Asian Journal of Research in Education and Social Sciences
e-ISSN: 2682-8502 | Vol. 8, No. 3, 89-101, 2026
https://asianscholarsnetwork.com/asnet-journals
SPECIAL ISSUE: TheSustainImpact International Conference 2026

Breaking Through and Limitations of Existing Frameworks for SDG4: A Critical Review of Studies Related to Learning Motivation

Zheng Jiahui[1,2*], Subadrah Madhawa Nair[1]

[1] Faculty of Education and Humanities, UNITAR International University, Petaling Jaya, Malaysia
[2] Sichuan Technology and Business University, Chengdu, China

*Corresponding Author: 15928756120@163.com

Received: 13 February 2026 | Accepted: 30 March 2026 | Published: 20 April 2026

DOI: https://doi.org/10.55057/ajress.2026.8.3.9

Abstract: *Learning motivation is a core psychological mechanism mediating instructional design, learning environments, and academic performance, especially in cognitively demanding domains like Advanced Mathematics in higher education. This literature review synthesizes the theoretical foundations, empirical evidence, methodological trends, and limitations of research on learning motivation in AI - mediated collaborative learning. Based on Self - Determination Theory, Expectancy–Value Theory, and Achievement Goal Theory, it clarifies how AI - mediated interventions and collaborative structures shape motivation and influence academic outcomes and self - confidence. Methodologically, contemporary research is empirical - oriented, uses theory - aligned measurement tools, and relies on structural equation modeling for mediation testing, but has issues like over - reliance on cross - sectional data, poor sample representativeness, mismatched measurement tools for AI, and insufficient group - level analysis. There are critical gaps in theoretical integration, empirical exploration of longitudinal dynamics and AI effects, and methodological innovation. Future research should focus on developing unified theoretical models, expanding empirical studies, innovating measurement tools and techniques, and addressing ethical and practical issues. The review offers an overview of current research and identifies key directions for motivation research in AI - enhanced higher education.*

Keywords: Learning Motivation; AI-Mediated Collaborative; Mediating Mechanism; Advanced Mathematics; SDG4

---

1. Introduction

Learning motivation is a core construct of educational psychology, fundamentally determining students' learning engagement, persistence, and academic achievement (Ryan & Deci, 2020). The pursuit of understanding and enhancing motivation aligns directly with the global commitment to Sustainable Development Goal 4 (SDG 4), which aims to "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all" (United Nations, 2015). At the heart of achieving this goal lies the imperative to foster intrinsic drive and equitable access to engaging learning experiences for every learner.

Despite the rich achievements in this field, existing literature still contains gaps that urgently need integration and critical analysis. First, many empirical studies present situational contradictions; for example, the same intervention strategies show vastly different effects in different cultures or educational stages, highlighting the limitations of theoretical application. Second, existing reviews largely focus on theoretical commentary within Western contexts, lacking a systematic critique of research findings from Southeast Asia, particularly Malaysia, a multicultural and multilingual educational environment. Insufficient dialogue between local research and mainstream international discourse makes it difficult for local educational practitioners to directly draw upon these findings. These gaps underscore the crucial importance of a systematic and critical review—specifically, what are the theoretical, empirical, and methodological gaps in current learning motivation research, particularly in the context of AI-mediated collaborative learning, and how can future research directions be refined to address these gaps while advancing SDG 4's commitment to inclusive and equitable quality education?

This paper clearly points out the gaps in the research on AI-mediated collaborative learning motivation in three core aspects: theory, empirical evidence, and methodology. Based on these gaps, it proposes four clear future research directions, aiming to provide clear problem guidance and development paths for subsequent research in this field, thereby promoting the in-depth development and practical application of AI-mediated collaborative learning motivation research.

To attain the aforementioned objectives, this paper is structured as follows: subsequent to the introduction, Part 2 will conduct a review of Method and Scope; Part 3 will explore Conceptual and Theoretical Foundations; Part 4 will present a Thematic Synthesis of Empirical Studies; Part 5 will examine Methodological Trends and Limitations; Part 6 will conduct a discussion on research gaps, and Part 7 will focus on future directions. and Part 8 will present the Conclusion.

This paper presents a comprehensive, theory-driven review of the literature dedicated to learning motivation, aiming to lay a rigorous conceptual and empirical groundwork for the critical scrutiny of existing learning motivation research frameworks in the context of SDG4. This review goes far beyond mere descriptive summarization; instead, it undertakes incisive critical synthesis, integrates disparate theoretical standpoints, and pinpoint gaps that remain unresolved in current scholarship. These efforts collectively serve to substantiate the necessity and academic merit of this critical review.

