Pre-University Students' Motivation and Online Learning Engagement: The Mediating Role of Attitude in using Generative AI Technology

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Abstract: *This research focuses on determining the motivational factors that influence online engagement among pre-university students. Based on the self-determination theory, the four motivational factors identified in this research include intrinsic and extrinsic motivation, accomplishment and amotivation. This research extends the framework to examining the mediating role of attitude to generative AI technology in the relationship between the four motivational factors with online learning engagement. Data from 103 respondents were collected online, demographic profiles were analyzed using SPSS, and Smart-PLS was used to test the conceptual model and assess item reliability through CFA. The results show five supported hypotheses, highlighting attitude and intrinsic motivation as key predictors of online learning engagement. Attitude has the strongest direct effect on online learning engagement, while intrinsic motivation influences both attitude and engagement. Indirect effects via attitude are significant for accomplishment, amotivation, and intrinsic motivation, indicating partial mediation. This study highlights the importance of using generative-AI tools in ensuring online learning engagement among pre-university students. Practical implications from this study include the need for training for academics and pre-university students to foster positive attitude towards using generative-AI technology.*

Keywords: *attitude, generative AI, motivation, online learning engagement, higher education*

1. INTRODUCTION

Online engagement refers to how individuals interact with digital content or platforms over the internet. In the context of education, it refers to how actively and effectively students participate in digital learning environments. It reflects students' interaction with the course content, their peers and instructors through online platforms (Hossain et al, 2022). On a similar but more meaningful term in the context of effective learning, online learning engagement (OLE) studies the depth and quality of student involvement with learning itself which includes deep thinking and reflection on the subject matter (Bergdahl, 2022; Hu and Xiao, 2025). The widespread use of online learning can be attributed to the quick uptake of computer-assisted learning and educational technologies. Generative Artificial Intelligence (Gen-AI) technologies such as ChatGPT, Grammarly and Quizlet have rapidly transformed the landscape of higher education. While these tools offer new possibilities for academic support in enhancing teaching and learning, it is critical to understand the motivational drivers influencing students' online learning engagement.

Many studies have offered promising results on factors influencing online engagement in learning, focusing mostly among undergraduate students (Ferrer et al., 2022, Bedi, 2023). This study, nonetheless, focused on pre-university students, addressing the notable lack of representation as highlighted in Hu and Xiao (2025). In Malaysia, for instance, students complete six years of primary education and five years of secondary education and relied predominantly on rote learning during their eleven years of school (Ani et.al., 2024). Furthermore, facing the challenge of relatively few attempts to use the self-determination theory (Hu and Xiao, 2025), this study adapts the framework of Ferrer et al. (2020), addressing the attitude of students toward generative artificial intelligence tools as a mediator to OLE. Moreover, while generative artificial intelligence (Gen-AI) tools are increasingly integrated into educational settings, little is known about how pre-university students' attitudes toward Gen-AI influence their online learning engagement. This gap highlights the need to examine Gen-AI mediated engagement specifically in pre-university learners, addressing both their motivational profiles and their attitude to adopt AI-enhanced learning tools.

1.1 RESEARCH OBJECTIVES

The dual purpose of this study is to firstly determine the motivational factors that influence OLE among pre-university students. Grounded in self-determination theory, this study focuses on four key motivational factors namely intrinsic and extrinsic motivation, accomplishment and amotivation. Following this, this study extends this framework by examining the mediating role of students' attitude on using Gen-AI tools between motivational factors and online learning engagement.

1.2 LITERATURE REVIEW

Engagement reflects students' level of involvement, interest, or devotion to a specific activity, mission, or relationship. The level of student engagement is measured by how actively and enthusiastically students are involved in academic, curricular, and extracurricular activities (Hossain et al., 2022), including the level of curiosity, initiative, and participation that students put into their learning experience. Educational achievement, personal motivation, and emotional commitment are strongly linked to students' engagement (Acosta-Gonzaga, 2023). For this reason, when the learning context becomes compelling, students are truly engaged and often perform better in school and develop a lasting passion for learning. However, learning can be challenging for students due to a lack of peer connection and technological concerns for online classes, which may impact students' interest and engagement (Hollister et al., 2022). Digital platforms make education more accessible and convenient by providing greater freedom of access, lower education prices, flexibility, adaptability to modern life, as well as the ability to divide content into modules and define assessment criteria (Liu et al., 2020). In contrast to this finding, students appeared to suffer even more with participation in online classes, even when expected grades increased; lecture attention, attendance, and perceived ability to keep up with schoolwork all decreased significantly (Hollister et al., 2022). To organize these insights systematically, this review is divided into two key themes: motivational factors and attitudes.

