teruk.	0.82	-3.28	12.50	0.130
K4	Virus COVID-19 merebak melalui titisan air yang terbentuk di saluran pernafasan pesakit semasa mereka bercakap, bersin, atau batuk.	1.13	-2.16	17.31	0.027
K6	Individu yang dijangkiti COVID-19 tidak akan menjangkiti orang lain sekiranya dia tidak mempunyai gejala.	1.33	-0.33	51.30	< 0.001
K7	Untuk mengelakkan jangkitan COVID-19, seseorang individu harus mengelak pergi ke tempat yang sesak.	2.11	-2.72	21.96	0.005
K8	Pemakaian pelitup muka boleh mengelakkan penularan COVID-19 di tempat kerja.	1.38	-2.56	16.45	0.036
K9	Penggunaan pensanitasi tangan (hand sanitizer) membantu mengelakkan penularan wabak COVID-19 di tempat kerja.	1.19	-2.96	13.50	0.096

Table 4.7
(Continued…)

Item	Question	*a*	*b*	χ^2 (df = 8)	P-values
K10	Pengasingan individu yang dijangkiti virus COVID-19 adalah cara yang berkesan untuk mengurangkan penyebaran virus.	1.43	-3.34	9.72	0.286
K12	Vaksinasi COVID-19 mengurangkan risiko menghadapi jangkitan COVID-19 yang teruk.	0.41	-3.55	10.94	0.205
K13	Individu yang telah menerima vaksinasi COVID-19 tidak akan mendapat jangkitan COVID-19.	2.18	-0.96	19.67	0.012
K14	Kontak rapat yang tidak mempunyai gejala COVID-19 tidak akan menjangkiti orang lain.	2.02	0.46	35.07	< 0.001
K16	Proses sanitasi dan disinfeksi secara rutin dan berkala di tempat kerja boleh membendung penularan COVID-19.	0.82	-3.42	8.92	0.350
K17	Individu yang telah dijangkiti COVID-19 tidak akan mendapat jangkitan buat kali kedua.	18.63	-0.73	2.00	0.981

a = discriminant, *b* = difficulty

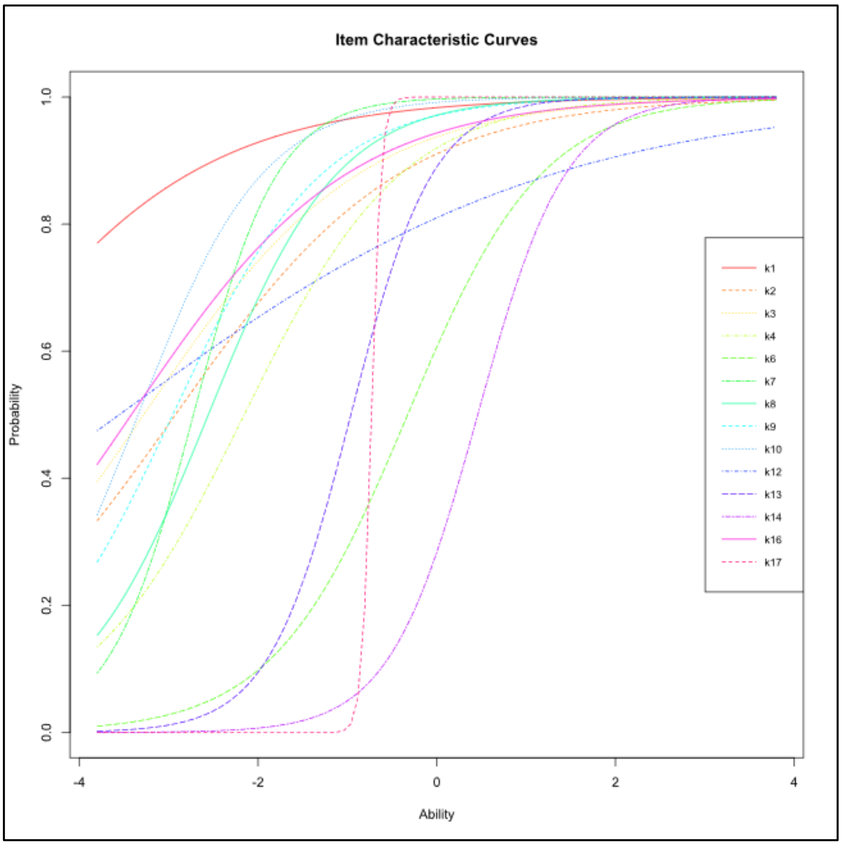

Figure 4.1 Item Characteristic Curves in Validation Part 1

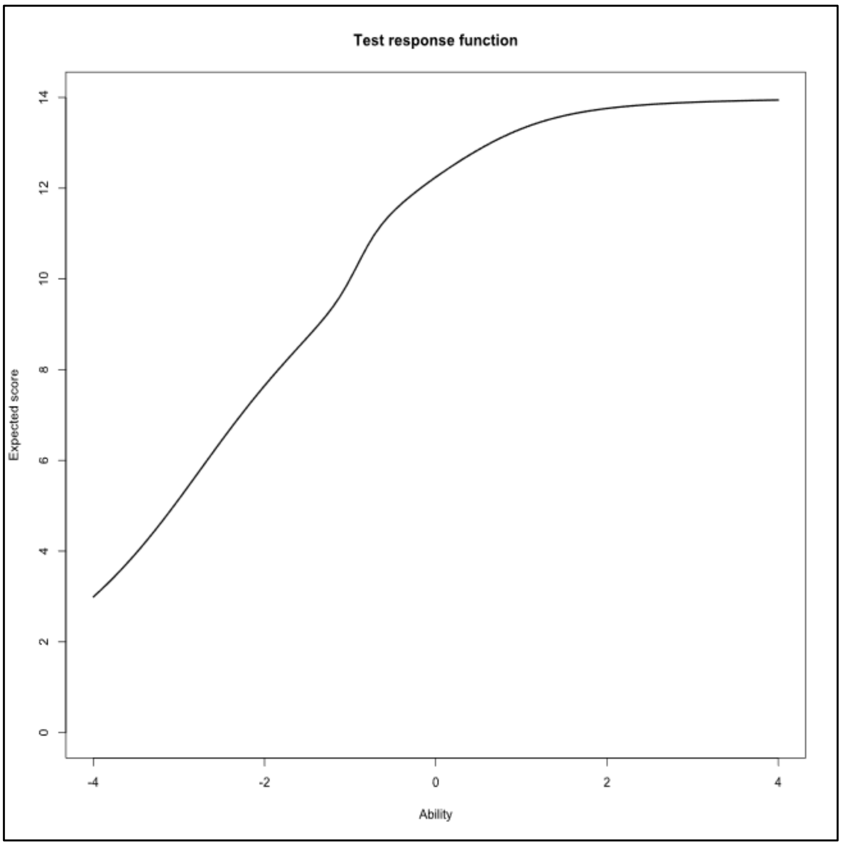

Figure 4.2 Test Response Function in Validation Part 1

4.2.3.3 Construct validity & reliability of the Stigma domain by EFA

Univariate normality was checked using histograms with normal curves, which revealed that several items in the stigma domain were not normally distributed (Figure 4.3). This finding was further supported by the Shapiro-Wilk test, where all items were found to be not normally distributed ($p < 0.05$). Multivariate normality was assessed using Mardia's tests for multivariate skewness and kurtosis. The assumption of multivariate normality was violated, as indicated by the significant result for kurtosis = 18.53 ($p < 0.05$) (Figure 4.4).

EFA was used at this stage to explore the underlying dimensional structure of the stigma domain and to provide initial evidence of construct representation. This exploratory evidence was subsequently reassessed through CFA in Validation Part 2 using an independent sample.

The KMO value was 0.72, indicating a middling level of sampling adequacy. Bartlett's test of sphericity was significant ($p < 0.001$), confirming that the data were suitable for factor analysis. Several methods were used to determine the number of factors to retain. The scree plot suggested the extraction of three factors (Figure 4.5), while parallel analysis indicated five factors (Figure 4.6). The Very Simple Structure (VSS) criterion 1 yielded a maximum value of 0.61 for two factors, and VSS complexity 2 achieved a maximum of 0.74 for four factors (Figure 4.7). The Velicer's Minimum Average Partial (MAP) criterion reached its minimum of 0.03 with three factors. Based on these considerations, the number of factors was fixed to three, and EFA was conducted using Principal Axis Factoring (PAF) with promax oblique rotation.

The initial EFA included 22 items (S1 - S22). Items were removed one by one based on the severity of the issues identified, such as cross-loadings, factor loadings less than 0.5, communalities less than 0.3, and factor correlations greater than 0.85, while also considering the preservation of conceptual coverage within the stigma domain. The final model consisted of 9 items, grouped under three factors: Stereotype, Fear, and Prejudice. These factor labels were assigned based on the conceptual content of the retained items and their coherence with the stigma literature and workplace context of the instrument. Factor loadings ranged from 0.558 to 0.968, and communalities from 0.426 to 0.866. Internal consistency was acceptable, with Cronbach's alpha values of 0.84 for Factor 1 (Stereotype), 0.73 for Factor 2 (Fear), and 0.85 for Factor 3 (Prejudice), reflecting very good, respectable, and very good reliability, respectively.

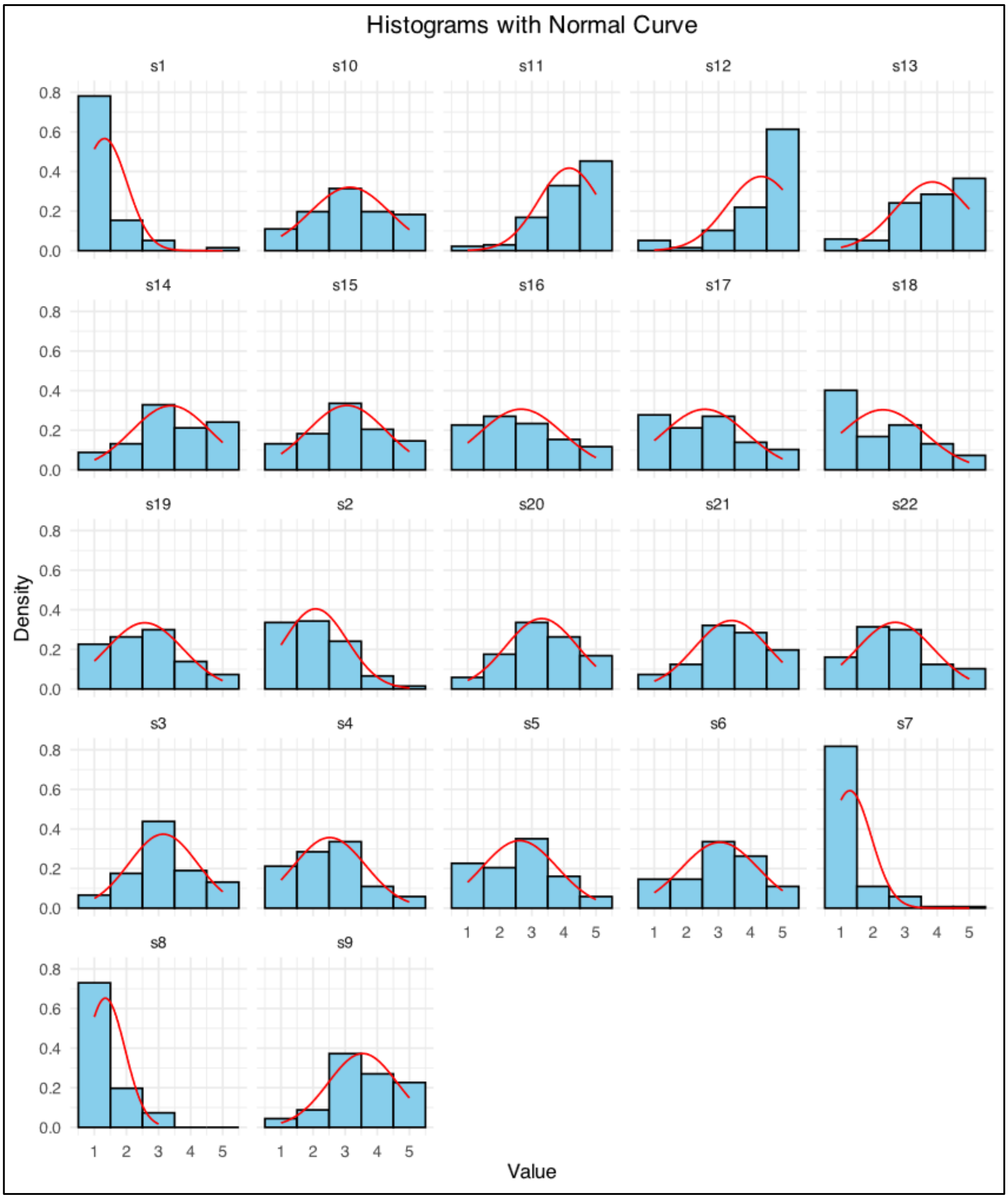

Figure 4.3 Univariate Normality EFA

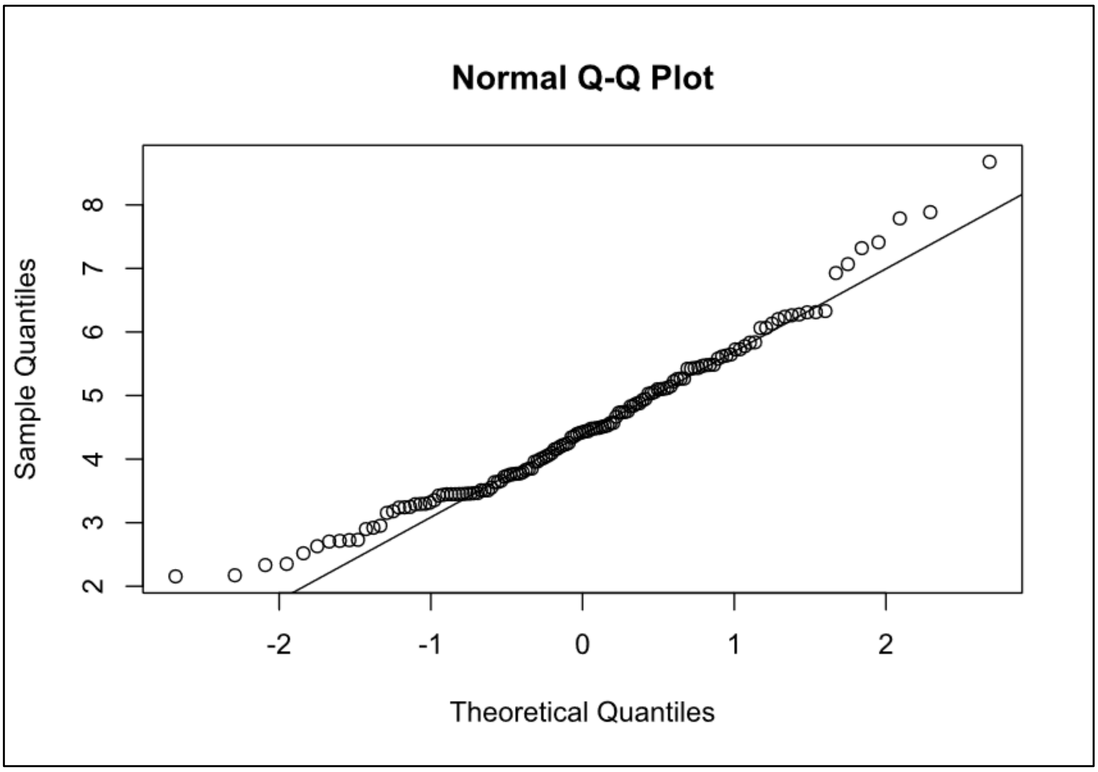

Figure 4.4 Multivariate Normality EFA

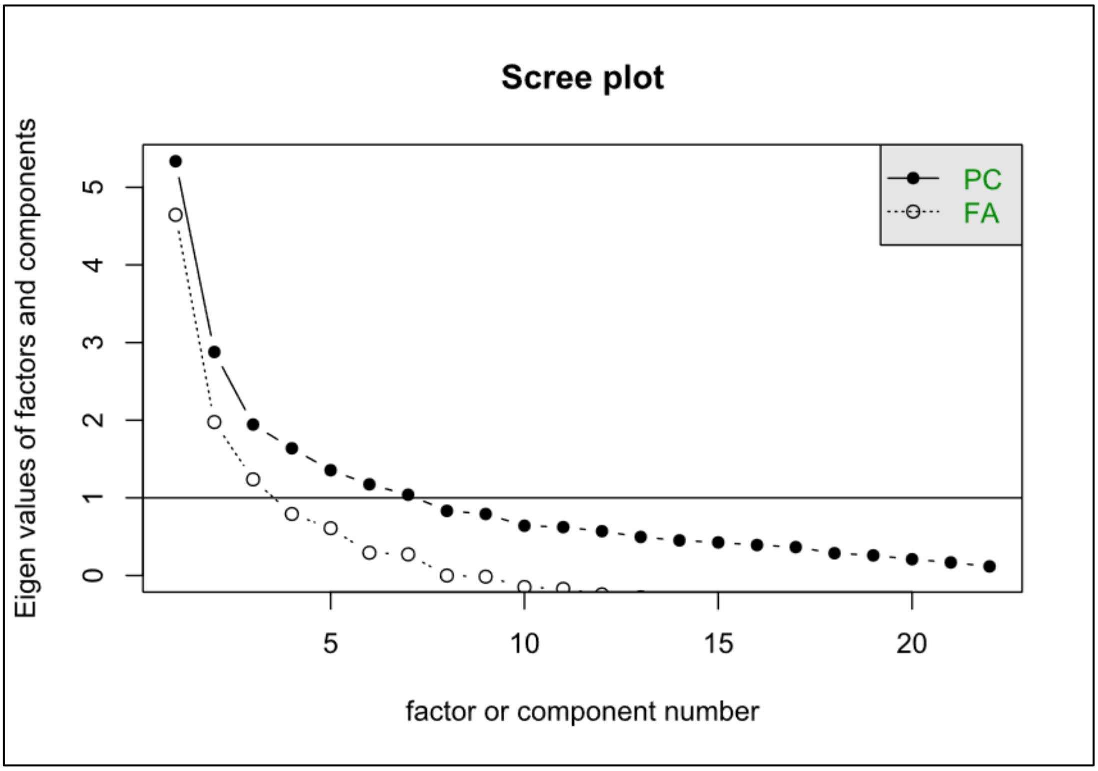

Figure 4.5 Scree Plot

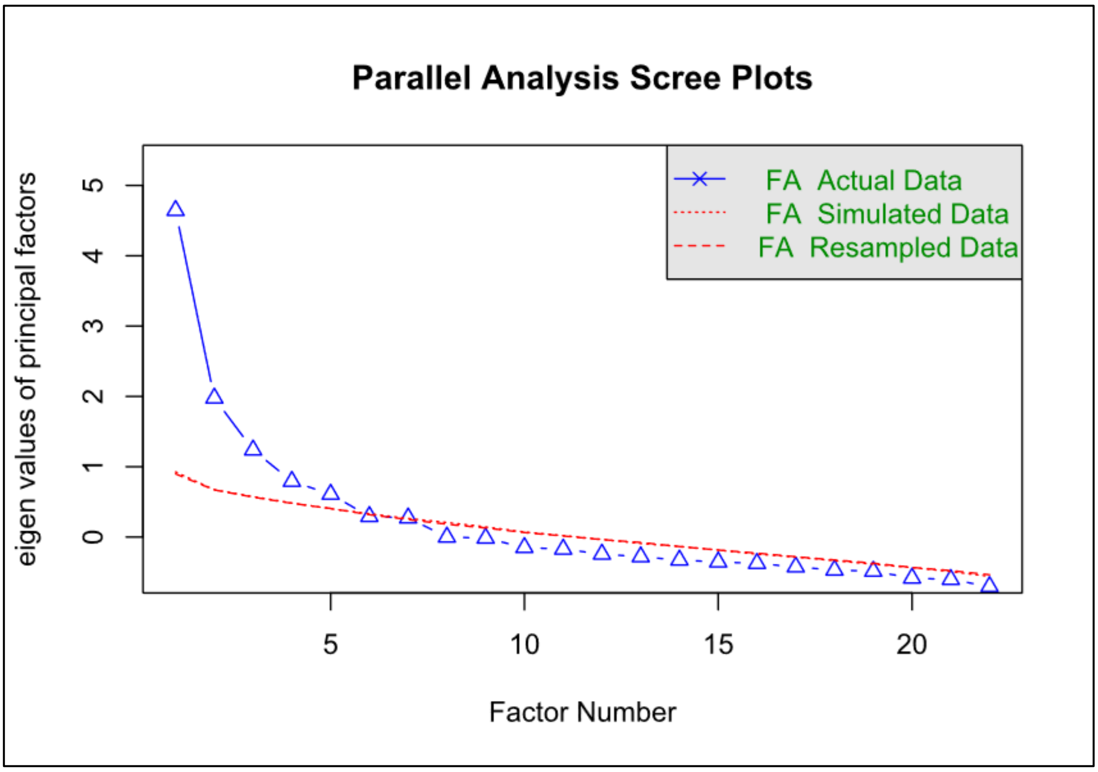

Figure 4.6 Parallel Analysis

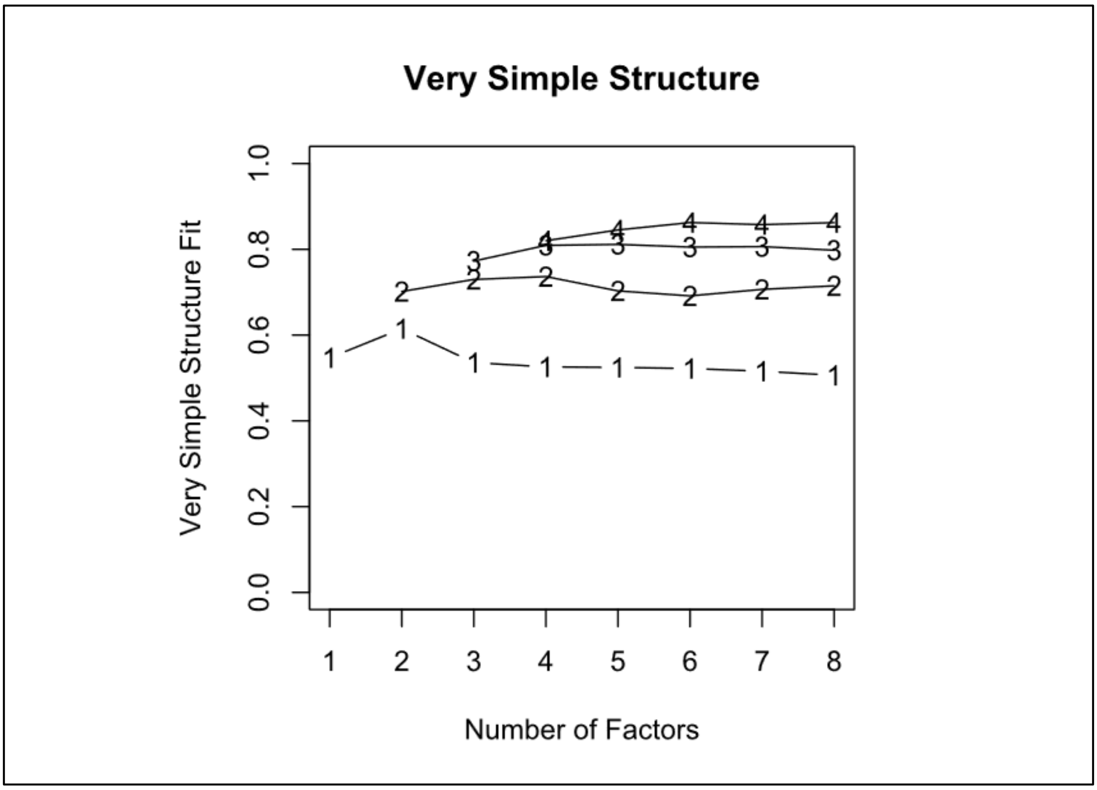

Figure 4.7 Very Simple Structure (VSS) Criterion

Table 4.8
Construct Validity & Internal Consistency of WoCKSS Stigma Domain by Exploratory Factor Analysis (EFA) and Cronbach's Alpha

Factor	Item	Question	Factor Loading	Communalities	Cronbach's Alpha
1 (Stereotype)	S4	Kebanyakan individu yang dijangkti COVId-19 tidak menjaga kebersihan.	0.796	0.652	0.84
	S5	Kebanyakkan individu yang dijangkti COVId-19 tidak menjaga Kesihatan mereka.	0.951	0.866	
	S6	Kebanyakkan individu yang dijangkti COVId-19 tidak mematuhi SOP yang telah ditetapkan.	0.668	0.446	
2 (Fear)	S7	Tiada sesiapa yang ingin dirinya dijangkiti COVID-19.	0.777	0.606	0.73
	S8	Tiada sesiapa yang dengan sengaja ingin menyebarkan virus COVID-19 di tempat kerja.	0.730	0.547	
3 (Prejudice)	S15	Saya bimbang saya terpaksa memikul tanggungjawab rakan sekerja yang dijangkiti COVID-19 apabila mereka tidak dapat melaksanakan tugas mereka.	0.558	0.436	0.85
	S16	Prestasi kerja mereka yang pernah dijangkiti COVID-19 menurun.	0.607	0.426	
	S17	Individu yang dijangkiti COVID-19 adalah beban kepada rakan sekerja.	0.968	0.850	
	S18	Individu yang dijangkiti COVID-19 adalah beban kepada Syarikat.	0.929	0.781	

Factors correlation: Stereotype←→Fear (r = 0.018), Stereotype←→Prejudice (r = 0.476) and Fear←→Prejudice (r = 0.051)

4.2.4 Validation Part 2: Confirmatory

4.2.4.1 Demographic Characteristics of the Respondents

The characteristics of the respondents involved in the validation part 2 are summarised in Table 4.9. The sample included 300 individuals, with an average age of 32.6 years (SD = 8.6). Most respondents were female (56.7%), while 43.3% were male. Regarding education, the majority held a bachelor's degree (59.7%), followed by those with Pre-University or Diploma qualifications (20.7%), SPM (12.7%), and Postgraduate degrees (7.0%). Monthly income varied, with the largest group earning between RM 2,501 and RM 4,849 (49.7%). Other income groups included those earning less than RM 2,500 (33.7%), and more than RM 4,850 (16%). In terms of COVID-19 infection history, 68.0% of the respondents had been infected, while 32.0% had not. Additionally, 12.0% of the respondents reported having family members who died due to COVID-19, while 88.0% did not. Most respondents were non-smokers (90.3%), with only 9.7% identifying as smokers.