2. Review Method and Scope

The literature review is based on core academic databases in the fields of educational technology, educational psychology, and higher education, including Web of Science, Scopus, ERIC, and ProQuest. The time scope is focused on post-2020 literature, with priority given to empirical studies, meta-analyses, and systematic reviews published between 2020 and 2025, ensuring alignment with the latest theoretical refinements and technological applications in AI-mediated learning.

Core keywords for literature retrieval include: learning motivation, Self-Determination Theory (SDT), Expectancy–Value Theory (EVT), Achievement Goal Theory, AI-mediated collaborative learning, higher education, Advanced Mathematics education, engineering education, academic performance, self-confidence, autonomy, perceived competence, motivational regulation.

The inclusion criteria for references are as follows:

i. Focus on higher education contexts, particularly in cognitively demanding domains such as Advanced Mathematics and engineering;
ii. Centered on learning motivation as a core construct, involving theoretical applications or empirical investigations of mainstream motivation frameworks;
iii. Incorporate AI-mediated support, collaborative learning, or technology-enhanced instructional designs;
iv. Explicitly address motivation as a mediating variable linking instructional interventions to learning outcomes;
v. Published as peer-reviewed empirical studies, meta-analyses, or systematic reviews to ensure methodological rigor.

3. Theoretical Foundations

Learning motivation is commonly conceptualised as the set of internal processes that initiate, direct, and sustain learning behaviour (Valenzuela et al.,2020). Among contemporary theoretical frameworks, Self-Determination Theory (SDT) (Deci et al.,1985) has emerged as the most influential in explaining motivation in educational contexts (Manzano-Sánchez et al.,2021). SDT distinguishes between autonomous motivation (intrinsic motivation and identified regulation) and controlled motivation (external and introjected regulation), arguing that learning outcomes are strongest when learners experience autonomy, competence, and relatedness (Gavarkovs et al.,2022).

Recent meta-analytic evidence strongly supports this distinction. In a large-scale meta-analysis, demonstrated that autonomous motivation is positively associated with persistence, engagement, and academic achievement across educational contexts, whereas controlled motivation shows weaker and more inconsistent relationships with performance (Howard et al., 2021). This finding underscores the importance of examining not only the level of motivation but also its quality when modelling learning processes.

In higher education, motivation is increasingly viewed as context-sensitive and malleable, shaped by instructional practices, feedback, and social interaction rather than fixed learner traits. This perspective provides a theoretical foundation for treating motivation as a mediator influenced by collaborative learning structures and AI-mediated support.

3.1 Self-Determination Theory (SDT)

Among the most influential frameworks in motivation research is Self-Determination Theory (SDT), which distinguishes between different types of motivation based on the degree of self-regulation and autonomy. SDT posits that motivation ranges from amotivation, through various forms of extrinsic motivation, to intrinsic motivation, with more autonomous forms associated with deeper engagement and better learning outcomes.

A central tenet of SDT is that motivation is supported when three basic psychological needs are satisfied: autonomy, competence, and relatedness. Extensive empirical evidence demonstrates that learning environments that support these needs foster more adaptive motivational patterns and improved academic performance. A comprehensive theoretical synthesis by (Ryan & Deci, 2020) clarifies how need-supportive contexts enhance learners' intrinsic motivation and internalisation of extrinsic goals.

In higher education contexts, SDT has been widely applied to examine how instructional practices influence student motivation. Recent empirical studies indicate that autonomy-supportive teaching, meaningful feedback, and collaborative learning opportunities are positively associated with intrinsic motivation and engagement. These findings are particularly relevant for AI-mediated collaborative learning, where technological systems may influence students' perceptions of autonomy and competence through adaptive prompts and feedback.

3.2 Expectancy–Value Theory

Another prominent framework in motivation research is **Expectancy–Value Theory (EVT)(**Atkinson,1957) which explains motivation as a function of learners' expectations of success and the value they attach to learning tasks. EVT posits that students are more inclined to participate in learning activities when they possess a belief in their potential for success (expectancy) and when they regard the task as beneficial, engaging, or significant (value).

Recent theoretical refinements of EVT emphasise the role of instructional context in shaping expectancy and value beliefs. (Eccles & Wigfield, 2020) provide an updated synthesis of EVT, highlighting how classroom practices, feedback, and peer interaction influence students' motivational beliefs over time.

In Advanced Mathematics education, expectancy–value beliefs are particularly salient. Students often perceive mathematics as difficult and high-stakes, which can undermine expectancy beliefs even among capable learners. Collaborative learning and adaptive support mechanisms may help mitigate these effects by providing peer support and formative feedback, thereby enhancing both expectancy and task value.

