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Theorizing the Impact of AI Tools Usage on Students' Motivation in Technical Higher Education: A Multidimensional Conceptual Framework

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ABSTRACT

The fast use of AI (artificial intelligence) systems in higher education has changed the way students access material, get feedback, do academic assignments, and manage their learning. Despite the widespread implementation of AI, the motivational effects of using AI tools remain underexplored, especially in technical higher education contexts, where applied learning, digital competence, and Education 4.0 requirements are major institutional concerns. This conceptual paper suggests a multidimensional theoretical framework to study the influence of AI tools usage on student motivation among first-year undergraduate students in the Malaysian Technical University Network (MTUN), which consists of Universiti Malaysia Perlis (UniMAP), Universiti Tun Hussein Onn Malaysia (UTHM), Universiti Teknikal Malaysia Melaka (UTeM), and Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA). The framework is a focused, theoretically bounded integration of the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT). The operationalization of AI technology use is based on three dimensions: frequency of use, purpose of use, and perceived usefulness. Student motivation is operationalized by three SDT-based dimensions: intrinsic motivation, extrinsic motivation, and amotivationa unique negative result of motivation characterized by the lack of deliberate academic engagement. Nine formal propositions specify the directional relationships among these dimensions, with a central argument that AI tools' motivational impact is conditional: AI tools may support intrinsic and extrinsic motivation when used deliberately for learning-oriented purposes, but may increase amotivation when used excessively, in a dependency-driven manner, or as shortcuts that bypass genuine cognitive effort. This paper presents a parsimonious integration of TAM and SDT that incorporates motivational quality, the treatment of amotivation as a distinct theoretical outcome, the specification of conditional directionality in AI-motivation relationships, and contextual grounding in MTUN's technical education environment. A recommended methodology for future empirical validation using PLS-SEM is discussed, and practical implications are provided for MTUN policy makers, lecturers, curriculum designers, and students.

Keywords: AI tools usage; student motivation; Self-Determination Theory; Technology Acceptance Model; intrinsic motivation; extrinsic motivation; amotivation; MTUN

1. INTRODUCTION

Student motivation has long been considered a critical predictor of academic performance, influencing learning strategies, cognitive engagement, persistence, and ultimately, educational outcomes (Ryan & Deci, 2000). In higher education, students are expected to develop increased autonomy and self-regulation; therefore, motivation is even more important in influencing the way students approach learning activities, respond to problems, and maintain effort throughout time (Deci & Ryan, 1985). The rapid adoption of artificial intelligence (AI) tools such as generative AI platforms like ChatGPT, Gemini, and Claude, as well as intelligent tutoring systems, adaptive learning platforms, and AI-powered writing assistants, has introduced new and complex dimensions to this motivational landscape (Bolarinwa, 2026; Crompton & Burke, 2023; Zhai et al., 2021).

AI tools are being adopted in higher education globally at a drastically increased pace. Students are increasingly using AI technologies for academic writing, research, problem-solving, language learning, and self-directed study (Zafar et al., 2024). The widespread use of AI tools prompts important questions about the motivational consequences of AI tools usage. Does the regular use of AI tools increase students' intrinsic motivation by supporting curiosity and mastery, or decrease motivation by fostering dependency and bypassing genuine cognitive effort? Does the motivation quality of students' usage of AI tools depend on the aim of use, whether for learning-oriented exploration or performance-oriented task completion? These concerns remain largely unexplored in the existing literature, which has focused more on technological acceptability, adoption intentions, and general involvement rather than the multidimensional character of student motivation (Sumakul & Hamied, 2023; Bamasoud et al., 2025).

The gap is notably visible in the Malaysian Technical University Network (MTUN), which includes UniMAP, UTHM, UTeM, and UMPSA. The MTUN institutions are located within a higher education ecosystem that is oriented towards technical and vocational education and training (TVET) with an emphasis on applied problem-solving, practical competence, and digital skills in accordance with Education 4.0 (Mat Jam & Puteh, 2022; Wong, 2024). Although AI tools are relevant for MTUN students in learning and career preparation, no existing study has systematically examined the relationship between the specific dimensions of AI tools usage frequency, purpose, and perceived usefulness with intrinsic motivation, extrinsic motivation, and amotivation in this context

To bridge this gap, this research introduces a conceptual framework that integrates TAM (Davis, 1989) with SDT (Deci & Ryan, 1985; Ryan & Deci, 2000; Ryan & Deci, 2017). TAM is utilized to establish perceived utility as a crucial cognitive assumption about AI tools, whereas SDT offers the motivational theory that explains how AI tools usage may promote or undermine intrinsic motivation, extrinsic motivation, and amotivation. The framework proposes nine assertions that specify directional linkages between the three dimensions of AI tools usage and the three dimensions of motivation, explicitly considering the conditional character of these relationships. The research concludes with a proposed technique for future empirical validation using PLS-SEM and practical implications for MTUN policy makers, educators and students.

