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Capability Gains and Psychological Risks of AI Users/Consumers: A Dual-Path Model of Digital Well-Being

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ABSTRACT

The rapid diffusion of generative artificial intelligence (AI) has reshaped students' learning practices, creating both performance-related benefits and psychological risks. This study examines how academic performance, smart learning, and AI-related creepiness influence students' mental well-being through a dual-path model. Drawing on Social Cognitive Theory and Consumer Vulnerability Theory, this study positions academic performance and smart learning as capability-gain factors, while creepiness is treated as a psychological risk factor. It also examines the moderating roles of self-efficacy and perceived behavioral control as psychological boundary conditions. Data were collected through an online survey of 1,486 AI users in Indonesia and analyzed using Moderated Regression Analysis and Hayes' PROCESS Macro. The findings show that academic performance and smart learning positively influence mental well-being, while creepiness does not directly reduce mental well-being. Self-efficacy strengthens the positive effects of academic performance and smart learning on mental well-being. In addition, perceived behavioral control significantly moderates the relationship between creepiness and mental well-being, indicating that students' perceived control shapes how AI-related creepiness is interpreted psychologically. This study contributes to digital well-being literature by showing that generative AI can simultaneously generate capability gains and psychological risks, and that its effect on mental well-being depends on students' psychological resources and perceived control.

Keywords: mental well-being, smart learning, academic performance, creepiness, self-efficacy, perceived behavioral control

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INTRODUCTION

In recent years, the rapid advancement of generative artificial intelligence (AI) systems such as ChatGPT, Gemini, Claude, and other large language model-based technologies has fundamentally transformed how individuals work, learn, and interact with information. International reports indicate that AI adoption has grown exponentially across multiple sectors, including education, professional occupations, and everyday activities (Kuupole et al., 2025).

AI is no longer merely a technical support tool. Rather, it has increasingly become embedded within the broader human cognitive ecosystem. This paradigm shift is particularly evident in quantitative research, where tools like ChatGPT Plus facilitate the generation of native Python code for

statistical modeling and data visualization (Glickman & Zhang, 2024). Furthermore, emerging tools like Gemini and specialized platforms such as SciSpace are redefining the academic workflow by automating literature discovery and enhancing the interpretability of complex analytical results through contextually adaptive responses (Markowitz et al., 2024).

At the global level, academic discourse on AI has shifted from a primary focus on technology adoption toward a more nuanced examination of its psychological and well-being implications for AI consumers/ AI users (Yuan et al., 2024). Recent studies highlight that AI utilization can enhance efficiency, productivity, and learning performance. However, parallel concerns have emerged regarding technological dependency, the erosion of cognitive autonomy, and feelings of discomfort or "creepiness" arising from perceptions of AI's autonomous intelligence (Riley et al., 2025). Consequently, AI is increasingly conceptualized as an inherently ambivalent phenomenon. simultaneously generating capability gains while introducing potential psychological risks (Baek & Kim, 2023).

In Asia, AI adoption rates are particularly high, especially in countries with rapidly expanding digital ecosystems such as China, South Korea, Japan, Singapore, and Indonesia (Bhat et al., 2025; Brauner et al., 2024; Kuupole et al., 2025; Low et al., 2025; Neyazi et al., 2023; Yuan et al., 2024). Within educational and professional contexts, AI is increasingly leveraged to enhance learning efficiency, accelerate task completion, and support both academic and occupational performance. However, the highly competitive cultures and performance-driven environments prevalent in many Asian societies may also intensify the psychological implications of AI use. (Wang et al., 2025). While, AI can serve as a strategic performance enhancement tool, it may simultaneously generate anxiety related to technological dependence, erosion of self-efficacy, and perceived threats to human autonomy (Riley et al., 2025).

These dynamics suggest that the impact of AI on mental well-being cannot be understood through a linear or unidirectional framework. Rather, empirical evidence positions AI as a dual-edged force as functioning as a capability enhancer that boosts efficiency, productivity, learning performance, memory, and creativity (Riley et al., 2025). Whereas it can simultaneously introduce psychological risks such as heightened anxiety, skill erosion, technological dependency, and discomfort from perceived autonomous agency (Baek & Kim, 2023).

In Indonesia, the use of generative AI has increased substantially in recent years. Students, professionals, and the general public increasingly rely on AI technologies to support learning activities, administrative tasks, research processes, and everyday decision making (Muhammad et al., 2025). In this context, users interact with AI applications as part of a digital service environment. Referring to Soaloon and Handayani (2025), this study conceptualizes AI users as consumers of AI services, as they engage with AI platforms either as premium or regular users who receive technological functionalities and information outputs from these systems. Through these interactions, users develop various attitudes and behavioral responses toward AI technologies, which may influence their learning experiences, performance outcomes, and psychological well-being. However, despite the rapid growth of AI usage in Indonesia, the majority of existing studies continue to focus primarily on issues such as technology acceptance, usage intention, or learning effectiveness.

Empirical research that specifically examines the psychological implications of AI consumers on mental well-being remains relatively limited (Shubina & Dzido, 2025). This gap is particularly salient in a society characterized by rapid digital penetration and heterogeneous levels of AI literacy, where variations in self-efficacy and perceived behavioral control may significantly shape individuals' psychological experiences of AI engagement (Soto-Sanfiel et al., 2025). In other words, AI usage does not automatically enhance or diminish mental well-being. Its impact is likely contingent upon AI consumers' internal psychological mechanisms and cognitive appraisals.