Table 4.9
Characteristics of Respondents Involved in Validation Part 2 (n = 300)

Variables	Mean (SD)	n (%)
Age	32.6 (8.6)	
Gender		
Female		170 (56.7)
Male		130 (43.3)
Education		
SPM		38 (12.7)
Pre-University / Diploma		62 (20.7)
Bachelor's degree		179 (59.7)
Postgraduate (Master / Degree)		21 (7.0)
Monthly income		
< RM 2500		101 (33.7)
RM 2501 - RM 4849		149 (49.7)
≥ RM 4850		48 (16.0)
COVID-19 infection history		
No		96 (32.0)
Yes		204 (68.0)
History of family members died due to COVID-19		
No		264 (88.0)
Yes		36 (12.0)

Table 4.9
(Continued…)

Variables	Mean (SD)	n (%)
Smoking status		
Not smoking		271 (90.3)
Smoking		29 (9.7)

4.2.4.2 Item Response Theory (IRT) for the Knowledge domain

The results of the IRT analysis for the Knowledge domain in validation part 2 are summarised in Table 4.10. Fourteen items (K1, K2, K3, K4, K6, K7, K8, K9, K10, K12, K13, K14, K16, K17), as retained from validation part 1, were included in the analysis. Each item was assessed based on its discrimination, difficulty, and item fit statistics.

Three items presented significant misfit: K1 ($p = 0.025$), K3 ($p = 0.043$), and K17 ($p = 0.012$). Item K1 had a low difficulty parameter (-4.47) and moderate discrimination (0.97) but was retained due to its importance in assessing basic knowledge of COVID-19 symptoms. K3, although misfitting, showed acceptable discrimination (1.03) and marginal difficulty (-3.04), warranting its retention. K17 exhibited a high discrimination parameter (3.17) and moderate difficulty (-1.33); despite its significant misfit, the values only slightly exceeded recommended cutoffs, and the item was retained. Other misfitting items ($p < 0.05$) were also preserved as they were supported by appropriate discrimination and difficulty estimates.

Table 4.10
IRT Analysis for the Knowledge Domain in Validation Part 2

Item	Question	*a*	*b*	χ^2 (df = 8)	P-values
K1	Gejala utama COVID-19 ialah demam, batuk dan sukar bernafas.	0.97	-4.47	17.55	0.025
K2	Tidak semua individu dijangkiti COVID-19 akan mengalami gejala teruk.	1.94	-2.13	28.81	< 0.001
K3	Mereka yang berumur lebih daripada 65 tahun dan mempunyai penyakit kronik mempunyai kebarangkalian lebih tinggi untuk mengalami gejala COVID-19 yang teruk.	1.03	-3.04	15.99	0.043
K4	Virus COVID-19 merebak melalui titisan air yang terbentuk di saluran pernafasan pesakit semasa mereka bercakap, bersin, atau batuk.	1.43	-2.04	7.15	0.520

Table 4.10
(Continued…)

Item	Question	*a*	*b*	χ^2 (df = 8)	P-values
K6	Individu yang dijangkiti COVID-19 tidak akan menjangkiti orang lain sekiranya dia tidak mempunyai gejala.*	1.42	-0.64	51.58	< 0.001
K7	Untuk mengelakkan jangkitan COVID-19, seseorang individu harus mengelak pergi ke tempat yang sesak.	2.02	-2.90	23.03	0.003
K8	Pemakaian pelitup muka boleh mengelakkan penularan COVID-19 di tempat kerja.	2.79	-2.21	7.94	0.440
K9	Penggunaan pensanitasi tangan (hand sanitizer) membantu mengelakkan penularan wabak COVID-19 di tempat kerja.	1.92	-2.51	28.83	< 0.001
K10	Pengasingan individu yang dijangkiti virus COVID-19 adalah cara yang berkesan untuk mengurangkan penyebaran virus.	1.21	-3.95	10.92	0.206
K12	Vaksinasi COVID-19 mengurangkan risiko menghadapi jangkitan COVID-19 yang teruk.	0.77	-2.60	60.04	< 0.001
K13	Individu yang telah menerima vaksinasi COVID-19 tidak akan mendapat jangkitan COVID-19.*	1.78	-1.48	42.28	< 0.001
K14	Kontak rapat yang tidak mempunyai gejala COVID-19 tidak akan menjangkiti orang lain.*	1.60	0.23	16.41	0.037
K16	Proses sanitasi dan disinfeksi secara rutin dan berkala di tempat kerja boleh membendung penularan COVID-19.	1.59	-2.52	19.51	0.012
K17	Individu yang telah dijangkiti COVID-19 tidak akan mendapat jangkitan buat kali kedua.	3.17	-1.33	19.51	0.012

a = discriminant, *b* = difficulty,

*respondents receive marks if they correctly identify the statement as incorrect

The Item Characteristic Curves (ICCs) displayed in Figure 4.8 illustrate variation in item characteristics. Easier items, including K1, K3, K4, K7, K10, and K12, appear left-shifted, indicating lower ability thresholds to achieve high probabilities of correct responses. In contrast, K14 (difficulty = 0.23) and K17 (difficulty = -1.33) were positioned to the right, suggesting they were relatively more difficult. In terms of discrimination, K2 (1.94), K7 (2.02), K8 (2.79), K9 (1.92), K13 (1.78), and K17 (3.17) demonstrated steeper slopes, indicating stronger differentiation between respondents with varying ability levels.

Approximately 76.34% of the total test information was located within the ability range of -3 to +3, demonstrating that the test was effective across a broad spectrum of respondent abilities. The Test Response Function (TRF) in Figure 4.9 illustrates a positive relationship between respondent ability and expected score, where higher levels of knowledge corresponded to higher predicted scores.

The unidimensionality assumption was supported by the results of the modified parallel analysis, which produced a non-significant p-value ($p = 0.644$), indicating that the items could be appropriately summed to yield a total knowledge score.

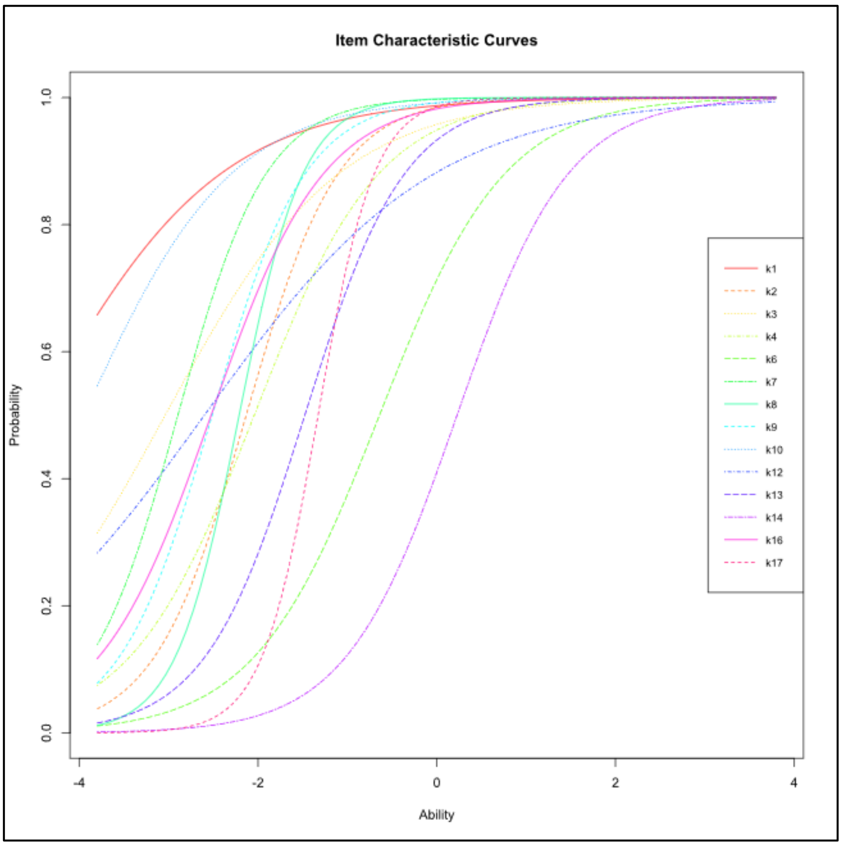

Figure 4.8 Item Characteristic Curves in Validation Part 2

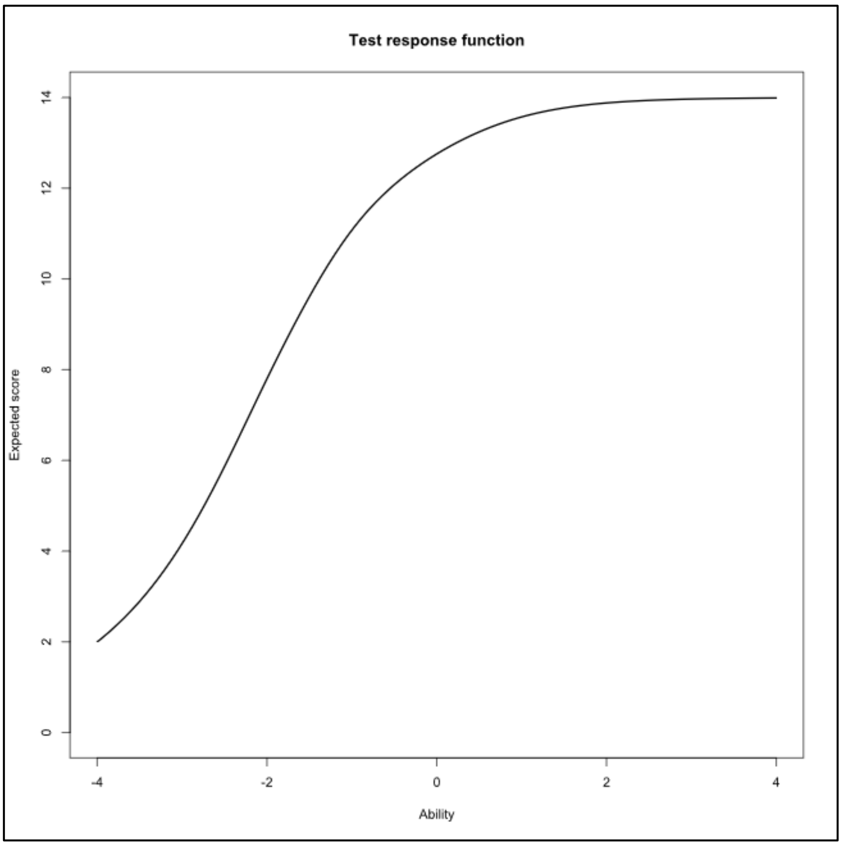

Figure 4.9 Test Response Function in Validation Part 2

4.2.4.3 Construct validity & reliability of the Stigma domain by CFA

Confirmatory Factor Analysis (CFA) was conducted to evaluate the construct validity and model fit of the stigma domain, based on the three-factor structure identified during Exploratory Factor Analysis (EFA). Model evaluation was carried out by examining fit indices, residuals, modification indices (MI), factor loadings, and factor correlations. Revisions were made iteratively until a satisfactory model was achieved.

Prior to conducting CFA, assumptions of univariate and multivariate normality were assessed. Histograms with overlaid normal curves (Figure 4.10) showed that several items were not normally distributed. This was further supported by the Shapiro-Wilk test, where all items had p-values < 0.05. Multivariate normality, assessed using Mardia's test for multivariate skewness and kurtosis, was also violated, with kurtosis = 31.85 and $p < 0.05$ (Figure 4.11).

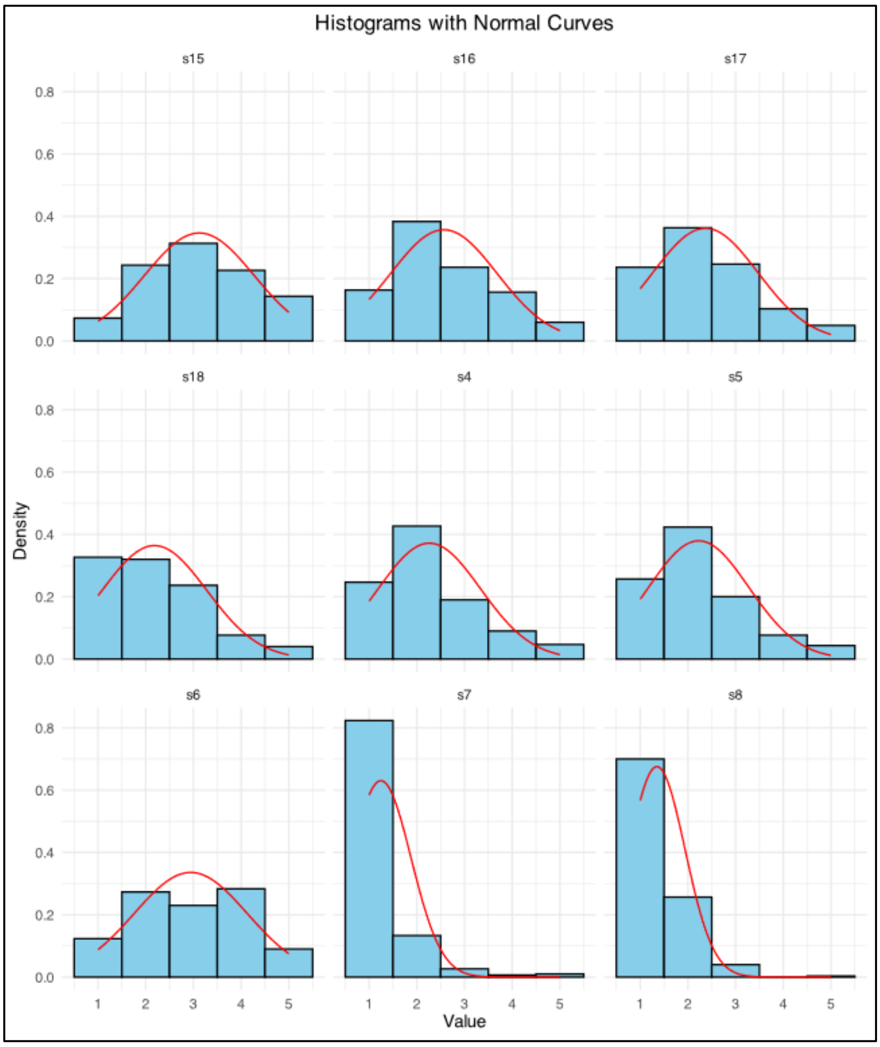

Figure 4.10 Univariate Normality CFA

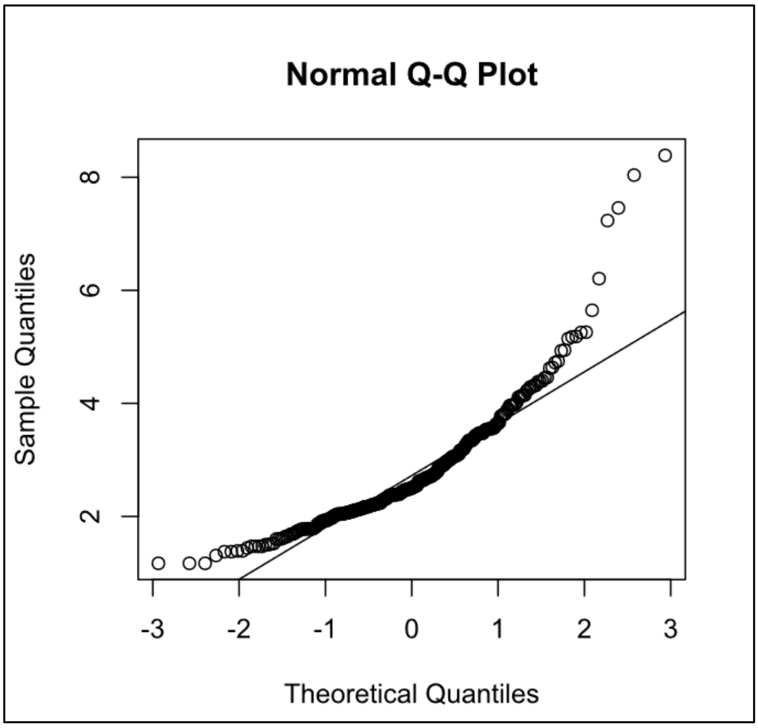

Figure 4.11 Multivariate Normality CFA

Table 4.11 summarises the fit indices of three CFA models. Model 1, which included all nine items identified from EFA, yielded a significant chi-square test (χ^2 (24) = 57.12, $p < 0.001$), RMSEA = 0.070 (90% CI: 0.047, 0.094), and close-fit p-value = 0.075. Although CFI = 0.97, TLI = 0.95, and SRMR = 0.054 were within acceptable thresholds, high MIs were observed between S17 and S18 (MI = 17.399), and S16 and S18 (MI = 10.828), indicating localised misfit. While the chi-square test was significant in Models 1 and 2, model evaluation considered multiple fit indices jointly, given the sensitivity of chi-square to model complexity and sample size. Items S15 and S16, both under the Prejudice factor, had low factor loadings and large residuals. Reallocating S16 and S17 to a different factor or introducing modifications that would alter the conceptual meaning of the model, was not theoretically justifiable. Thus, S15 was removed in the next model.

Model 2, which excluded item S15, showed minor improvement. The chi-square value was χ^2 (17) = 40.37, $p = 0.001$, with RMSEA = 0.071 (90% CI: 0.043, 0.100) and close-fit p-value = 0.102. CFI and TLI increased slightly to 0.98 and 0.96, respectively, and SRMR decreased to 0.049. However, item S16 continued to show high residuals and MI values (S16 ~ S18 MI = 22.171), warranting its exclusion in the final model.

Table 4.11
Fit Indices of the Model

Fit Indices	Model		
	Model 1	Model 2	Model 3
χ^2 (df)	57.12 (24)	40.37 (17)	8.91 (11)
χ^2 P-value	< 0.001	0.001	0.630
SRMR	0.054	0.049	0.021
RMSEA	0.070	0.071	0.000
90% CI	0.047, 0.094	0.043, 0.100	0.000, 0.055
CFit P-value	0.075	0.102	0.927
CFI	0.97	0.98	1.00
TLI	0.95	0.96	1.00
AIC	6431.64	5591.33	4778.92
BIC	6509.42	5661.70	4841.89

Model 3, which excluded both S15 and S16, demonstrated excellent model fit. The chi-square test was non-significant (χ^2 (11) = 8.91, $p = 0.630$), with RMSEA = 0.000 (90% CI: 0.000, 0.055) and close-fit p-value = 0.927. Fit indices were excellent: CFI = 1.00, TLI = 1.00, and SRMR = 0.021. AIC and BIC were substantially reduced to 4778.92 and 4841.89, respectively, confirming this as the best-fitting model.

Construct validity and internal consistency of the final model (Model 3) are presented in Table 4.12. Three factors were confirmed: Stereotype, Fear, and Prejudice. This final structure retained the same three-factor conceptual framework identified in EFA, although two items from the Prejudice factor were removed during CFA to improve model fit while preserving theoretical coherence. The low correlations among the retained latent factors further supported the conceptual distinctiveness of stereotype, fear, and prejudice in the final model. Factor loadings ranged from 0.594 to 0.999. Composite reliability (omega) for each factor was acceptable: 0.691 (Stereotype), 0.867 (Fear), and 0.893 (Prejudice), indicating adequate to very good internal consistency. The final CFA structure is illustrated in Figure 4.12.

Table 4.12
Construct Validity & Internal Consistency of WoCKSS Stigma Domain by Confirmatory Factor Analysis (CFA) and Composite Reliability

Factor	Item	Question	Factor Loading	Omega
F1 (Stereotype)	S4	Kebanyakan individu yang dijangkti COVID-19 tidak menjaga kebersihan	0.699	0.691
	S5	Kebanyakkan individu yand dijangkiti COVID-19 tidak menjaga Kesihatan mereka	0.594	
	S6	Kebanyakkan individu yang dijangkti COVId-19 tidak mematuhi SOP yang telah ditetapkan	0.860	
F2 (Fear)**	S7	Tiada sesiapa yang ingin dirinya dijangkiti COVID-19*	0.863	0.867
	S8	Tiada sesiapa yang dengan sengaja ingin menyebarkan virus COVID-19 di tempat kerja*	0.931	
F3 (Prejudice)	S17	Individu yang dijangkiti COVID-19 adalah beban kepada rakan sekerja	0.789	0.893
	S18	Individu yang dijangkiti COVID-19 adalah beban kepada syarikat	0.999	

*Negative question, **reverse coding

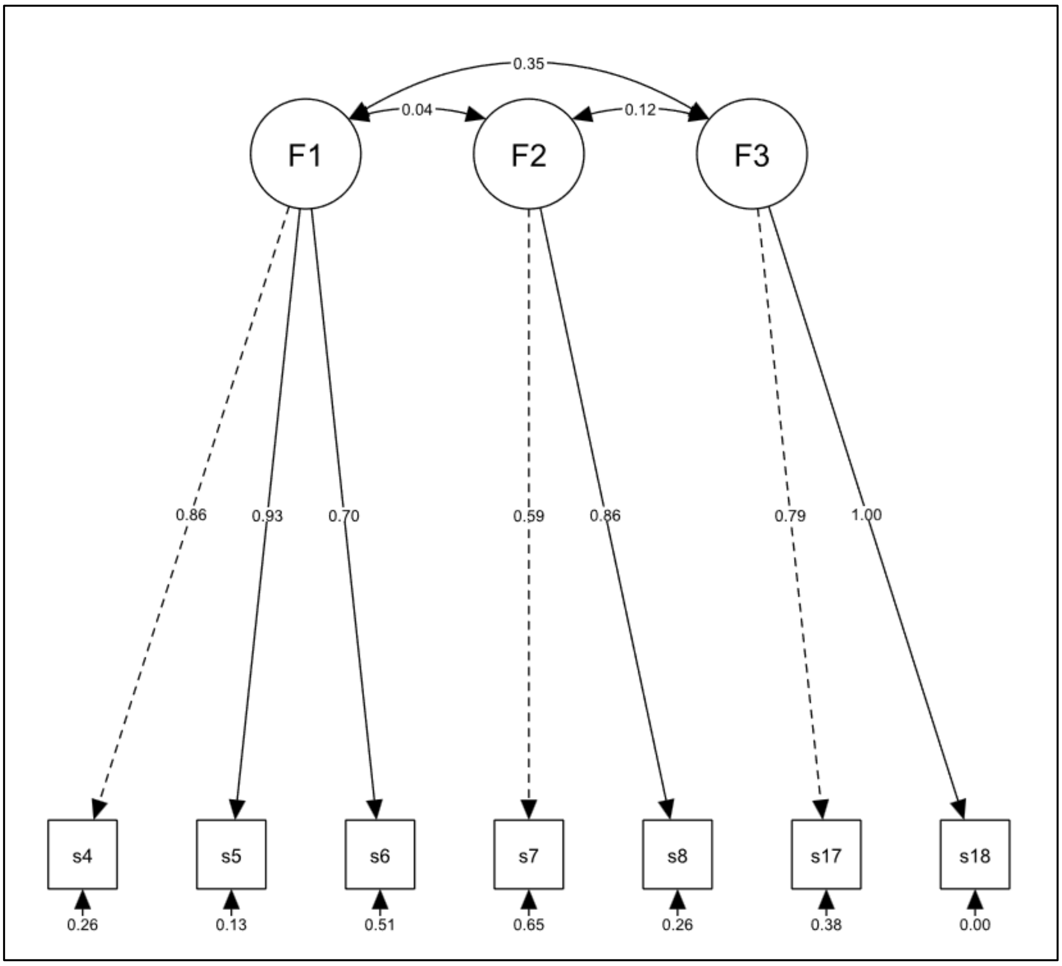

Figure 4.12 Path Diagram of Model 3 (Final Model)

4.2.5 Results Summary for Phase 1 – WoCKSS Validation

Objective 1 of this research was successfully accomplished through the rigorous development and comprehensive validation of the WoCKSS questionnaire. Figure 4.13 provides a summary of the Phase 1 findings, which includes content validation, face validation, exploratory validation (covering IRT, EFA, and Cronbach's alpha), and confirmatory validation (covering IRT, CFA, and McDonald's omega).

The knowledge domain demonstrated acceptable item properties based on the IRT analysis, with retained items reflecting appropriate difficulty and discrimination. For the stigma domain, EFA identified a three-factor structure (Fear, Stereotype, Prejudice) with satisfactory internal consistency. CFA confirmed the construct validity of this structure in a larger sample, supported by strong fit indices and reliability values. These findings support the psychometric robustness of the WoCKSS for assessing workplace COVID-19 knowledge and stigma. The final version of the WoCKSS questionnaire is provided in Appendix 1.

