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Journal of Educational Theory and Management

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AI-Supported Personalized Learning and University Students' Learning Motivation: A Qualitative Study Based on Self-Determination Theory

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ARTICLE INFO

Article history
Received: 7 January 2026
Accepted: 17 January2026
Published Online: 30 March 2026

Keywords:
AI-supported personalized learning
learning motivation
self-determination theory
higher education
qualitative study

ABSTRACT

AI-supported personalized learning is increasingly adopted in higher education, yet students' motivational experiences in such environments remain insufficiently understood. Guided by Self-Determination Theory (SDT), this qualitative study explores how AI-supported personalized learning shapes university students' learning motivation, focusing on autonomy, competence, engagement, and perceived risks of overdependence. Semi-structured interviews were conducted with eight Chinese undergraduates who used AI-supported tools for coursework. Data were analyzed through thematic analysis using NVivo 14. Findings indicate that AI-supported personalization can enhance motivation by supporting autonomy (flexible pacing and individualized pathways) and competence (timely, specific, scaffolded feedback), which strengthens engagement, confidence, and persistence. However, participants also reported concerns about excessive reliance, shallow processing, and reduced independent thinking. Overall, the motivational value of AI-supported personalized learning depends on balancing technological support with instructional designs that protect learners' cognitive autonomy.

1. Introduction

Self-Determination Theory (SDT) provides a framework for this inquiry, emphasizing the fulfillment of psychological needs for autonomy and competence (Ryan & Deci, 2000; Ryan & Deci, 2017). AI personalization may support these needs by enhancing learner control and delivering tailored feedback. However, potential risks exist, such as overreliance on automation and diminished deep cognitive engagement (Al-Zahrani, 2024).

Current research on AI in education primarily focuses on outcomes and system effectiveness, with less attention given to students' subjective motivational experiences in personalized contexts (Topham et al., 2025). There is a particular lack of qualitative evidence regarding how university students perceive autonomy, competence, engagement, and the risk of overdependence.

This qualitative study, guided by SDT, investigates how AI-supported personalized learning influences university students' motivation. It explores their perceptions of autonomy and competence, their learning engagement, and concerns about overdependence. By centering student experiences, the study aims to advance the understanding of motivation in AI-mediated education and inform the design of human-centered learning environments.

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 DOI: http://doi.org/10.12345/jetm.v10i1.34846

2. Literature Review

AI-supported personalized learning refers to the application of artificial intelligence technologies to adapt learning content, pace, and feedback based on learners' data and interaction behaviors. In higher education, such systems are commonly associated with increased flexibility, efficiency, and learner-centered instructional approaches, particularly through adaptive learning pathways and automated feedback mechanisms (Mahmoud & Sørensen, 2024; Inuwa et al., 2025). Prior studies suggest that personalization and timely feedback can enhance students' engagement and persistence by reducing cognitive load and clarifying learning objectives (Fisher et al., 2025; Evans et al., 2024).

However, emerging research has also raised concerns about the motivational consequences of excessive automation in AI-supported learning environments. Answer-generation functions and highly automated feedback may encourage surface-level learning, overreliance, and reduced self-regulation, especially when learners rely on AI tools without sufficient reflective engagement (Hadi Mogavi et al., 2023; Yan et al., 2025). These mixed findings suggest that AI-supported personalized learning constitutes a complex motivational context rather than a uniformly beneficial intervention.

Self-Determination Theory (SDT) provides a well-established framework for understanding how learning environments influence motivation through the satisfaction or frustration of basic psychological needs, particularly autonomy and competence (Ryan & Deci, 2000; Ryan & Deci, 2017). Within AI-supported learning contexts, features such as adaptive pacing, learner control, and scaffolded feedback have been shown to support perceived autonomy and competence, thereby enhancing motivation (Annamalai & Nasor, 2025; Huang et al., 2025).

At the same time, SDT-informed research cautions that when technological support limits opportunities for autonomous decision-making or deep cognitive processing, the quality of motivation may be undermined despite short-term efficiency gains (Stenling et al., 2025; Yang, 2024). From this perspective, AI-supported personalized learning can function as both a need-supportive and need-frustrating environment, depending on how learners interact with technological affordances.