Existing scholarship predominantly analyzes AI through two distinct theoretical lenses. One perspective positions AI as a performance-augmenting instrument that enhances efficiency and capabilities, typically rooted in Social Cognitive Theory (Li et al., 2025). The other views AI as a prospective source of psychological strain or technostress, drawing primarily from Consumer

Vulnerability Theory (Chirayath et al., 2025). However, empirical efforts to integrate these two perspectives within a unified and comprehensive conceptual framework remain limited (Shubina & Dzido, 2025). Moreover, the role of internal psychological factors, such as self-efficacy and perceived behavioral control in explaining how AI usage shapes mental well-being remains insufficiently theorized and empirically validated (Soto-Sanfiel et al., 2025).

LITERATURE REVIEW

Table 1. Dual-Path Model

Amplifier	Buffer
Social Cognitive Theory	Consumer Vulnerability Theory
Self-efficacy as amplifier	Perceived Behavior Control as buffer
Human as agent	Human as potentially exposed
Competence-driven growth	Control-limited condition
Technology as tool	Technology as risk structure
Gain mechanism	Risk mechanism

The psychological consequences of generative AI usage cannot be adequately explained through a single theoretical perspective. While, some studies emphasize the capability-enhancing potential of AI in improving learning outcomes and performance (Peng et al., 2026; Yan et al., 2026), other research highlights the psychological risks that may arise from technological dependence, uncertainty, and perceived loss of control (Bastani et al., 2025; Liang & Reiß, 2025). These contrasting findings suggest that interactions with AI simultaneously involve empowering and potentially vulnerable AI consumers' experiences (Ren et al., 2025).

To capture this complexity, the present study adopts a dual-path model that integrates insights from Social Cognitive Theory and Consumer Vulnerability Theory, two complementary perspectives for understanding human–technology interactions. Social Cognitive Theory emphasizes human agency, self-regulation, and perceived capability in shaping individuals' behavior and adaptation, while Consumer Vulnerability Theory highlights situations in which individuals may become vulnerable when they experience powerlessness or limited control in complex marketplace or technological environments (Bandura, 2006).

This research attempt to provide comparative theoretical framework. Self-efficacy is positioned as a psychological amplifier because prior research shows that efficacy beliefs can strengthen academic outcomes and function as a moderator in academic relationships (Brown et al., 1989). Meanwhile, perceived behavioral control is positioned as a control-based buffer because it reflects individuals' perceived control over a behavior, and meta-analytic evidence shows that PBC can moderate behavioral relationships within the Theory of Planned Behavior (Hagger et al., 2022). Integrating these perspectives allows a more comprehensive explanation of how AI usage can generate both capability gains and psychological risks, ultimately shaping individuals' mental well-being. Prior research on smart learning shows that AI and social media can positively affect academic performance and mental well-being, whereas studies on AI-related creepiness show that smart technologies can also trigger discomfort, distrust, and resistance (Shahzad et al., 2024).

Within this framework, the capability gain path is grounded in Social Cognitive Theory, which conceptualizes individuals as proactive agents capable of regulating their behavior and leveraging technological resources to enhance performance. From this perspective, AI can function as a cognitive support tool that facilitates smart learning and improves academic performance, both of which contribute positively to individuals' mental well-being (Zhang, 2025). These benefits are further strengthened by self-efficacy, which represents individuals' confidence in their ability to effectively utilize AI for learning and task completion (Alqurni, 2026). Higher levels of self-efficacy enable AI consumers to engage more actively with AI technologies, thereby maximizing the capability-enhancing potential of AI-supported learning environments.

In contrast, the risk exposure path draws on Consumer Vulnerability Theory, which emphasizes that individuals may become psychologically vulnerable when interacting with complex digital systems. In AI contexts, feelings of creepiness may emerge when AI consumers perceive AI systems as intrusive, unpredictable, or beyond their control, potentially undermining their mental well-being (Kuupole et al., 2025; Mobarak et al., 2025). However, this negative impact is not inevitable. Perceived behavioral control reflects individuals' perceived ability to regulate and manage their interactions with AI technologies, which can reduce feelings of vulnerability and psychological threat. By integrating these two pathways, the present study conceptualizes generative AI as an ambivalent technological system that simultaneously functions as a capability-enhancing tool and a potential source of psychological risk (Wang & Lin, 2025).

Social Cognitive Theory

Social Cognitive Theory (SCT) was introduced by Albert Bandura (1986) to explain how human behavior is shaped through the interaction of personal factors, behavior, and the environment. This theory emphasizes that individuals are active agents who are capable of regulating their behavior and evaluating their own experiences. Within this framework, successful experiences in completing tasks or achieving certain outcomes can strengthen individuals' perceptions of competence and self-capability. In the context of AI use in learning, Social Cognitive Theory helps explain how adaptive learning processes (smart learning) and academic achievement (academic performance) may contribute to individuals' psychological states (Alqurni, 2026; Bandura, 2001). When individuals are able to utilize AI technologies effectively to understand learning materials, complete assignments, and improve their academic performance, these experiences can reinforce their sense of competence and perceived control over the learning process (Shi et al., 2026).

Consumer Vulnerability Theory

Consumer Vulnerability Theory (CVT) was developed within consumer research to explain situations in which individuals become susceptible to harm or negative outcomes due to imbalances in power, information, or control within marketplace or technological environments (Baker et al., 2005; Baker et al., 2015). This theory underscores that vulnerability transcends mere individual shortcomings, frequently arising instead from structural conditions characterized by consumers' limited knowledge, restricted control, or asymmetrical relationships with complex systems (Yuan et al., 2024). Within this framework, consumers interacting with advanced technologies may experience uncertainty, discomfort, or perceived loss of control when they are unable to fully understand or regulate the technology they use.