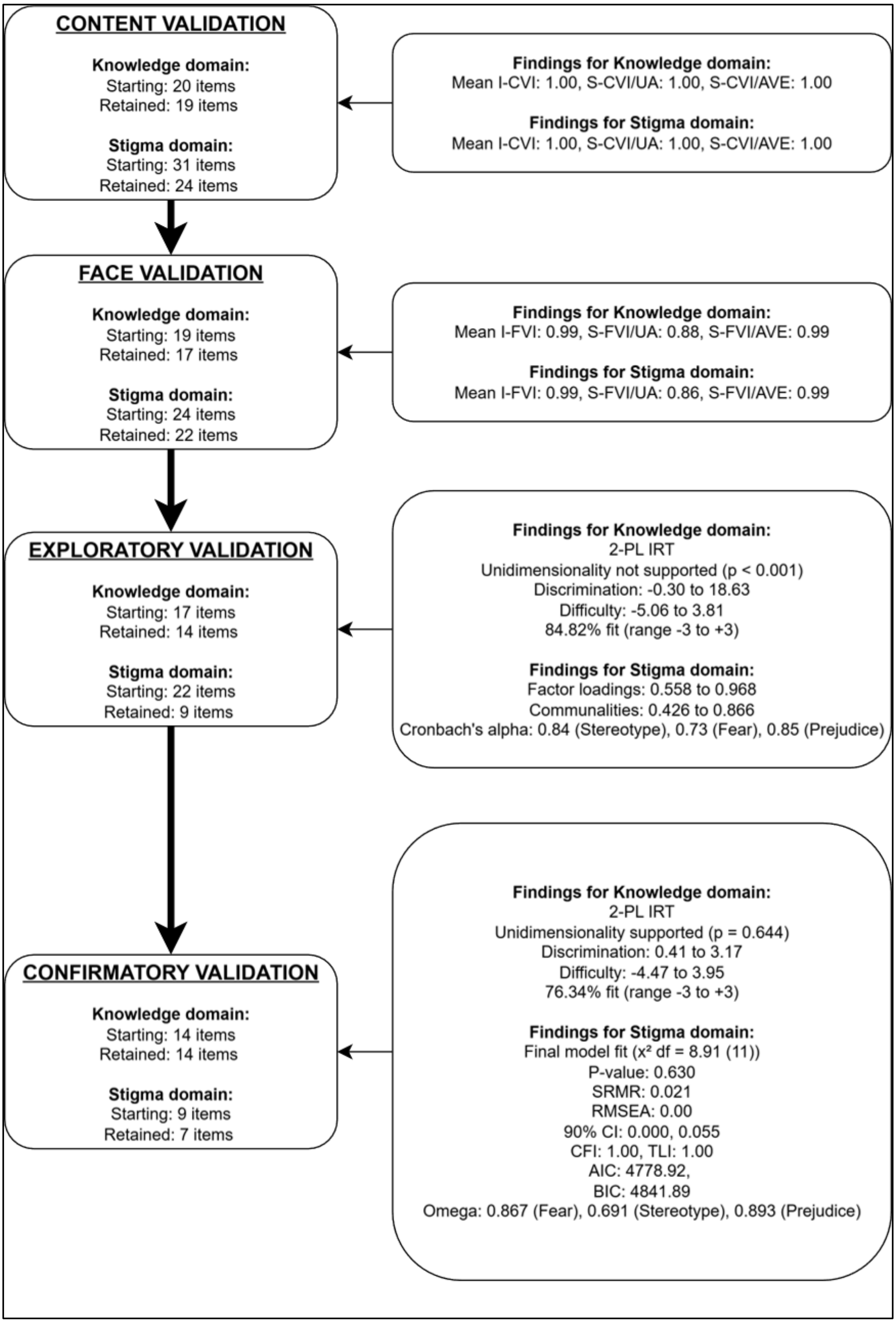

Figure 4.13 Summary of Findings for Phase 1

4.3 Phase 2: COVID-19 Stigma Characterisation Through Social Network Analysis (SNA)

A total of 179 factory workers participated in this Phase 2 survey cycle, resulting in a response rate of 71.6%. The egocentric network data collected from these 179 factory workers yielded 791 nominated alters/dyadic relationships.

Table 4.13 provides the demographic characteristics of the 179 factory workers who participated in the study. The majority were male (79.9%), with a smaller proportion of female workers (20.1%). Most participants had completed SPM (74.9%), while others had Pre-University/Diploma qualifications (14.0%), and a small number had university degrees (7.82%). Job positions were varied, with most working in Productions (61.5%), followed by Technical and Engineering (15.1%), Logistics and Material Handling (9.5%), and Administration (14.0%). Nearly 60% of participants reported having a COVID-19 infection history, while 7.82% had lost a family member due to COVID-19. The average COVID-19 knowledge score was 81.5%, and 68.7% of respondents were categorized as having COVID-19 stigma.

Table 4.13
Descriptive Statistics of Ego

Variable	N (%)	Mean (SD)
Age		
18 - 29 years old	71 (39.66)	
30 - 44 years old	79 (44.13)	
> 44 years old	29 (16.2)	
Gender		
Female	36 (20.1)	
Male	143 (79.9)	
Education		
SPM	134 (74.9)	
Pre-University/ Diploma	25 (14.0)	
University (Bachelor degree/ Master/ PhD)	14 (7.82)	
Not complete high school	6 (3.35)	
Job position		
Productions	110 (61.5)	
Logistics and Material Handling	17 (9.50)	
Technical and Engineering	27 (15.1)	
Administration	25 (14.0)	
Chronic illness		
No	171 (95.5)	
Yes	8 (4.47)	
COVID-19 history		
No	72 (40.2)	
Yes	107 (59.8)	

Table 4.13 (Continued…)

Variable	N (%)	Mean (SD)
Family Member's Death Due to COVID-19		
No	165 (92.2)	
Yes	14 (7.82)	
Smoking status		
No	90 (50.3)	
Yes	89 (49.7)	
COVID-19 knowledge score		81.5 (13.1)
Having COVID-19 stigma		
No	56 (31.3)	
Yes	123 (68.7)	

Table 4.14 summarises the characteristics of the 791 nominated alters in the egocentric network. The average duration of acquaintance between egos and alters was 12.3 years (SD = 11.2). A majority of alters did not influence the egos' COVID-19 stigma perceptions (83.6%), while 16.4% did. Alters were primarily family members (25.8%), while a notable proportion were co-workers. The gender distribution of alters showed a higher percentage of males (65.4%) compared to females (34.6%).

Table 4.14
Descriptive Statistics of Alters

Variable	n (%)	Mean (SD)
Duration knowing the alters (years)		12.3 (11.2)
Perceived Influence of alters on ego's COVID-19 stigma		
No	661 (83.6)	
Yes	130 (16.4)	
Relationship		
Family	204 (25.8)	
Friends	168 (21.2)	
Colleague	323 (40.8)	
Superior/employer	29 (3.67)	
Others	67 (8.47)	
Alter's gender		
Male	517 (65.4)	
Female	274 (34.6)	

4.3.1 Egocentric Network Analysis of Workplace COVID-19 Stigma

This section presents the findings from the egocentric network analysis, which examines how ego-level and alter-level characteristics shape workers' perceptions of COVID-19 stigma. The results directly address Objective 2 by identifying the relational and demographic factors that influence stigma within workers' personal networks.

4.3.1.1 Multiple Logistic Regression (MLogR)

To identify factors within egocentric networks that contribute to workplace COVID-19 stigma, a multiple logistic regression analysis (MLogR) was performed using a block-wise modelling approach. The outcome variable was stigma status (stigma vs no stigma). Three blocks of variables were introduced sequentially: demographic characteristics (Model 1), health-related variables (Model 2), and egocentric network variables (Model 3). This stepwise inclusion enabled an evaluation of how each domain contributes to the prediction of COVID-19 stigma among factory workers.

The model performance statistics are summarised in Table 4.15. Each subsequent model demonstrated an improvement in fit and predictive capacity. Model 1 (demographics) yielded an AIC of 211.52 and correctly classified 72.1% of cases, with an area under the curve (AUC) of 0.740 and a Nagelkerke R^2 of 0.196. Upon inclusion of health-related variables in Model 2, model performance improved modestly, with a reduced AIC of 211.12 and an AUC of 0.753. The final model (Model 3), incorporating egocentric network variables, achieved the best fit (AIC = 208.63), highest classification accuracy (73.74%), and strongest discriminative ability (AUC = 0.802), with Nagelkerke R^2 increasing to 0.330. Hosmer-Lemeshow p-values across all models exceeded $p > 0.05$, indicating acceptable model fit.

Table 4.15
Model Performance

Model fit statistics	Model 1	Model 2	Model 3
AIC	211.52	211.12	208.63
Classification accuracy (%)	72.07	70.95	73.74
Area under curve (AUC)	0.740	0.753	0.802
Hosmer and Lemeshow (p-value)	0.961	0.675	0.536
Nagelkerke R^2	0.196	0.226	0.330
Variance Inflation Factor (VIF)	All < 5	All < 5	All < 5

The regression coefficients and adjusted odds ratios for all three models are presented in Table 4.16. In Model 1, age and job position emerged as significant predictors of COVID-19 stigma. Respondents aged 30 to 44 years were significantly less likely to report stigma compared to those aged 18 to 29 (aOR = 0.29, 95% CI: 0.13 to 0.63, p = 0.002), while the age group above 44 years did not show a significant likelihood compared to those aged 18 to 29 (aOR = 0.53, 95% CI: 0.17 to 1.61, p =

0.260). Workers in technical and engineering roles were also significantly less likely to report stigma than those in administrative roles (aOR = 0.24, 95% CI: 0.07 to 0.87, p = 0.029). Other job categories, such as production (aOR = 0.40, p = 0.114) and logistics/material handling (aOR = 2.94, p = 0.360), were not significantly likely to associate with stigma as compared to those in administrative role. Gender (aOR = 1.81, p = 0.184) and education (aOR = 1.92, p = 0.162) were also not significant predictors in this model.

Model 2, which incorporated health-related variables, showed that respondents with a history of COVID-19 infection were significantly less likely to report stigma (aOR = 0.46, 95% CI: 0.21 to 0.97, p = 0.043). However, COVID-19 knowledge was not significantly associated with stigma (aOR = 0.99, 95% CI: 0.97 to 1.02, p = 0.712). The inclusion of these health variables did not substantially change the direction or significance of the demographic predictors from Model 1.

Model 3 introduced compositional network variables, providing additional insight into the social structure associated with workplace stigma. In this final model, age remained statistically significant. Workers aged 30 to 44 years were significantly less likely to report stigma compared to those aged 18 to 29 (aOR = 0.27, 95% CI: 0.11 to 0.66, p = 0.004). Job position however becomes not significant in this model ($p > 0.05$). Gender homophily was also a significant predictor, where greater same-gender composition within an ego's network was associated with increased odds of reporting stigma (aOR = 1.03, 95% CI: 1.01 to 1.05, p = 0.009). Additionally, interactions with family (aOR = 1.02, 95% CI: 1.00 to 1.04, p = 0.049) and interactions with superiors or employers were positively associated with the presence of COVID-19 stigma (aOR = 1.05, 95% CI: 1.00, to 1.11, p = 0.039). Other relationship types were not statistically associated with COVID-19 stigma ($p > 0.05$).

These results demonstrate that both individual-level characteristics and the structural composition of personal networks contribute meaningfully to the experience of COVID-19 stigma in workplace settings. The sequential block-wise modelling approach clarified the incremental value of demographic, health, and network-related predictors in explaining stigma-related outcomes.

Table 4.16
Factors Within Egocentric Networks That Associate with COVID-19 Stigma among Factory Workers

Variables	Model 1			Model 2			Model 3		
	B	Adj. OR (95% CI)	P	B	Adj. OR (95% CI)	P	B	Adj. OR (95% CI)	P
Intercept	1.2978	3.66 (1.15, 11.63)	0.028	2.1982	9.01 (0.52, 157.45)	0.132	0.4100	1.51 (0.06, 39.11)	0.805
Age (years old)									
18 - 29	0	1		0	1		0	1	
30 - 44	-1.2512	0.29 (0.13, 0.63)	0.002	-1.2136	0.30 (0.13, 0.66)	0.003	-1.3038	0.27 (0.11, 0.66)	0.004
> 44	-0.6423	0.53 (0.17, 1.61)	0.260	-0.5255	0.59 (0.19, 1.86)	0.369	-0.6982	0.50 (0.14, 1.77)	0.280
Gender									
Female	0	1		0	1		0	1	
Male	0.5931	1.81 (0.76, 4.34)	0.184	0.5703	1.77 (0.73, 4.27)	0.205	0.1053	1.11 (0.34 3.65)	0.862
Education									
Higher education	0	1		0	1		0	1	
≤ SPM	0.6531	1.92 (0.77, 4.80)	0.162	0.6439	1.90 (0.73, 4.96)	0.187	0.5835	1.79 (0.65, 4.92)	0.257
Job position									
Administration	0	1		0	1		0	1	
Productions	-0.9097	0.40 (0.13, 1.25)	0.114	-0.8359	0.43 (0.14, 1.35)	0.150	-0.5792	0.56 (0.16, 1.91)	0.356
Logistic & Material Handling	1.0776	2.94 (0.29, 29.55)	0.360	0.8584	2.36 (0.23, 24.04)	0.469	1.0536	2.87 (0.24, 34.00)	0.404
Technical & Engineering	-1.4126	0.24 (0.07, 0.87)	0.029	-1.3315	0.26 (0.07, 0.96)	0.043	-1.2546	0.29 (0.07, 1.13)	0.075
COVID-19 infection history									
No				0	1		0	1	
Yes				-0.7868	0.46 (0.21, 0.97)	0.042	-0.8439	0.43 (0.18, 1.02)	0.055
COVID-19 knowledge				-0.0055	0.99 (0.97, 1.02)	0.712	-0.0164	0.98 (0.95, 1.02)	0.323
Compositional variable									
Gender homophily							0.0269	1.03 (1.01, 1.05)	0.009
Male alters							0.0026	1.00 (0.99, 1.02)	0.770
Relation - Family							0.0199	1.02 (1.00, 1.04)	0.049
Relation - Friends							0.0023	1.00 (0.99, 1.02)	0.754
Relation - Superior/ Employer							0.0519	1.05 (1.00, 1.11)	0.039
Relation - Others							0.0153	1.02 (0.99, 1.04)	0.242
Duration knowing the alter							0.0054	1.01 (0.94, 1.07)	0.865

4.3.1.2 Binary Logistic Multilevel Modelling (MLM)

To further examine the predictors of perceived influence of alters on ego's COVID-19 stigma, a series of binary logistic multilevel models (MLM) were fitted to account for the hierarchical structure of the data, where multiple alters were nested within each ego. The binary outcome variable indicated whether an alter was perceived to influence the ego's stigma perception. The results are presented in Table 4.17.

Table 4.17
Binary Logistic Multilevel Modelling Predicting the Perceived Influence of Alters on Ego's COVID-19 Stigma

Variables	Model 0		Model 1		Model 2	
	B	P	B	P	B	P
Intercept	-3.849	< 0.001	-2.444	0.303	-1.504	0.544
Ego-level Predictors						
Ego's COVID-19 knowledge			-0.028	0.318	-0.029	0.333
Ego's COVID-19 stigma						
No			0		0	
Yes			1.322	0.140	1.247	0.175
Alter-level Predictors						
Alter's gender						
Female					0	
Male					0.739	0.092
Relationship with alter						
Family					0	
Friends					-1.892	0.005
Colleagues					-1.675	0.009
Superior					-2.908	0.022
Others					-0.326	0.638
Duration knowing the alter					-0.026	0.262
Model fit Statistics						
AIC	484.7		485.4		481.4	
BIC	494.0		504.1		528.1	
Log likelihood	-240.3		-238.7		-230.7	
Deviance	480.7		477.4		461.4	
Model comparison (P-value)	-		0.194		0.014	
Random effects (variance)	14.53		13.44		14.06	
ICC	0.815		0.803		0.810	
Conditional R^2	0.815		0.809		0.822	
Marginal R^2	0		0.03		0.06	

Model 0, the null model, included only a random intercept to quantify the degree of variation at the ego level. The intraclass correlation coefficient (ICC) was 0.815, indicating that 81.5% of the variance in perceived influence was attributable to differences between egos. This substantial between-ego variability provided strong justification for using a multilevel modelling approach. The random effect variance was 14.53. The marginal R^2 was 0, indicating that no variance was explained by fixed effects. The model fit statistics were AIC = 484.7 and BIC = 494.0.

Model 1 introduced ego-level predictors, namely ego's COVID-19 knowledge and stigma status. Neither variable was statistically significant. Ego's knowledge had a coefficient of B = -0.028 ($p = 0.318$), while ego stigma status had B = 1.322 ($p = 0.140$). Model fit showed no meaningful improvement over the null model, with AIC = 485.4 and BIC = 504.1. However, the marginal R^2 increased slightly to 0.03, suggesting that the inclusion of ego-level variables explained 3.0% of the variance in perceived influence. The random effect variance slightly decreased to 13.44, and the ICC remained high at 0.803.

Model 2 incorporated additional alter-level predictors, including gender, relationship type, and duration of acquaintance. This model yielded the best overall fit (AIC = 481.4; BIC = 528.1; log likelihood = -230.7; deviance = 461.4) and the highest marginal R^2 of 0.06, indicating that fixed effects explained 6.0% of the variance in perceived influence. The random effect variance was 14.06, and the ICC increased marginally to 0.810.

Among the alter-level predictors, relationship type emerged as a significant factor. Compared to family members (reference group), friends (B = -1.892, $p = 0.005$), colleagues (B = -1.675, $p = 0.009$), and superiors or employers (B = -2.908, $p = 0.022$) were significantly less likely to be perceived as influential. Alters classified as "others" did not differ significantly from family members (B = -0.326, $p = 0.638$). Alter gender was not significantly associated with perceived influence (B = 0.739, $p = 0.092$), and the duration of knowing the alter also remained non-significant (B = -0.026, $p = 0.262$). Model comparison using likelihood ratio tests confirmed that Model 2 represented a statistically significant improvement over the null model ($\chi^2 = 16.00$, df = 6, $p = 0.014$), whereas Model 1 did not ($p = 0.194$). The increase in marginal R^2 from 0 to 0.06 across models suggests that fixed-effect predictors, particularly alter-level characteristics, contributed modestly to the explanatory power of the model. In contrast, the consistently high conditional R^2 and ICC values highlight the substantial influence of between-ego variability in shaping perceived influence outcomes. To further examine the variability between egos, the distribution of random intercepts was visually inspected. The dotplot and histogram in Figure 4.14 show considerable spread in ego-specific intercepts, consistent with the high ICC values reported across models. No extreme or influential clusters were detected, indicating that the random-effects structure was stable and that the model estimates were not disproportionately driven by any single ego.

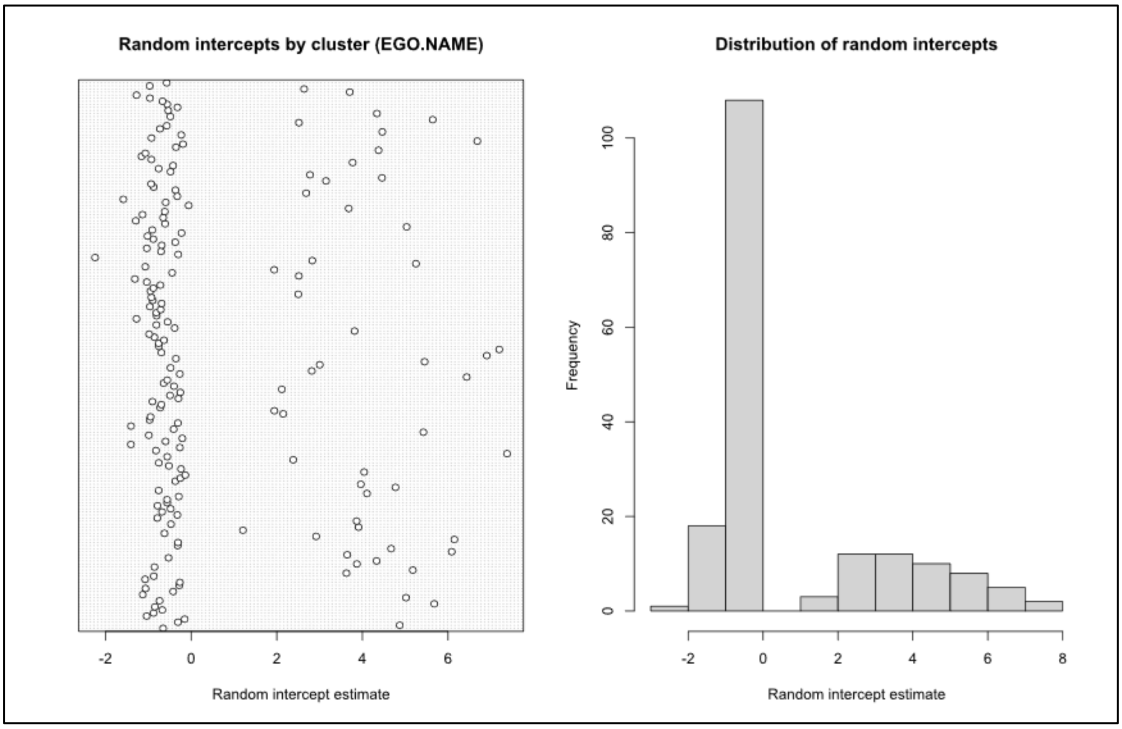

Figure 4.14 Distribution of Random Intercepts for Egos

Model assumptions were adequately met. The outcome variable was imbalanced, with 130 out of 791 alters (16.4%) reported as influential, but the distribution remained suitable for binary logistic multilevel modelling. Multicollinearity was not detected, as all Variance Inflation Factor (VIF) values were below 2, with the highest recorded at 1.56. Linearity in the logit was evaluated for both continuous predictors. Generalised additive model comparisons indicated no evidence of non-linearity for ego knowledge ($p = 1.627$), confirming that a linear specification was appropriate. For duration of knowing the alter, the smooth term approached but did not reach statistical significance ($p = 0.053$), suggesting only weak evidence of non-linearity, and therefore the linear term was retained for parsimony. Random intercept influence diagnostics demonstrated that the distribution of cluster-level effects was centred and continuous, with no egos exceeding the two standard-deviation threshold. This indicates the absence of influential clusters that could unduly affect model estimates. Residual diagnostics in Figure 4.15 demonstrated that Pearson residuals were generally symmetrically distributed around zero across all models. Although Model 2 displayed a wider vertical spread of residuals, there were no discernible patterns to indicate heteroscedasticity, non-linearity, or model misspecification.

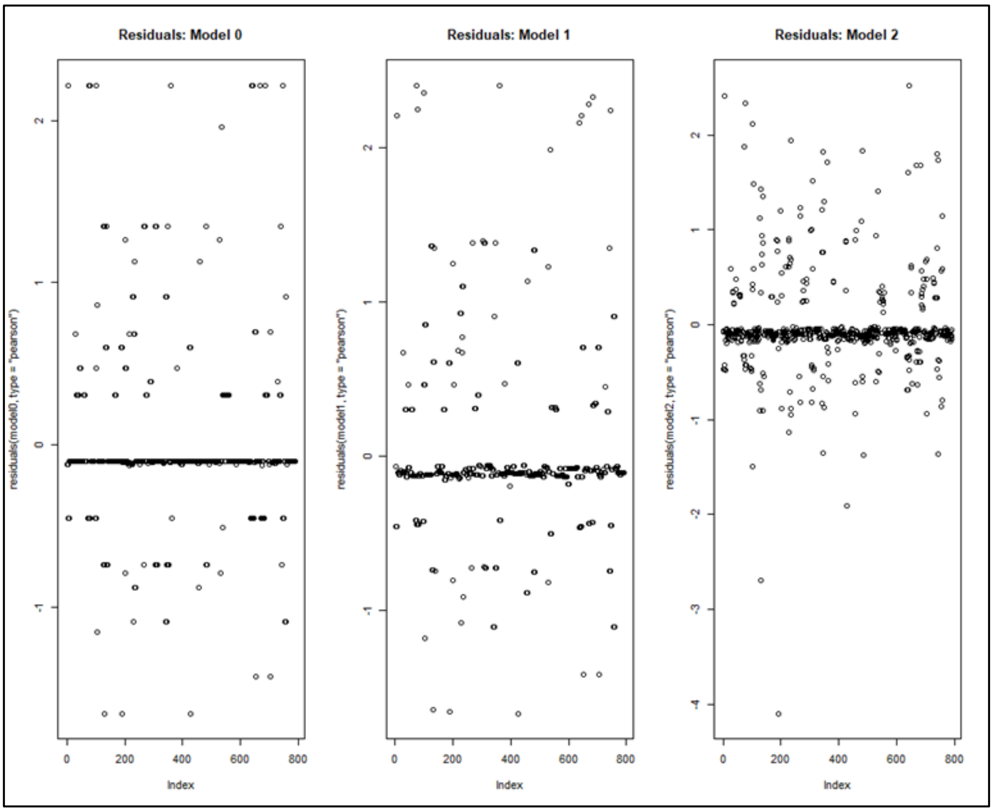

Figure 4.15 Residual Plots for Multilevel Logistic Regression Models.

4.3.2 Sociocentric Network Analysis of Workplace COVID-19 Stigma

The sociocentric analysis evaluates the overall workplace network to determine how structural characteristics influence the presence and distribution of COVID-19 stigma. This section contributes to Objective 3 by analysing centrality, positional structure, and relational patterns that shape network-level stigma dynamics.

4.3.2.1 Descriptive and Visualisation of Sociocentric Workplace Network

The sociocentric workplace network comprised 178 employees (nodes) and 551 directed ties, constructed based on ego nominations of general workplace connections rather than stigma-specific ties. Each ego identified individuals within their work environment with whom they interacted, forming a directed network representing perceived social proximity. Although stigma status was assessed for each alter, the ties themselves were not limited to or defined by stigma-related interactions.

The overall network density was 0.017, indicating that only 1.7% of all possible directed ties were observed. This suggests that direct opportunities for rapid diffusion through the full network were limited. However, because all nodes belonged to a single connected component, stigma-related attitudes could still circulate indirectly through chains of workplace interaction rather than through dense all-to-all contact. This low density is partly attributable to the study's nomination limit, whereby each respondent could nominate a maximum of five alters, thus constraining the total number of observable ties within the network. Reciprocity was 0.298, suggesting that nearly 30% of reported ties were mutual, reflecting a moderate level of bidirectional recognition in workplace relationships. All 178 nodes were part of a single connected component, indicating complete reachability within the network and no isolated subgroups. Centralisation indices suggested a relatively low level of hierarchical structure within the network. Degree centralisation was 0.028, indicating minimal inequality in the distribution of ties across nodes. Betweenness centralisation was 0.156, reflecting moderate variability in the extent to which certain individuals served as intermediaries in connecting others.

Descriptive statistics for node-level network metrics are summarised in Table 4.18. On average, each individual was connected to approximately six others (degree: mean = 6.19, SD = 2.97). The eigenvector centrality was relatively low (mean = 0.07, SD = 0.16), reflecting limited access to influential nodes. There was considerable variability in betweenness centrality (mean = 675.02, SD = 799.17), suggesting that some individuals played stronger intermediary roles within the network. The average closeness centrality was 0.27 (SD = 0.03), indicating that many individuals were relatively peripheral in the global structure.

In terms of positional and group structure, the mean coreness was 3.84 (SD = 1.21), suggesting that most individuals were embedded within moderately cohesive subgroups. The clustering coefficient was 0.25 (SD = 0.25), pointing to moderate local density or "clumpiness" in the immediate egocentric networks. The geodesic distance, representing the shortest paths between nodes, averaged 3.72 (SD = 0.45), indicating that any two employees were typically separated by fewer than four steps.