Overall, while existing studies acknowledge both the motivational potential and risks of AI-supported personalized learning, qualitative research examining university students' subjective motivational experiences remains limited. In particular, there is a lack of in-depth qualitative evidence on how students perceive autonomy support, competence support, learning engagement, and dependence risks in AI-supported personalized learning contexts. Addressing this gap requires a qualitative exploration grounded in SDT to capture students' lived experiences and interpretive meanings.

3. Methodology

3.1 Research Design

This study adopted a qualitative research design to explore university students' motivational experiences in AI-supported personalized learning environments. A qualitative approach was considered appropriate because it allows for an in-depth examination of learners' subjective perceptions, interpretations, and meaning-making processes that cannot be fully captured through quantitative measures (Creswell & Poth, 2018). Guided by Self-Determination Theory (SDT), the study focused on students' perceived autonomy, competence, learning engagement, and concerns about overdependence on AI-supported learning tools.

3.2 Participants

Eight Chinese undergraduate students from diverse academic disciplines participated in this study through purposive sampling. All participants had prior experience using AI-supported tools, including generative AI systems and adaptive learning platforms, for academic learning tasks. The sample size was considered adequate, as thematic saturation was reached with no substantially new themes emerging in the later interviews (Guest et al., 2006). An overview of participants' academic backgrounds and AI tool usage is presented in Table 1.

3.3 Data Collection

Data were collected through online semi-structured interviews, each lasting approximately 25 to 35 minutes. The interview protocol was developed based on SDT and prior studies on AI-supported learning, with questions focusing on learners' experiences of autonomy support, feedback and competence development, learning engagement, and perceived risks of overreliance on AI tools. Open-ended questions were used to encourage participants to elaborate on their personal learning experiences and reflections. All interviews were audio-recorded with participants' consent and transcribed verbatim for analysis.

3.4 Data Analysis

The interview transcripts were analyzed using thematic analysis following the procedures outlined by Braun and Clarke (2006). NVivo 14 software was employed to support systematic coding and theme development. Initial codes

DOI: http://doi.org/10.12345/jetm.v10i1.34846

were generated inductively from the data and subsequently refined through iterative comparison with SDT concepts. Related codes were then organized into broader themes that captured shared patterns across participants' experiences. To enhance analytical rigor, an audit trail and reflective memos were maintained throughout the analysis process.

Table 1 Basic Information of Participants and Overview of AI Tool Usage

Participant	Major	Year of Study	AI Use Experience
P1	Elderly Care Management	Year 2	Frequently utilizes generative AI tools such as "Doubao" and "DeepSeek" for concept explanation, idea expansion, and homework assistance.
P2	Business English	Year 1	Integrates the adaptive learning platform (U Campus), oral training system (FiF), and generative AI (Wenxin Yiyan) for personalized practice, error reinforcement, and knowledge consolidation.
P3	International Economics and Trade	Year 3	Generative AI tools (ChatGPT, iFlytek Spark), adaptive practice platforms, and automated feedback systems (such as Biaige) are widely utilized to support course learning, thesis writing, and professional practice.
P4	Materials Science and Engineering	Year 2	Primarily utilizes generative AI tools like DeepSeek and Doubao to explain abstract concepts and analyze incorrect answers, while leveraging online platforms for adaptive practice.
P5	Computer Science	Year 4	Proficiently utilizes multiple AI tools (iFlytek Listen, Grammarly, Quizlet AI, Squirrel AI) for knowledge organization, grammar checking, career path planning, and personalized review.
P6	Teach Chinese as Foreign Language	Year 2	Employing professional teaching systems for pronunciation correction, utilizing generative AI (ChatGPT, Wenxin Yiyan) to generate instructional example sentences, correct grammar, and organize knowledge frameworks.
P7	Accountancy	Year 2	Use adaptive question banks (Changke, XuetangX) for targeted practice on incorrect answers, and leverage generative AI (Wenxin Yiyan) to organize class notes and knowledge frameworks.
P8	Journalism and Communication	Year 3	Deeply relies on generative AI (Wenxin Yiyan) for press release drafting, structural refinement, copy polishing, and idea generation.