In the context of AI consumer, Consumer Vulnerability Theory helps explain how individuals may experience psychological discomfort when interacting with autonomous and opaque AI systems (Baker et al., 2015). Feelings such as creepiness can arise when AI consumers perceive AI as unpredictable, intrusive, or beyond their control, potentially undermining their psychological well-being (Soaloon & Handayani, 2025). However, when individuals perceive a higher level of perceived behavioral control over their interactions with AI, they are better able to regulate their usage and reduce potential psychological risks associated with AI engangement (Baek & Kim, 2023).

Academic Performance

Academic performance refers to the level of individual achievement in completing academic tasks or learning activities, typically reflected in evaluative outcomes such as grades, quality of assignments, or demonstrated competencies. In this study, academic performance is conceptualized not merely as formal grades (Shahzad et al., 2024). From a social cognitive theory perspective, academic performance represents an outcome of mastery experience. When individuals achieve strong performance outcomes,

such experiences reinforce their sense of competence and contribute positively to their psychological well-being. Within the proposed framework, academic performance functions as an evaluative outcome in the capability gain path, serving as a mechanism through which AI enables capability development translates into improved mental well-being (Zhang, 2025).

Smart Learning

Smart learning refers to an adaptive learning process in which individuals strategically leverage AI technologies to enhance comprehension, learning efficiency, and information processing. Unlike academic performance, which focuses on outcomes, smart learning emphasizes the learning process itself (Yang et al., 2025). Key characteristics of smart learning include adaptive learning behavior, critical engagement with AI-generated outputs, the ability to explore ideas interactively with AI systems, and the integration of AI into higher-order cognitive processes. In this model, smart learning is conceptualized as a process-level capability mechanism that facilitates psychological empowerment and ultimately contributes to mental well-being through enhanced cognitive engagement and perceived competence (Huang et al., 2025).

Creepiness

Creepiness refers to feelings of discomfort, unease, or anxiety that arise when individuals perceive AI technologies as acting autonomously, invasively, or unpredictably. It extends beyond mere distrust, representing an intuitive psychological response to perceived opacity and autonomy in AI systems (Ding, 2025). It is defined as the characteristics include feelings of being constantly monitored, uncertainty regarding how AI systems operate, and a perceived loss of predictability. Creepiness reflects a situational condition that generates psychological exposure and a perceived loss of control. In the proposed model, creepiness constitutes the central construct in the Risk Exposure Path, representing the primary mechanism through which AI may negatively affect mental well-being (Mobarak et al., 2025; Soaloon & Handayani, 2025).

Mental Well-being

Mental well-being refers to an individual's psychological state characterized by emotional balance, perceived competence, life satisfaction, and minimal psychological distress (Tennant et al., 2007). It encompasses both hedonic well-being, reflecting happiness and life satisfaction and eudaimonic well-being, reflecting self-actualization, personal growth, and meaning (Lemon & Harris, 2025). In this study, mental well-being is conceptualized as a digital well-being outcome. Specifically, the psychological consequence of individuals' interactions with AI systems. It serves as the primary dependent variable, influenced positively by the Capability Gain Path and negatively by the Risk Exposure Path (Chirayath et al., 2025).

Self-Efficacy

Self-efficacy refers to an individual's belief in their capability to execute the actions required to achieve desired outcomes in specific situations (Yang & Delgado, 2025). It does not concern control over the environment per se, but rather confidence in one's own competence. In the AI context, self-efficacy reflects AI consumers' beliefs that they are capable of effectively utilizing AI, understanding and critically evaluating AI-generated outputs, and integrating AI into their tasks appropriately. Within the proposed model, self-efficacy functions as an amplifying moderator that strengthens the positive effects of the Capability Gain Path (Yang et al., 2025).

Perceived Behavioral Control

Perceived Behavioral Control (PBC) refers to an individual's perception of the extent to which they possess control over a particular behavior, including the ability to regulate, limit, or direct that behavior (Kuupole et al., 2025). Unlike self-efficacy, which concerns internal competence, PBC emphasizes regulatory control over one's actions. In the AI context, PBC reflects the ability to self-regulate AI usage. For example, limiting reliance to avoid dependency, managing usage intensity, and preventing over-immersion in AI systems. Within the model, PBC functions as a buffering moderator in the Risk Exposure Path, mitigating the negative psychological consequences of perceived creepiness and technological stress (Liu, 2025).

Hypothesis

This study seeks to examine the role of self-efficacy as an amplifier and perceived behavioral control (PBC) as a buffer within the dual-path framework. Conceptually, this positioning is highly consistent with the foundations of social cognitive theory and control theory (Kuupole et al., 2025). From an SCT perspective, self-efficacy represents a core personal resource that strengthens individuals' capacity to translate technological engagement into adaptive outcomes. Higher levels of self-efficacy are expected to amplify the positive effects of AI-driven capability gains (Alqurni, 2026).

Conversely, grounded in control theory, perceived behavioral control reflects individuals' perceived capacity to regulate their interactions with external systems. As such, PBC functions as a protective boundary condition that mitigates the adverse psychological effects associated with AI-related risk exposure. Individuals who perceive greater control over their engagement with AI are less likely to experience diminished well-being in response to perceived creepiness or technological stressors (Kirk et al., 2025).

Furthermore, this study positions mental well-being as the central outcome variable, as it captures the psychological dimension of consumer experience within the digital ecosystem. By foregrounding mental well-being, the research moves beyond performance-based metrics and technology acceptance indicators, offering a more holistic understanding of how AI shapes consumer psychological states (Li, 2025).