Overall, the network can be characterised as moderately sparse yet well-connected, with noticeable variation in structural positions and local clustering patterns.

These characteristics provide a meaningful foundation for subsequent inferential modelling to identify structural and individual-level determinants of tie formation.

Table 4.18
Descriptive Statistics of Structural Network Metrics for the Sociocentric Workplace Network (n = 178 Nodes)

Network characteristics	Metric	Definition	Mean	SD
Centrality	Degree	Number of ties (incoming and outgoing) connected to a given node	6.19	2.97
Centrality	Eigenvector	Connection to nodes that are themselves well connected	0.07	0.16
Centrality	Betweenness	How often a given nodes falls along the shortest path between two nodes: a connector	675.02	799.17
Centrality	Closeness	Inverse measure of centrality; large numbers mean nodes are highly peripheral	0.27	0.03
Positional structure	Coreness	Core nodes are connected to each other and to others	3.84	1.21
Group structure	Clustering coefficient	Density of ties in each node's egocentric network; measure of "clumpiness"	0.25	0.25
Relational structure	Geodesic distance	The shortest path between two nodes	3.72	0.45

The sociocentric workplace network was visualised to provide further insight into the relational structure and distribution of COVID-19 stigma among employees (Figure 4.16). In the sociograph, each node represents an individual employee, and each directed tie indicates a reported workplace connection, irrespective of stigma-related interactions. Node colour reflects stigma status, with red denoting employees classified as having stigma and blue indicating those without stigma. Employees with high connectivity, specifically those within the top 5% of degree centrality, are distinguished by thick black borders to indicate their central position within the network.

The network layout was generated using the Kamada-Kawai algorithm, which optimises the spatial distribution of nodes based on relational proximity to enhance the clarity of observed patterns such as tie density and clustering. The visualisation reveals that stigma is distributed throughout the network rather than confined to isolated subgroups, indicating its embeddedness within the broader workplace interactions (Figure 4.16).

Eleven individuals were identified as central actors based on degree centrality values at or above the 95th percentile. Although a strict 5% cutoff of the total 178 nodes would correspond to approximately nine individuals, the inclusion criterion accounted for all nodes with degree centrality equal to or exceeding the percentile threshold, resulting in 11 central actors. The sociograph further reflects moderate local clustering and global cohesion, consistent with the descriptive network metrics presented in Table 4.18.

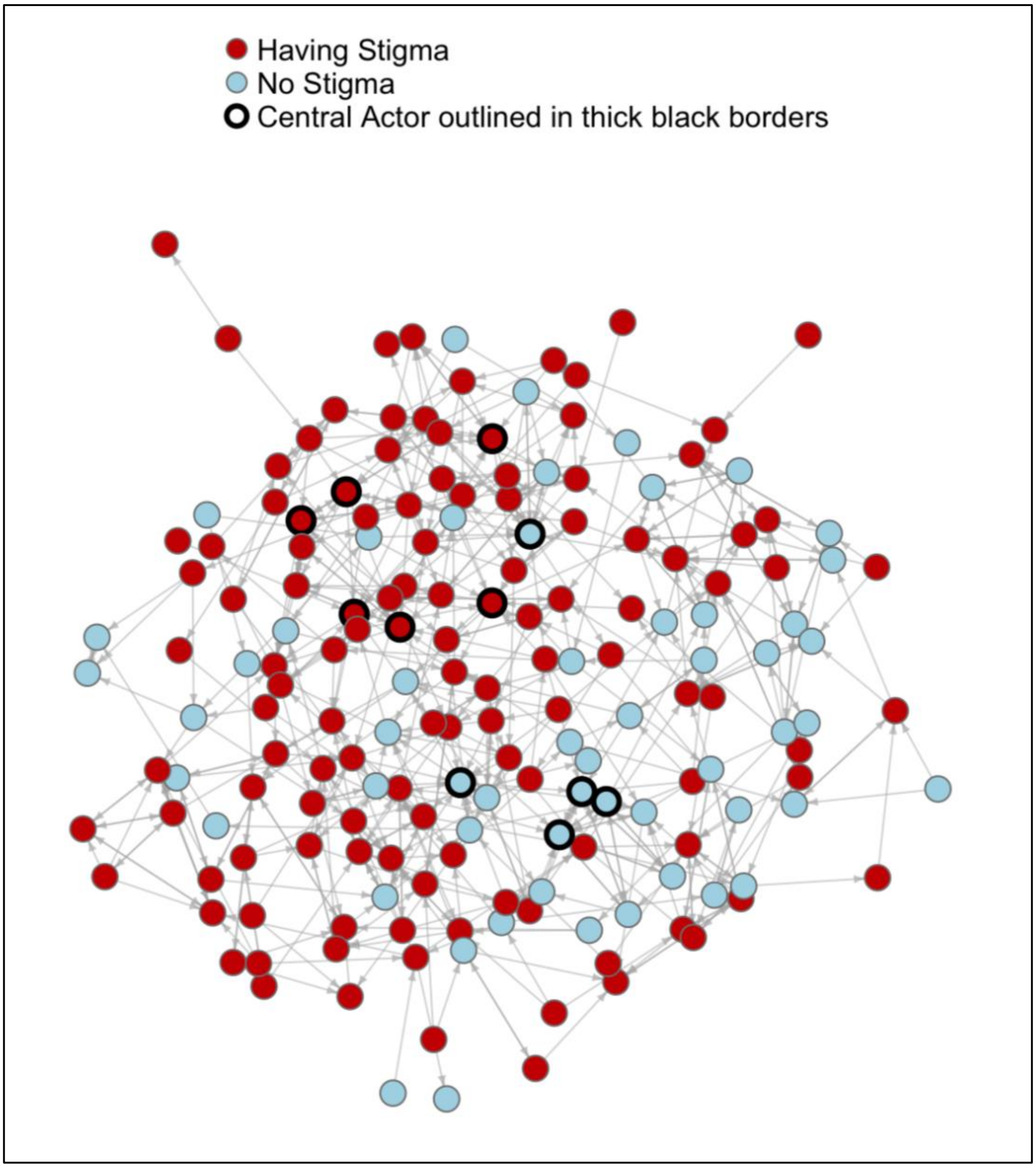

Figure 4.16 Sociocentric Workplace Network Illustrating the Distribution of COVID-19 Stigma Among Employees.

4.3.2.2 Exponential Random Graph Modelling (ERGM)

To investigate the underlying mechanisms of tie formation within the workplace sociocentric network, three Exponential Random Graph Models (ERGMs) were fitted following a stepwise modelling approach (Table 4.19). These models incrementally introduced structural tendencies, homophily effects, and individual-level attributes to assess their influence on the probability of tie presence.

Model 0, which included only the baseline edge term, demonstrated a significantly negative estimate (PE = -4.030, SE = 0.040, $p < 0.001$), indicating a sparse network with low baseline connectivity among workers.

Model 1 extended the baseline model by incorporating structural and homophily terms. Reciprocity exhibited a strong and significant positive effect (PE = 3.240, SE = 0.160, $p < 0.001$), suggesting that mutual connections were prevalent within the network. Homophily effects were observed for gender (PE = 0.710, SE = 0.110, $p < 0.001$), job position (PE = 0.800, SE = 0.090, $p < 0.001$), and stigma status (PE = 0.310, SE = 0.080, $p < 0.001$). Age group showed a significant effect (PE = 0.150, SE = 0.080, $p = 0.048$), while smoking status was also significant (PE = 0.170, SE = 0.080, $p = 0.030$). Compared to Model 0, Model 1 yielded improved model fit (AIC = 5011 vs. 5553) and met convergence criteria.

Model 2, the most comprehensive model, retained all structural and homophily effects while adding non-directional individual-level covariates. Reciprocity remained significant (PE = 3.130, SE = 0.160, $p < 0.001$). Homophily effects remained strong for gender (PE = 1.110, SE = 0.120, $p < 0.001$), job position (PE = 0.860, SE = 0.090, $p < 0.001$), age group (PE = 0.180, SE = 0.080, $p = 0.026$), and stigma status (PE = 0.420, SE = 0.090, $p < 0.001$), whereas smoking became non-significant (PE = 0.080, SE = 0.080, $p = 0.356$). At the individual node level, being male (compared to female) was associated with a lower likelihood of forming ties (PE = -0.530, SE = 0.070, $p < 0.001$). Being in the oldest age group (>44 years) significantly increased the likelihood of tie formation (PE = 0.210, SE = 0.080, $p = 0.012$), while the middle age group (30-44 years) did not differ significantly from the reference group (PE = 0.020, SE = 0.060, $p = 0.731$). COVID-19 knowledge (PE = 0.0003, SE = 0.002, $p = 0.871$) and smoking status (PE = 0.100, SE = 0.060, $p = 0.108$) were not significant predictors. Notably, workplace COVID-19 stigma status had a significant negative effect (PE = -0.160, SE = 0.060, $p = 0.005$), indicating that individuals who experienced stigma were generally less likely to be involved in workplace ties as either senders or receivers, despite the earlier observed homophily pattern.

Table 4.19
Exponential Random Graph Models of Workplace Network Ties: The Role of Structural Factors, Homophily, and Stigma

Variables	Model 0			Model 1			Model 2		
	PE	SE	P-value	PE	SE	P-value	PE	SE	P-value
Structural									
Edges	-4.03	0.04	<0.001	-5.65	0.13	<0.001	-5.18	0.39	<0.001
Reciprocity				3.24	0.16	<0.001	3.13	0.16	<0.001
Homophily									
Gender				0.71	0.11	<0.001	1.11	0.12	<0.001
Job position				0.80	0.09	<0.001	0.86	0.09	<0.001
Age group				0.15	0.08	0.048	0.18	0.08	0.026
Smoking status				0.17	0.08	0.030	0.08	0.08	0.356
Stigma status				0.31	0.08	<0.001	0.42	0.09	<0.001
Non-directional covariates									
Gender									
Female							0		
Male							-0.53	0.07	<0.001
Age group (years old)									
18 - 29							0		
30 – 44							0.02	0.06	0.731
> 44							0.21	0.08	0.012
COVID-19 knowledge							0.0003	0.002	0.871
Smoking status									
No							0		
Yes							0.10	0.06	0.108
Stigma status									
No							0		
Yes							-0.16	0.06	0.005
Model fit statistics									
AIC		5553			5011			4950	
BIC		5562			5069			5059	
Deviance		5551			4997			4924	

Model 2 achieved the best overall fit (AIC = 4950, BIC = 5059, deviance = 4924) and satisfied all convergence diagnostics. MCMC summary statistics showed acceptable standard errors and time-series corrected SEs. Geweke diagnostics indicated convergence for most terms, with the joint p-value of 0.091 suggesting overall acceptable convergence. These diagnostics confirm that Model 2 adequately converged and replicated key network statistics, validating the inclusion of both structural and covariate effects. These findings underscore the importance of structural mechanisms and sociodemographic similarity in shaping workplace interactions. Stigma status appeared to exert a dual influence, fostering tie formation through homophily while simultaneously reducing overall engagement in the network. Full diagnostic plots and model evaluation outputs are presented in Appendix 2.

4.3.2.3 Quadratic assignment procedures correlations (QAP)

Quadratic Assignment Procedure (QAP) correlation was conducted to examine whether employees with similar structural positions in the network were more likely to share the same COVID-19 stigma status. The dependent matrix was a binary stigma homophily matrix, where each dyad (pair of employees) was coded as 1 if they shared the same stigma status and 0 if not. Independent matrices were constructed from the absolute differences in node-level network metrics, representing centrality, positional structure, group structure, and relational structure.

The results are presented in Table 4.20. Among the centrality metrics, eigenvector centrality showed the strongest and statistically significant negative association (r = -0.442, $p < 0.001$), indicating that dyads who occupy similar positions as defined by eigenvector centrality were more likely to share the same stigma status. Coreness was also significantly associated (r = -0.028, p = 0.020), suggesting that individuals embedded within similar core regions of the network tend to align in stigma classification.

Degree centrality showed a weak, marginally non-significant negative association (r = -0.009, p = 0.059), while betweenness centrality presented a large coefficient (r = -2.966) but was not statistically significant (p = 0.886), indicating no meaningful relation between occupying a bridging position and shared stigma. Both closeness centrality (r = -0.275, p = 0.547) and geodesic distance (r = -0.020, p = 0.546) were not significant, suggesting that general proximity or average path length between actors did not relate to stigma similarity. The clustering coefficient also did not reach significance (r = -0.073, p = 0.201), implying that being embedded in similarly tight-knit neighbourhoods was not a strong predictor.

Table 4.20
Correlation Between Stigma Status and Node-Level Network Metrics

Network characteristics	Metric	Estimate	P-value
Centrality	Degree	-0.009	0.059
Centrality	Eigenvector	-0.442	< 0.001
Centrality	Betweenness	-2.966	0.886
Centrality	Closeness	-0.275	0.547
Positional structure	Coreness	-0.028	0.020
Group structure	Clustering coefficient	-0.073	0.201
Relational structure	Geodesic distance	-0.020	0.546

To ensure the appropriateness of using the Quadratic Assignment Procedure (QAP), key assumptions were evaluated. Structural preservation was confirmed by comparing the observed and permuted stigma matrices, showing that attribute permutations did not alter the network structure (Appendix 3, Figure A). Monotonicity was assessed through Spearman's correlation (ρ = -0.14) and scatterplots, which showed weak but consistent trends between stigma similarity and network metric differences (Appendix 3, Figures B to H). The stigma status distribution was also sufficiently varied, with 56 nodes without stigma and 122 with stigma. These checks supported the use of QAP in this context.

To further illustrate the network mechanisms underpinning the observed QAP correlations, network visualisations for eigenvector centrality and coreness in relation to COVID-19 stigma status are presented in Figures 4.17 and 4.18. In both graphs, nodes representing employees are coloured according to stigma status: red indicates individuals with stigma and blue represents those without stigma. The size of each node reflects its value for the relevant network metric, highlighting individuals with higher centrality or deeper integration in the network core.

The eigenvector centrality graph shows that employees with and without stigma occupied influential positions within the network, although several highly central nodes shared the same stigma status. This visual pattern complements the QAP finding that employees occupying similar influential positions were more likely to share the same stigma status.

In contrast, the coreness graph demonstrates a more even distribution of employees with and without stigma among those with high coreness values. This aligns with the weaker but significant association identified in the QAP analysis, indicating that individuals embedded within the network's core share stigma status to some degree, but not as strongly as those aligned in influence.

Overall, these network visualisations supplement the statistical results, revealing that influential and core-embedded positions may facilitate homophily in COVID-19 stigma status. The visual distribution of similarly classified nodes across comparable structural positions complements the QAP findings and illustrates the structural patterning of stigma within the workplace network.

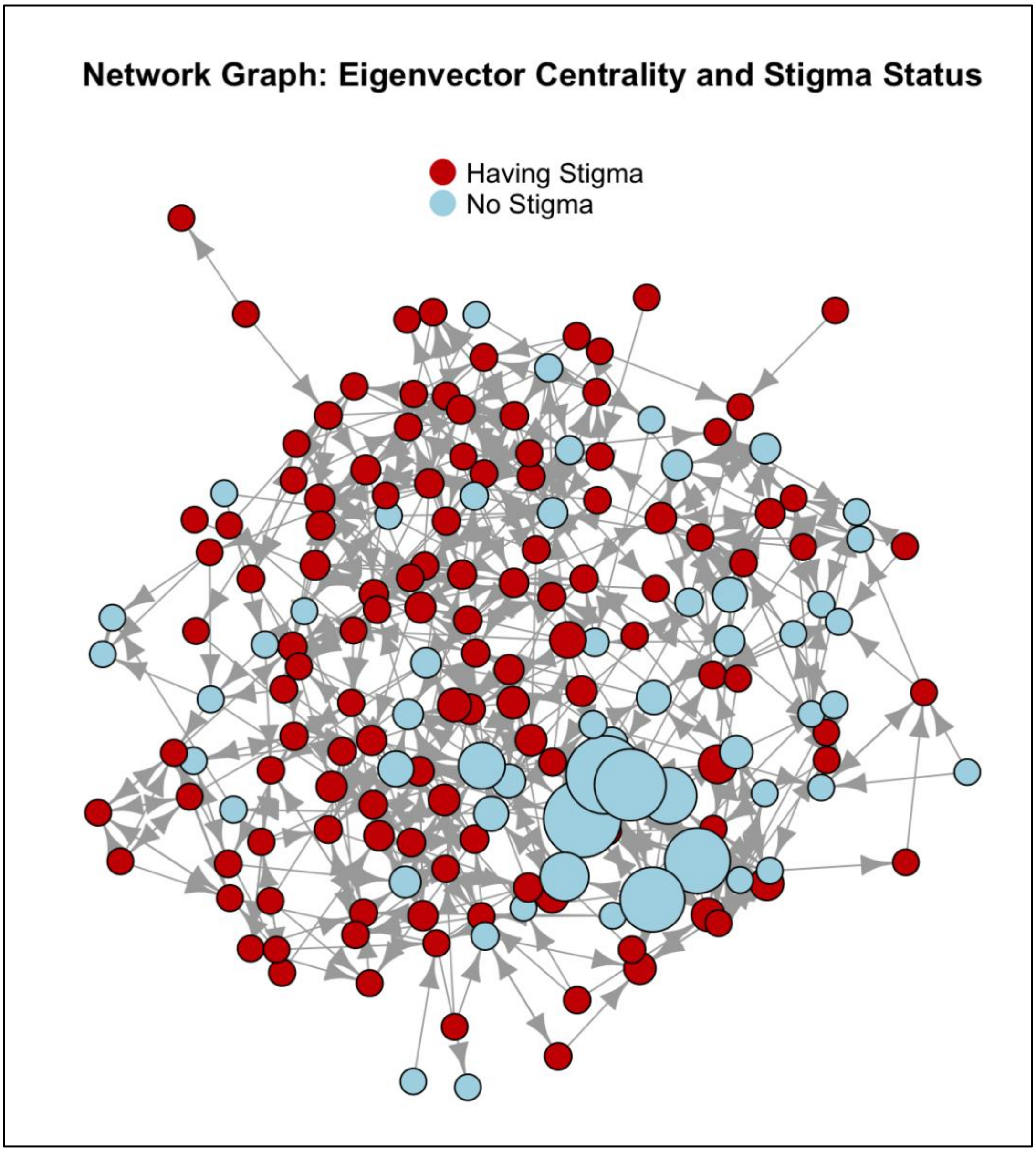

Figure 4.17 Eigenvector Centrality vs Stigma Status

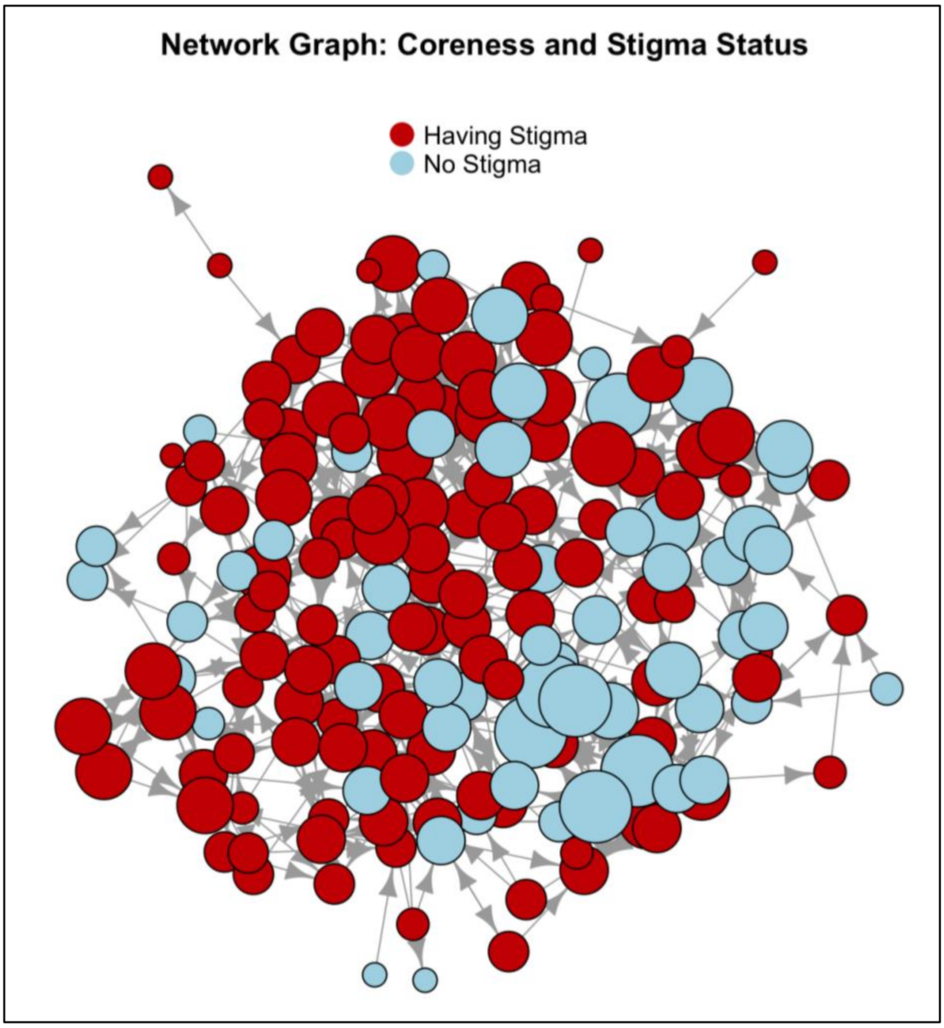

Figure 4.18 Coreness vs Stigma Status

4.3.3 Results Summary for Phase 2 – Social Network Analysis

4.3.3.1 Results Summary for Objective 2

Objective 2 examined how individual and relational factors shaped COVID-19 stigma within workplace networks. This was analysed using MLogR and MLM, each providing complementary perspectives.

In the MLogR analysis, stigma was significantly less reported among workers aged 30 to 44. Although a history of COVID-19 infection and job position particularly technical or engineering roles initially showed a protective effect, the association diminished after adjusting for network variables. Gender and education were not significant predictors. At the network level, stigma was more likely among those with greater gender homophily and frequent interactions with family and superiors. Other relational features, including alter gender, other relationship type, and acquaintance duration, were not significantly associated.

The MLM analysis showed that most variation in perceived influence of alters was due to differences between egos rather than between alters. This reflects the nested data structure, where multiple alters are clustered within each ego, and the random intercept captures variation at the ego level. Ego-level factors, such as knowledge and stigma status, were not significant. However, relationship type was important. Compared to family members, friends, colleagues, and superiors were significantly less likely to be perceived as influential. Alter gender and acquaintance duration did not significantly influence perception.

Model 2 provided the best fit in the MLM analysis. Overall, findings from both MLogR and MLM suggest that personal and structural attributes of workers and their networks jointly contribute to COVID-19 stigma in workplace settings.

4.3.3.2 Results Summary for Objective 3

Objective 3 examined how structural and relational features of the workplace sociocentric network were associated with the distribution of COVID-19 stigma. This was explored through descriptive network analysis, ERGM, and QAP.

The workplace network consisted of 178 employees and 551 directed ties. Although the overall density was low, the network was fully connected and showed moderate reciprocity. Centralisation indices were minimal, suggesting a relatively decentralised structure with modest variability in tie distribution and intermediary roles.

ERGM findings indicated that tie formation was significantly influenced by structural and sociodemographic factors. Reciprocity had a strong positive effect on tie probability. Homophily was evident for gender, job position, age group, and stigma status. Although smoking status was initially significant, it did not remain in the final model. Node-level effects showed that male employees and those experiencing stigma were generally less likely to form ties. Model 2 provided the best overall fit and met all convergence requirements, supporting the inclusion of both structural and compositional predictors.

QAP results complemented the ERGM findings by indicating that employees with similar structural characteristics were more likely to share the same stigma status. The strongest and most significant correlation was observed for eigenvector centrality, followed by coreness. Degree centrality showed a marginal association, while betweenness, closeness, clustering coefficient, and geodesic distance were not significant. These results suggest that individuals who are similarly influential or embedded in the network core tend to align in stigma classification, although other structural features such as proximity or bridging position did not explain stigma similarity. All key QAP assumptions were met, including network structure preservation, dyadic dependence, monotonic trends, and adequate variation in stigma status.

Overall, the ERGM and QAP findings suggest that COVID-19 stigma in the workplace network is shaped by how employees are connected and positioned in the network. Instead of being randomly spread, stigma tends to cluster among individuals who share similar influence or occupy core areas within the network.

CHAPTER 5
DISCUSSION

5.1 Overview

This chapter discusses the findings of the study in relation to the existing literature. The results are presented according to the two phases of the research. Phase 1 focused on the development, validation and reliability assessment of the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS). The validation process included content and face validation, Item Response Theory (IRT) for the knowledge domain, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and reliability testing. These analyses provided strong psychometric support for the factorial structure and internal consistency of the WoCKSS.

Phase 2 examined workplace COVID-19 stigma using social network analysis. The egocentric analysis assessed how demographic factors, individual attributes, and characteristics of alters influence stigma through multiple logistic regression (MLogR) and multilevel modelling (MLM). The sociocentric analysis evaluated network patterns using Exponential Random Graph Modelling (ERGM) and the Quadratic Assignment Procedure (QAP) to understand how structural features, relational ties, and homophily relate to stigma distribution.

Together, both analytical perspectives offer a comprehensive view of workplace COVID-19 stigma by linking individual characteristics, interpersonal relationships, and workplace network structures. These two phases are conceptually interdependent. The validated constructs identified in Phase 1, particularly fear, stereotype, and prejudice, provided a robust measurement foundation for interpreting the relational and structural patterns observed in Phase 2.

These findings collectively address the primary research question by demonstrating how validated stigma constructs operate within workplace social networks, linking individual perceptions to relational and structural dynamics. The integration of psychometric validation and social network analysis provides a dual-level understanding of stigma, highlighting how both interpersonal influence and network position contribute to its distribution. This study therefore contributes to theory by introducing a workplace-specific stigma measurement framework and applying it within a network context, offering new insight into how stigma is structured and maintained in organisational settings.