3.3 Achievement Goal Theory

Achievement Goal Theory (Nicholls,1979) offers a complementary perspective by focusing on the goals learners pursue in achievement contexts. Contemporary formulations distinguish primarily between **mastery goals**, which emphasise learning and understanding, and **performance goals**, which focus on demonstrating competence relative to others. Research consistently shows that mastery-oriented goals are associated with deeper learning strategies, persistence, and adaptive responses to challenge.

Recent meta-analytic work synthesising post-secondary research indicates that mastery goals positively predict engagement and conceptual learning, whereas performance-avoidance goals are associated with anxiety and disengagement (Pepin et al., 2021). These findings are particularly relevant in collaborative learning contexts, where social comparison may activate performance concerns.

4. Thematic Synthesis of Empirical Studies

Theme 1: Motivation in Mathematics and Engineering Education

A substantial body of post-2020 research demonstrates that technology-enhanced learning environments influence motivation primarily through changes in perceived autonomy, competence, and feedback quality. A recent systematic review by Dong et al. (2024) synthesized evidence on factors influencing college students' self-regulated learning in online learning environments. The factors affecting self-regulated learning in online learning environment are divided into seven aspects, namely cognitive quality, motivational quality, autonomy support, goal structures and social expectations, feedback and considerations of achievement, perceived control and perceived value.(Dong et al., 2024)Meta-analytic reviews

Asian Journal of Research in Education and Social Sciences
e-ISSN: 2682-8502 | Vol. 8, No. 3, 89-101, 2026
https://asianscholarsnetwork.com/asnet-journals
SPECIAL ISSUE: TheSustainImpact International Conference 2026

show that technology does not exert uniform motivational effects; instead, its impact depends on how technological features align with learners' psychological needs (Finkelstein, 2025).

In AI-mediated learning environments, adaptive feedback and personalisation are repeatedly identified as mechanisms that support motivation. Xu et al. (2025) provided large-scale empirical evidence that AI-driven personalised feedback enhances learners' engagement and achievement goals by strengthening perceived competence and supporting self-regulated learning. Although framed within a motivational lens, their findings demonstrate that AI influences learning outcomes indirectly via motivational processes. Wang and Zhu (2024) determined that the majority of favourable learning outcomes resulting from AI interventions are attributed to alterations in learner motivation and engagement, rather than direct cognitive impacts. However, existing empirical studies mostly focus on short-term collaborative scenarios in single-discipline, homogeneous learning groups, such as group discussion-style learning in basic humanities subjects. They do not consider the differentiated needs of group motivation regulation in different disciplines (such as science and engineering versus humanities) and different collaborative modes (such as project-based collaboration versus problem-solving collaboration), nor do they explore the adaptability of AI support strategies in learning groups of different ages and ability levels, resulting in insufficient cross-scenario transferability of research conclusions.

Theme 2: Motivation in Collaborative Learning Environments

A large-scale empirical study showed that students engaged in collaborative learning reported higher intrinsic motivation and engagement than those in individual learning conditions, particularly when collaboration was structured to support autonomy and competence (Yue et al., 2024).This empirical finding aligns closely with existing research based on Self-Determination Theory (SDT), and related studies have further enriched the support dimensions of collaborative learning. Recent research grounded in SDT demonstrates that collaborative learning environments that support autonomy , competence, and relatedness tend to foster higher levels of intrinsic motivation (Radkowitsch et al., 2020).Their findings indicate that collaboration itself is not inherently motivating; rather, its motivational impact depends on how interaction is organised and supported.However, these studies did not explore in depth the potential impact of different environmental conditions on the experimental results, which may limit the generalizability of the conclusions.

Theme 3: Motivation in AI-Mediated Collaborative Learning

Motivation is a core psychological variable linking technology design and learning outcomes in AI-mediated educational research (Chichekian & Benteux, 2022; Li, 2025). Existing research has explored the mechanisms of motivational influence, practical effects, and existing problems in AI-mediated scenarios from multiple dimensions, often using classic motivational theories such as self-determination theory and expectancy-value theory to construct analytical frameworks (Ragland et al.,2023; Dahalan et al.,2023; Xu and Hong ,2025). This paper reviews existing research from the perspectives of autonomy support, expectancy beliefs, motivational regulation, affective risk, and the mediating mechanisms of motivation, and clarifies the entry point of this study based on existing research limitations.