1.2.1 STUDENTS' MOTIVATIONAL FACTORS

The four motivational factors identified based on Ryan and Deci (2000a) are accomplishment, amotivation, extrinsic and intrinsic motivation.

Accomplishment refers to one's ability to successfully complete a task, aim, or objective. Students' accomplishments are varied, viewed in many ways, such as academic efficacy and competence, positive academic self-concept, and self-assessment of completing a task (Hossain et al., 2022). Another related study by Taip et al. (2023), found that increasing online learning methods led to improved students' commitment and academic success. These findings contradicted the worry that online learning could negatively impact students' dedication and academic achievement. Similarly, another study postulated a positive and significant association between academic success and online learning platforms (Abuhassna et al., 2020).

Amotivation is a situation where an individual is uninspired or disinterested in engaging in a particular activity (Ryan and Deci, 2000a). It represents a feeling of being uncommitted towards the task, unfocused, and lose purpose to take action to learn. Students who reported more amotivation had lower GPAs, a lower level of match in the college, and a lower level of self-reported college adjustment (Norvilitis et al., 2022). Amotivated students may feel disconnected from school or academic work. As a result, they may experience a lack of effort in completing individual and group assessments, poor attendance, poor exam performance, and disengagement during the learning process, as they might not see the aim or purpose in their education or have low self-efficacy. Kotera et al. (2021), for instance, found that amotivation was favorably connected with inadequate and loathed self, while negatively associated with intrinsic motivation, energy, dedication, absorption, and comforted self.

Extrinsic motivation focuses on external outcomes, which indirectly influence someone's actions. For example, a student studies hard on a task to receive a good grade or to avoid feelings of shame or self-criticism rather than doing it because they find the task intrinsically interesting and enjoyable. According to Bakar et al. (2022), there is a strong positive relationship between extrinsic motivation, such as academic grades and academic achievements, among undergraduates. In general, students' motivation enhances their academic performance and serves as an excellent predictor of students' academic advancement.

According to Gustiani et al. (2022), students' participation in online learning due was due to their autonomy or self-determination over the regulations of online learning. They attended their online class merely to avoid awkwardness and penalties for being absent as a method of self-regulation. Some of them participated in online learning activities because they perceived them as values that aligned with one of their life goals. Most participants in online classes are driven by extrinsic factors such as the prohibition of absenteeism and grades (Mansour et al. (2021).

Intrinsic motivation is the drive to engage in an activity because it is enjoyable, interesting, or personally meaningful, rather than for external rewards or outcomes. Key factors for pleasurable and successful learning include interest in material, relevance to the profession and life, good instruction, and interactive pedagogies (Seemiller et al., 2021). Intrinsic motivation is often linked to better engagement and long-term satisfaction in the learning activities, as it could develop students into a deeper sense of fulfillment and personal growth. A notable study by Fishbach et al. (2021), linked intrinsic motivation with a lack of rewards. Rewards have a beneficial impact on two intrinsic motivators, such as involvement during free choice and self-reported good experiences. Rewarding a task increases both people's desire to perform the task. Students who received need-supportive task instructions from teachers showed better intrinsic motivation (Mendoza et al., 2023). This finding implies that while intrinsic motivation for the task does not always result in enhanced task performance, it might directly improve online task performance through self-assessment practice as a behavioral learning method. The next section discusses attitudes toward Gen AI tools.

1.2.2 ATTITUDE

Attitude refers to a person's consistent way of thinking or feeling about someone or something, which is generally reflected in their actions. Attitude is a mindset that shapes how we perceive and react to situations, which is rooted in someone's personal views and emotions. Attitude can be the foundation of habit formation; changes can be a useful beginning point for behavior modification (Verplank and Orbell, 2022). A person's attitude towards AI may be influenced by their perception of their own learning (Sindermann et al., 2020).