5.2 Phase 1: Development and Validation of Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS)

The development and validation of the WoCKSS contribute to the ongoing efforts in measuring COVID-19 knowledge and stigma in workplace settings, particularly within the manufacturing sector in Malaysia. This scale was developed to reflect the cultural, socioeconomic, and educational diversity of Malaysian factory workers, aiming to provide a contextually relevant and accessible tool. The decision to construct the scale in Malay, the national language, was intended to enhance its clarity, accessibility, and contextual appropriateness for the target population.

WoCKSS incorporates constructs such as stereotype, fear, and prejudice, which are key dimensions of workplace stigma (Nochaiwong et al., 2021). Stereotypes may lead to assumptions about individuals based on their COVID-19 status, prejudice can contribute to exclusionary behaviours, and fear may result in avoidance and workplace tensions. By capturing these dimensions, WoCKSS offers a structured approach to understanding stigma in the workplace. Unlike existing COVID-19 stigma scales developed for community, clinical, or survivor settings, WoCKSS was designed specifically to reflect workplace-based interactions, industrial hierarchies, and the knowledge context in which stigma-related fear, judgement, and misinformation may arise among factory workers.

5.2.1 Content and Face Validity

The content and face validity assessments conducted in Phase 1 supported WoCKSS as a contextually relevant and comprehensible instrument for assessing COVID-19 knowledge and stigma in workplace settings.

The content validity of WoCKSS was assessed by a multidisciplinary panel of four experts specialising in public health, microbiology, epidemiology, and primary care. Each item was evaluated based on relevance, clarity, simplicity, and ambiguity. The retained items achieved an I-CVI score of 1.00, indicating unanimous agreement among experts. Furthermore, the mean S-CVI/UA (1.00) and S-CVI/AVE (1.00) exceeded the recommended thresholds of ≥ 0.8 and ≥ 0.9, confirming that the scale items comprehensively represent the constructs of COVID-19 knowledge and stigma (Polit et al., 2007).

These high CVI scores reflect the alignment of the WoCKSS items with their theoretical constructs, consistent with findings from prior studies, such as the Arabic version of the Coronavirus Anxiety Scale (El Sayed et al., 2020). The inclusion of diverse expertise among the panel members ensured that the scale captured a broad range of perspectives relevant to workplace COVID-19 stigma. Additionally, the iterative refinement process based on expert feedback ensured that only the most relevant and clear items were retained, reducing construct-irrelevant variance.

Face validity findings further supported the applicability of WoCKSS. Conducted with 10 respondents representing diverse job roles and educational backgrounds within the manufacturing sector, the assessment captured a range of perspectives on the clarity and comprehensibility of the scale items. The mean I-FVI scores were 0.99 for both the knowledge and stigma domains, while the S-FVI/UA values were 0.88 and 0.86 for the knowledge and stigma domains, respectively, confirming the clarity and relevance of the scale for the target population.

Respondent feedback played a pivotal role in refining the scale. For example, technical terms related to COVID-19 protocols were simplified to align with language commonly used in workplace settings, ensuring accessibility for workers with varying educational levels. These refinements align with findings from studies on COVID-19 stigma in Iran (Faghankhani et al., 2022), which emphasised the importance of tailoring instruments to the linguistic and cultural characteristics of the target population.

While the findings demonstrate strong content and face validity, certain limitations should be acknowledged. The face validity assessment involved only 10 respondents from a single manufacturing company. Although this meets the minimum acceptable standard (Yusoff, 2019b), the reliance on a single company may limit the generalisability of the findings. Expanding the sample to include participants from multiple manufacturing sites with varying demographic and organizational characteristics would enhance the robustness and external validity of the results.

It is important to highlight that the selection of the company was based on a stratified random sampling technique, whereby one company was randomly chosen from a list provided by the Selangor Task Force for COVID-19 (STFC). This approach aimed to minimise bias by ensuring a fair representation of manufacturing companies within the target population. However, despite these precautions, there remains the possibility of selection bias, as the chosen company may not fully reflect the diversity of workplace environments across the broader manufacturing sector.

Another potential limitation is the recruitment process for the CVI evaluation. While the panel comprised highly qualified experts from diverse fields such as public health, microbiology, epidemiology, and primary care, their perspectives might not capture the full range of dimensions associated with workplace COVID-19 stigma. A broader panel with additional expertise, particularly in industrial psychology or organisational behaviour, might provide a more comprehensive evaluation.

Despite these limitations, the validation process did not stop at content and face validity. Exploratory and confirmatory analyses, including IRT, EFA, and CFA, were conducted to further assess the scale's psychometric properties. These additional steps provided a more rigorous evaluation, reinforcing the validity and reliability of WoCKSS. Moreover, the strong performance of the scale in both content and face validation reflects its alignment with Malaysian workplace realities, where communication patterns, hierarchical norms, and linguistic cues differ from foreign contexts. Ensuring conceptual relevance to local cultural norms was essential, as stigma manifestations in collectivist and multi-ethnic settings may follow different trajectories from those described in global literature. WoCKSS is conceptually distinct from existing COVID-19 stigma scales because it was developed specifically for workplace-based interactions in an industrial context and designed to assess not only stigma-related attitudes, but also the knowledge context that may shape fear, judgement, and misinformation among factory workers.

5.2.2 Item Response Theory Analysis (IRT)

The IRT analysis of the knowledge domain within WoCKSS provides important insights into its psychometric properties. Both exploratory and confirmatory stages employed the two-parameter logistic (2-PL) model to assess item difficulty, discrimination, and unidimensionality. These analyses guided scale refinement while identifying areas for improvement. The 2-PL model was selected for its ability to estimate difficulty (b) and discrimination (a) parameters, offering a more flexible approach than the one-parameter logistic (1-PL) model, which assumes uniform discrimination across all items. This flexibility was particularly advantageous for evaluating knowledge-based constructs, where items vary in their ability to differentiate respondents with different knowledge levels (Edelen & Reeve, 2007).

In the exploratory stage, the 2-PL model indicated that most items exhibited acceptable difficulty (b) parameters, with most values falling within the recommended range of -3 to +3 (Baker, 2001). However, K1 ($b = -5.40$) and K17 ($b = 3.81$) were at the extreme ends, suggesting that they were either too easy or too difficult for the target population. Despite this, they were retained due to their theoretical importance and relevance to COVID-19 knowledge in the workplace. The discrimination (a) parameters ranged from moderate to high, with most values falling between 0.65 and 1.34, indicating that the items could effectively differentiate respondents based on their knowledge levels (Baker, 2001). Some items, such as K7 ($a = 2.11$) and K13 ($a = 1.78$), exhibited particularly high discrimination, making them effective for detecting differences in knowledge levels. However, a few items demonstrated lower discrimination values, suggesting potential limitations in their ability to distinguish between high- and low-knowledge respondents.

Unidimensionality, a key assumption of the 2-PL model, was not supported in the exploratory stage, as indicated by modified parallel analysis ($p < 0.001$). This finding suggests that the knowledge items may not have reflected a single underlying dimension at that stage, and that item responses may have been influenced by additional sources of variation, such as local item dependence or secondary dimensions. The relatively small sample size may also have contributed to unstable parameter estimates, making it more challenging to confirm a single latent structure (Edelen & Reeve, 2007; Hambleton & Cook, 1983). Given these findings, further refinement and additional validation were necessary to improve the measurement properties of the scale.

The confirmatory stage addressed these challenges by utilising a larger sample size, which improved parameter stability and allowed for more rigorous validation. Research has shown that increasing sample size improves the accuracy and reliability of IRT parameter estimates, reducing measurement errors and strengthening model assumptions (Hambleton & Cook, 1983; Zahiruddin et al., 2018). The difficulty and discrimination parameters in the confirmatory stage remained consistent with the exploratory findings, confirming the stability of the retained items. Unidimensionality was confirmed in this stage, as indicated by modified parallel analysis ($p = 0.644$), reinforcing the validity of the scale in measuring a single underlying construct. The improved unidimensionality may also reflect refinements in item selection, which helped address sources of multidimensionality identified in the exploratory stage.

Further evidence of the scale's robustness was provided through Item Characteristic Curves (ICCs) and the Test Response Function (TRF). The ICCs showed that easier items, such as K1 and K3, exhibited flatter slopes, while more difficult items, like K17, displayed steeper slopes, indicating their stronger discriminatory power across varying ability levels. These findings align with prior research demonstrating that ICCs for high-discrimination items have steep slopes, reflecting their ability to effectively distinguish between respondents at specific ability levels (Arifin & Yusoff, 2017). The TRF analysis confirmed that the scale performed optimally within the mid-range of respondent abilities, with approximately 76% of information concentrated within the -3 to +3 range, suggesting that the scale is most effective for respondents with moderate knowledge levels. This result aligns with the findings of Edelen & Reeve (2007), who observed that IRT models optimize measurement precision at mid-range abilities.

Comparisons with prior studies further contextualise these findings. Wesonga and colleagues (2024) applied IRT to assess COVID-19 knowledge and attitudes among university students, reporting similar trends in item discrimination and information concentration within mid-range ability levels. However, they found a broader range of item difficulty, likely reflecting the heterogeneous knowledge levels among university students. In contrast, WoCKSS displayed a narrower range, attributable to its workplace-specific context, where workers had relatively uniform exposure to COVID-19 information. Similarly, findings from WoCKSS align with Richardson and Bélanger (2020), who developed a COVID-19 knowledge test for health educators. Both studies encountered challenges in achieving unidimensionality in early validation stages, largely due to the complex nature of COVID-19 knowledge, which spans clinical, preventive, and epidemiological aspects. However, both scales achieved unidimensionality following item refinement, highlighting the importance of tailoring measurement tools to specific populations.

The WoCKSS IRT analyses demonstrated several strengths. Moderate to high discrimination values ensured effective differentiation of respondents, and parameter consistency across exploratory and confirmatory stages reinforced scale reliability. The successful validation of unidimensionality during the confirmatory stage, facilitated by a larger sample size and refined item selection, further strengthened the credibility of the scale. Additionally, the TRF and ICCs confirmed that the scale effectively captured knowledge levels across a broad range, with optimal precision concentrated in the mid-range.

Despite these strengths, the unidimensionality challenges observed in the exploratory stage underscore the importance of adequate sample sizes in psychometric evaluations. Small samples may contribute to instability in parameter estimates, reducing the likelihood of detecting a single underlying construct (Hambleton & Cook, 1983). These findings emphasise the need for careful attention to sample size and model assumptions when conducting IRT analyses, particularly in the early validation stages.

The iterative validation process confirms that the WoCKSS knowledge domain is a psychometrically sound instrument for assessing workplace COVID-19 knowledge. The application of the 2-PL model provided a detailed evaluation of item characteristics, reinforcing its value in psychometric research. Importantly, the psychometric clarity achieved through IRT analysis strengthened the interpretive confidence in Phase 2 findings.

5.2.3 Construct Validity and Reliability

5.2.3.1 Exploratory Factor Analysis (EFA)

EFA was conducted to identify the underlying factor structure of the WoCKSS stigma domain, ensuring that the scale appropriately captured distinct but related dimensions of workplace COVID-19 stigma. Before factor extraction, sampling adequacy was confirmed using the Kaiser-Meyer-Olkin (KMO) measure, which yielded a value of 0.7, meeting the recommended threshold (Kaiser, 1974). This result indicated that the sample was appropriate for factor analysis. Bartlett's test of sphericity was also significant ($p < 0.001$), confirming that the correlation matrix was suitable for factor extraction (Tabachnick & Fidell, 2013). These preliminary assessments established the appropriateness of the data for EFA.

Factor extraction was conducted using Principal Axis Factoring (PAF), which was selected over Maximum Likelihood (ML) because PAF does not assume multivariate normality and is better suited for identifying latent constructs when normality assumptions are violated (Fabrigar et al., 1999). Unlike ML, which assumes normally distributed indicators, PAF focuses on shared variance rather than unique variance, making it a more robust choice for the current data structure (Costello & Osborne, 2005).

To determine the optimal number of factors, multiple statistical criteria were used, including the scree plot, Kaiser's criterion, the Very Simple Structure (VSS) test, and the Minimum Average Partial (MAP) test (Velicer, 1976). The scree plot revealed an inflection point, suggesting a three-factor solution, which was further supported by eigenvalues greater than 1.0. The VSS and MAP tests, which provide additional statistical confirmation, reinforced the appropriateness of this three-factor solution. Relying solely on eigenvalues > 1 can lead to over-extraction (Horn, 1965), and thus the combination of these methods ensures a more robust and theoretically sound factor retention decision.

Given that the extracted factors were expected to be correlated, Promax oblique rotation was applied rather than an orthogonal rotation such as Varimax. Promax rotation is appropriate when factors are interrelated, as it allows for better interpretability without forcing factors to be uncorrelated (Costello & Osborne, 2005). This decision was supported by the results, which showed that Fear, Stereotype, and Prejudice were distinct yet correlated subscales, reinforcing the theoretical foundation of the scale.

The factor loadings met the predefined cut-off of ≥ 0.5, confirming that each item contributed meaningfully to its respective construct (Hair et al., 2019). Communalities were all above 0.4, ensuring that a substantial proportion of variance was accounted for by the extracted factors. Additionally, inter-factor correlations remained below 0.70, indicating that the three subscales, which were Fear, Stereotype, and Prejudice, were related but sufficiently distinct. These findings are consistent with those reported by Nochaiwong and colleagues (2021), who also identified a three-factor stigma structure when validating the COVID-19 Public Stigma Scale (COVID-PSS).

5.2.3.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted to validate the factorial structure of the WoCKSS stigma domain, building upon the model identified during Exploratory Factor Analysis (EFA). CFA is a theory-driven method that assesses whether the hypothesised latent constructs reflect the observed data, making it a critical step in scale validation (Brown, 2015). The three-factor model comprising Stereotype, Fear, and Prejudice was tested to determine its fit and structural soundness.

Although two items (S15 and S16) were removed during model refinement due to low factor loadings, high residuals, and substantial modification indices, the original three-factor conceptual framework was retained. This decision reflects the importance of maintaining theoretical coherence and consistency with the EFA findings. Psychometric literature supports the retention of fewer items per factor when those items exhibit strong factor loadings and conceptual clarity (Hair et al., 2019). For example, Bonetto et al. (2022) and Elgohari et al. (2021) similarly refined their COVID-19 stigma instruments by eliminating poorly performing items while preserving the theoretical model.

The final CFA model (Model 3) demonstrated excellent fit: the chi-square test was non-significant ($\chi^2 = 8.91$, df = 11, p = 0.630), and other fit indices surpassed recommended thresholds. The RMSEA value was 0.00, with a 90% confidence interval of 0.000 to 0.055, and a close-fit p-value of 0.927. The Standardised Root Mean Square Residual (SRMR) was 0.021, well below the acceptable threshold of 0.08. Both the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were 1.00, indicating a perfect model fit. These results exceed the minimum criteria proposed by Hu & Bentler (1999), who recommend RMSEA < 0.06, CFI and TLI ≥ 0.95, and SRMR ≤ 0.08. Similar fit indices have been reported in previous stigma scale validations, such as the COVID-19 Public Stigma Scale (COVID-PSS) developed by Nochaiwong et al. (2021).

A particular consideration in this analysis was the Prejudice factor, which was represented by only two items (S17 and S18) in the final model. Although conventional practice recommends a minimum of three items per factor, this guideline may be relaxed under certain conditions. As noted by Marsh et al. (1998) and Worthington & Whittaker (2006), two-item factors can be considered adequate if the items are highly correlated and theoretically cohesive. In the present study, both items exhibited strong loadings (0.789 and 0.999) and high internal consistency (omega = 0.893), supporting the decision to retain the factor. This approach is consistent with other COVID-19 stigma scale development studies, including those by Elgohari et al. (2021), which prioritised model fit and content validity over the number of items.

By integrating robust statistical evidence, theoretical reasoning, and comparison with previous research, the CFA results reinforce the validity of the WoCKSS stigma domain's three-factor model. The final model offers a psychometrically sound and conceptually grounded instrument for measuring workplace COVID-19 stigma among factory workers in Malaysia.

5.2.3.3 Reliability Analysis

The internal consistency of the WoCKSS stigma domain was assessed using two complementary reliability measures: Cronbach's alpha during the exploratory phase and McDonald's omega during the confirmatory phase. Each coefficient serves a specific purpose in psychometric evaluation and reflects differing assumptions about item properties.

During the EFA, Cronbach's alpha values for the three identified stigma subscales which is Stereotype, Fear, and Prejudice were all above the conventional threshold of 0.70, indicating strong internal consistency. Cronbach's alpha is widely used in preliminary reliability testing and assumes tau-equivalence, meaning that all items are presumed to contribute equally to the latent construct (Tavakol & Dennick, 2011). However, this assumption is often violated in multidimensional psychological constructs, where items may have varying degrees of association with the underlying factor (Trizano-Hermosilla & Alvarado, 2016).

To address the limitations of alpha, McDonald's omega was calculated during CFA to provide a more accurate estimate of internal consistency. Unlike alpha, omega does not require tau-equivalence and instead incorporates individual factor loadings and error variances in its estimation. As such, omega offers a more realistic representation of reliability, especially for scales developed from complex, non-homogeneous constructs (Dunn et al., 2014; Hayes & Coutts, 2020).

The omega values derived from the final CFA model were: 0.867 for Fear, 0.893 for Prejudice, and 0.691 for Stereotype. All values were within acceptable to strong ranges, with the exception of the Stereotype subscale, which was marginally below the conventional cut-off. Similar variability in omega values has been observed in previous COVID-19 stigma scale validations. For example, Elgohari et al. (2021) reported omega values ranging from 0.63 to 0.92 across subdomains, while Bonetto et al. (2022) retained subscales with moderate reliability to preserve theoretical consistency.

The high reliability of the Fear and Prejudice subscales is particularly noteworthy given that the Prejudice factor was represented by only two items in the final model. While conventional practice recommends at least three items per factor, research suggests that two-item factors can still yield adequate reliability when items are strongly correlated and conceptually cohesive (Marsh et al., 1998; Worthington & Whittaker, 2006). In this case, the high loading values and internal consistency provide strong support for retaining the Prejudice subscale.

Taken together, the use of both Cronbach's alpha and McDonald's omega enabled a more nuanced reliability assessment. The consistency of these findings across both exploratory and confirmatory phases reinforces the psychometric strength of the WoCKSS stigma domain in capturing workplace COVID-19 stigma.

5.3 Phase 2: COVID-19 Stigma Characterisation Through Social Network Analysis (SNA)

5.3.1 Egocentric Network Analysis of Workplace COVID-19 Stigma

5.3.1.1 Multiple Logistic Regression (MLogR)

In the MLogR model, workers aged 30 to 44 years were significantly less likely to report stigma compared to their younger counterparts aged 18 to 29. However, no significant difference was observed between the youngest group and those aged above 44 years, suggesting that older adults in this study remained equally likely to report stigma as younger individuals. This pattern contrasts with some prior evidence which suggested that older adults are more likely to harbour COVID-19 stigma due to heightened perceived vulnerability, age-related psychosocial stressors, and exposure to ageist narratives during the pandemic (Donizzetti & Lagacé, 2022; Hopf et al., 2021). However, it is plausible that the occupational setting in this study modulated the relationship between age and stigma. Mid-career employees may possess greater exposure to workplace policies, higher health literacy, and more stable psychological resources, enabling them to appraise infection risk with less emotional reactivity. In contrast, younger adults remain particularly susceptible to stigma-inducing messages circulating on digital platforms. Social media has been consistently identified as a major conduit for COVID-19 misinformation, heightening fear, confusion, and stigmatising attitudes among youth populations (Borah et al., 2022; Elbarazi et al., 2022; Matchanova et al., 2024). This vulnerability is further exacerbated by limited discernment in evaluating health-related information online, making younger adults more prone to internalising stigma narratives during times of crisis.

In terms of occupational roles, participants in technical and engineering roles reported significantly lower levels of workplace COVID-19 stigma compared to those in administrative roles. This protective trend, however, diminished after adjusting for compositional network variables in the final model. Individuals in technical and engineering roles are often more exposed to operational protocols, physical workplace attendance, and routine risk mitigation procedures, which may foster a sense of control and reduce fear-based perceptions. Prior studies suggest that familiarity with safety routines and consistent exposure to workplace settings can contribute to lower psychological distress and stigma, even in high-risk environments (Caricati et al., 2022; Dost et al., 2024). In contrast, administrative staff often face unique challenges in maintaining social interaction, clear communication with supervisors, and a stable professional identity due to the nature of their work environment. These conditions can contribute to feelings of isolation, uncertainty, and perceived stigma (McTaggart & McLaughlin, 2025; Nolan et al., 2021). Furthermore, job satisfaction and mental well-being in this group are closely linked to perceived organisational support, which may not always be consistently experienced across hierarchical levels (Rožman et al., 2023). These findings support the view that occupational context shapes stigma through distinct psychosocial mechanisms and reinforce the need to interpret such differences within the framework of workplace subcultures and role-specific experiences (Wibowo et al., 2023).

When network compositional variables were added, gender homophily emerged as a significant predictor of workplace COVID-19 stigma. These compositional variables reflected the makeup of each ego's nominated network, including the extent to which alters shared particular characteristics. The finding suggests that, beyond individual-level factors, the gender composition of a respondent's immediate social network was associated with stigma status. Egos whose personal networks consisted mostly of same-gender alters were more likely to report stigma. This supports the idea that people with similar social characteristics, such as gender, tend to form tightly connected groups where attitudes are more likely to align (McPherson et al., 2001; Valente, 2010). Jackson et al. (2022) found that men were less likely to engage in empathetic conversations and more likely to avoid emotional topics, especially in male-dominated online spaces. Lee & Butts (2020) similarly observed that men often downplayed emotionally sensitive content, which may limit open discussion and feedback in same-gender groups. Laniado et al. (2016) showed that people tend to interact more with others of the same gender on online platforms, and that male-male interactions were often task-focused rather than relational. These findings suggest that gender-homophilous networks, especially those dominated by men, may restrict the flow of supportive or corrective dialogue that could help challenge stigma. As a result, high gender homophily in egocentric networks may strengthen stigma-related beliefs through shared norms and reduced exposure to alternative views. These results emphasise the importance of examining both individual traits and the gender composition of personal networks when addressing stigma in workplace settings.

Although COVID-19 infection history and knowledge were included as predictors, their associations with stigma were not statistically significant in the final model. This suggests that individual-level experience and awareness may not be sufficient to shape stigma-related outcomes in the workplace. This finding contrasts with earlier studies, such as Haddad et al. (2021), which reported a significant inverse relationship between COVID-19 knowledge and stigma in a Lebanese population. One plausible explanation for this discrepancy lies in the timing of data collection. Haddad's study was conducted during the early phase of the pandemic, when knowledge gaps and uncertainty were more pronounced, and fear-driven stigma was likely influenced by misinformation. In contrast, the current study was conducted in 2024, after several years of public health education, institutional learning, and lived experience with the disease. In such a matured context, knowledge may no longer play a central role in shaping stigma, as attitudes may have become more entrenched and socially mediated.

While the MLogR analysis identified important individual and relational factors within egocentric networks, it focused mainly on the composition of personal ties rather than how those ties function within the broader social structure. For example, gender homophily and relationship types revealed how the makeup of a person's network influences stigma but did not fully explain how influence may operate across different interpersonal ties or how network position shapes exposure to stigma-related attitudes. To explore these deeper relational processes, the study continued with multilevel and sociocentric network analyses. These next steps allowed for a more detailed understanding of how stigma may be reinforced and patterned through interactional, relational, and structural processes within the workplace network. These findings highlight that stigma in the workplace is not only an individual cognitive disposition but is strongly linked to the relational environments in which workers are embedded. The demographic and relational predictors identified in the MLogR models represent the compositional foundations on which later network processes operate, and they provide the first layer of explanation for how stigma perceptions take shape before being structurally reinforced in the workplace network.

5.3.1.2 Binary Logistic Multilevel Modelling (MLM)

MLM was applied to examine how specific ego-alter relationships influence whether an alter is perceived to shape the ego's views about workplace COVID-19 stigma. This method accounts for the hierarchical structure of the data, where multiple alters are nested within each ego. MLM is appropriate for such data as it captures both individual and relational level influences and adjusts for dependency among observations within the same ego. As discussed by Ledermann & Kenny (2017), multilevel approaches are particularly useful for studying contextual and dyadic effects in social networks. It is important to note that the MLM outcome reflects perceived influence as reported by the ego, rather than objectively verified influence, and should therefore be interpreted as perceived relational salience within the ego's personal network.

Among the tested variables, relationship type emerged as the most influential predictor. Family members were significantly more likely to influence the ego's perception of stigma than other alters such as friends, colleagues, or superiors. This aligns with cultural expectations in Malaysian society, where family plays a central role in shaping emotional, moral, and behavioural responses. As noted by Abu Bakar & Connaughton (2019), Malaysian familial relationships often serve as key sources of trust, advice, and value transmission. This is also consistent with findings by Bogart et al. (2020), who reported that family members may either reinforce or mitigate stigma depending on their beliefs, health literacy, and the emotional tone of communication. Other relationships were perceived as significantly less influential. Friends and colleagues, despite being part of daily work interactions, were less likely to shape stigma perceptions. Superiors or employers also had lower influence despite their formal authority. Valente (2010) highlights that social influence often stems from emotional closeness and perceived similarity, which can outweigh formal roles or hierarchical authority in shaping attitudes and behaviours. The strong influence of family ties also reflects broader Malaysian sociocultural norms, where collectivism, filial obligation, and close-knit household structures shape emotional responses and moral judgements. In such contexts, health related attitudes are often constructed within the family unit, which makes familial influence particularly salient in shaping workers' orientations towards stigma and perceived risk.

Alter gender and duration of acquaintance were not statistically significant. Although previous studies such as Jackson et al. (2022) and Lee & Butts (2020) described gender differences in emotional communication, such patterns did not translate into measurable differences in perceived influence in this context. Similarly, longer acquaintance did not predict higher influence. This suggests that a person's role in the ego's social system may override how long they have known each other. As Valente (2010) proposed, the influence of a social tie is often shaped more by role salience than by time-based familiarity.

Statistical results supported the strength of the multilevel design. The intraclass correlation coefficient (ICC) exceeded 0.80 in all models, indicating that most variation in perceived influence was explained by ego-level differences. The final model, which included both ego and alter characteristics, explained 6% of the variance through fixed effects, while the remainder was attributable to unobserved ego-level factors. This reinforces the idea that perceived influence is individualised and shaped by personal context, with relational variables adding modest yet meaningful explanatory power.