Artificial Intelligence-Mediated and Autonomous Support

Autonomy is a core component of motivation and a core dimension of self-determination theory (Choudhry and Bokharey,2013; Nicholson et al.,2022; Ntumi et al.,2025)). An autonomously supportive learning environment enables learners to develop a sense of will and agency in their learning activities. The effect of AI-mediated learning environments on learners' autonomy is dual; whether it ultimately enhances or weakens autonomy depends on the system's adaptive design and the way control is configured.

Existing empirical studies on AI systems supporting learners' autonomy and intrinsic motivation generally lack sufficient consideration of the complexity of application scenarios, leading to significant controversy regarding the universality and credibility of their conclusions. While Li et al. proposed that In a large-scale experimental demonstrated that adaptive support mechanisms increased learner persistence and engagement by allowing learners to regulate pacing and task selection (Li et al., 2025).

However, this study neglected the inherent tension between "individual choice" and "group collaboration" in collaborative learning, simply presupposing that adaptive mediation mechanisms can be directly transferred to collaborative scenarios without considering unique variables in collaborative learning such as group decision-making and task division. This results in significant deficiencies in the cross-scenario applicability of their research conclusions. More importantly, existing research defines the "degree of AI control" vaguely and one-sidedly, using only "whether or not learning pace adjustment and task selection permissions are provided" as the criterion, without conducting in-depth analysis of the essential attributes of AI intervention. Systematic reviews report that learners may experience AI-generated prompts or interventions as controlling when they are overly directive or poorly aligned with learners’ goals, leading to reduced intrinsic motivation (S. Lee & Eronen, 2025; U. Lee et al., 2025).

Such research remains at the level of phenomenological description. It fails to clarify the quantitative boundaries of "over-control" or explore the differentiated perceptions of AI control among different types of learners (e.g., autonomy-oriented vs. dependency-oriented). Ultimately, this renders the design recommendation of "supporting autonomy rather than replacing decision-making" a vague principle lacking practical guidance. Essentially, existing research still avoids the core contradiction: how should AI balance the needs of individual autonomy and group collaboration in the social context of collaborative learning? The fragmented and superficial nature of relevant empirical evidence also makes it difficult to support effective designs for enhancing motivation in AI-assisted collaborative learning.

Expectancy Beliefs in AI-Mediated Learning
Expectancy value theory provides a complementary analytical perspective for understanding the motivational mechanisms in AI-mediated learning environments (zhang et al.,2023). Expectancy beliefs refer to learners' expectations of learning success, and this variable effectively predicts learners' effort and persistence. AI-mediated systems can directly or indirectly influence learners' expectancy beliefs by providing predictive analytics, formative feedback, and adaptive task ranking.

Existing empirical research has confirmed the positive shaping effect of AI on expectancy beliefs: when AI systems visualize learners' learning progress and match the difficulty of learning tasks with learners' abilities, learners' expectancy beliefs are significantly enhanced; Technology-enhanced collaborative learning environments increased students’ expectancy beliefs and achievement indirectly through motivational pathways (Kohler, 2024); AI can also boost students' perceived worthiness and expectations of success through personalized content delivery methods, which adapt to individual performance histories and expertise levels (Rizvi, 2023). However, AI-generated predictions and analyses may also produce unintended motivational consequences. When learners perceive such feedback as deterministic or over-evaluative, it can significantly reduce the expectancy beliefs of low-performing learners. This risk also highlights a core principle of AI feedback design: feedback should be positioned at the formative and developmental level, rather than at the summative and evaluative level.

Artificial intelligence-mediated and motivational regulation

Motivation regulation is a crucial process for maintaining learners' sustained engagement in learning (Järvenoja et al.,2025) It refers to learners' ability to monitor and manage their own motivational state, including regulating learning effort, interest, and persistence. In collaborative learning, motivation regulation often exhibits group-level characteristics, primarily manifested in mutual encouragement among peers, shared motivation, and the coordinated maintenance of collective learning effort.AI-mediated learning environments can support motivational regulation by monitoring engagement patterns and providing prompts that encourage reflection, goal adjustment, or re-engagement. Empirical studies in CSCL contexts demonstrate that groups receiving adaptive, process-oriented support are more likely to maintain motivation over time (Saqr et al., 2023).Systematic reviews further indicate that AI systems capable of supporting regulation—rather than merely delivering content—are more effective in sustaining motivation in complex learning environments (Salleh et al., 2025). This finding also aligns closely with sociocultural theories that view motivation regulation as a socially distributed, technology-mediated process.