Researchers examine how attitude influences perceived ease of use and students' intention to use online learning platforms in Malaysian distance learning and found that attitudes play a role in regulating the association between perceived ease of use and intention in online distance learning institutions. From an academician perspective, the analysis found that attitude towards distance education plays a complete mediation role in the effect of digital literacy level on course teaching satisfaction, but only partially in the effect of digital literacy level on satisfaction with infrastructure (Sever and Cati, 2021). This discovery enables institutions to create high-quality online platforms that benefit students.

Drawing from the established connections between students' motivation, online learning engagement and attitude on using Gen-AI tools identified in the previous studies, Figure 1 illustrates the conceptual framework:

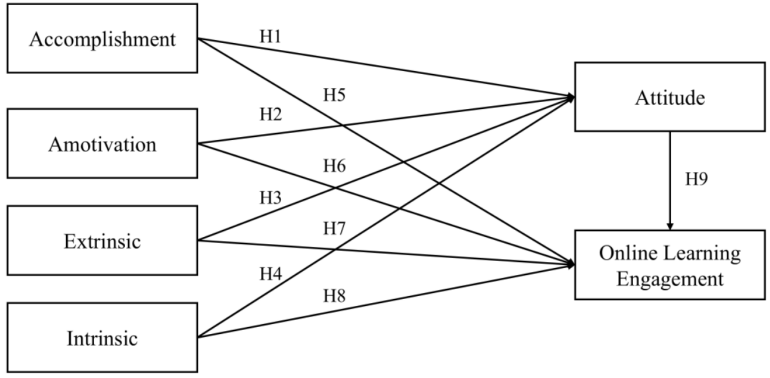

Figure 1: Proposed Conceptual Framework.

Overall, previous studies have highlighted several key factors involving four key motivational factors namely intrinsic and extrinsic motivation, accomplishment and amotivation together with examining the mediating role of students' attitude on using Gen-AI tools between motivational factors and online learning engagement. Therefore, the next section outlines the methodology used to empirically test this relationship.

2. METHODOLOGY

2.1 SAMPLE

To examine the proposed relationship within the context of the previously outlined theoretical framework, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed. PLS-SEM was used because the study focuses on predicting how motivational factors influence online learning engagement (OLE) among pre-university students. It is suitable for exploratory research, works well with smaller samples and non-normal data, and handles complex models better than CB-SEM, which requires larger samples and is mainly used for theory confirmation. An additional sampling criterion for PLS-SEM, known as the "ten times rule," requires that the sample size be at least ten times greater than the highest number of paths in either the formative or structural measurement models (Chin, 1998; Hair et al., 2021). Consequently, the study's sample size of 103 participants was deemed adequate and dependable for the analysis.

The study employed purposive sampling to recruit participants who met the specific criterion of being pre-university students. This approach ensured that the sample was aligned with the study's objective to examine motivational factors that influence OLE among pre-university students.

2.2 RESEARCH DESIGN

In this study, a modified questionnaire was utilized to evaluate the relationships between variables. This study adapts Ferrer et al.'s (2020) framework, extending it to examine students' attitudes toward generative AI tools as a mediator influencing Online Learning Engagement (OLE). Motivation constructs- accomplishment motivation, amotivation, intrinsic motivation, and extrinsic motivation were measured using the Academic Motivation Scale (Vallerand et al., 1992). Attitudes toward online learning were measured using Davis's Technology Acceptance Model (1989), while the mediator construct was operationalized through items adapted from recent studies on AI acceptance in education. All constructs were assessed on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) to ensure reliability and consistency across measures.

This study received ethical approval from the institutional ethics committee. Participants were informed about the study purpose, confidentiality, and voluntary participation, and were provided electronic informed consent before completing the questionnaire.

2.3 DATA ANALYSIS

The researchers successfully obtained 103 fully complete questionnaires from their online data collection efforts. The study employed SPSS and Smart-PLS for data analysis. The reliability of individual items was assessed through confirmatory factor analysis (CFA).