H1: Academic performance influences mental well-being positively

Academic performance reflects students' success in meeting academic demands through observable evaluative outcomes, such as grades, learning achievement, and academic progress. In the university context, academic performance is not only an indicator of cognitive achievement but also part of students' broader academic experience, which is closely connected to their health and well-being. Sanci et al. (2022), for instance, emphasize that universities are increasingly expected to promote students' health and well-being in order to optimize academic success and support students' transition to future careers. The study also positions health, well-being, learning factors, and academic performance as interrelated domains within the university student experience.

Mental well-being refers to positive mental health, covering both affective and psychological functioning. Tennant et al. (2007) explain that mental well-being is often used interchangeably with positive mental health and includes both hedonic aspects, such as happiness and life satisfaction, psychological functioning, and self-realization. In this sense, academic performance may contribute to mental well-being because successful academic experiences can strengthen students' sense of competence, self-acceptance, control, and emotional stability. When students perceive that they are able to meet academic demands, they may experience lower academic pressure and stronger confidence in managing their academic life.

Empirical findings also suggest that academic-related factors are connected to students' well-being, although the relationship may not always be strong or linear. According Au et al. (2023), sense of

belonging, resilience, time management skills, and academic performance as predictors of psychological well-being among university students. Their study found that academic performance and sense of belonging added a small, but it is significant amount of variance to self-acceptance, although academic performance alone was not a significant predictor. This indicates that academic performance is still relevant to well-being, but its effect may depend on student characteristics and academic context.

Furthermore, academic stress has been shown to be strongly related to poorer mental well-being among college students. Barbayannis et al. (2022) found that higher academic stress was significantly correlated with lower mental well-being. This finding supports the argument that students' academic experiences can shape their psychological condition. Therefore, when academic performance improves, students may feel more capable of handling academic demands, which can reduce stress and support better mental well-being.

H2: Smart learning influences mental well-being positively

Smart learning refers to a technology-enhanced learning process that provides adaptive, personalized, and context-aware learning support. Hwang (2014) explains that smart learning environments can detect students' learning status and environmental contexts, allowing appropriate information and support to be provided at the right place and time. These environments can also offer guidance, feedback, hints, learning tools, and adaptive learning tasks based on students' needs, behaviors, and performance.

In AI-supported learning, smart learning enables students to access resources, receive personalized feedback, explore ideas, and regulate their learning more independently. Smart learning as an educational paradigm that uses AI and social media to enrich learning experiences and outcomes, while also supporting self-directed learning and engagement through educational resources, collaborative platforms, and personalized feedback loops (Shahzad et al., 2024).

This argument is further supported by Alqurni (2026), who explains that agentic AI can adapt to learner needs, guide learning paths, provide personalized scaffolding, and support students' decisions about "what, when, and how to learn." Perceived agency of AI predicts usefulness, ease of use, and autonomy support, while self-efficacy and autonomy support contribute to self-learning motivation. Similarly, Liang and Reiß (2025) state that AI tools provide "real-time feedback and personalized learning support" and allow students to decide when to seek assistance, how to engage with content, and how far they rely on AI-generated suggestions, which can strengthen agency and competence.

Therefore, smart learning may improve mental well-being because adaptive and supportive learning experiences can reduce cognitive burden, strengthen perceived control, and create more meaningful learning. also indicate that smart learning can create engaging and inclusive educational environments that support both academic performance and mental well-being (Shahzad et al., 2024).

H3: Creepiness influences mental well-being negatively

Creepiness refers to an affective discomfort that emerges when users feel uncertain, uneasy, or threatened during their interaction with technology. In the context of generative AI, It can be a feeling of discomfort experienced when users are unsure how to interact with AI (Baek & Kim, 2023). For instance, AI chatbot gives inaccurate or irresponsible answer that may create discomfort and unease, particularly when users perceive AI as overly human-like, intrusive, or difficult to control.

This stand is consistent with the broader literature on creepy technology, such as Raff et al. (2024) who explain that perceived creepiness can arise from a lack of transparency in technology, especially when users do not clearly understand how the system makes decisions or recommendations. Their study also shows that creepiness functions as a novel inhibitor in smart technology use and is associated with resistance, discomfort, uneasiness, and insecurity toward the technology.

Seberger et al. (2024) in the qualitative study interprete that a technology can be perceived as beneficial and creepy at the same time. They argue that well-being technologies may still generate

affective discomfort when they are embedded in data-hungry app culture, privacy-invasive practices, and surveillance-based digital environments. This is important because it shows that technology designed to support well-being does not automatically produce psychological comfort; instead, it can also create tension, discomfort, and vulnerability.

Therefore, as an unprecedented hypothesis students using AI for learning, creepiness may reduce mental well-being because students may feel uncomfortable, watched, uncertain about how their data are used, or disturbed by AI responses that feel too personal or overly human-like. Such experiences can weaken students' sense of security, control, and psychological comfort.

H4: Self-Efficacy moderates the relationship between academic performance and mental well-being

Self-efficacy is typically cast as an intrinsic psychological asset that potentiates the beneficial outcomes of AI engagement (Wang et al., 2026). This portrayal resonates with Social Cognitive Theory, which posits humans as agentic actors capable of regulating their actions and utilizing technological capabilities to enhance skills and overall functioning (Li et al., 2025). Within this perspective, self-efficacy reflects the capability gain pathway, grounded in the premise that AI consumers can deliberately deploy AI to refine outcomes and thereby enhance psychological homeostasis (Alqurni, 2026). In other words, individuals who possess stronger beliefs in their capabilities are more likely to leverage AI effectively and experience positive psychological outcomes from their achievements.