However, existing research on AI-mediated motivation regulation has significant limitations. It hasn't fully addressed the specificities and complexities of motivation regulation in collaborative learning, and the practical applicability and depth of conclusions need testing. Firstly, it mainly focuses on AI technology functions like monitoring and prompting, neglecting AI's potential interference with natural motivation regulation and peer interaction. Excessive AI prompts may crowd out peer autonomy and weaken self - regulation willingness. Also, the timing and intensity boundaries for AI - supported regulation are undefined. Secondly, research on the effectiveness of AI - mediated regulation is simplistic, using basic metrics and failing to analyze AI's role in cultivating regulation abilities or promoting self - regulation, falling into the "emphasizing short - term effects while neglecting ability development" pitfall. Thirdly, though Salleh et al.'s (2025) review integrated multiple studies, empirical research has small sample sizes and simple designs. There's a lack of large - sample, multi - round quasi - experimental studies and cost - benefit analysis, making it hard to implement recommendations in teaching. Overall, existing research has only preliminarily confirmed AI's potential in collaborative learning motivation regulation, but hasn't resolved core contradictions and remains at a superficial exploratory stage.

Mediating mechanisms of motivation in AI-mediated learning

Existing empirical research concludes that AI - mediated learning environments influence learning outcomes mainly through motivation. Instructional designs leveraging AI for motivational stimulation boost learners' engagement and performance more than those focusing on tech automation. The "AI - mediated - motivational stimulation - learning outcome" logic is supported by quantitative research. Lo et al. (2022) verified that learning experience affects academic achievement via motivation and engagement. However, current research on the motivational mediation mechanism in AI - mediated learning is superficial, lacking in - depth exploration of collaborative learning's social nature. There are limitations in deconstructing mediation mechanisms, scenario adaptability, and research design completeness, reducing the theory's explanatory power and practical value, leaving gaps for future research.

Current research on motivational mediation mechanisms in AI-mediated collaborative learning has four key limitations: it only conducts holistic analysis without exploring the mediation path characteristics of motivational sub-dimensions and refined theoretical support for AI's priority motivational dimensions; it focuses on individual learning scenarios, failing to investigate the multi-level mediation logic of "individual motivation-group motivation-collective learning outcome" and the secondary mediation of group motivation as well as relevant moderating effects; it inadequately considers the boundary conditions of the motivational mediation chain, with no clear definition of moderating variables like technology, scenario and group and no basis for personalized adjustment; it lacks disciplinary adaptability, as existing conclusions are hard to transfer to specialized and challenging disciplines such as STEM, without exploring the impact of disciplinary characteristics on motivational mediation mechanisms and providing practical guidance.

In general, existing research merely verifies that motivation is a key mediating variable in AI-mediated learning, but does not conduct in-depth research by integrating the social nature of collaborative learning, disciplinary characteristics and learners' group differences.

Existing literature confirms that AI-mediated learning environments shape students' autonomy, competence beliefs, aspirational beliefs and motivational regulation abilities to affect their motivational processes, and supportive AI intermediaries can effectively boost learning motivation and sustain learners' engagement in challenging learning. However, AI-mediated motivational gains are not guaranteed: poorly designed AI mechanisms may weaken learners' autonomy and aspirational beliefs, and even trigger anxiety and other emotional risks. This highlights the significance of theory-driven AI design and empirical research on motivational mechanisms in AIED research. Notably, there is a prominent research gap: no studies have clearly explored the mediating role of learning motivation in AI-mediated collaborative learning for advanced mathematics, a highly specialized and challenging subject.

5. Methodological Trends and Limitations

Contemporary research on learning motivation in AI-mediated collaborative learning is empirically oriented (Saqr et al.,2020), centering on mediation effect verification with mainstream frameworks of cross-sectional and quasi-experimental studies, while meta-analyses and systematic reviews serve as core evidence-synthesizing tools; it also increasingly integrates AI technological contexts with classic motivation theories to form theory-driven research paradigms. Yet this research has three key limitations: over-reliance on cross-sectional designs fails to track the dynamic changes of motivation in long-term learning and establish causal relationships between variables, significant heterogeneity in intervention design leads to inconsistent findings and hinders cross-study comparison, and the neglect of boundary conditions of motivation’s mediating role limits the generalizability of conclusions.

Such research samples higher education students, focusing on cognitively demanding disciplines like Advanced Mathematics and high-stakes contexts. Its measurement tools align with classic motivation theories, mostly using mature scales based on SDT, EVT and Achievement Goal Theory, and some complement data with objective indicators. However, there are flaws: convenience sampling leads to poor sample representativeness and limited external validity, traditional scales face adaptability challenges in AI-mediated scenarios and may distort constructs, and single-dimensional indicators oversimplify measurement, resulting in incomplete assessment.