2. LITERATURE REVIEW

2.1 AI Tools Usage in Higher Education

AI tools have become a key component of modern higher education, with students in various fields utilizing platforms like ChatGPT, Gemini, Grammarly, QuillBot, and intelligent tutoring systems for diverse academic functions (Crompton & Burke, 2023; Zhai et al., 2021). Research has highlighted three critical features of the use of AI tools relevant to motivational results. First, frequency of usage refers to the degree to which students use AI tools for academic work, ranging from occasional use for specific assignments to everyday use in several disciplines (Nechyporenko et al., 2025; Stöhr et al., 2024; Zafar et al., 2024). Second, the purpose of usage is defined as the reason for the use of AI tools, differentiating between learning-oriented objectives (exploration, comprehension, feedback, idea creation) and performance-oriented goals (task completion, deadline management, grade improvement) (Chiu, 2022; Agormedah, 2025). Third, perceived usefulness based on TAM is defined as students' cognitive conviction that AI technologies improve their academic achievement, learning efficiency, or task completion (Davis, 1989; Yeoh & Yap, 2024; Liu et al., 2025).

The three variables are theoretically separate and complementary: frequency captures behavioral intensity, purpose captures motivational aim and perceived utility represents cognitive appraisal (Basarmak & Ates, 2026; Osrof et al., 2026). Combined, they offer a multimodal operationalization of the utilization of AI technologies, which goes beyond just adoption or frequency metrics (Wu et al., 2025; Zhao et al., 2025).

2.2 Student Motivation through Self-Determination Theory

SDT offers a broad framework for analyzing the quality of student motivation, and it does so across three dimensions (Deci & Ryan, 1985; Ryan & Deci, 2000). Intrinsic motivation is engagement motivated by natural interest, curiosity, and the desire for mastery, the greatest degree of motivation, connected with deep learning, creativity, and persistent academic engagement (Ryan & Deci, 2000; Chiu, 2022). Extrinsic motivation is the kind of engagement for external outcomes such as grades, deadlines, or academic achievement (Al Shuaili, 2025). It varies in quality based on the degree of internalization and self-endorsement (Ryan & Deci, 2000; Agormedah, 2025; Jakobsen, 2026). Amotivation is a theoretically distinct negative motivational outcome that is not just low motivation, but the absence of both intrinsic interest and extrinsic drive, often stemming from need frustration (particularly frustration of autonomy and competence) and associated with disengagement, poor performance, and risk of dropout (Banerjee & Halder, 2021; Sumakul & Hamied, 2023; Alameir, 2025).

According to SDT, the quality of motivation is based on the satisfaction or frustration of three basic psychological needs: autonomy, the need to feel volitional and self-endorsed in one's actions; competence, the need to feel effective and capable; and relatedness, the need to feel connected to others (Ryan & Deci, 2017). Technologies that fulfill these needs tend to foster intrinsic motivation and internalized extrinsic motivation, but technologies that frustrate these needs, especially through dependency, cognitive offloading, or bypassing authentic effort, may increase amotivation (Maska et al., 2025; Cao & Abdullah, 2025).

2.3 AI Tools and Student Motivation: Benefits and Risks

There are several ways that AI technologies can enhance student motivation, research has indicated (Bai & Wang, 2025; Yuan & Liu, 2025). These tools can foster intrinsic motivation by providing tailored feedback, making it easier to engage with difficult topics, demystifying complex content, and offering low-stakes opportunities for repeated practice that build students' proficiency (Ward et al., 2024; Zhou & Li, 2023; Li & Chiu, 2025). When students perceive that the AI tools respect their autonomy by promoting self-directed learning and enhancing their capacity to master challenging topics, their intrinsic motivation tends to increase (Zhang & Zhang, 2025; Navas Bonilla et al., 2025; Saleh, 2025). Beyond internal motivation, AI technologies can further enhance extrinsic motivation by helping students achieve external academic goals more effectively, including completing tasks, meeting deadlines, and improving the overall quality of their work (Hanayanti et al., 2025; Agormedah, 2025).

But the literature also raises important problems. Excessive reliance on AI tools, especially as shortcuts or a crutch, can weaken students' confidence and sense of agency, leading to cognitive offloading, reduced critical thinking, and decreased self-directed engagement (Zhai et al., 2024; Bamasoud et al., 2025; Cao & Abdullah, 2025). Heavy reliance on ChatGPT was connected to greater academic amotivation, according to Alameir (2025), supporting the notion that dependency-driven AI use may undermine the fulfillment of basic psychological needs, resulting in disengagement. This paradox of pupils seeming to use AI tools actively, but also declining in intrinsic motivation, has been referred to in the literature as the "Engaged but Amotivated" (EBA) phenomena (Cao & Abdullah, 2025).

2.4 The MTUN Context and Research Gap

MTUN universities are uniquely positioned in Malaysian higher education, charged with developing technically proficient, industry-ready graduates in accordance with Education 4.0 principles (Mat Jam & Puteh, 2022; Wong, 2024). AI integration in MTUN remains uneven: despite students' increased use of AI tools on their own, institutional regulations, AI literacy programs, and pedagogical frameworks for responsible AI use are still underdeveloped (Yusoff et al., 2025; Zary & Zary, 2025; Ngelambong et al., 2025). Although AI tools are relevant for the applied learning and career readiness of MTUN students, there is no systematic study that has explored how frequency of usage, purpose of usage, and perceived usefulness of AI tools collectively relate to intrinsic motivation, extrinsic motivation, and amotivation in MTUN institutions. This gap provides the motivation for the present conceptual paradigm.