However, the extent to which these outcomes translate into psychological benefits also depends on how individuals interpret their success. From a perspective emphasizing self-belief, achievement becomes more meaningful when it is attributed to internal competence. In this regard, strong self-efficacy reinforces positive attribution processes and enhances the emotional benefits of achievement (Soaloon & Handayani, 2025).

Consequently, individuals with higher self-efficacy are more likely to perceive their academic accomplishments as a reflection of their own abilities, which strengthens the positive psychological outcomes associated with these achievements. In contrast, when self-efficacy is low, good performance may not fully translate into improved well-being. Therefore, self-efficacy is expected to strengthen the positive relationship between academic performance and mental well-being, such that the psychological benefits are greater at higher levels of self-efficacy (Lin & Zhu, 2024).

H5: Self-Efficacy moderates the relationship between smart learning and mental well-being

The effectiveness of smart learning depends not only on learning strategies but also on individuals' confidence in managing the learning process (Zhang & Chen, 2025). Self-belief plays a critical role in shaping the quality of learning engagement. Individuals with higher self-efficacy tend to be more persistent, reflective, and proactive when utilizing AI in their learning activities (Zhang & Chen, 2025).

In AI-supported environments, smart learning involves more than simply accessing technological tools. Learners are required to interpret AI-generated responses, assess their relevance, and integrate them into their understanding of academic material (Xiao-hua et al., 2025). These processes require cognitive effort and active engagement. When individuals believe in their capability to manage these learning interactions, AI-assisted learning is more likely to be perceived as empowering rather than demanding, thereby contributing positively to their psychological well-being (Bhagat & Sveum, 2025).

However, when individuals have lower levels of self-efficacy, the same adaptive learning processes may become psychologically demanding (Heydarnejad, 2025). Limited confidence in using AI tools may lead to uncertainty or frustration when interacting with complex technologies (Alqurni, 2026). As a result, the psychological benefits of smart learning may not fully emerge. Therefore, self-efficacy is expected to strengthen the positive relationship between smart learning and mental well-being.

The effectiveness of smart learning depends not only on the availability of digital technologies, but also on students' confidence in managing technology-supported learning processes. Smart learning enables students to access learning resources, receive personalized feedback, engage in collaborative

learning, and regulate their learning more independently. Shahzad et al. (2024) explain that smart learning integrates AI and social media into more dynamic learning ecosystems that provide educational resources, collaborative platforms, and personalized feedback loops. These features can support self-directed learning, engagement, academic performance, and mental well-being.

However, the psychological benefits of smart learning may vary depending on students' self-efficacy. In online and technology-supported learning contexts, self-efficacy reflects students' belief in their ability to learn, manage time, and use technology effectively. Zhou and Yu (2021) argue that students with stronger confidence in online learning are more able to manage learning tasks, balance study and life, and maintain better psychological and physical well-being. This indicates that self-efficacy can help students transform digital learning experiences into more positive psychological outcomes.

Self-efficacy may strengthen the positive effect of smart learning on mental well-being because students with high self-efficacy are more likely to use smart learning actively, persistently, and strategically (Bandura, 1986). Hayat et al. (2020) show that academic self-efficacy influences positive learning-related emotions and metacognitive learning strategies, which are important for effective learning. Similarly, Liu et al. (2022) indicate that academic self-efficacy can strengthen the effect of technology-supported collaborative learning on learner performance. These findings suggest that self-efficacy can act as a psychological amplifier that helps students gain greater benefits from smart learning. Therefore, students with higher self-efficacy are more likely to perceive smart learning as useful, manageable, and empowering, which can enhance their sense of control, competence, and psychological comfort. In contrast, students with lower self-efficacy may feel less confident in interpreting AI-generated responses, evaluating information, or integrating digital feedback into their learning process.

H6: Perceived behavior control moderates the relationship between creepiness and mental well-being

Consumer Vulnerability Theory explains that vulnerability does not only arise from individual weakness, but also from situations where consumers experience powerlessness, limited control, or imbalance in their interaction with a system. Baker et al. (2005) define consumer vulnerability as "a state of powerlessness" that arises from an imbalance in interactions and occurs when control is not in the individual's hands, creating dependence on external factors. In the context of AI-supported learning, students may become psychologically vulnerable when AI is perceived as intrusive, opaque, unpredictable, or difficult to regulate. This condition is closely related to creepiness because AI creepiness may arise from discomfort, privacy concerns, and human-like conversational cues in generative AI interaction (Baek & Kim, 2023)

Perceived behavioral control refers to individuals' perceived ability to perform and control a particular behavior. Ajzen (2002) explains that perceived behavioral control consists of self-efficacy and controllability, meaning that individuals evaluate both their capability to perform an action and the extent to which the behavior is under their control. In AI use, perceived behavioral control reflects students' belief that they can manage, verify, limit, or stop using AI when the interaction becomes uncomfortable.

From the perspective of Consumer Vulnerability Theory, students with low perceived behavioral control may be more vulnerable to AI-related creepiness because they feel less capable of managing privacy risks, evaluating AI-generated responses, or controlling their dependence on AI. Privacy risk and information asymmetry can reduce trust, while explainability and transparency can reduce uncertainty in AI interaction (Dang & Li, 2025). Klimova and Pikhart (2025) also emphasize that AI use in education may bring risks such as technostress, privacy concerns, surveillance concerns, anxiety, and over-reliance. This supports the argument that AI may become psychologically threatening when students feel unable to understand or control their interaction with the technology.