Together, these findings show that stigma is not only experienced individually but also shaped by relational patterns within personal networks. While multiple logistic regression showed that the composition of egocentric networks, such as homophily and relationship types, is associated with ego-reported stigma, the MLM results demonstrate that only specific ties are perceived as influential in shaping these attitudes.

From a theoretical perspective, these egocentric findings are consistent with viewing stigma as a socially constructed and relational process. Goffman's work highlights how stigma is produced through daily interactions and through the judgements made by others, which helps to explain why emotionally significant ties, particularly family, play a prominent role in shaping workers' perceptions (Goffman, 1963). Link and Phelan's framework further supports this interpretation by showing how labelling, stereotyping, separation, and status loss are reinforced within social relationships that hold emotional or moral authority (Link & Phelan, 2001). In this study, the strong influence of family members suggests that perceptions of stigma are shaped not only within the factory environment but also within the wider social systems that workers participate in. These multilayered influences indicate that stigma should be understood as a product of both personal interpretation and the relational contexts that span household, community, and workplace settings.

5.3.2 Sociocentric Network Analysis of Workplace COVID-19 Stigma

While the egocentric analyses highlighted how individual characteristics and specific relationships shape stigma perceptions, the sociocentric analyses extend this understanding by examining how these attitudes are patterned within the overall workplace network and how structural positioning contributes to the emergence and maintenance of stigma.

5.3.2.1 Descriptive Structure of the Workplace Network

In this study, each of the 178 respondents was invited to nominate up to five workplace contacts by providing the name and job title of each colleague with whom they frequently communicated, either within professional or personal contexts. Respondents were asked the question: *Siapakah rakan sekerja anda yang anda rasa paling rapat dan kerap berkomunikasi dengan anda?* ("Who are your work colleagues you feel closest to and frequently communicate with?"). Respondents identified those individuals they felt closest to and engaged with most often, yielding a maximum of 890 possible ties (178 × 5). However, in a fully connected sociocentric network of 178 individuals, the number of possible directed ties would be 31,506 (178 × 177). This means that only about 2.8% of all possible ties could even be observed due to the nomination cap. This design constraint limits the visible connections in the network and contributes to the low observed density of 1.7%. Such sparse networks are also common in manufacturing settings, where the organisation of work often revolves around defined roles and structured tasks. Thornton et al. (2013) noted that factory workers tend to engage in purposeful, role-based networking rather than informal or spontaneous social interactions. These structured patterns can lead to interactions staying within functional groups, with fewer cross-departmental ties, further contributing to the low overall network connectivity (Hébert-Dufresne et al., 2023; Thornton et al., 2013).

Although the network was sparse, all employees remained connected within the same overall network, with no isolated individuals. This suggests that attitudes or behaviours, including stigma-related views, could still circulate across the workplace through indirect social pathways, even when direct ties between all employees were absent. The low degree and betweenness centralisation values indicate that influence was not concentrated in only a few individuals, but was instead distributed more broadly across the network. In practical terms, this means that workplace interactions were less dependent on a small number of dominant actors and more likely to occur through multiple peer connections. Such a structure may support the gradual formation and sharing of beliefs across the workplace, rather than relying mainly on top-down influence from a few central individuals (Valente, 2010).

The moderate clustering coefficient (mean = 0.25) and coreness value (mean = 3.84) observed in this workplace network suggest the presence of locally cohesive subgroups. Such subgroups can act as echo chambers where shared beliefs, including those related to stigma, are reinforced through frequent interactions and mutual affirmation. Studies have shown that networks with higher clustering and core structures are more likely to support persistent attitudes, especially when individuals are embedded within overlapping social environments. For instance, Lee et al. (2025) demonstrated that tightly clustered communities within COVID-19 misinformation networks were more susceptible to echo chamber effects and resistant to corrective information. Similarly, Baumann et al. (2020) found that actors positioned in core regions of radicalisation networks exhibited increased cohesion and reduced exposure to dissenting views. Peters et al. (2022) further highlighted that small, dense subgroups within social networks could reinforce stigmatising beliefs, even when broader networks offer support. These findings underscore the potential role of clustering and coreness in sustaining localised stigma within workplace networks.

Importantly, employees who held stigmatising attitudes were not positioned at the network periphery or structurally excluded from workplace interactions. Instead, they were distributed across the network and engaged in regular interactions with colleagues. This distribution suggests that stigma in this context does not spread through isolation but through attitudinal clustering, where individuals with similar beliefs are more likely to be socially connected. One explanation is latent homophily, which refers to the formation of ties among individuals not through active selection but due to shared environments and exposure to similar discourses (Becker & Arnold, 1986; Wu et al., 2024). Wu et al. (2024) further emphasised that in workplace discursive spaces, stigma can be reinforced through repeated interactions, identity management practices, and organisational norms. These embedded interactions help normalise and sustain stigma-related beliefs over time.

In summary, the network structure observed here provides important contextual information for examining the potential mechanisms underlying stigma-related patterns in the workplace. While descriptive statistics offer useful insight into the overall structure of the network, they cannot by themselves explain how stigma is maintained or clustered. Nevertheless, the combination of a sparse but fully connected network, together with moderate clustering and core formation, suggests that workplace ties, although limited in number, may still be sufficient to support the circulation of attitudes within connected subgroups. These descriptive findings therefore provide a useful interpretive context for the ERGM and QAP results that follow.

5.3.2.2 Exponential Random Graph Modelling (ERGM)

The ERGM results show that tie formation within the workplace network was not random. Instead, it was influenced by both structural features and individual similarities. One of the strongest structural effects was reciprocity (PE = 3.130), indicating that employees who nominated others as workplace contacts were highly likely to be nominated in return. Reciprocity is a common feature in social networks and often reflects mutual trust, frequent interaction, and stronger social bonds. Almaatouq and colleagues (2016) found that reciprocal friendships were not only more intimate but also had a greater impact on behavioural change. In their behavioural experiment, individuals were more likely to increase physical activity when peer encouragement came from a reciprocal tie. Moreover, reciprocal relationships had a stronger role in the early stages of behavioural diffusion. These findings support the idea that mutual ties can facilitate the reinforcement of shared attitudes or norms within workplace networks.

The ERGM also revealed evidence of homophily, with individuals more likely to form ties with others who shared similar attributes. Specifically, employees were significantly more likely to connect with those of the same gender (PE = 1.110), job position (PE = 0.860), age group (PE = 0.180), and stigma status (PE = 0.420). These patterns align with broader literature on homophily in social and organisational networks. McPherson et al. (2001) described homophily as a fundamental organising principle, noting that people tend to associate with others who are similar in sociodemographic characteristics, beliefs, and experiences. Valente (2012) similarly highlighted that health communication is often more persuasive when delivered through peers who are socially or culturally similar, particularly when addressing sensitive topics like illness or stigma.

The homophily observed in relation to stigma status is particularly noteworthy. The tendency for employees with similar stigma classification to form ties suggests that stigma may cluster within attitudinally aligned subgroups rather than being evenly distributed across the network. While the ERGM provides statistical evidence for this clustering, qualitative studies offer complementary insights. For example, Ssali et al. (2012) found that people living with HIV often expressed stigma-related concerns within trusted peer groups. Similarly, Lee et al. (2023) demonstrated that seroconcordant partner selection, interpreted as a form of homophily, was more likely among individuals with negative attitudes toward people living with HIV. These patterns helped reinforce social boundaries and maintain stigma-related beliefs. Such findings support the interpretation that attitudinal clustering around stigma may be driven by perceived similarity and the comfort of interaction within like-minded relationships (Lee et al., 2023).

At the same time, the model found that employees who reported stigma were significantly less likely to form ties in general (PE = -0.160). This suggests a dual process: while stigma fosters tighter bonds within demographically similar groups, it concurrently leads to broader social exclusion. Leung et al. (2016) observed a similar pattern among migrant domestic workers in Hong Kong, where individuals facing marginalisation built strong in-group ties but remained disconnected from the broader network, thereby limiting their access to diverse resources and influence. Comparable dynamics may be evident in this workplace setting, where stigmatised individuals are integrated within subgroups yet less connected across the broader network. These patterns may also contribute to subtle forms of network segregation. Lee & Butts (2020) found that even minimal avoidance behaviours in social networks can reduce connectivity and hinder the spread of information.

Other demographic characteristics also shaped tie formation. The ERGM showed that male employees were significantly less likely to form ties overall (PE = -0.530), suggesting a general tendency toward lower engagement in reported workplace interactions. This aligns with prior research indicating that men often score lower on certain measures of social connectivity, such as betweenness and closeness centrality, which may reduce their embeddedness in relational structures (Freeman, 1978). However, this does not exclude the possibility of some male employees occupying central positions. As seen in the descriptive analysis, several top-ranked individuals in degree centrality were male, indicating that while males were less likely on average to form ties, a few may have held formal or influential roles that increased their visibility in the network.

Employees aged over 44 years were significantly more likely to form ties (PE = 0.210), which may reflect their greater tenure, accumulated workplace trust, or job responsibilities that necessitate broader engagement. As discussed by Valente (2012), socially credible and embedded individuals are often more effective as change agents in health communication networks. In organisational settings, such credibility often coincides with age or seniority, which may explain the higher propensity for older employees to engage more widely within the workplace network.

Interestingly, COVID-19 knowledge was not significantly associated with tie formation (PE = 0.0003). While knowledge is often assumed to enhance influence, this result highlights the importance of trust and social alignment. Bogart et al. (2020) similarly found that empowering individuals with HIV to act as prevention advocates was most effective not merely through knowledge transfer, but by fostering trust, reducing internalised stigma, and strengthening social ties. Their findings suggest that social influence depends more on the perceived credibility and relational closeness of the messenger than on their factual knowledge alone, particularly in health communication within peer networks.

Together, these findings show that tie formation within the workplace network was shaped by both structural mechanisms and similarity between employees. In particular, employees who shared characteristics such as gender, job position, age group, and stigma status were more likely to be connected through homophily, while employees with stigma status were generally less likely to be involved in workplace ties overall. This combination of findings suggests that stigma was not randomly distributed within the network, but tended to cluster within particular relational patterns while also being associated with reduced network engagement among affected employees. These results indicate that workplace ties may reflect and potentially reinforce stigma-related attitudes within specific social groupings.

5.3.2.3 Quadratic assignment procedures correlations (QAP)

The QAP results showed that employees who occupied similar positions in the workplace network were more likely to share the same COVID-19 stigma status. This supports the idea that shared stigma attitudes can arise not only through direct relationships but also through structural equivalence. Structural equivalence refers to individuals who hold similar positions in the network, even if they are not directly connected, and may behave or think alike due to similar experiences within the network (Valente, 2012).

Among the tested metrics, eigenvector centrality demonstrated the strongest and most statistically significant correlation with stigma similarity (r = -0.442, p < 0.001). This suggests that individuals with similar access to influential others in the network were more likely to share similar stigma attitudes. Previous studies support this pattern. Patterson & Goodson (2017) observed a relationship between eigenvector centrality and health behaviour, indicating that well-connected individuals could influence health-related decisions and behaviours within social networks. Valente (2012) highlighted the role of central actors in spreading social norms and beliefs.

In addition, coreness showed a significant association with stigma similarity (r = -0.028, p = 0.020). Coreness reflects how embedded an individual is within the dense core of the network. Employees in similar core positions may experience stronger group cohesion and repeated interactions, which can reinforce shared beliefs. Similar findings were reported by Patterson et al. (2021) and Ramos-Vidal et al. (2020), who noted that individuals embedded in tightly connected subgroups were more likely to exhibit aligned behaviours and attitudes.

Other centrality measures showed weaker or non-significant associations. Degree centrality showed a small and non-significant correlation with stigma similarity (r = -0.009, p = 0.059). This indicates that having a similar number of ties does not necessarily predict whether individuals share the same stigma status. Similarly, betweenness centrality was not significantly related to stigma alignment (r = -2.966, p = 0.886). Individuals with high betweenness often serve as connectors between different parts of the network (Freeman, 1978). Although they are exposed to diverse groups, this position might reduce alignment with any single group's norms.

Some network features that describe proximity and grouping did not show significant links with stigma similarity in this study. These include closeness centrality

(r = -0.275, p = 0.547), clustering coefficient (r = -0.073, p = 0.201), and geodesic distance (r = -0.020, p = 0.546). Closeness shows how near an individual is to others in the network, while clustering refers to how connected someone's contacts are to each other. Geodesic distance measures the average number of steps between two people. Interestingly, although earlier studies found that closeness and clustering can influence shared norms (Freeman, 1978; Patterson et al., 2021), these associations were not seen in the current setting. These findings may suggest that in this workplace, broader influence and stronger group embedding, as reflected by eigenvector centrality and coreness, could play a more important role in shaping shared stigma attitudes than local proximity or subgroup clustering.

Taken together, the results suggest that COVID-19 stigma is not randomly distributed across the network. Instead, it appears to be shaped by broader structural features, particularly influence and embeddedness. Individuals with similar levels of prominence, as indicated by eigenvector centrality, and those embedded in similarly cohesive network cores, as reflected by coreness, were more likely to share stigma attitudes. Interestingly, structural metrics commonly associated with proximity and information flow, such as closeness and clustering, were not significant in this context. This contrast highlights the importance of examining network effects within the specific social and organisational environment in which they occur.

These network-based findings are consistent with Stangl et al. (2019) conceptualisation of stigma as a socially embedded process. Rather than being merely an internalised trait or label, stigma in this workplace appeared to be shaped and reinforced by how individuals were positioned in the network. Those with similar levels of influence or embeddedness tended to share stigma attitudes, reflecting how social roles, expectations, and group norms can shape perceptions. This highlights the importance of structural context in the performance and maintenance of stigma, supporting Stangl's view that stigma is enacted through social interaction and embedded within broader organisational dynamics.

Overall, Phase 2 demonstrates that workplace COVID-19 stigma among factory workers emerges from the interaction of individual characteristics, relational contexts, and organisational network structures. Egocentric models showed that age, occupational role, gender homophily, and particularly family relationships shape how stigma is perceived and by whom workers feel influenced. Sociocentric models revealed that tie formation and the clustering of stigma attitudes are structured by reciprocity, sociodemographic homophily, and differential embeddedness within the network core, rather than by simple proximity or the number of ties alone. These complementary perspectives indicate that stigma is not an isolated psychological response but a property of the social fabric of the workplace, where individual attitudes measured by WoCKSS are continually negotiated, reinforced, or challenged through patterned social interactions. This integrated view lays the foundation for the implications discussed in the following sections.

From a practical perspective, these findings suggest that workplace stigma interventions should not rely solely on general awareness campaigns, but should also consider how employees are positioned within the workplace network. For agencies such as the Ministry of Health Malaysia and the Department of Occupational Safety and Health (DOSH), this means that stigma reduction strategies may be strengthened by identifying central or well-connected employees as peer communicators, promoting cross-departmental interaction to reduce homophily-based clustering, and supporting structured reintegration of workers who may be at risk of social exclusion. In organisational settings, network-informed approaches may help target not only individuals with stigmatising attitudes, but also the relational environments in which these attitudes are reinforced.

5.4 Strengths and Limitations of the Study

This study has several strengths, particularly in its dual-phase design combining rigorous psychometric validation with social network analysis. In Phase 1, the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS) was developed through a methodologically sound process, incorporating content and face validation to ensure conceptual clarity and cultural relevance. High indices of content and face validity (CVI and FVI) supported the relevance, clarity, and comprehensibility of the scale items in accordance with established criteria (Polit et al., 2007). The application of Item Response Theory (IRT) for the knowledge domain offered detailed insight into item performance beyond classical test theory (Edelen & Reeve, 2007). This was complemented by exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) for the stigma domain, confirming its multidimensional structure. Reliability assessment using McDonald’s omega further confirmed the internal consistency of the final instrument (Hair et al., 2019). Although the exploratory IRT phase did not fully support unidimensionality, the confirmatory analyses reinforced the structural validity of the scale, illustrating the iterative nature of psychometric validation and the necessity of adequate sample sizes for stable models (Hambleton & Cook, 1983).

The development of WoCKSS for Malaysian factory workers enhances its contextual specificity, capturing workplace stigma phenomena that general measures might overlook (Nochaiwong et al., 2021). This localisation accounted for cultural and linguistic factors critical for valid and meaningful measurement within this unique occupational setting (Faghankhani et al., 2022).

Phase 2 extended the analysis through Social Network Analysis (SNA) using both egocentric and sociocentric approaches, providing comprehensive insight into how social connections are associated with the distribution and patterning of stigma. Employing various statistical techniques such as multiple logistic regression (MLogR), multilevel modelling (MLM), exponential random graph modelling (ERGM), and the quadratic assignment procedure (QAP) enabled identification of both individual and structural factors shaping stigma dynamics (Borgatti et al., 2024; Ledermann & Kenny, 2017). This multifaceted methodology represents a strength by capturing the complexity of relational and network influences on stigma.

Despite these strengths, certain limitations warrant consideration. The use of self-administered questionnaires may have introduced response biases, including socially desirable responses and variability in comprehension (Bowling, 2005; van de Mortel, 2008). Additionally, the cross-sectional design restricts causal inference, limiting conclusions to associations and preventing examination of stigma change over time (Levin, 2006). The study's execution within a single, well-regulated factory with a homogenous Malaysian workforce may reduce external validity, as findings might not generalise to diverse or less regulated industrial settings (Polit & Beck, 2010). In addition, organisation-specific norms, communication practices, and managerial culture may have shaped both network formation and stigma expression, limiting the extent to which observed homophily patterns can be assumed to reflect broader workplace processes.

Furthermore, the sociocentric network data were subject to nomination limits, restricting respondents to naming five workplace contacts. While this approach reduces participant burden, it potentially truncates network data, excluding peripheral but potentially influential ties. This truncation may have biased measures of network structure and centrality (Borgatti et al., 2024; Kossinets, 2006). Approximately 25%

non-response further hampers completeness by omitting relational data from absent actors, potentially introducing non-random missingness that affects network representativeness (Kossinets, 2006). Although analysis conditions and assumptions were satisfied, such partial network data warrant cautious interpretation. Future research should consider enhanced recruitment strategies, repeated follow-up of non-respondents, less restrictive nomination procedures, and longitudinal study designs to improve the capture of network complexity, peripheral ties, and the temporal dynamics of stigma.

CHAPTER 6
CONCLUSION

6.1 Overview of the Study

This study was conducted in two phases to address the conceptualisation, measurement, and structural understanding of COVID-19 stigma within workplace settings. Phase 1 focused on the development and psychometric validation of the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS), specifically tailored for factory workers. Phase 2 employed Social Network Analysis (SNA) to investigate how individual attributes and relational structures influenced the formation and distribution of stigma within a food manufacturing workplace. The study incorporated both egocentric and sociocentric approaches to capture multilevel stigma dynamics using advanced analytical methods, including Multiple Logistic Regression (MLogR), Multilevel Modelling (MLM), Exponential Random Graph Modelling (ERGM), and Quadratic Assignment Procedure (QAP).

This study was necessary because workplace COVID-19 stigma had remained insufficiently understood as both a measurement problem and a relational phenomenon embedded within organisational networks. Existing COVID-19 stigma instruments were not developed specifically for Malaysian industrial settings, and previous research had given limited attention to how stigma may be shaped by interpersonal ties, homophily, and structural position in the workplace. By integrating psychometric validation with egocentric and sociocentric social network analysis, this thesis addressed both the conceptual gap in workplace stigma measurement and the structural gap in understanding how stigma becomes patterned within workplace relationships. In doing so, the study advances stigma research by positioning workplace COVID-19 stigma as a socially embedded process, and contributes to network science by applying multi-level network approaches to the study of health-related stigma in an occupational setting.

6.2 Key Findings

Phase 1 resulted in the successful development and validation of the WoCKSS. The scale demonstrated strong content and face validity, as assessed through expert reviews and target user feedback. Exploratory analyses using Item Response Theory (IRT) and Exploratory Factor Analysis (EFA) helped refine the scale by removing poorly performing items. Confirmatory validation using CFA and confirmatory IRT provided evidence for the scale's structural integrity and internal consistency. McDonald's omega further supported the reliability of the final stigma subscales. Although unidimensionality was not initially achieved in exploratory IRT, this was addressed during the confirmatory phase.

In Phase 2, MLogR analysis showed that workplace COVID-19 stigma was significantly less reported among workers aged 30 to 44 years and those in technical or engineering roles. Gender homophily and certain network compositional characteristics, including relationship patterns involving superiors, were also associated with increased odds of stigma. However, neither COVID-19 knowledge nor infection history remained significant after adjusting for network variables.

Multilevel Modelling (MLM) revealed that the perceived influence of alters on the ego's stigma perception was significantly shaped by relationship type. Family members were more likely to influence stigma perceptions than friends, colleagues or superiors. Alter gender and duration of acquaintance were not significant. High intraclass correlation coefficients (ICC) indicated that most of the variation in perceived influence was attributable to ego-level differences.

Exponential Random Graph Modelling (ERGM) provided evidence that tie formation in the workplace network was influenced by both structural and compositional factors. Reciprocity was strongly predictive of tie presence, while homophily effects were observed for gender, job position, age group, and stigma status. Individuals experiencing stigma were less likely to be connected within the broader network, indicating reduced social integration despite the presence of attitudinally similar peers.

Quadratic Assignment Procedure (QAP) correlations showed that employees with similar positions in the network, especially in terms of eigenvector centrality and coreness, were more likely to share the same COVID-19 stigma status. Although the associations were modest in magnitude, the consistent significance of eigenvector centrality and coreness suggests that broader influence and deeper group embedding may play a meaningful role in shaping shared attitudes within the workplace network.

Collectively, these findings address the research questions outlined in Chapter 1. The WoCKSS demonstrated sound psychometric performance in measuring workplace COVID-19 stigma, fulfilling the requirement of Objective 1. The egocentric analyses showed that individual attributes and tie-level relational factors explain meaningful variation in stigma perceptions, thereby addressing Objective 2. The sociocentric analyses further demonstrated that structural features of the workplace network, including reciprocity, homophily and positional influence, shape the distribution of stigma across the organisation, fulfilling Objective 3. These integrated findings substantiate the thesis argument that stigma emerges through a combination of individual, relational and structural mechanisms. Taken together, these findings indicate that workplace COVID-19 stigma is not only measurable as a multidimensional construct, but also socially patterned through individual, relational, and structural mechanisms within workplace networks.

6.3 Contributions to Knowledge

This study contributes to knowledge at conceptual, empirical, and methodological levels. Empirically, it introduces the WoCKSS as a psychometrically robust instrument specifically designed to measure workplace-related COVID-19 stigma among factory workers and provides one of the earliest detailed examinations of stigma in Malaysian industrial settings. It further shows that workplace COVID-19 stigma is not only measurable as a multidimensional construct, but also patterned through individual, relational, and structural mechanisms within workplace networks.

Conceptually, the study demonstrates how fear, stereotype, and prejudice, as identified in Phase 1, map onto interactional and structural processes observed in Phase 2. This reinforces the view that stigma is not merely an attitudinal construct but a relational and positional phenomenon situated within patterned social structures. In this way, the study extends existing stigma frameworks, including the Health Stigma and Discrimination Framework, by showing how stigma may be structured and sustained within workplace networks.

Methodologically, the study advances the application of Social Network Analysis in stigma research, which has been underexplored in the context of COVID-

19. While much of the existing literature focuses on HIV- or mental health-related stigma, this study is among the first to examine COVID-19 stigma using both egocentric and sociocentric network methods. The integration of psychometric validation with models such as ERGM and QAP also demonstrates a novel analytical framework that may be adapted to other occupational health issues in which social influence and network positioning are important.

6.4 Implications for Practice and Policy

The findings have practical implications for workplace health management and organisational policy. Understanding that stigma is shaped not only by individual traits but also by relational patterns suggests that interventions should move beyond awareness campaigns to address underlying network dynamics. Promoting inclusive peer interactions, improving communication between hierarchical levels, and fostering diverse workplace networks may help reduce stigma and improve psychosocial outcomes for workers. The validated WoCKSS instrument can also be used by health practitioners, researchers, and policymakers to monitor stigma trends and evaluate the effectiveness of intervention strategies.

These findings are also relevant for occupational health authorities and organisational leaders seeking to promote resilient and cohesive workforces. Because stigma was influenced by both interpersonal networks and structural embedding, interventions limited to individual education or informational campaigns may be insufficient. Instead, policies should incorporate peer-led communication strategies, strengthen cross-departmental engagement, and identify central actors who can act as positive influence agents. Such network-oriented strategies align with contemporary public health approaches that emphasise community structures, social integration and relational communication in shaping behavioural outcomes.

In practice, different network positions may require different intervention approaches. Central or core-embedded workers may be useful as peer communicators because of their visibility and influence, whereas peripheral workers may require more deliberate inclusion to reduce isolation and prevent stigma from becoming concentrated at the margins of workplace interaction. Organisational hierarchy should also be considered during implementation, as communication across supervisory and peer levels may affect whether stigma-reduction efforts are accepted or resisted. Over time, such interventions may not only reduce stigma attitudes but also encourage more inclusive and cross-group interaction patterns within the workplace.

6.5 Study limitations

This study is not without limitations. As detailed earlier, Phase 2 was conducted within a single large food manufacturing company where safety and health policies were well established. All factory workers were Malaysian locals, which may limit the generalisability of the findings to other industrial settings with different workforce compositions or operational cultures. Additionally, as with any cross-sectional and self-reported data collection, response bias and temporal inferences must be interpreted cautiously. In addition, because WoCKSS was developed specifically for workplace COVID-19 stigma, its direct applicability to other infectious diseases or future outbreak contexts may be limited without conceptual and psychometric adaptation.

6.6 Recommendation for Future Research

Future research should consider applying the WoCKSS in different types of workplaces, such as smaller factories, multinational companies, or organisations with more diverse workforces. It may also be valuable to adapt and revalidate the conceptual framework of WoCKSS for other communicable disease contexts, in order to examine whether the workplace stigma dimensions identified in this study remain transferable beyond COVID-19. Comparing factories of varying sizes and organisational structures may help clarify how workplace environments influence stigma dynamics. It would also be valuable to extend this approach to other communicable diseases, using similar social network frameworks to broaden understanding of stigma formation, reinforcement, and mitigation across occupational contexts.