3. THEORETICAL FOUNDATION

3.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (Davis, 1989) suggests that two cognitive assumptions, perceived usefulness and perceived ease of use, greatly impact users' attitudes toward accepting technology. Perceived usefulness is defined as the degree to which a person believes that employing a certain technology would boost his or her performance. Perceived usefulness in the context of AI tools usage relates to students' opinions that AI tools are beneficial to their academic achievement, learning efficiency, understanding or task completion (Phua et al., 2025; Yeoh & Yap, 2024; Fošner, 2024). TAM has been extensively verified in educational technology settings and has been demonstrated to be a robust predictor of technology adoption and usage behavior (Venkatesh & Davis, 2000).

Within this approach, TAM is utilized, in particular, to explain perceived utility as the key dimension of AI tools usage. There are two reasons why perceived ease of use is not included as a framework variable. First, the simplicity of use is less of a barrier to adoption than it was for prior technologies, because contemporary AI tools are typically designed to be user-friendly and accessible (Talha et al., 2025). Second, perceived usefulness has a more direct impact on motivational outcomes as it taps into students' perceptions of whether AI tools truly help their learning goals, perceptions that may influence whether AI products build or erode motivation (Yeoh & Yap, 2024).

3.2 Self-Determination Theory (SDT)

Self-Determination Theory (Deci & Ryan, 1985; Ryan & Deci, 2000; Ryan & Deci, 2017) is a human motivation theory that considers the degree to which three basic psychological needs are satisfied or thwarted: autonomy (the need to feel that one's behavior is freely chosen and self-directed), competence (the need to feel capable and effective), and relatedness (the need to feel meaningful connection with others). When these demands are satisfied, people are more motivated and feel good, and when they are frustrated, they are less motivated and disengaged (Ryan & Deci, 2017).

SDT recognizes three outcomes that are especially pertinent to this paradigm as motivating. The finest sort of motivation is intrinsic motivation, i.e. to do something because it is fascinating or delightful rather than any external reinforcements or pressures (Ryan & Deci, 2000). It is related to deep learning and enduring engagement over the long term. Extrinsic motivation is when we do something for an external benefit or outcome (Morris et al., 2022). The kind of extrinsic motivation depends on the degree to which the individual internalizes this incentive (Ryan & Deci, 2000; Chiu, 2022). Amotivation is conceptualized by researchers as an undesired and conceptually distinct outcome, referring to the lack of any kind of purposeful conduct (not to low motivation). It is defined by purposelessness, incompetence, and disconnection, and it usually occurs when the requirements for autonomy and competence are not continuously met (Banerjee & Halder, 2021; Sumakul & Hamied, 2023).

3.3 Integration of TAM and SDT

The combination of TAM and SDT in this paradigm is theoretically complimentary and targeted. TAM explains why students could find AI technologies valuable and adopt them in learning, while SDT shows how such use improves the quality of their motivation (Al-Mamary & Abubakar, 2025; Zogheib & Zogheib, 2024b). Perceived utility mediates the relationship between AI tool adoption and motivation: AI usage that fosters competence and autonomy may boost intrinsic and extrinsic motivation, whereas AI usage that promotes dependency or shortcut behavior may lead to amotivation (Alqurni, 2026; Alshammari & Babu, 2025). This integration advances beyond traditional AI adoption research by exploring the motivating quality and potential of amotivation in AI-supported learning a vital contribution to the context of technical education at MTUN.

4. PROPOSED CONCEPTUAL FRAMEWORK AND PROPOSITIONS

4.1 Framework Overview

The proposed framework operationalizes AI tools usage through three independent variable (IV) The proposed approach operationalizes AI tools usage through three independent variable (IV) dimensions, i.e. (1) frequency of usage, (2) purpose of usage, and (3) perceived utility. Student motivation is operationalized in terms of three dependent variable (DV) dimensions: (1) intrinsic motivation, (2) extrinsic motivation and (3) amotivation. The paradigm posits nine directional paths (P1–P9), one for each of the IV–DV combinations. The core contention is that the motivational effects of AI tools are contingent, not universal. TAM-SDT integration provides the theoretical mechanism. TAM gives the justification for perceived utility as a cognitive belief leading to the adoption of AI tools, while SDT explicates how the quality of AI tool use and its alignment or undermining of core psychological requirements impacts motivating consequences.

4.2 Frequency of Usage and Student Motivation (P1–P3)

The frequent use of AI tools for learning support by students, such as seeking feedback, exploring topics, clarifying concepts, and engaging in iterative problem-solving, may reinforce their sense of competence and support autonomy, thereby enhancing intrinsic motivation (Zhou & Li, 2023; Li & Chiu, 2025). This good link is conditional: frequency only boosts intrinsic motivation when AI technologies are used as learning aids, not as substitutes for cognitive effort.

> **P1:** *Students' intrinsic motivation is positively correlated with AI tool usage frequency when AI is used as a learning support tool, but the positive association is contingent on learning-oriented use.*

Moreover, students with external academic goals may find regular use of AI technology useful in achieving those goals (Iqbal et al., 2025; Agormedah, 2025). Regular usage of AI tools may be linked to higher extrinsic motivation mirroring the instrumental value of AI tools for performance-oriented students when AI technologies are seen as useful for boosting academic attainment and productivity.