Prior research also supports the importance of control in reducing digital vulnerability. Hu et al. (2025) show that digital technostress can create cognitive fatigue, emotional exhaustion, reduced

perceived control, and technological helplessness, while online self-control can reduce the harmful effects of digital stressors. Similarly, Rodríguez-Ruiz et al. (2024) indicate that students' AI use is related to personal psychological characteristics, including self-control and self-efficacy. This suggests that students' capacity to regulate themselves is important in AI-supported learning, especially when they face uncertain or uncomfortable AI interactions.

Therefore, perceived behavioral control may function as a psychological buffer in the relationship between creepiness and mental well-being. Students with high perceived behavioral control are more likely to feel capable of regulating AI use, checking AI-generated information, protecting their privacy, and discontinuing AI use when necessary. In contrast, students with low perceived behavioral control may feel less able to manage intrusive, unclear, or uncomfortable AI interactions. Furthermore, problematic AI chatbot use may emerge when users become overly dependent on AI chatbots and experience loss of self-reliance in solving problems (Yao et al., 2025)

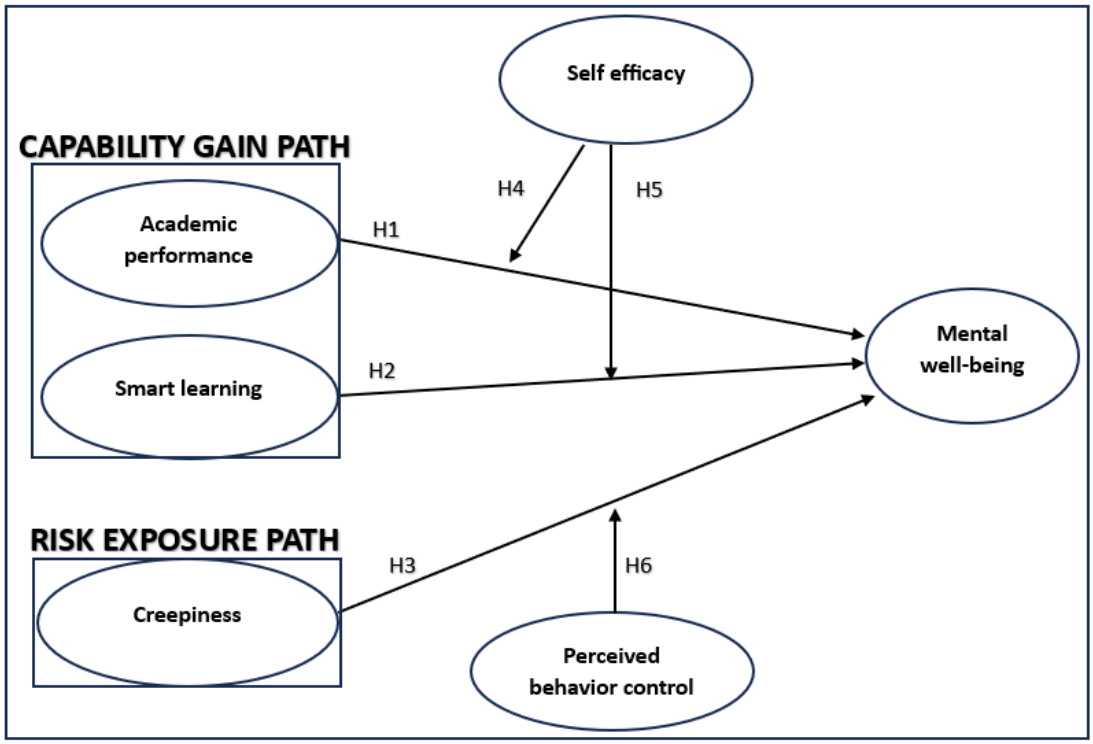


Figure 1. Model is Adapted from Seberger et al. (2024), Salah et al. (2023), Shahzad et al. (2024)

METHOD

Data collection

Data was collected through online survey using google forms. The distribution samples was taken by snowball sampling. The sample in this research is AI users who use AI apps to improve their study. The total questionnaires that can be processed were 1486. In term of sample demography, it consists for several characteristic. For users' experience: 1–6 months: 253 (17,03%), 6 months–1 year: 465 (31,29%), 1–3 years: 617 (41,52%), and more than > 3 years: 151 (10,16%). Duration per day: less than 3 hours: 1.076 (72,41%), 3–6 hours: 327 (22,01%), and more than 6 hours: 83 (5,59%). Ever own AI premium account: never 1.189 (80,01%) and ever 297 (19,99%).

Education categories; bachelor: 1.017 respondents (68,44%), Studying Master: 457 (30,75%), Studying Doctoral: 12 (0,81%). Type of AI (ever used can be more than one): ChatGPT: 1.386 (93,27%), Gemini: 1.000 (67,29%), DeepSeek: 279 (18,78%), Perplexity: 92 (6,19%), SciSpace: 82 respondents (5,52%), Blackbox AI: 37 (2,49%), Claude: 22 respondents (1,48%), and other AI tools (less than 1%). Province of

respondents' origin 36 of 38 Indonesia provinces filled this questionnaire. Central Java 279 (18,78%), Yogyakarta: 256 (17,23%), West Java: 156 (10,50%), East Java 117 (7,87%), East Borneo 86 (5,79%), Riau 81 (5,45%), Lampung: 65 (4,37%), Banten: 57 (3,84%), DKI Jakarta: 57 (3,84%), South Borneo 44 (2,96%), West Nusa Tenggara 35 (2,36%), Jambi: 29 (1,95%), Central Borneo 29 (1,95%), and the other provinces less than 1.5%.