Quantitative methods dominate, with SEM as the main tool for testing mediation effects, meta-analyses used to synthesize evidence, and some experimental designs with control groups. Nevertheless, these methods have deficiencies: SEM is sensitive to sample size and model specification, and over-optimization may inflate the mediating effect; meta-analyses fail to deeply analyze heterogeneity sources, leading to superficial conclusions; most studies focus on individual-level analysis and ignore group-level mechanisms; current methods focus on correlational and mediational analysis but lack causal analysis techniques.

6. Research Gaps

Research gaps in AI-mediated collaborative learning motivation research lie in three core aspects: Theoretical, Empirical and Methodological Gaps, with four clear directions proposed for future research.

Theoretical Gaps

Classic motivation theories (SDT, EVT, Achievement Goal Theory) are mostly applied in isolation, with no in-depth exploration of the interaction between different motivational constructs. AI-specific variables (algorithmic transparency, adaptive logic, etc.) are excluded from theoretical models, lacking theoretical explanations for how AI reshapes learners' psychological needs. Mainstream theories are rooted in individual psychology, with no theoretical constructs to describe and explain AI-mediated group motivational processes, leading to a disconnect with the social nature of collaborative learning.

Empirical Gaps

Diverse AI interventions are conflated as "AI support" without comparative analysis of their differentiated impacts on specific motivational dimensions, and there is no consistent evidence for the optimal AI functions in cognitively demanding domains such as Advanced Mathematics. Most studies adopt cross-sectional designs with homogeneous samples, lacking longitudinal tracking of motivational evolution and empirical data across different educational stages, cultural backgrounds and prior knowledge levels. Research focuses on AI's positive motivational effects while ignoring negative outcomes (algorithmic anxiety, etc.) and relevant mitigation strategies, and the bidirectional reciprocal relationship between motivation and affective constructs remains untested.

Methodological Gaps

Traditional motivation scales are not tailored to AI-mediated collaborative learning scenarios, easily causing mismeasurement of core motivational constructs. Research over relies on quantitative methods (SEM, meta-analysis), with scarce application of mixed-methods integrating qualitative approaches. Individual-level analysis dominates, with underdeveloped group-level analytical techniques for social shared motivational processes. Rigorous causal inference techniques are lacking, and confounding factors cannot be ruled out, limiting the validity of conclusions on AI's causal impact on motivation.

7. Future Research Directions

Theoretical advancement: Integrate classic motivation theories with AI-specific attributes to build a unified theoretical framework, and construct group-level motivational theories to explain socially shared regulation processes in AI-supported collaboration.

Empirical expansion: Conduct 6–12-month longitudinal studies to track motivational changes in Advanced Mathematics learning, use heterogeneous samples to test the generalizability of motivational mechanisms, and compare the effects of distinct AI functions to identify context-specific optimal interventions.

Methodological innovation: Develop and validate AI-adapted motivation scales, promote mixed-methods research combining quantitative and qualitative approaches, introduce group-level analytical tools, and adopt rigorous causal inference designs to confirm AI interventions' causal effects on motivation.

Practical and ethical research: Explore and test the effectiveness of strategies for mitigating negative motivational outcomes in real classrooms, and design AI interventions tailored to diverse learners' motivational needs to advance educational equity.

8. Conclusion

Future research in AI - mediated collaborative learning motivation has multiple gaps in theoretical, empirical, and methodological aspects. Theoretical gaps include isolated application of classic theories and lack of AI - specific and group - level theories. Empirical gaps involve non - comparative analysis of AI interventions and limited longitudinal studies. Methodological gaps consist of inappropriate scales and over - reliance on quantitative methods. Future directions cover theoretical integration, empirical expansion, methodological innovation, and practical and ethical research.

Acknowledgement
The authors would like to express their gratitude to UNITAR International University for their support of this research**.**

Conflict of Interest Statement
The authors declare that there is no conflict of interest regarding the publication of this study.

References

Atkinson, J. W. (1957). Motivational determinants of risk-taking behavior. Psychological Review, 64(6), 359–372. https://doi.org/10.1037/h0041068

Chichekian, T., & Benteux, B. (2022). The potential of learning with (and not from) artificial intelligence in education. *Frontiers in Artificial Intelligence*, *5*. https://doi.org/10.3389/frai.2022.903051

Choudhry, F. R., & Bokharey, I. Z. (2013). Perception of mental health in Pakistani nomads: An interpretative phenomenological analyses. *International Journal of Qualitative Studies on Health and Well-Being*, *8*. https://doi.org/10.3402/qhw.v8i0.22469

Dahalan, F., Alias, N., & Shaharom, M. S. N. (2023). Gamification and Game Based Learning for Vocational Education and Training: A Systematic Literature Review. Education and Information Technologies, 29. https://doi.org/10.1007/s10639-022-11548-w

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

De Smedt, Fien, et al. "Assessing and Mapping Reading and Writing Motivation in Third to Eight Graders: A Self-Determination Theory Perspective." Frontiers in Psychology, vol. 11, 28 July 2020, doi.org/10.3389/fpsyg.2020.01678, https://doi.org/10.3389/fpsyg.2020.01678.