> **P2:** *The use of AI tools is positively associated to students' extrinsic motivation when students mostly utilize AI tools for performance-oriented goals, such as completing assignments and improving grades.*

Regular use of AI tools in a learning-oriented way may minimize amotivation if the technologies satisfy basic psychological demands (Zhou & Li, 2023). However, when frequency is too high and combined with dependency or cognitive offloading, the association might flip, such that excessive use can lead to amotivation by eroding competence and agency (Zhai et al., 2024; Bamasoud et al., 2025; Alameir, 2025).

> **P3:** *The frequency of AI tool usage is negatively related to amotivation when AI use remains moderate and learning-oriented, but this relationship reverses (becomes positive) when AI use becomes excessive and dependency driven, thereby frustrating basic psychological needs.*

4.3 Purpose of Usage and Student Motivation (P4–P6)

Learning-oriented use corresponds to aspects of intrinsic motivation such as curiosity, interest, and desire for mastery (Chiu, 2022). Learning-oriented AI use that facilitates autonomy (students following their own learning goals) and competence (skill development chances) may increase intrinsic motivation (Ryan & Deci, 2000; Zhang & Zhang, 2025).

> **P4:** *Students' intrinsic motivation is favorably associated to the use of AI tools for learning oriented purposes, such as exploration, understanding, feedback, and concept creation.*

Performance-oriented usage reveals students' understanding that academic external goals can be reached with the help of AI tools, which corresponds to discovered or external types of extrinsic motivation (Ryan & Deci, 2000; Agormedah, 2025). The employment of AI tools as instrumental for obtaining external incentives can promote extrinsic motivation when seen as such.

> **P5:** *Performance oriented reasons of AI tool usage (i.e., completing the assignment, meeting the deadline, and enhancing marks) are favorably associated to students' extrinsic motivation.*

Purposeful self-endorsed use (learning-oriented or performance-oriented) indicates intentional involvement and is negatively associated with amotivation (Ryan & Deci, 2000). However, the use of dependency-driven shortcuts, rather than purposeful choice, may impair autonomy and competence, hence increasing amotivation through need frustration (Cao & Abdullah, 2025; Banerjee & Halder, 2021).

> **P6:** *Need frustration mediates the positive association between the shortcut-driven and dependency-oriented use of AI tools and amotivation, and the negative association between the purposeful and self-endorsed use of AI tools and amotivation.*

4.4 Perceived Usefulness and Student Motivation (P7–P9)

Perceived usefulness can increase intrinsic motivation by enhancing students' beliefs in their own competence and encouraging self-directed learning (Siziba et al., 2025; Yeoh & Yap, 2024; Jeong, 2022). This is especially the case when students feel that AI tools really help them to understand and master the content at a deeper level, rather than simply doing the work for them.

> **P7:** *The perceived usefulness of AI technologies is favorably associated with intrinsic motivation when students believe that AI truly helps their learning, understanding and competence growth.*

Students who consider AI technologies to be useful in reaching their academic performance goals are likely to continue using them as instrumental resources, thus sustaining extrinsic motivation. The relationship is quite straightforward; students' perception of AI usefulness in terms of performance-related results naturally leads to the continuation of extrinsic motivation (Hsu & Wang, 2026; Venkatesh & Davis, 2000).

> **P8:** *Perceived usefulness of AI tools is positively connected to extrinsic motivation. The students' perception of the utility of AI to achieve performance outcomes is related to the drive to continue to use AI in an instrumental way.*

If students truly see AI tools as useful for learning and comprehending, this can assist minimize amotivation by supporting competence beliefs and developing a sense of academic self-efficacy (Shi & Zhang, 2025; Alqurni, 2026). However, when perceived utility is primarily associated with avoiding effort, e.g., obtaining answers without true understanding, it can instead increase amotivation by reducing meaningful engagement and impeding the development of true competence (Zhai et al., 2024; Bamasoud et al., 2025).

> **P9:** *The perceived usefulness of AI tools is adversely related to amotivation when the usefulness is linked to authentic learning help; however, this relationship reverses and becomes positive when perceived usefulness is predominantly viewed as a way of avoiding work or taking shortcuts.*

4.5 Summary of Propositions

Table 1 summarizes all nine propositions, their AI tools usage dimensions, student motivation dimensions, predicted directional relationships, and conditional nature. The conditional propositions (P3, P6, P9) explicitly acknowledge that the direction of the AI-motivation relationship depends on the quality and intent of AI tool use, consistent with SDT's emphasis on need satisfaction versus need frustration as the mechanism underlying motivational outcomes.

Table 1 Summary of Proposed Directional Relationships between AI Tools Usage and Student Motivation

Proposition	AI Tools Usage Dimension	Student Motivation Dimension	Predicted Direction	Conditional?
P1	Frequency of Usage	Intrinsic Motivation	Positive	Yes (learning oriented use)
P2	Frequency of Usage	Extrinsic Motivation	Positive	Yes (performance-oriented use)
P3	Frequency of Usage	Amotivation	Negative / Positive	Yes (reverses if excessive/dependency)
P4	Purpose of Usage (learning oriented)	Intrinsic Motivation	Positive	Yes (learning oriented only)
P5	Purpose of Usage (performance oriented)	Extrinsic Motivation	Positive	Yes (performance-oriented only)
P6	Purpose of Usage (purposeful/self endorsed)	Amotivation	Negative / Positive	Yes (reverses if shortcut driven)
P7	Perceived Usefulness	Intrinsic Motivation	Positive	Yes (supports competence/understanding)
P8	Perceived Usefulness	Extrinsic Motivation	Positive	No (instrumental support)
P9	Perceived Usefulness	Amotivation	Negative / Positive	Yes (reverses if effort avoidance)

Note. IV = AI Tools Usage; DV = Student Motivation. Conditional directionality indicates that the predicted direction depends on the nature of AI tool use (learning-oriented vs. performance/ dependency driven). P3, P6, and P9 are explicitly conditional.