3.5 Ethical Considerations and Limitations

Ethical principles were strictly observed throughout the study. Participation was voluntary, informed consent was obtained from all participants, and pseudonyms (P1–P8) were used to ensure anonymity. All data were securely stored and used solely for research purposes. This study is subject to several limitations, including a small sample size and reliance on self-reported data, which may limit the generalizability of the findings. In addition, as a cross-sectional qualitative study, the results reflect participants' experiences at a specific point in time.

4. Findings

The thematic analysis revealed three interrelated themes that characterize university students' motivational experiences in AI-supported personalized learning environments. Together, these themes reflect the dual role of AI-supported personalization as both a motivational resource and a potential challenge.

4.1 AI-Supported Personalization as Autonomy-Competence Support

Participants consistently reported that AI-supported personalized learning enhanced motivation by simultaneously supporting autonomy and perceived competence. Rather than experiencing these needs separately, students described autonomy and competence as mutually reinforcing through personalized control over learning pace, content focus, and feedback.

AI tools allowed learners to revisit difficult concepts, skip familiar material, and seek assistance when needed, enabling more self-directed learning decisions. As one participant noted, AI-supported learning helped them "focus only on what I did not understand instead of following a fixed schedule" (P2). This flexibility was perceived as shifting learning toward a more autonomous and self-regulated process.

Timely and specific AI-generated feedback further strengthened perceived competence by helping students identify errors, clarify underlying concepts, and improve task performance. Participants emphasized that clear, step-by-step feedback increased confidence and persistence, which in turn supported greater autonomy in subsequent learning decisions. Overall, AI-supported personalization was experienced as fostering motivation through a reinforcing cycle between autonomy and competence.

 DOI: http://doi.org/10.12345/jetm.v10i1.34846

4.2 Perceived Risks of Overdependence and Shallow Engagement

Despite these motivational benefits, participants also expressed concerns about the risks associated with excessive reliance on AI-supported learning tools. Several students reported consulting AI tools immediately when encountering difficulties, sometimes before engaging in independent problem-solving. This tendency was perceived as limiting deep cognitive engagement and analytical reasoning.

One participant observed that directly relying on AI-generated solutions could replace systematic debugging and reflective thinking processes (P5). Others noted that frequent use of AI-generated answers might encourage surface-level understanding, particularly in tasks requiring complex reasoning or creativity.

Importantly, students demonstrated awareness of these risks and emphasized the need to critically evaluate AI-generated responses rather than accept them unreflectively. This awareness suggests that motivational outcomes are shaped not only by technological affordances but also by learners' self-regulatory strategies and critical engagement with AI tools.

4.3 Expectations for Cognitively Supportive AI Learning Environments

Participants also articulated clear expectations for future AI-supported learning environments. Rather than viewing AI primarily as an answer-providing tool, students expressed a preference for AI systems that function as cognitive partners by supporting thinking through questioning, explanation, and reflection.

As one participant stated, they hoped AI could "ask questions that guide my thinking instead of directly giving answers" (P1). Participants further highlighted the value of features such as progress visualization, real-world task scenarios, and reflective prompts to sustain long-term motivation. These expectations reflect students' desire for AI-supported learning environments that balance efficiency with cognitive autonomy and meaningful engagement.

5. Discussion and Implications

Specifically, students reported that the ability to choose their learning content and pace supported their need for autonomy. Simultaneously, the immediate and targeted feedback from the system bolstered their sense of competence. These two perceptions reinforced each other, leading to greater learning engagement. However, a significant concern emerged: when AI provides answers too directly, some students tend to outsource cognitive effort to the machine, reducing active processing. This pattern may undermine sustained motivation and skill development in the long term.

A key finding is that students were not passive recipients. Many demonstrated awareness of the risks of interdependence and actively emphasized the importance of maintaining critical judgment when using AI tools. This suggests that learners' own agency and meta-cognitive strategies are crucial in determining whether the impact of AI is positive or negative.

These results offer practical implications. In terms of design, AI systems should aim to guide rather than replace thinking, for instance by incorporating reflective prompts or explanatory guidance. Institutionally, educators should guide students in using AI responsibly, such as by requiring them to evaluate and justify AI-generated solutions. Aligning system design with supportive teaching practices can help maximize motivational benefits while mitigating potential risks.

This study has limitations, including sample size and a single cultural context. Future research could employ longitudinal designs or integrate behavioral data to further explore the dynamic relationship between AI and learning motivation across diverse educational settings.

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