Building on the current findings, future studies should design and evaluate network interventions that target central or influential actors within workplace networks to reduce stigma. Network-based interventions have shown promise in reducing HIV-related stigma by leveraging social influence, empathetic contact, and structural change, leading to measurable reductions in stigma and improved health outcomes. Prinsloo & Greeff (2016) described a community "hub" intervention in South Africa that effectively mobilised key actors and reduced public stigma. More recently, Comfort et al. (2025) reported that community network interventions decreased HIV stigma and enhanced social support among affected populations, while Bogart et al. (2020) demonstrated similar outcomes through the Game Changers social network intervention in Uganda, which empowered people with HIV to act as advocates within their networks.

Testing such network-targeted interventions within industrial workplace settings could provide novel insights into scalable stigma reduction strategies relevant to occupational health contexts. Furthermore, longitudinal and mixed-method approaches would allow examination of stigma evolution and factors that promote its reduction, thereby informing sustainable, context-sensitive interventions.

Future research should also consider integrating mixed-methods approaches to better understand the mechanisms underlying stigma formation and reinforcement. Qualitative interviews with workers positioned at different levels of network influence could provide insight into how fear, stereotype, and prejudice are enacted through everyday communication. Combining longitudinal network data with repeated WoCKSS assessments would further clarify whether changes in network centrality or subgroup structure precede shifts in stigma attitudes. Such approaches would deepen theoretical understanding of how individual perceptions interact with structural forces over time. Future studies may also examine multiplex workplace networks, including formal, informal, and digital communication ties, to determine whether stigma is patterned differently across overlapping channels of interaction.

6.7 Final reflection

This study has provided a comprehensive understanding of workplace COVID-19 stigma by developing and validating a targeted measurement tool and applying Social Network Analysis to examine how stigma is patterned within an organisational setting. The results reflect the multi-layered nature of stigma, consistent with Stangl's conceptualisation of stigma as a socially constructed process involving identity, interaction and structure.

The findings support the broader stigma framework, which positions stigma as emerging from intersecting drivers and facilitators, shaped by social norms, roles and institutional settings. In this study, workplace structures, peer relationships and organisational culture acted as both facilitators and barriers to stigma. Stigma experiences and practices, such as avoidance or stereotyping, were linked to employees' network positions and attributes, showing that stigma was not confined to individual attitudes but was also embedded in relational dynamics.

By demonstrating that employees with similar levels of network influence and group involvement, particularly those with comparable eigenvector centrality and coreness, were more likely to share stigma attitudes, the study highlights the importance of structural and positional influence. This supports Stangl's idea that stigma is performed and reinforced through social interaction and context. The sociocentric findings also align with the framework's emphasis on outcomes, showing how stigma may reduce social integration and affect workplace cohesion.

Through this lens, COVID-19 stigma can be seen not only as a health-related label but as a form of social marking that interacts with organisational norms and perceived roles. This study, therefore, bridges individual perceptions and structural realities, providing a grounded application of Stangl's theory to a contemporary workplace issue.

Taken together, the two phases of this thesis illustrate that stigma is best understood through a multi-layered lens that accounts for cognitive, relational and structural dimensions. By integrating psychometrics with social network analysis, this study provides a more holistic explanation of how stigma emerges and persists in workplace environments. The methodological and conceptual contributions offer a foundation for future research and practical interventions aimed at strengthening workplace well-being and social cohesion.

Beyond its empirical findings, this thesis also marked an important development in my own research thinking. It shifted my understanding of stigma from a phenomenon that can be assessed primarily through individual attitudes to one that must also be examined through relationships, network position, and organisational context. Methodologically, the study required movement from scale development and validation to increasingly complex relational and structural analyses, broadening my perspective on how biostatistical and network-based methods can be combined to address applied public health questions. This progression has helped shape a broader research identity centred on the integration of psychometrics, social structure, and workplace health

Although COVID-19 is now managed as an endemic illness and public attention has reduced, the relevance of these findings remains significant. Episodes of stigma continue to arise in workplaces during outbreaks of COVID-19, influenza, tuberculosis and other communicable diseases. This research offers evidence that stigma is shaped by network structures rather than individual attitudes alone, which is valuable for agencies such as the Department of Occupational Safety and Health (DOSH) when designing guidance for communication, staff reintegration and risk management. Network-informed approaches can help organisations identify influential actors, strengthen supportive ties and reduce misinformation, which are essential for maintaining productivity and preventing unnecessary social disruption when new infections occur.

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APPENDICES

APPENDIX 1

Final Version of WoCKSS

UNIVERSITI TEKNOLOGI MARA

B. PENGETAHUAN TENTANG COVID-19 DI TEMPAT KERJA

Berdasarkan pernyataan di bawah, tandakan (√) pada jawapan yang **paling tepat**.

	Soalan	Betul	Salah	Tidak pasti
1.	Gejala utama COVID-19 ialah demam, batuk dan sukar bernafas.	☐	☐	☐
2.	Tidak semua individu dijangkiti COVID-19 akan mengalami gejala teruk.	☐	☐	☐
3.	Mereka yang berumur lebih daripada 65 tahun dan mempunyai penyakit kronik mempunyai kebarangkalian lebih tinggi untuk mengalami gejala COVID-19 yang teruk.	☐	☐	☐
4.	Virus COVID-19 merebak melalui titisan air yang terbentuk di saluran pernafasan pesakit semasa mereka bercakap, bersin, atau batuk.	☐	☐	☐
5.	Individu yang dijangkiti COVID-19 tidak akan menjangkiti orang lain sekiranya dia tidak mempunyai gejala.	☐	☐	☐
6.	Untuk mengelakkan jangkitan COVID-19, seseorang individu harus mengelak pergi ke tempat yang sesak.	☐	☐	☐
7.	Pemakaian pelitup muka boleh mengelakkan penularan COVID-19 di tempat kerja.	☐	☐	☐
8.	Penggunaan pensanitasi tangan *(hand sanitizer)* membantu mengelakkan penularan wabak COVID-19 di tempat kerja.	☐	☐	☐
9.	Pengasingan individu yang dijangkiti virus COVID-19 adalah cara yang berkesan untuk mengurangkan penyebaran virus.	☐	☐	☐
10.	Vaksinasi COVID-19 mengurangkan risiko menghadapi jangkitan COVID-19 yang teruk.	☐	☐	☐
11.	Individu yang telah menerima vaksinasi COVID-19 tidak akan mendapat jangkitan COVID-19.	☐	☐	☐
12.	Kontak rapat yang tidak mempunyai gejala COVID-19 tidak akan menjangkiti orang lain.	☐	☐	☐
13.	Proses sanitasi dan disinfeksi secara rutin dan berkala di tempat kerja boleh membendung penularan COVID-19.	☐	☐	☐
14.	Individu yang telah dijangkiti COVID-19 tidak akan mendapat jangkitan buat kali kedua.	☐	☐	☐

C. STIGMA TERHADAP COVID-19 DI TEMPAT KERJA

COVID-19 telah memasuki fasa peralihan endemik di mana kehidupan telah telah kembali seperti sedia kala. Majoriti rakyat telah menerima vaksin penuh manakala tatacara pengendalian piawai (SOP) seperti pemakaian pelitup muka dan penjarakan sosial di tempat awam juga telah dilonggarkan oleh kerajaan.

Berdasarkan situasi semasa DI TEMPAT KERJA, nyatakan tahap persetujuan anda terhadap pernyataan-pernyataan di bawah.

Tandakan (√) pada jawapan yang menggambarkan pendapat anda.

		Sangat tidak setuju	Tidak setuju	Agak setuju	Setuju	Sangat setuju
1.	Kebanyakkan individu yang dijangkiti COVID-19 tidak menjaga kebersihan.	☐	☐	☐	☐	☐
2.	Kebanyakkan individu yang dijangkiti COVID-19 tidak menjaga kesihatan mereka.	☐	☐	☐	☐	☐
3.	Kebanyakan individu yang dijangkiti COVID-19 tidak mematuhi SOP yang telah ditetapkan.	☐	☐	☐	☐	☐
4.	Tiada sesiapa yang ingin dirinya dijangkiti COVID-19.	☐	☐	☐	☐	☐
5.	Tiada sesiapa yang dengan sengaja ingin menyebarkan virus COVID-19 di tempat kerja.	☐	☐	☐	☐	☐
6.	Individu yang dijangkiti COVID-19 adalah beban kepada rakan sekerja.	☐	☐	☐	☐	☐
7.	Individu yang dijangkiti COVID-19 adalah beban kepada syarikat.	☐	☐	☐	☐	☐

APPENDIX 2

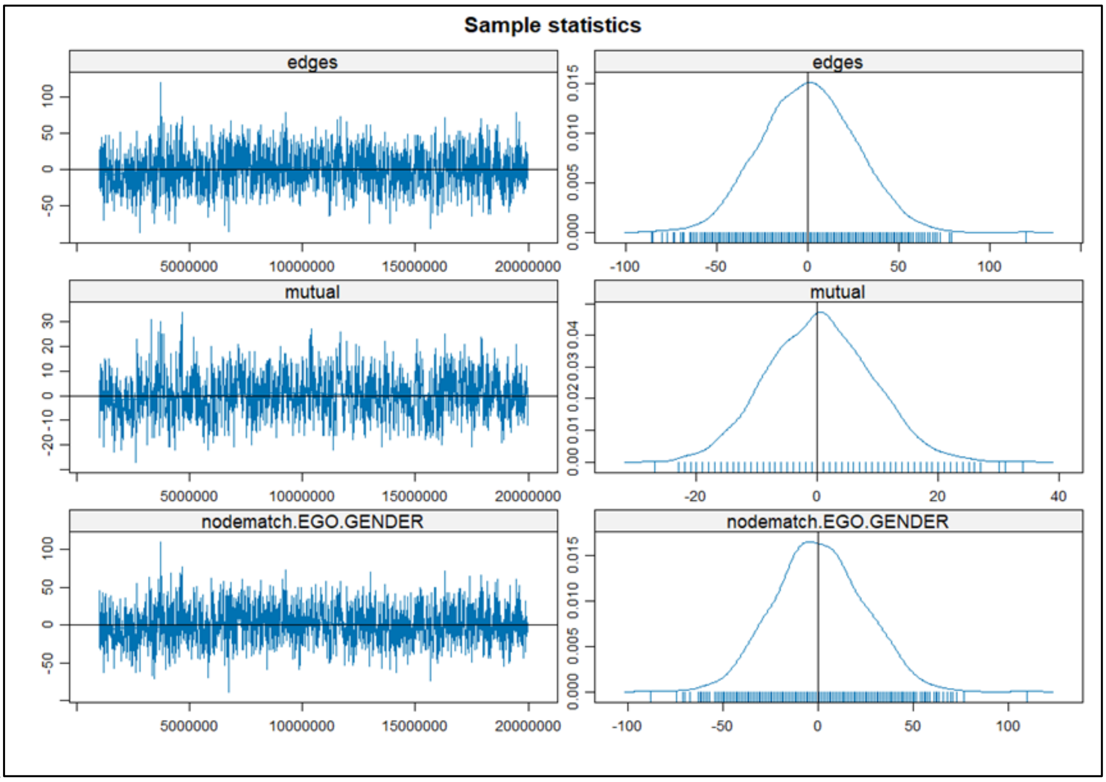
Detailed diagnostic plots and goodness-of-fit assessments for ERGM

MCMC Diagnostics

Figures show the MCMC diagnostics for all terms in Model 2. For each parameter, the left panel shows the trace plot to check stability across iterations, and the right panel shows the density plot to view the distribution of estimates. The trace plots indicate good mixing, and the density plots show roughly normal distributions centred around the mean, suggesting that the model has converged. The terms assessed include

- Structural terms: edges, mutual
- Homophily effects: nodematch for gender, job position, age group, smoking, and stigma status
- Covariates: nodefactor terms (e.g. gender, age group, smoking) and nodecov for knowledge

These results are supported by Geweke diagnostics, with most terms showing acceptable z-scores and reduced autocorrelation at higher lags.



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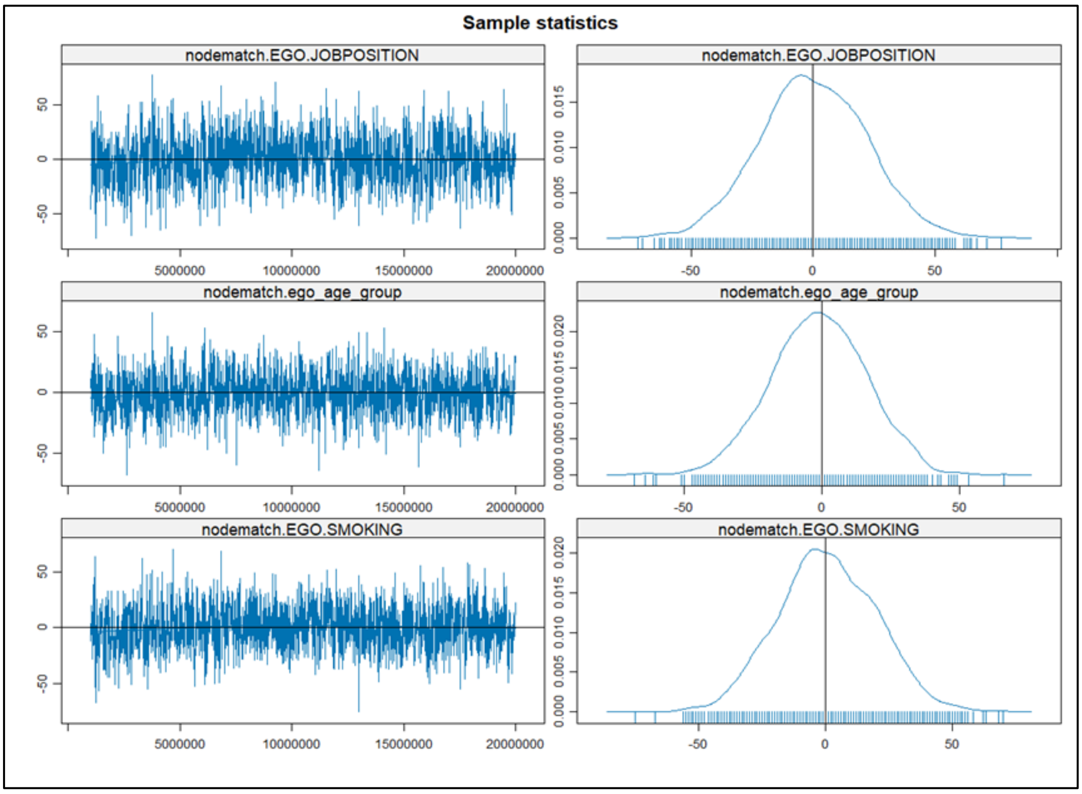
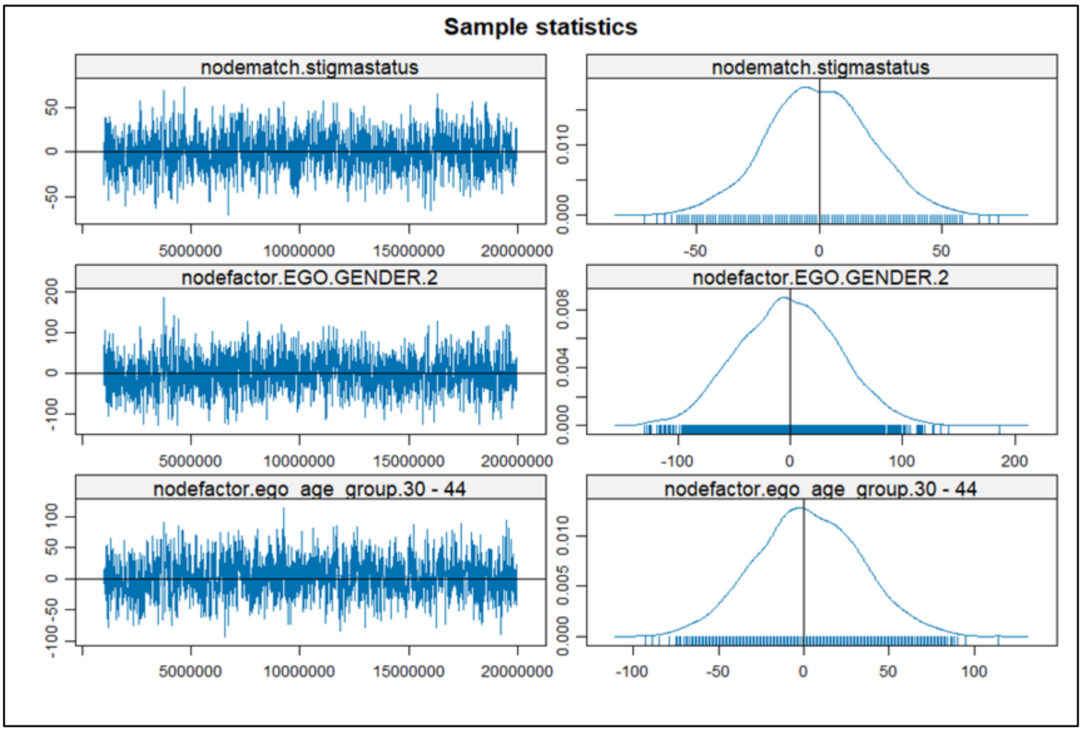
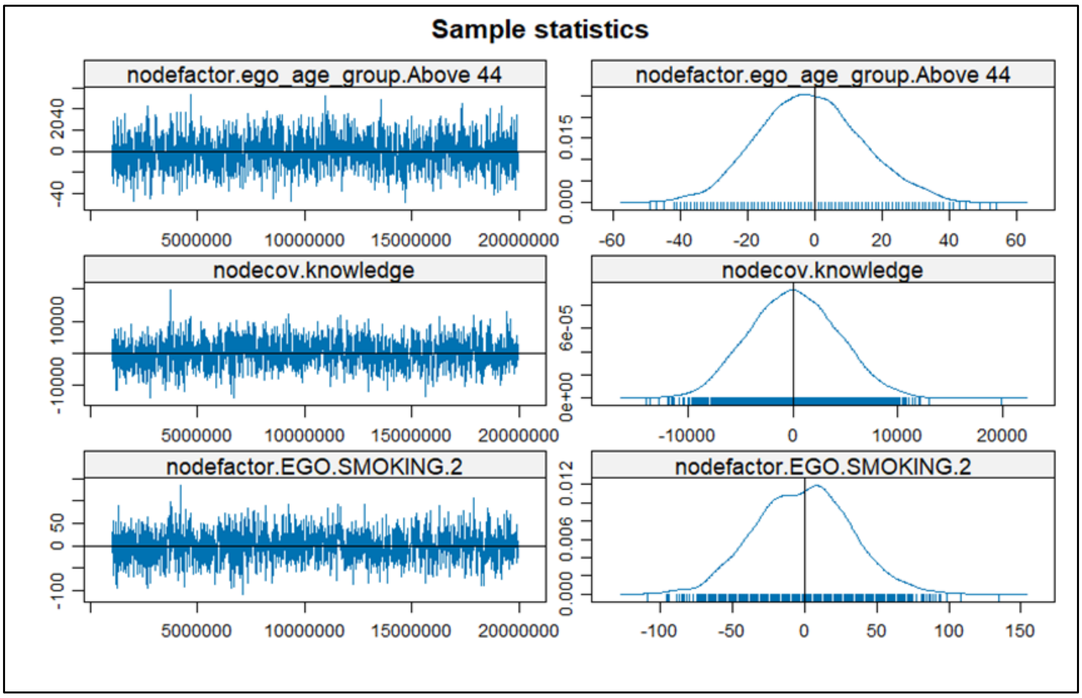
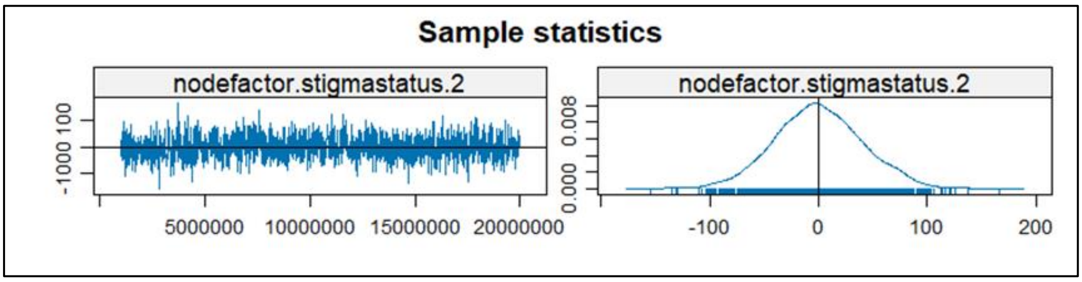

Sample statistics
nodematch.EGO.JOBPOSITION
nodematch.EGO.JOBPOSITION
nodematch.ego_age_group
nodematch.ego_age_group
nodematch.EGO.SMOKING
nodematch.EGO.SMOKING

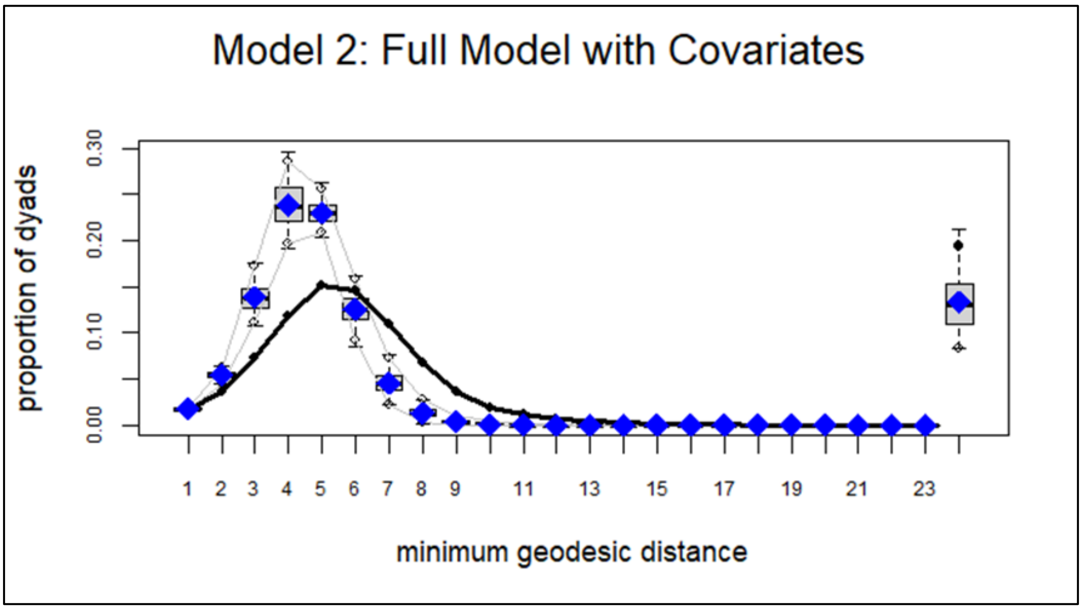

Sample statistics
nodematch.stigmastatus
nodematch.stigmastatus
nodefactor.EGO.GENDER.2
nodefactor.EGO.GENDER.2
nodefactor.ego_age_group.30 - 44
nodefactor.ego_age_group.30 - 44


Sample statistics
nodefactor.ego_age_group.Above 44
nodecov.knowledge
nodefactor.EGO.SMOKING.2


Sample statistics
nodefactor.stigmastatus.2

Goodness-of-Fit (GOF)

This is the GOF assessment for Model 2 based on minimum geodesic distance distribution. The blue markers represent the observed network statistics, while the black line and error bars indicate the average and variability of simulated statistics from the model. The close alignment between observed and simulated values across dyadic distances suggests that Model 2 provides a good representation of the observed network structure.