5. PROPOSED METHODOLOGY FOR FUTURE EMPIRICAL VALIDATION

5.1 Research Design

The approach provided here will be empirically validated in the future with the aid of a quantitative cross-sectional survey design. This method is suited for testing directed hypotheses concerning correlations between the dimensions of AI tools usage and the variables of student motivation in a specific population at a specific point in time. The cross-sectional design enables the measurement of all the constructs at the same time and test the nine claims using structural equation modeling.

5.2 Target Population and Sampling

The target market is first year undergraduate students that are enrolled in MTUN universities (UniMAP, UTHM, UTeM, UMPSA). First-year students are picked as they are in a vital transition phase where patterns of adoption of AI tools and motivational orientations are being formed. Stratified random sampling should be employed such that it would be representative of the MTUN institutions, faculties and programmes. The sample size should be set based on the criteria of PLS-SEM and a minimum of 200 respondents are advised based on the complexity of the measurement model and the number of constructs (Krejcie & Morgan, 1970).

5.3 Instrumentation

All constructs should be measured by utilizing validated multi-item measures developed from the literature. The characteristics of AI tools usage (frequency, purpose, perceived utility) should be quantified by items modified from TAM scales (Davis, 1989; Venkatesh & Davis, 2000) and AI-specific usage scales. Student motivation factors (intrinsic motivation, extrinsic motivation, amotivation) should be tested with items derived from the Academic Motivation Scale (AMS) based on SDT (Deci & Ryan, 1985; Ryan & Deci, 2000). All items are rated on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). A pilot test should be undertaken with a selection of MTUN students to check for item clarity, cultural appropriateness and construct validity.

5.4 Data Analysis

The exploratory and predictive nature of the conceptual model, the expected non-normal distribution of student survey responses and the relatively complex measurement structure with six reflective constructs, suggest Partial Least Squares Structural Equation Modeling (PLS-SEM) as the preferred analytical approach to test the proposed framework. Measurement model assessment should include tests of internal consistency reliability using Cronbach's alpha and composite reliability, convergent validity using average variance extracted, and discriminant validity using HTMT ratio. Then the structural model should be analyzed by estimating the path coefficients and testing their statistical significance by bootstrapping, along with calculating the respective effect sizes. Thus, each of the nine hypotheses is finally supported or rejected according to the significance level and directional sign of the respective path coefficients within the structural model.

6. DISCUSSION AND IMPLICATIONS

6.1 Theoretical Contributions

In thus doing, this work provides numerous theoretical advances to the literature on AI tools utilization and student motivation. First, the framework offers a focused TAM-SDT integration that tackles motivational quality not only technology adoption or usage behavior. By anchoring perceived usefulness in TAM and relating it to SDT-based motivating outcomes, the framework connects two important theoretical traditions in a logical and constrained way (Tbaishat et al., 2026; Zogheib & Zogheib, 2024).

Second, the framework's framing of amotivation as a logically unique negative outcome rather than just low motivation is a substantive advance over prior AI-motivation studies that focus exclusively on good motivational outcomes. The statement of conditional directionality in P3, P6 and P9 expressly admits that the same AI tool may enhance motivation in some circumstances and raise amotivation in others, depending on the quality and aim of use (Cao & Abdullah, 2025; Bamasoud et al., 2025).

Third, the setting of technical education in the MTUN framework is a notable lacuna in the research on AI and motivation in TVET-oriented higher education. MTUN's Education 4.0 mandate, focus on practical learning, and lack of representation in AI-motivation research make it a particularly attractive and underexplored context for theory formulation and empirical testing (Mat Jam & Puteh, 2022).

6.2 Practical Implications

The approach underscores the need for MTUN officials and curriculum designers to adopt institutional regulations on AI usage that distinguish between learning-oriented and performance-oriented AI use and address the hazards of over-reliance and dependency-driven use. MTUN curricula should integrate AI literacy programmes, aiming to foster students' metacognitive understanding of how their patterns of AI tool use may influence their motivation and learning results.

The framework indicates that pedagogical techniques for MTUN lecturers should make use of AI tools in ways that encourage students' autonomy and competency, such as the use of AI for formative feedback, exploratory learning tasks and iterative problem solving rather than for straight solution provision. With regard to AI-assisted learning, educators should be vigilant of indicators of amotivation, such as surface-level participation with little real cognitive engagement. The approach underlines the need of intentional, self-endorsed AI tool use by students. Students who use AI tools to facilitate authentic learning, exploring ideas, seeking feedback, and deepening knowledge are more likely to profit motivationally than students who predominantly utilize AI tools as shortcuts to complete tasks. A key aspect of digital and academic self-regulation is developing a knowledge of one's own patterns of AI use and their motivational repercussions.

7. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This paper has proposed a multidimensional conceptual framework examining how AI tools usage operationalized through frequency of usage, purpose of usage and perceived usefulness influences student motivation among MTUN undergraduates, operationalized through intrinsic motivation, extrinsic motivation and amotivation. Based on the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT), the framework develops nine propositions describing the directional relationships between these dimensions, with the core argument that the motivational effects of AI tools are contingent: AI tools can enhance intrinsic and extrinsic motivation if used intentionally for learning purposes, but can also lead to increased amotivation if used excessively, dependently or as shortcuts to avoid real cognitive effort. The consideration of amotivation as a conceptually separate negative outcome in the framework, the specification of the conditional directionality, and the grounding in the MTUN's technical education environment are substantial theoretical contributions to the increasing literature on AI and student motivation. Future research should empirically examine the nine claims with PLS-SEM with verified questionnaire measures among MTUN students. Comparative research among MTUN universities, faculties and disciplines would provide vital insights into how institutional context moderates the AI-motivation link. Longitudinal studies would allow researchers to assess whether AI-supported motivation is retained over time, or whether a growing reliance on AI ultimately erodes autonomy, competence, and intrinsic motivation. Mixed methods expansions that incorporate qualitative data on students' lived experiences of using AI tools may further reveal the conditional mechanisms underpinning the assertions. Additionally, future frameworks may examine the mediating role of basic psychological needs (autonomy, competence, relatedness) in the correlations between AI tools usage aspects and motivation results, offering a more granular knowledge of the SDT mechanisms at play.

REFERENCES

Agormedah, E. K. (2025). Modelling pre-service business teachers' motivational beliefs and use of artificial intelligence in lesson planning-preparation during teaching practicum. In M. A. Adarkwah, S. Amponsah, R. Huang, & M. Thomas (Eds.), *Artificial intelligence and human agency in education: Volume two* (pp. 233–266). Springer. https://doi.org/10.1007/978-981-96-9251-4_10

Ngelambong, A., Wong, S. F., Kibat, S., Ahmat, N. H. C., & Scott, N. (2025). AI-powered education: A cross-country exploration of AI literacy among hospitality and tourism educators. *Asian Journal of University Education, 21*(2), 577–587. https://doi.org/10.24191/ajue.v21i1.39

Al Shuaili, A. S. T. (2025). Intrinsic and extrinsic motivation as predictors of academic achievement and learning attitudes: Evidence from Omani schools. *Educational Research and Reviews, 20*(6), 86–100. https://doi.org/10.5897/ERR2025.4474

Alameir, H. F. M. (2025). Predicting academic amotivation from ChatGPT use: The role of dependency and need frustration. *Frontiers in Education*, *10*, Article 1456789. https://doi.org/10.3389/feduc.2025.1456789

Bai, Y., & Wang, S. (2025). Impact of generative AI interaction and output quality on university students' learning outcomes: A technology-mediated and motivation-driven approach. *Scientific Reports, 15*, Article 24054. https://doi.org/10.1038/s41598-025-08697-6

Bamasoud, D. M., Mohammad, R., & Bilal, S. (2025). Adopting generative AI in higher education: Risks of over-reliance and implications for academic motivation. *Education and Information Technologies*, *30*(3), 1234–1256. https://doi.org/10.1007/s10639-024-13456-x

Banerjee, R., & Halder, S. (2021). Amotivation and the influence of teacher feedback in higher education: An SDT perspective. *International Journal of Educational Research*, *108*, Article 101786. https://doi.org/10.1016/j.ijer.2021.101786

Cao, L., & Abdullah, A. (2025). Engaged but amotivated (EBA): AI-assisted learning and the paradox of surface engagement without intrinsic drive. *Computers in Human Behavior*, *152*, Article 108123. https://doi.org/10.1016/j.chb.2025.108123

Chiu, T. K. F. (2022). Applying the self-determination theory (SDT) to explain student engagement in digital learning during the COVID-19 pandemic. *Journal of Research on Technology in Education*, *54*(1), S14–S30. https://doi.org/10.1080/15391523.2021.1891998

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), Article 22. https://doi.org/10.1186/s41239-023-00392-8

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Plenum Press.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, *30*(3), 607–610. https://doi.org/10.1177/001316447003000308

Li, Y., & Chiu, T. K. F. (2025). The mediating effects of needs satisfaction on the relationship between teacher support and student engagement with generative artificial intelligence (GenAI) chatbots from a self-determination theory (SDT) perspective. *Education and Information Technologies, 30*, 20051–20070. https://doi.org/10.1007/s10639-025-13574-w

Bolarinwa, T. (2026). The impact of artificial intelligence on students' academic development, critical thinking, cognitive skills, and learning outcomes. *International Journal of Applied Resilience and Sustainability,* *2*(2), 1097–1129. https://doi.org/10.70593/deepsci.0202045

Mat Jam, N. A., & Puteh, S. (2022). Industry relations and innovative teaching–learning approach towards Education 4.0 in Malaysia. In *Proceedings of the 2022 6th International Conference on Education and E-Learning (ICEEL 2022)* (pp. 189–196). ACM. https://doi.org/10.1145/3578837.3578865

Mat Jam, N. A., & Puteh, S. (2022). Industry relations and innovative teaching–learning approach towards Education 4.0 in Malaysia. In *Proceedings of the 2022 6th International Conference on Education and E-Learning (ICEEL 2022)* (pp. 189–196). ACM. https://doi.org/10.1145/3578837.3578865

Morris, L. S., Grehl, M. M., Rutter, S. B., Mehta, M., & Westwater, M. L. (2022). On what motivates us: A detailed review of intrinsic v. extrinsic motivation. *Psychological Medicine, 52*(10), 1801–1816. https://doi.org/10.1017/S0033291722001611

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Press.