Table 2. Validity and Reliability

Variables	Items	Pearson Coefficient) (5% >0.051)	Sig	Cronbach alpha
Mental well-being	MWB1	0.850	0.000	
	MWB2	0.811	0.000	
	MWB3	0.894	0.000	0.905
	MWB4	0.883	0.000	
	MWB5	0.818	0.000	
Self-efficacy	SE1	0.832	0.000	
	SE2	0.878	0.000	0.881
	SE3	0.870	0.000	
	SE4	0.855	0.000	
Perceived behavior control	PBC1	0.930	0.000	
	PBC2	0.941	0.000	0.921
	PBC3	0.917	0.000	
Academic Performance	AP1	0.829	0.000	
	AP2	0.855	0.000	0.871
	AP3	0.871	0.000	
	AP4	0.844	0.000	
Smart learning	SL1	0.835	0.000	
	SL2	0.830	0.000	0.852
	SL3	0.825	0.000	
	SL4	0.850	0.000	
Creepiness	C1	0.764	0.000	
	C2	0.821	0.000	0.793
	C3	0.759	0.000	
	C4	0.809	0.000	

Data Analysis Technique

Data analysis will begin with validity and reliability testing, followed by data quality assessments, including tests for normality and multicollinierity. Based on table above, all the indicators were valid and reliable. Then, model evaluation will be conducted using Moderated Regression Analysis (MRA) with centering and Macro PROCESS. Indirect effects can be examined through the interaction among the variables. Data will be processed using SPSS and the extension by Hayes V5 (the newest version).

Table 3. Multicollinierity test

Variables	Tolerance	VIF	P Normality Kolmogorov Smirnov
Self-efficacy	0.285	3.506	0.000
Perceived behavior control	0.285	3.508	0.000
Academic Performance	0.233	4.284	0.000
Smart learning	0.253	3.954	0.000
Creepiness	0.657	1.523	0.000

Note: Tolerance <0,10, VIF > 10 = multicollinierity, P>0.05 = normal distribution

Multicollinierity test showed that among independent variables there is not high correlation which indicated each independent can be idenitified by tolerance coefficients more than 0.10. While, normality test cannot be reached due to high sample which were 1486 became so sensitive. Based on Lumley et al. (2002), studies with large sample sizes are relatively robust to violations of the normality

assumption because many statistical methods rely on the Central Limit Theorem. Therefore, non-normal data may not be a serious problem when the sample size is sufficiently large. It is also supported by Li et al. (2012) who argue that abnormal data in regression analysis can be tolerated in large samples.

Table 4. MRA with Centering

Hypothesis	Relationship	Beta	Sig	Result
H1	AP → MWB	0.413	0.000	Significant
H2	SL → MWB	0.161	0.000	Significant
H3	C → MWB	0.003	0.835	Insignificant
H4	AP*SE → MWB	-0.011	0.691	Insignificant
H5	SL*SE → MWB	0.045	0.105	Insignificant
H6	C*PBC → MWB	0.031	0.058	Insignificant

Table 5. Macro PROCESS

Hypothesis	Beta	Sig	Result
H1. AP → MWB	0.4937	0.000	Significant
H2. SL → MWB	0.3363	0.000	Significant
H3. C → MWB	-0.1036	0.2732	Insignificant
H4. AP*SE → MWB	0.0623	0.0006	Significant
H5. SL*SE → MWB	0.0859	0.000	Significant
H6. C*PBC → MWB	0.0740	0.0010	Significant

Hypothesis testing is used two methods MRA with mean centering and Macro PROCESS Hayes. This research attempt to compare the methods whether any difference result or not due to manual and automatic centering. MRA needs to be completed by centering because of the several advantages especially in conduction behavioral research (Iacobucci et al., 2017). Centering helps to interprete clearling among the correlation variables, make the R square is more stabil, and decrease micro multicollinierity. Then, regarding Dawson (2014), mean centering is common procedure to identify main effect interaction and decrease correlation among main variables.

Compared to MRA, Macro PROCESS helps researchers obtain more systematic and comprehensive results in explaining moderation effects by automatically handling centering and creating interaction term formation, unlike MRA which manually need to be set (Hayes, 2022). Overall, Hayes' PROCESS Macro offers a more comprehensive and practical approach because it does not only report the interaction coefficient, but also provides conditional effects for deeper moderation interpretation. It also reduces manual calculations, supports bootstrap confidence intervals, and can handle more complex models such as moderated mediation and serial mediation.

According MRA with centering, it shows that H1 and H2 were significant which was interpreted by the p value less than 0.05, while the other hypothesis were insignificant. However, according macro process by Hayes found different result. It showed that H1, H2, H4, H5, H6 were significant (p-value,0.05). Then, the only insignificant hypothesis was H3. The standing of this research is on PROCESS macro finding which is more comprehensive.

Discussion

First implication, when students have good academic performance, they are more likely to experience academic success, a sense of competence, and satisfaction with their learning process. From a psychological perspective, successful academic experiences can strengthen positive feelings by reducing academic stress, enhancing students' perceived competence, and supporting positive psychological functioning. It is consistent with Barbayannis et al. (2022), finding, Poor academic performance may increase pressure, anxiety, and perceptions of academic failure, which can undermine students' mental well-being. Therefore, academic performance is expected to have a positive influence on students' mental well-being. In this sense, good academic performance does not only represent cognitive achievement, but

may also become a source of positive academic experience that supports mental well-being (Tennant et al., 2007).