Dong, X., Yuan, H., Xue, H., Li, Y., Jia, L., Chen, J., Shi, Y., & Zhang, X. (2023). Factors influencing college students' self-regulated learning in online learning environment: A systematic review. *Nurse Education Today*, 106071. https://doi.org/10.1016/j.nedt.2023.106071

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value Theory to Situated expectancy-value theory: a developmental, Social cognitive, and Sociocultural Perspective on Motivation. Contemporary Educational Psychology, 61(1), 1–13. https://doi.org/10.1016/j.cedpsych.2020.101859

Finkelstein, N. D. (2025). A principled way to think about AI in education: guidance for action based on goals, models of human learning, and use of technologies. ArXiv (Cornell University). https://doi.org/10.48550/arxiv.2510.01467

Gavarkovs, Adam, et al. "Motivational Design for Web-Based Instruction in Health Professions Education: Protocol for a Systematic Review and Directed Content Analysis." JMIR Research Protocols, vol. 11, no. 11, 9 Nov. 2022, p. e42681, https://doi.org/10.2196/42681. Accessed 28 Feb. 2023.

Howard, J. L., Bureau, J., Guay, F., Chong, J. X. Y., & Ryan, R. M. (2021). Student Motivation and Associated outcomes: a meta-analysis from self-determination Theory. Perspectives on Psychological Science, 16(6), 1300–1323. https://doi.org/10.1177/1745691620966789

Järvenoja, H., Törmänen, T., Lehtoaho, E., Turunen, M., Suoraniemi, J., & Edwards, J. (2025). Investigating peer influence on collaborative group members' motivation through the lens of socially shared regulation of learning. British Journal of Educational Psychology. https://doi.org/10.1111/bjep.12754

Kohler, K. (2024). You only need to change your direction: A look at the potential impact of ChatGPT on education. Technology in Language Teaching & Learning, 6(1), 1–18. https://doi.org/10.29140/tltl.v6n1.1103

Lee, S., & Juuso Eronen. (2025). Transforming English education in Japan by utilizing large language models for tailored learning and diverse skill development. Discover Education, 4(1). https://doi.org/10.1007/s44217-025-00856-1

Lee, U., Jeong, Y., Kim, S., Son, Y., Byun, G., Kim, H., & Lim, C. (2025). How Can Video Generative AI Transform K-12 Education? Examining Teachers' Perspectives through TPACK and TAM. ArXiv (Cornell University). https://doi.org/10.48550/arxiv.2503.08003

Li, C. (2025). The integration and innovative practice of intelligent AI and local opera in college teaching. Frontiers in Psychology, 15. https://doi.org/10.3389/fpsyg.2024.1521777

Li, S., Zeng, C., Liu, H., Jia, J., Liang, M., Cha, Y., Lim, C. P., & Wu, X. (2025). A meta-analysis of AI-enabled personalized STEM education in schools. International Journal of STEM Education, 12(1). https://doi.org/10.1186/s40594-025-00566-y

Lo, K. W. K., Ngai, G., Chan, S. C. F., & Kwan, K. (2022). How Students' Motivation and Learning Experience Affect Their Service-Learning Outcomes: A Structural Equation Modeling Analysis. Frontiers in Psychology, 13(13). https://doi.org/10.3389/fpsyg.2022.825902

Manzano-Sánchez, David, et al. "Future Academic Expectations and Their Relationship with Motivation, Satisfaction of Psychological Needs, Responsibility, and School Social Climate: Gender and Educational Stage." International Journal of Environmental Research and Public Health, vol. 18, no. 9, 25 Apr. 2021, p. 4558, https://doi.org/10.3390/ijerph18094558.