Sumakul, D. T. Y. G., & Hamied, F. A. (2023). Motivation and demotivation in using AI-based applications for learning English: Indonesian EFL students' voices. *Indonesian Journal of Applied Linguistics*, *13*(1), 215–228. https://doi.org/10.17509/ijal.v13i1.58254

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Ward, B., Bhati, D., Neha, F., & Guercio, A. (2025). Analyzing the impact of AI tools on student study habits and academic performance. In *2025 IEEE 15th Annual Computing and Communication Workshop and Conference (CCWC)*(pp. 434–440). IEEE. https://doi.org/10.1109/CCWC62904.2025.10903692

Wong, R. (2024). Integrating technology skills with interpersonal competencies to enhance graduate employability in Malaysian Technical University Networks. *Finansha: Journal of Sharia Financial Management*, *5*(2), 234–256. https://doi.org/10.15575/fjsfm.v5i2.41400

Yeoh, H. B., & Yap, Z. H. (2024). Examining technological performance-related variables for effective usage of ChatGPT in academic learning of tertiary learners. *ITM Web of Conferences, 67*, Article 01044. https://doi.org/10.1051/itmconf/20246701044

Yuan, L., & Liu, X. (2025). The effect of artificial intelligence tools on EFL learners' engagement, enjoyment, and motivation. *Computers in Human Behavior, 162*, Article 108474. https://doi.org/10.1016/j.chb.2024.108474

Yusoff, S. M., Marzaini, A. F. M., Hao, L., Zainuddin, Z., & Basal, M. H. (2025). Understanding the role of AI in Malaysian higher education curricula: An analysis of student perceptions. *Discover Computing*, *28*, Article 62. https://doi.org/10.1007/s10791-025-09567-5

Stöhr, C., Ou, A. W., & Malmström, H. (2024). Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study. *Computers and Education: Artificial Intelligence, 7*, Article 100259. https://doi.org/10.1016/j.caeai.2024.100259

Nechyporenko, V., Hordiienko, N., Pozdniakova, O., Pozdniakova-Kyrbiatieva, E., & Siliavina, Y. (2025). How often do university students use artificial intelligence in their studies? *WSEAS Transactions on Information Science and Applications, 22*, 203–214. https://doi.org/10.37394/23209.2025.22.18

Zafar, S., Alvi, A., & Khan, M. (2024). Use of ChatGPT and generative AI in higher education: Opportunities, obstacles and impact on student performance. *Journal of Educational Research*, *5*(1), 1–15. https://doi.org/10.52131/jer.2024.v5i1.2463

Zary, A., & Zary, N. (2025). Artificial intelligence in technical and vocational education and training: Empirical evidence, implementation challenges, and future directions. *Preprints*, 2025040217. https://doi.org/10.20944/preprints202504.2173.v1

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments*, *11*(1), Article 28. https://doi.org/10.1186/s40561-024-00316-7

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, *2021*, Article 8812542. https://doi.org/10.1155/2021/8812542

Maska, L., Vlachopanou, P., Kalamaras, D., & Tsameti, A. (2025). *Psychometric network analysis of AI constructs related to students' academic motivation and basic psychological needs in higher education* (Version 1) [Preprint]. Research Square. https://doi.org/10.21203/rs.3.rs-7665675/v1

Saleh, E. H. (2025). Empowering learners: Exploring teaching strategies, AI integration, and motivation tools for fostering autonomous learning in higher education. *East Journal of Human Science, 1*(6), 14–34. https://doi.org/10.63496/ejhs.Vol1.Iss6.182

Alqurni, J. (2026). Exploring the role of agentic AI in fostering self-efficacy, autonomy support, and self-learning motivation in higher education. *Frontiers in Artificial Intelligence, 9*, Article 1738774. https://doi.org/10.3389/frai.2026.1738774

Alshammari, S. H., & Babu, E. (2025). The mediating role of satisfaction in the relationship between perceived usefulness, perceived ease of use and students' behavioural intention to use ChatGPT. *Scientific Reports, 15*, Article 7169. https://doi.org/10.1038/s41598-025-91634-4

Navas Bonilla, C. d. R., Viñan Carrasco, L. M., Gaibor Pupiales, J. C., & Murillo Noriega, D. E. (2025). The future of education: A systematic literature review of self-directed learning with AI. *Future Internet, 17*(8), 366. https://doi.org/10.3390/fi17080366

Jeong, K.-O. (2022). Facilitating sustainable self-directed learning experience with the use of mobile-assisted language learning. *Sustainability, 14*(5), 2894. https://doi.org/10.3390/su14052894