3. RESULTS

Demographic Profile

The demographic data represents a total of 103 respondents. Most participants are 18 years old (71.8%), followed by 17-year-olds (9.7%) and 19-year-olds (7.8%). The sample includes a small number of respondents aged 16, 21, 20, and 23, each constituting less than 4% of the total. In terms of gender, 58.3% are female, while 41.7% are male. Ethnic distribution is led by Chinese participants, who make up 64.1% of the group, followed by Malays at 11.7%, Indians at 1.0%, and others at 23.3%. Regarding academic programs, most respondents (62.1%) are enrolled in the Foundation in Business program. Foundation in Arts accounts for 35.9%, and only 1.0% are in Foundation in Science. When it comes to experience with AI technology, more than half of the respondents (53.4%) have used AI for less than one year. About a third (33.0%) have 1–3 years of experience, and 13.6% have more than three years of experience.

Model assessment using PLS-SEM

The measurement model in this study was evaluated using reflective indicator metrics, in line with PLS-SEM procedures. Reliability was first confirmed through Cronbach's Alpha and Composite Reliability (CR), with all constructs exceeding the recommended threshold of 0.7, indicating strong internal

consistency (Ab Hamid et al., 2017; Sarstedt, 2019). For instance, the CR values ranged from 0.804 (OLE) to 0.932 (Extrinsic). Convergent validity was assessed using Average Variance Extracted (AVE). All constructs achieved AVE values above the 0.5 threshold, supporting sufficient convergent validity (Hair Jr. et al., 2021). Such constructs include Accomplishment (AVE = 0.776) and Intrinsic Motivation (AVE = 0.658). Indicator reliability was confirmed as most item loadings exceeded 0.7. Although a few loadings (e.g., ATT5 = 0.602) were slightly below the ideal, they were retained due to theoretical relevance and overall model fit. These results demonstrate that the measurement model is reliable and valid, and suitable for structural path analysis.

Heterotrait-Monotrait (HTMT) ratio values among six constructs: Accomplishment, Amotivation, Attitude, OLE, Extrinsic, and Intrinsic are below the conservative threshold of 0.85 (Henseler et al., 2015). Overall, the constructs demonstrate acceptable levels of distinction for further structural modeling.

Structural Model Analysis

The path coefficients for the modelled relationships between the constructs are generated by PLS as shown in figure 2. The predictive power R2 and predictive relevance were used to evaluate the model's ability to predict the outcome variables (Hair et al., 2021). R-Square levels of 0.67, 0.33, and 0.19 are considered strong, moderate, and weak, respectively. The R-squared values of the endogenous latent variables Attitude and Online Learning Engagements are 59.3% and 56.5% respectively, indicating a moderate level of model fitness for both variables.

Table 1 summarizes the hypothesis testing results for the structural model analyzing relationships between variables such as Accomplishment, Amotivation, Intrinsic and Extrinsic motivation, Attitude, and OLE (Online Learning Engagement). Out of the nine proposed hypotheses, five are supported based on significant p-values (< 0.05). Specifically, H3 (Extrinsic -> Attitude), H4 (Intrinsic -> Attitude), H6 (Amotivation -> OLE), H8 (Intrinsic -> OLE), and H9 (Attitude -> OLE) show significant relationships, indicating these paths have meaningful influence on their respective dependent variables.