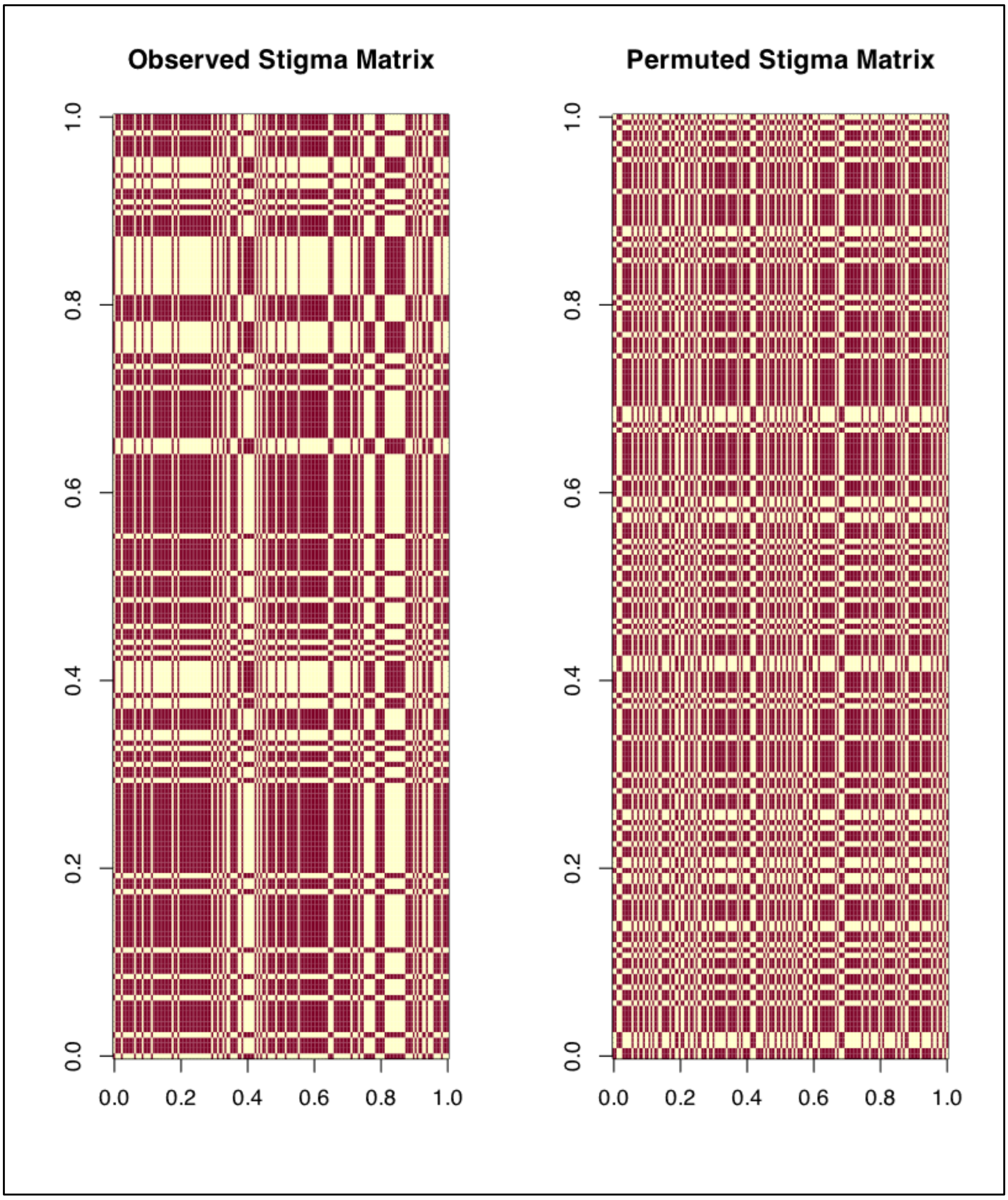


APPENDIX 3

QAP Assumptions check

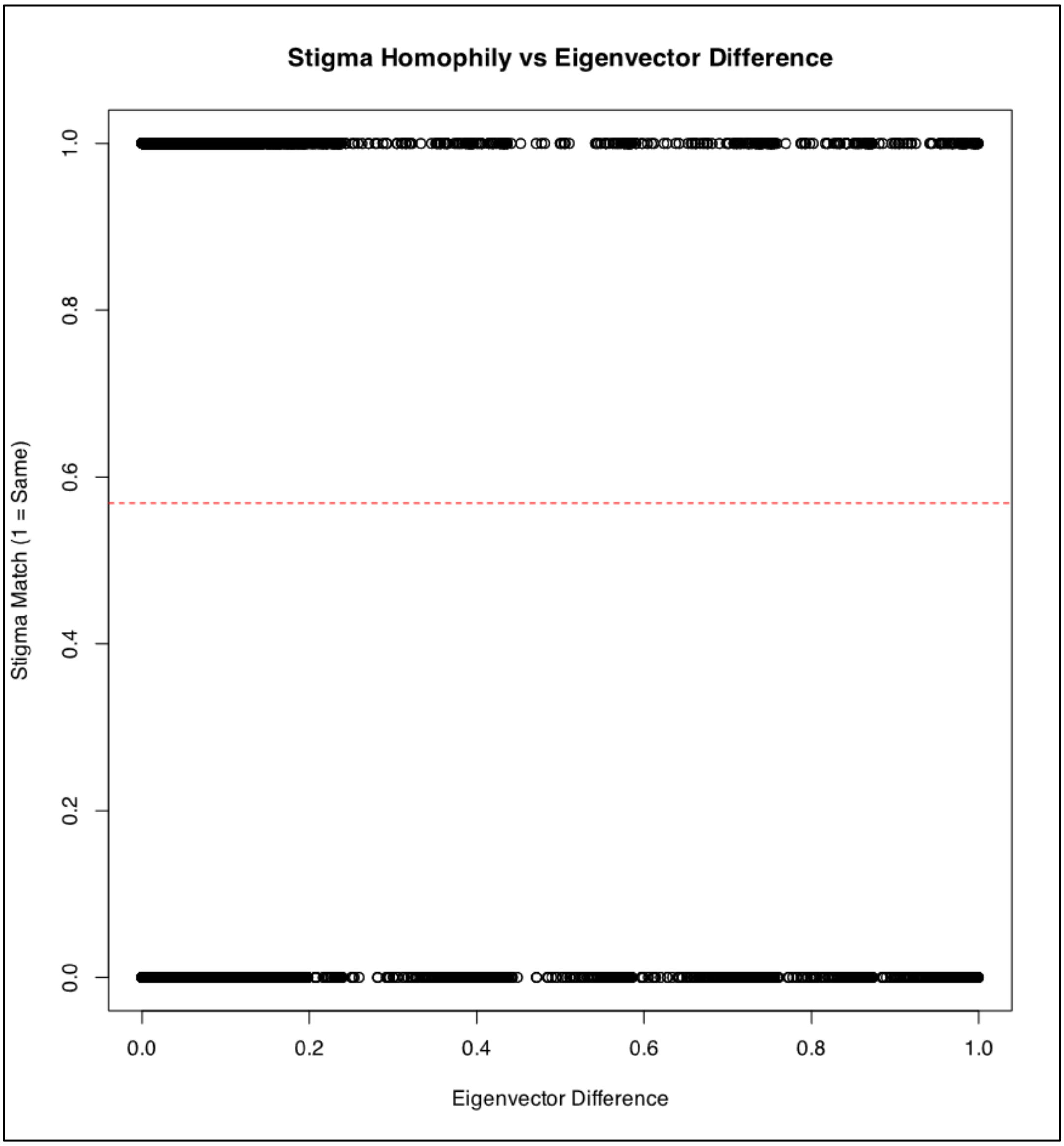
Structural preservation

The figure shows the observed stigma similarity matrix (left) and a randomly permuted version (right). The permutation disrupted the attribute alignment while preserving the matrix structure, confirming the structural preservation assumption required by QAP.



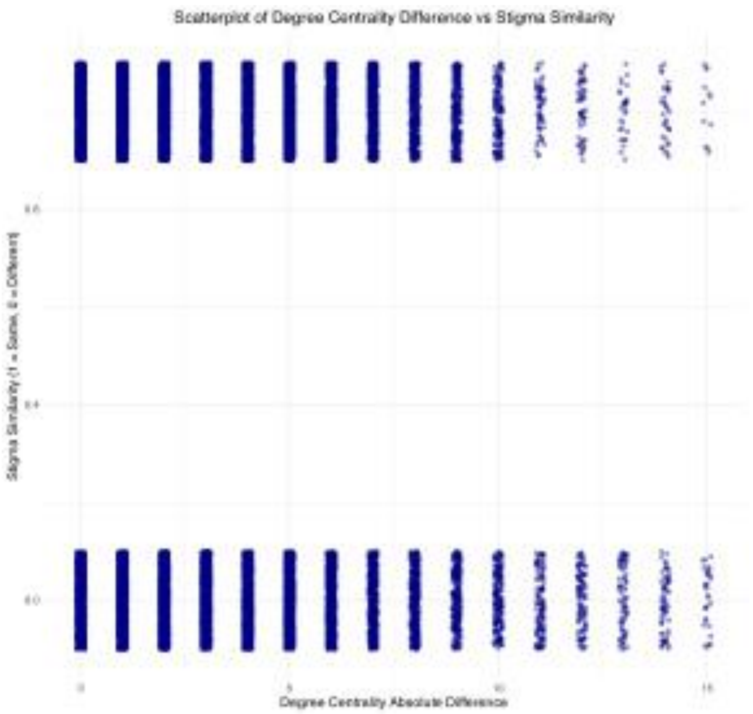
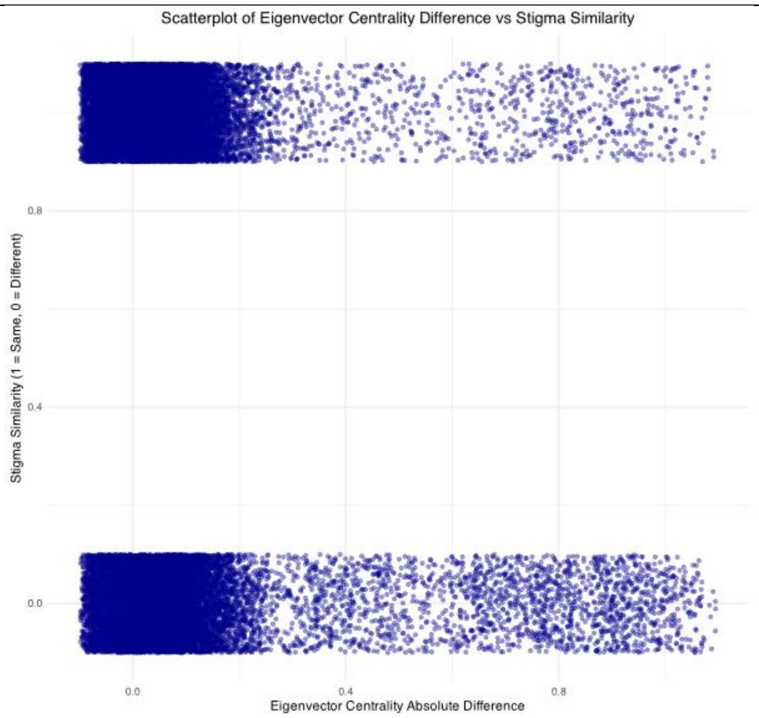
Monotonic/ Linear trend

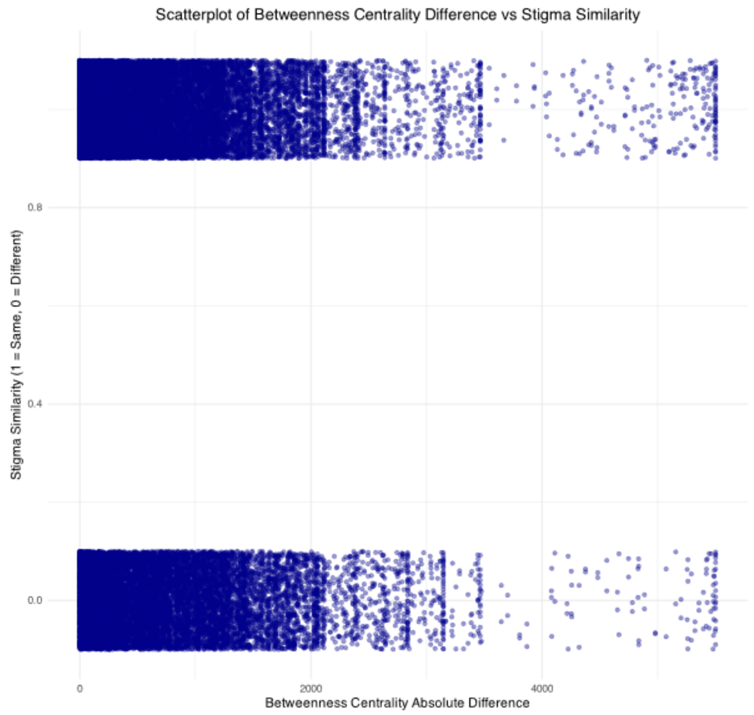
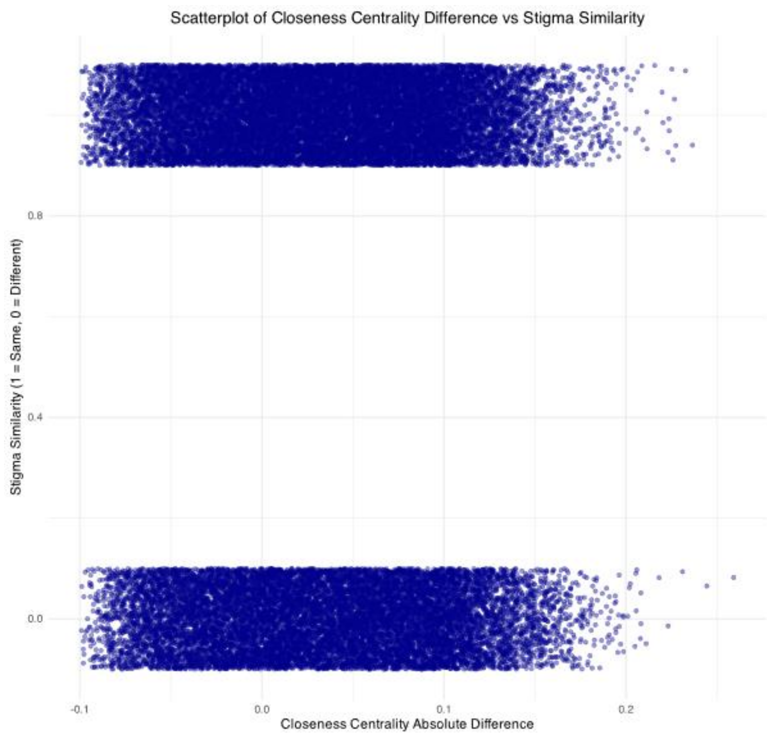
The scatterplot displays stigma similarity (binary outcome) against eigenvector centrality difference. Although the outcome is binary, a weak inverse monotonic trend is visually observed and confirmed by Spearman's correlation (ρ = –0.14), satisfying the monotonicity assumption.

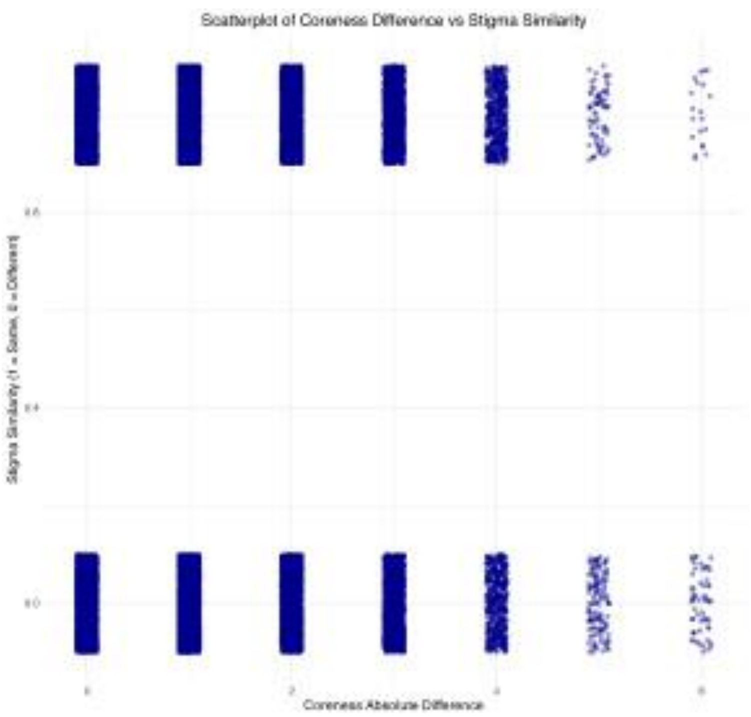
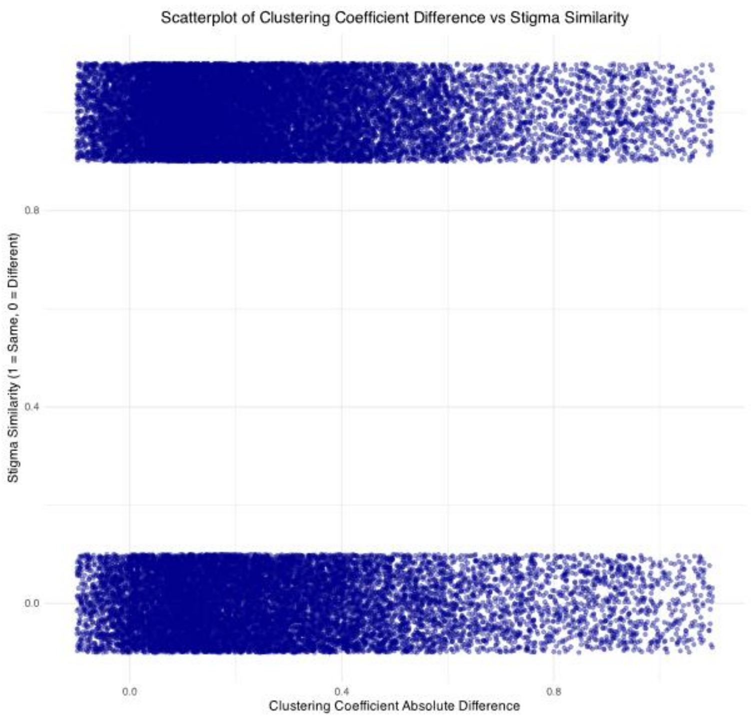


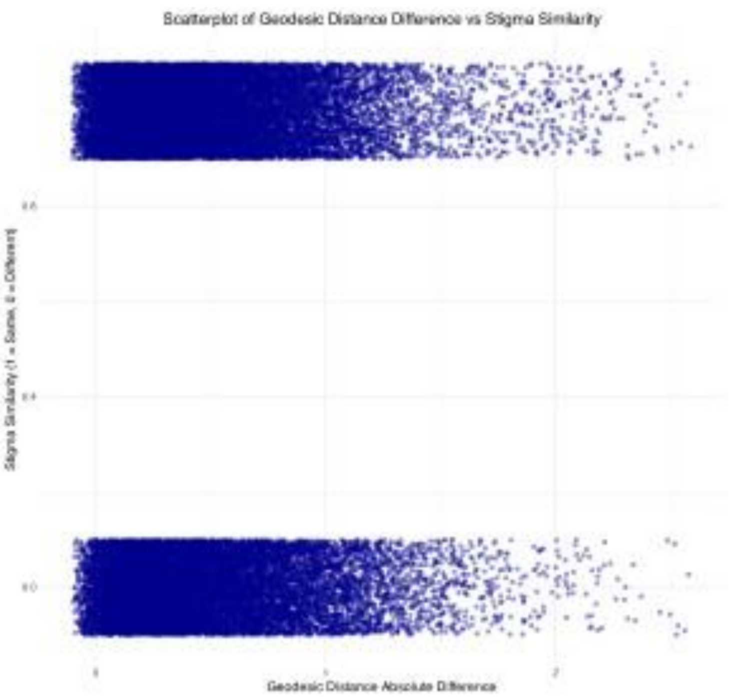
Predictor-outcome relationship pattern for all metrics

Supplementary scatterplots were generated for each network metric to explore monotonicity with stigma similarity. Visual patterns were strongest for eigenvector centrality and coreness, while other metrics showed weaker or no trends. These findings guided the interpretation of QAP regression results.

	Degree centrality difference does not show a clear relationship with stigma similarity.
	A weak inverse monotonic pattern: dyads more similar in eigenvector centrality tend to share stigma.

	Betweenness centrality difference shows no meaningful relationship with stigma similarity.
	Closeness centrality difference has no clear association with stigma similarity.

	A weak inverse pattern: dyads with similar coreness are slightly more likely to share stigma.
	Clustering coefficient difference does not predict stigma similarity.

	Geodesic distance difference shows no strong pattern with stigma similarity.

APPENDIX 4

Manuscript 1: International Journal of Public Health Science

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Examining stigma dynamics: a scoping review of social network analysis in communicable disease contexts

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ABSTRACT

The global COVID-19 pandemic has brought attention to the profound impact of stigma on individuals, communities, and societies. Social network analysis (SNA), based on network theory, offers a transformative approach to investigate the complex interplay of social structures, relationships, and information dissemination in communicable disease contexts. This scoping review aims to examine the utilization of SNA in studying stigma dynamics related to communicable diseases, assess the current research landscape, identify gaps, and highlight key findings. Three databases (Scopus, Web of Science, and PubMed) were searched for studies on SNA and stigma in communicable diseases. From the identified studies, three eligible articles were selected for review, providing insights into the role of stigma as a barrier to social integration, thereby impacting network centrality. The review also explores patterns of stigma communication on social media and examines the impact of interventions on individuals' social networks. Overall, this review emphasizes the value of SNA in comprehending the intricate relationships between social networks and stigma in communicable disease contexts.

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1. INTRODUCTION

Social network analysis (SNA), which originates from network theory, presents itself as a robust approach to examining the intricacies and trends of connections within social structures. By shedding light on the pathways through which information, influence, and behaviour move within social networks, this analytical instrument not only provides valuable insights into the network architecture but also offers a fresh lens through which to analyse the intricate interplay between social structures, information flow, and relationships [1], [2]. Moreno's seminal research on sociograms in 1934 established the fundamental principles that underpin SNA, underscoring its capacity to illuminate group dynamics and social interactions [2].

SNA enables the quantitative analysis, visualisation, and mapping of network features like density, connectedness, and centrality; thus, it provides crucial insights into the dissemination processes of diverse phenomena across networks [3], [4]. Through the use of SNA, scholars have the ability to reveal the invisible structure of social networks, elucidating the complex network of relationships, influences, and actions that contribute to the dissemination and repercussions of social phenomena [5]. Researchers can gain insights into

APPENDIX 5

Manuscript 2: BMC Public Health

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BMC Public Health

RESEARCH Open Access

Content and face validity of Workplace COVID-19 Knowledge & Stigma Scale (WoCKSS)

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Abstract

Background The COVID-19 pandemic has led to fear, rumours, and stigma, particularly against those infected with the virus. In Malaysia, the manufacturing industry is particularly vulnerable to COVID-19 clusters, making it critical to assess stigma attitudes among workers. To address this issue, The Workplace COVID-19 Knowledge & Stigma Scale (WoCKSS) was developed specifically for use in the manufacturing industry which served as the sample population for testing this scale. It was developed in the Malay language to ensure alignment with the local context. This study examines the content and face validity of WoCKSS, which can help assess the level of knowledge and stigma associated with COVID-19 among workers.

Methods The WoCKSS was developed with 20 and 31 items for knowledge and stigma domains, respectively, based on an extensive review of COVID-19 literature. Content validation was conducted by four experts using a content validation form to assess the relevancy of each item to the intended construct. Content Validity Index (CVI) was calculated to measure the agreement between the experts on the relevance of each item to the intended construct. Face validation was then conducted by randomly selecting 10 respondents from the manufacturing industry, who rated the clarity and comprehension of each item using a face validation form. The Item Face Validity Index (I-FVI) was calculated to determine the clarity and comprehension of each question, and only items with an I-FVI ≥ 0.83 were retained.

Results The WoCKSS achieved excellent content validity in both knowledge and stigma domains. Only 19 items from the knowledge domain and 24 items from the stigma domain were retained after CVI analysis. All retained items received a CVI score of 1.00, indicating perfect agreement among the experts. FVI analysis resulted in 17 items for the knowledge domain and 22 items for the stigma domain. The knowledge domain achieved a high level of agreement among respondents, with a mean I-FVI of 0.91 and a S-FVI/UA of 0.89. The stigma domain also showed high agreement, with a mean I-FVI of 0.99 and a S-FVI/UA of 0.86.

Conclusion In conclusion, the WoCKSS demonstrated high content and face validity. However, further testing on a larger sample size is required to establish its construct validity and reliability.

Keywords COVID-19, Workplace, Knowledge, Stigma, Manufacturing industry, Content validity, Face validity, WoCKSS

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APPENDIX 6

Manuscript 3: BMJ Open

Open access Original research

BMJ Open

Validation of the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS) in Malaysia: a cross-sectional study using item response theory and factor analyses

Izyan Hazwani Baharuddin ,[1,2] Nyi Nyi Naing ,[3] Meg Patterson ,[4] Siti Munira Yasin,[2] Khalid Ibrahim,[2] Nurhuda Ismail [2]

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ABSTRACT

Objective To validate the Workplace COVID-19 Knowledge and Stigma Scale (WoCKSS) using item response theory (IRT), exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

Design Cross-sectional psychometric validation.

Setting Manufacturing companies registered in Malaysia.

Participants A total of 137 factory workers participated in the exploratory phase and 300 in the confirmatory phase. Inclusion criteria were Malaysian nationality and ability to read Malay.

Methods The knowledge domain was examined using the two-parameter logistic IRT model in two stages: an exploratory IRT analysis in phase 1 to screen items and a confirmatory IRT analysis in phase 2 to evaluate the final item set. The stigma domain was analysed using EFA followed by CFA. Reliability was assessed using Cronbach's alpha and McDonald's omega (ω). The development process and content and face validity results were previously published.

Results 14 knowledge items were retained after exploratory IRT and formed the final knowledge scale evaluated in confirmatory IRT. For these final items, discrimination parameters ranged from 0.77 to 3.17 and difficulty values from −4.47 to 0.23, with unidimensionality supported (p=0.644). EFA supported a three-factor stigma structure (stereotype, fear, prejudice), and CFA confirmed excellent model fit (χ^2=8.91, df=11, p=0.630; root mean square error of approximation=0.00; Comparative Fit Index=1.00; Tucker-Lewis Index=1.00; standardised root mean square residual=0.021). Composite reliability by McDonald's omega ranged from 0.691 to 0.893.

Conclusion WoCKSS is a reliable and valid instrument for assessing workplace COVID-19 knowledge and stigma in industrial sectors in Malaysia.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ This study uses robust psychometric methods including item response theory (IRT), exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) with separate exploratory and confirmatory datasets.

⇒ The instrument is validated in the Malay language and tailored to the workplace context, where COVID-19 stigma was highly prevalent.

⇒ The tool addresses a gap in occupational health research by focusing on factory workers, an understudied population.

⇒ Cross-sectional data limit causal interpretation.

⇒ Findings are based on convenient sampling and may result in answer bias.

INTRODUCTION

The COVID-19 pandemic created significant health, social and economic disruption worldwide, accompanied by widespread fear and misinformation. Such uncertainty contributed to stigmatising attitudes towards individuals infected with COVID-19, mirroring patterns observed during previous infectious disease outbreaks such as Severe Acute Respiratory Syndrome (SARS), Ebola and H1N1, where fear and blame reinforced social exclusion.[1 2] Stigma is known to influence health-seeking behaviour, psychological well-being and social cohesion and is shaped by broader social norms and social processes, as described in foundational stigma theories.[3 4] In Malaysia, the manufacturing sector recorded a high concentration of workplace clusters, where close physical proximity and shared facilities heightened both transmission anxiety and stigma among workers.[5 6] Although COVID-19 has transitioned to endemic management, its social consequences, including stigma, have not resolved in parallel. In Malaysia, continued public health monitoring of COVID-19 beyond the acute pandemic phase, particularly in workplace settings, underscores the need for context-specific and psychometrically robust measurement tools.

AUTHOR'S PROFILE

Izyan Hazwani Baharuddin obtained Bachelor of Science in Biomedical Science (Hons.) in 2012 from International Islamic University Malaysia. She obtained her MSc in Medical Statistics (2015) from Universiti Sains Malaysia with a thesis titled "Validity & Reliability of the Malay Translated Version of the Index of Dental Anxiety and Fear Scale (IDAF-4C+) among Secondary School Children in Negeri Sembilan". Currently she is as Biostatistics lecturer in Faculty of Dentistry, Universiti Teknologi MARA since 2016.

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