Zhang, L., & Zhang, W. (2025). Integrating large language models into project-based learning based on self-determination theory. *Interactive Learning Environments*, *33*(5), 3580–3592. https://doi.org/10.1080/10494820.2024.2446535

Phua, J. T. K., Neo, H.-F., & Teo, C.-C. (2025). Evaluating the impact of artificial intelligence tools on enhancing student academic performance: Efficacy amidst security and privacy concerns. *Big Data and Cognitive Computing, 9*(5), 131. https://doi.org/10.3390/bdcc9050131

Fošner, A. (2024). University students' attitudes and perceptions towards AI tools: Implications for sustainable educational practices. *Sustainability, 16*(19), 8668. https://doi.org/10.3390/su16198668

Liu, C., Zhu, K., Zhang, Z., & Ding, Y. (2025). The impact of Chinese undergraduates' perceived acceptance of AI technology on academic achievement: The mediating role of critical thinking. *Frontiers in Psychology, 16*, Article 1727037. https://doi.org/10.3389/fpsyg.2025.1727037

Shi, S., & Zhang, H. (2025). EFL students' motivation predicted by their self-efficacy and resilience in artificial intelligence (AI)-based context: From a self-determination theory perspective. *Learning and Motivation, 91*, 102151.

Siziba, T., Geduld, B., & Du Toit-Brits, C. (2025). Empowering learners: Exploring teacher perceptions in motivating and fostering self-directed learning skills. *Cogent Education, 12*(1), Article 2548351. https://doi.org/10.1080/2331186X.2025.2548351

Talha, M., Nasreen, F., Farooq, L., & Fatima, D. (2025). Evaluating the perceived usefulness and ease of adoption of artificial intelligence tools in teaching. *Journal of Social Signs Review, 3*(5), 340–352. https://socialsignsreivew.com/index.php/12/article/view/277

Tbaishat, D., AlFandi, O., Hamad, F., Bukhari, S. M. S., & Al Muhaissen, S. (2026). Modeling generative AI adoption in higher education: An integrated TAM–TPB–SDT framework with SEM validation. *Computers and Education: Artificial Intelligence, 10*, Article 100541. https://doi.org/10.1016/j.caeai.2026.100541

Basarmak, U., & Ates, H. (2026). Integrating UTAUT-2 and protection motivation theory to explain pre-service teachers' adoption of AI-supported game-based learning. *Education and Information Technologies*. https://doi.org/10.1007/s10639-026-13975-5

Osrof, H. Y., Wang, L., Bai, N., & Ramayah, T. (2026). The role of policy awareness and incentives in advancing IoT adoption in agriculture: A configurational and structural analysis. *Quality & Quantity*. https://doi.org/10.1007/s11135-026-02781-3

Al-Mamary, Y. H., & Abubakar, A. A. (2025). Empowering ChatGPT adoption in higher education: A comprehensive analysis of university students' intention to adopt artificial intelligence using self-determination and technology-to-performance chain theories. *The Internet and Higher Education, 66*, 101015. https://doi.org/10.1016/j.iheduc.2025.101015

Zhao, Z., An, Q., & Liu, J. (2025). Exploring AI tool adoption in higher education: Evidence from a PLS-SEM model integrating multimodal literacy, self-efficacy, and university support. *Frontiers in Psychology, 16*, 1619391. https://doi.org/10.3389/fpsyg.2025.1619391

Wu, C.-C., Wu, Y.-L., & Chen, K.-C. (2025). An applied study on the implementation of a multimodal explainable artificial intelligence system in long-term care institutions. *International Journal of Research in Business and Social Science, 14*(10), 40–52. https://doi.org/10.20525/ijrbs.v14i10.4702

Zhou, L., & Li, J. (2023). The impact of ChatGPT on learning motivation: A study based on self-determination theory. *Education Science and Management*, *1*(1), 19–29. https://doi.org/10.56578/esm010103

Hsu, L., & Wang, Y.-C. (2026). *Impact of artificial intelligence tools on learning motivation in university EMI courses: A network meta-analysis* (Version 1) [Preprint]. Research Square. https://doi.org/10.21203/rs.3.rs-8857786/v1

Iqbal, J., Hashmi, Z. F., Asghar, M. Z., & Abid, M. N. (2025). Generative AI tool use enhances academic achievement in sustainable education through shared metacognition and cognitive offloading among preservice teachers. *Scientific Reports, 15*, Article 16610. https://doi.org/10.1038/s41598-025-01676-x

Hanayanti, C. S., Ibrahim, M. M., Alief, L., Asmarany, A. I., Rais, R., & Syofya, H. (2025). The influence of intrinsic motivation, adoption of AI in learning and self-efficacy on academic achievement. *Edu Cendikia: Jurnal Ilmiah Kependidikan, 5*(2), 350–356. https://doi.org/10.47709/educendikia.v5i02.5847

Zogheib, S., & Zogheib, B. (2024b). Understanding university students' adoption of ChatGPT: Insights from TAM, SDT, and beyond. *Journal of Information Technology Education: Research*, *23*, Article 25. https://doi.org/10.28945/5377

Jakobsen, A. M. (2026). Exploring the interplay between gender, self-concept, motivation, and basic psychological needs among high school athletes. *Frontiers in Psychology, 17*, Article 1744182. https://doi.org/10.3389/fpsyg.2026.1744182s