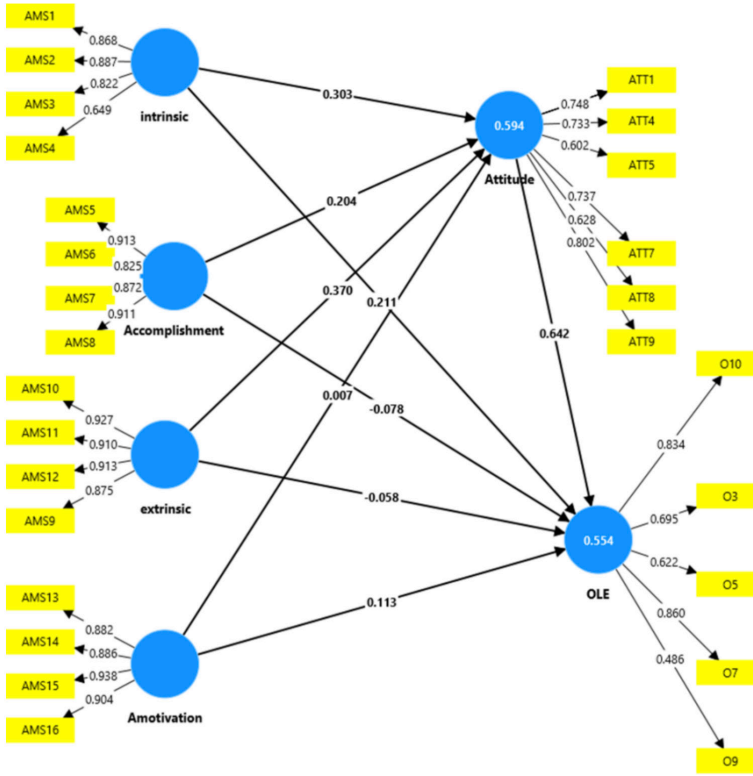

Figure 2. Path Coefficients

The strongest influence is observed in H9, where Attitude significantly predicts OLE ($\beta = 0.659$, $p = 0.000$), suggesting that a positive attitude greatly enhances students' engagement in online learning. Intrinsic motivation is also a consistent predictor of both Attitude (H4: $\beta = 0.308$, $p = 0.003$) and OLE (H8: $\beta = 0.175$, $p = 0.006$), emphasizing the importance of internal drivers in learning contexts. Conversely, H1, H2, H5, and H7 are not supported, implying that Accomplishment and Extrinsic motivation do not significantly influence Attitude or OLE in this model.

Hypothesis	Path	Beta	T-statistic	P-value	Decision
H1	Accomplishment -> Attitude	0.201	1.871	0.061	Not Supported
H2	Amotivation -> Attitude	0.008	0.125	0.900	Not Supported
H3	Extrinsic -> Attitude	0.369	3.532	0.000	Supported
H4	Intrinsic -> Attitude	0.308	3.023	0.003	Supported
H5	Accomplishment -> OLE	0.085	0.738	0.461	Not Supported
H6	Amotivation -> OLE	0.154	3.619	0.006	Supported
H7	Extrinsic -> OLE	0.054	0.444	0.657	Not Supported
H8	Intrinsic -> OLE	0.175	2.591	0.006	Supported
H9	Attitude -> OLE	0.659	7.418	0.000	Supported

Table 1. Direct relationship

Table 2 presents the results of indirect relationships between motivational factors (Accomplishment, Amotivation, Extrinsic, and Intrinsic) and Online Learning Engagement (OLE) through the mediating variable "Attitude." The strength and significance of these relationships are assessed using Beta values, T-statistics, and P-values. The analysis reveals that both Accomplishment ($\beta = 0.132$, $T = 1.786$, $p > 0.001$) and Amotivation ($\beta = 0.005$, $T = 0.122$, $p > 0.05$) have significant indirect effects on OLE via Attitude. However, their associated hypotheses (H1a and H2a) are marked as rejected, which might imply these effects contradict theoretical expectations, or direct paths were not significant in a broader model context. In contrast, the path from Extrinsic motivation to OLE via Attitude ($\beta = 0.243$, $T = 3.067$, $p < 0.05$) is not statistically significant, yet the result states it "Fully Mediates," possibly suggesting that the direct path was non-significant, and only the indirect effect exists. The Intrinsic path ($\beta = 0.203$, $T = 2.692$, $p < 0.05$) is significant and thus considered to "Partially Mediate" the relationship with OLE.

Hypothesis	Path	Beta	T-statistic	P-value	Result
H1a	Accomplishment -> Attitude -> OLE	0.132	1.786	0.074	Rejected
H2a	Amotivation -> Attitude -> OLE	0.005	0.122	0.903	Rejected
H3a	Extrinsic -> Attitude -> OLE	0.243	3.067	0.002	Fully Mediate
H4a	Intrinsic -> Attitude -> OLE	0.203	2.692	0.007	Partially Mediate