Nicholls, J. G. (1979). Quality and equality in intellectual development. American Psychologist, 34(11), 1071–1084. https://doi.org/10.1037/0003-066X.34.11.1071

Nicholson, J., Heyman, M., English, K., & Biebel, K. (2022). The ParentingWell Practice Approach: Adaptation of Let's Talk About Children for Parents With Mental Illness in Adult Mental Health Services in the United States. Frontiers in Psychiatry, 13. https://doi.org/10.3389/fpsyt.2022.801065

Nik, S., Shamsuddin, N., Ibrahim, N., Hamid, R., Zin, S. M., Nazatul Shahreen Zainal Abidin, & Hasrudy Tanjung. (2025). Fostering Learning Motivation: The Effects of AI (Artificial Intelligence) Adoption among Students in Higher Education Institutions. International Journal *of Research and Innovation in Social Science*, *IX*(III), 2662–2671. https://doi.org/10.47772/ijriss.2025.90300209

Ntumi[1], S., Courage Kwaku, K., Agyemang, K., & Nyarko, B. (2025). Assessing what matters: integrating social-emotional learning into classroom assessment for pupil well-being in Ghanaian basic schools. Scientific Reports. https://doi.org/10.1038/s41598-025-33328-5

Pepin, B., Biehler, R., & Gueudet, G. (2021). Mathematics in Engineering Education: a Review of the Recent Literature with a View towards Innovative Practices. International Journal of Research in Undergraduate Mathematics Education, 7(2), 163–188. https://doi.org/10.1007/s40753-021-00139-8

Radkowitsch, A., Vogel, F., & Fischer, F. (2020). Good for learning, bad for motivation? A meta-analysis on the effects of computer-supported collaboration scripts. International Journal of Computer-Supported Collaborative Learning, 15(1), 5–47. https://doi.org/10.1007/s11412-020-09316-4

Ragland, E. C., Radcliffe, S., & Karcher, E. L. (2023). A review of the application of active learning pedagogies in undergraduate animal science curricula. Journal of Animal Science, 101. https://doi.org/10.1093/jas/skac352

Rizvi, S. (2023). Revolutionizing Student Engagement: Artificial Intelligence's Impact on Specialized Learning Motivation. International Journal of Advanced Engineering Research and Science, 10(9), 27–31. https://doi.org/10.22161/ijaers.109.4

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and Extrinsic Motivation from a self-determination Theory perspective: Definitions, theory, practices, and Future Directions. Contemporary Educational Psychology, 61(1), 1–11. https://doi.org/10.1016/j.cedpsych.2020.101860

Saqr, M., López-Pernas, S., Helske, S., & Hrastinski, S. (2023). The longitudinal association between engagement and achievement varies by time, students' profiles, and achievement state: A full program study. Computers & Education, 199, 104787. https://doi.org/10.1016/j.compedu.2023.104787

Saqr, Mohammed, et al. "Robustness and Rich Clubs in Collaborative Learning Groups: A Learning Analytics Study Using Network Science." Scientific Reports, vol. 10, no. 1, 2 Sept. 2020, https://doi.org/10.1038/s41598-020-71483-z.

United Nations. (2015). Transforming our world: The 2030 Agenda for Sustainable Development. https://sdgs.un.org/2030agenda

Wainaina, P. K., & Sun, Y. (2025). Educators' perceptions and willingness to integrate Generative Artificial Intelligence in teaching and research: evidence from Kenyan higher education. *Discover Education*, *4*(1). https://doi.org/10.1007/s44217-025-00820-z

Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. Expert Systems with Applications, 252, 124167. https://doi.org/10.1016/j.eswa.2024.124167

Xu, E., Feng, X., Ning, K., Wang, Y., Zhou, L., & Li, H. (2025). The effectiveness of technical-supported collaboration in promoting students' learning outcomes: a meta-analysis based on empirical literature. Humanities and Social Sciences Communications, 12(1). https://doi.org/10.1057/s41599-025-05766-z

Xu, Q., & Hong, H. (2025). Emotional Intelligence and Language Learning Performance of ESL Learners: Mediating Effects of L2 Grit and L2 Motivation. Journal of Intelligence, 13(11), 146. https://doi.org/10.3390/jintelligence13110146

Xu, Q., Liu, Y., & Li, X. (2025). Unlocking student potential: How AI-driven personalized feedback shapes goal achievement, self-efficacy, and learning engagement through a self-determination lens. Learning and Motivation, 91, 102138. https://doi.org/10.1016/j.lmot.2025.102138

Yue, M., Lyu, W., Suh, J., Zhang, Y., & Yao, Z. (2024). MathVC: An LLM-Simulated Multi-Character Virtual Classroom for Mathematics Education. ArXiv (Cornell University). https://doi.org/10.48550/arxiv.2404.06711

Zhang, D., Gao, S., & Liu, R. (2023). A study on the mechanisms of teachers' academic emotions and motivational beliefs on learning engagement in the context of online training. Frontiers in Psychology, 14. https://doi.org/10.3389/fpsyg.2023.1255660