Table 2. Indirect relationship

4. DISCUSSION

The primary goal of this study is to identify the motivating factors that influence pre-university students' engagement on online learning. The self-determination theory provides a valuable lens for examining the motivational factors underlying students' adoption and use of Gen-AI tools in online learning. This study examines four major motivational factors: amotivation, accomplishment, intrinsic and extrinsic motivation. We expand the framework in investigating the mediating role of attitude toward using Gen-AI tools between motivational factors and online learning engagement. From the four motivational factors identified, intrinsic motivation and amotivation are found to significantly influence OLE. Intrinsic motivation significantly influences OLE, similar to the study of Wang (2022) and Aruğaslan et al. (2025), suggesting that intrinsically motivated students are self-determined in ensuring learning takes place effectively. Secondly, amotivation significantly influenced students' engagement on online learning, suggesting that unmotivated students are unable to engage in their online learning. In line with Ferrer et al. (2020) and He and Ong (2025), amotivated students typically find themselves unable to control or are incompetent, leading to the inability to understand the connection between their actions and learning outcomes.

Nonetheless, the importance of accomplishment cannot be overlooked. Our findings imply the need to strengthen students' confidence, as existing research demonstrates its substantial influence in students' attitude towards online

learning (Hossain et al., 2023, Taip et al, 2023). Similarly, the non-significant influence of amotivation on attitudes toward online learning may be attributed to low levels of amotivation reported by students (Rosli et al., 2022). Another possibility is that students were already sufficiently supported or engaged, thereby reducing the impact of amotivation on their attitude towards online learning.

Secondly, with regards to the mediation role of attitude of the pre-university students in using Gen-AI technology, this study found that attitude fully mediates the relationship between extrinsic motivation with OLE and partially mediates the relationship between intrinsic motivation and OLE. External rewards such as obtaining good grades were found to motivate students to engage in online learning, via attitude towards Gen-AI technology. Previous studies such as those conducted by He and Ong (2025), Akram and Li (2024), and Ryan and Deci (2020b) confirmed extrinsically motivated students are stimulated to engage in online learning - for instance, using public or virtual recognition of their achievement which encourages opportunities for them to showcase their work. This study, however, found that the relationship is only mediated through their mindset in using Gen-AI tools. Additionally, this study confirms that intrinsic motivation does not directly influence OLE but can be enhanced through their attitude in using Gen-AI. This finding deepens our understanding of how attitude in using Gen-AI platforms impacts students' engagement in online learning. While this study contradicts the findings of Ferrer et al. (2020), this result serves as new insights in understanding how online engagement improves among Generation Z students.

This study is limited by its focus on pre-university students within a specific educational context, which may restrict the generalizability of its findings to other student populations. The reliance on self-reported data may introduce bias, particularly in assessing motivation and attitudes toward Gen-AI tools. Additionally, cross-sectional design prevents causal inferences between motivational factors, attitudes, and online learning engagement. While the mediation role of attitude was explored, other potential mediators or moderators such as digital literacy or prior experience with Gen-AI were not examined. Future studies should adopt longitudinal designs and consider a broader range of variables and student demographics.

5. CONCLUSION

This study significantly advances our understanding of factors influencing online learning engagement among pre-university students. The findings indicate that the more amotivated the students are, the lower their engagement in online learning. Next, intrinsically motivated students not only influence OLE directly, but also influence OLE through their attitude in using Gen-AI tools. While extrinsic motivation does not significantly influence OLE directly, extrinsic motivation influenced OLE through their attitude on using Gen-AI tools. These findings suggest that policymakers should encourage intrinsic motivation and include Gen-AI tools in pre-university curricula, while educators can boost engagement by promoting positive attitudes toward Gen-AI and addressing sources of amotivation to reduce disengagement.

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8. AUTHORS' CONTRIBUTION

Abd.Ghani, H. and M.Ibrahim, H. designed and organized the experiments. M.Ibrahim, H. conducted the experiments and prepared the data. M.Ibrahim, H. contributed to the analysis of the results. Abd.Rahman, R. led the writing of the manuscript. All authors offered valuable feedback and contributed to shaping the research, analysis, and manuscript.

9. CONFLICT OF INTEREST DECLARATION

We certify that the article is the authors' and co-authors' original work. The article has not received prior publication and is not under consideration for publication elsewhere. This research/manuscript has not been submitted for publication, nor has it been published in whole or in part elsewhere. We testify to the fact that all authors have contributed significantly to the work, validity and legitimacy of the data and its interpretation for submission to IJELHE.

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