Second implication, smart learning can positively influence students' mental well-being because it provides a more flexible, adaptive, and supportive learning environment. A smart learning environment enables students to access learning resources more easily, receive more personalized support, and engage in learning activities that are more responsive to their needs. Hwang (2014) explains that smart learning environments can detect students' learning status and provide appropriate learning support at the right place and time. It also can help students manage academic tasks more effectively, reduce learning-related pressure, and increase their sense of control in the learning process.

When students perceive that their learning process is more accessible, structured, and aligned with their needs, they are more likely to experience positive learning conditions. Such positive learning experiences can support mental well-being because students feel more assisted, more capable, and less overwhelmed by academic demands. In this regard, smart learning is not only a technological learning approach, but also a supportive academic condition. Previous research such as Shahzad et al. (2024), supports the positive role of smart learning in students' mental well-being. Smart learning can contribute positively to students' mental well-being by creating more engaging, flexible, and supportive learning experiences. Therefore, smart learning can be understood as a learning factor that helps students experience a more effective and psychologically supportive academic process.

Third implication, the result shows that creepiness does not have a significant effect on students' mental well-being. This finding indicates that students' uncomfortable feelings toward AI do not necessarily translate into lower psychological well-being (Baek & Kim, 2023). One possible explanation is that students may perceive AI primarily as a practical academic tool rather than as a direct psychological threat. In the learning context, students may focus more on the immediate benefits of AI, such as efficiency, convenience, and academic assistance, rather than its potential risks. Therefore, even when AI feels strange, overly personal, or unpredictable, such feelings may not be strong enough to directly disturb students' psychological comfort or mental well-being (Abbas et al., 2024; Kokolakis, 2017). Perceived creepiness may first affect how users evaluate and continue using AI technology, rather than immediately affecting their mental well-being. In other words, creepiness may reduce trust, create hesitation, or increase resistance toward AI (Baek & Kim, 2023). However, its effect on mental well-being may require stronger exposure, higher awareness, or additional psychological conditions.

Another explanation can be understood through the privacy paradox perspective by Kokolakis (2017). Users often express privacy concerns but still continue using digital technologies when the perceived benefits are more immediate than the perceived risks (Kokolakis, 2017). In the context, students may realize that AI has potential risks, such as data privacy issues, reduced creativity, weaker critical thinking, or dependence on AI-generated answers. However, these risks may feel abstract, distant, or not directly connected to their mental condition. As a result, students may tolerate the creepy or uncomfortable aspects of AI because its academic benefits are more visible and useful in the short term.

Furthermore, according to Abbas et al. (2024), the negative effects of AI may appear more clearly in cognitive or academic outcomes which is associated with procrastination, memory loss, and lower academic performance which emerge in students' learning behavior. Therefore, perceived creepiness may not directly reduce mental well-being. Thus, although creepiness remains an important negative perception in AI use, its psychological impact on mental well-being may only become stronger under certain conditions (Abbas et al., 2024; Baek & Kim, 2023; Kokolakis, 2017).

Fourth implication, the result supports the moderating role of self-efficacy in the relationship between academic performance and mental well-being. This finding indicates that positive psychological effect of academic performance becomes stronger when students have higher self-efficacy. This argument is consistent with Brown et al. (1989), who showed that self-efficacy can moderate the relationship between academic factors and academic outcomes. Their study found that self-efficacy beliefs had facilitative effects on academic performance and persistence.

Students with good academic performance generally experience academic success, a sense of achievement, and satisfaction with their learning process (Lizarte Simón et al., 2024). These experiences can support mental well-being because academic success may strengthen students' sense of competence and confidence in managing academic demands. It is supported by Lera et al. (2023) finding that self-efficacy plays an important role in connecting educational practices with academic performance and students' well-being. In addition, academic self-efficacy reflects students' beliefs in their ability to successfully manage academic tasks and demands, and prior studies have shown that it is closely related to students' academic achievement, adjustment, and psychological well-being in university contexts (Lizarte Simón et al., 2024). In this sense, self-efficacy can be positioned as a psychological amplifier. It strengthens the way academic performance is translated into mental well-being through competence, confidence, emotional stability, and readiness to face future academic challenges.

In contrast, students with low self-efficacy may still achieve good academic performance, but they may not fully experience it as a source of mental well-being. This explanation aligns with Grøtan et al. (2019), who found a strong association between mental distress, academic self-efficacy, and study progress among college students. Students with severe mental distress were more likely to report low academic self-efficacy and delayed study progress, indicating that self-efficacy is closely connected to both academic functioning and students' mental condition.

Fifth implication, the finding supports the moderating role of self-efficacy in the relationship between smart learning and mental well-being. This means that the positive effect of smart learning on students' mental well-being becomes stronger when students have higher self-efficacy. Smart learning provides students with flexible access to learning resources, personalized support, adaptive learning experiences, and technology-based academic assistance. According Shahzad et al. (2024), smart learning plays a positive role in the relationship between educational technology and students' mental well-being, and it can be understood as a learning experience that supports students' psychological condition.

Moreover, Zhou and Yu (2021) found that online learning self-efficacy is positively related to students' well-being in online learning contexts. This indicates that self-efficacy is an important psychological resource that helps students gain benefits from digital learning environments. Students with high self-efficacy are more likely to believe that they can use learning technologies effectively, regulate their independent learning process, complete academic tasks, and overcome difficulties when using digital platforms. As a result, they are better able to transform smart learning facilities into positive and less stressful learning experiences.

Students with higher self-efficacy tend to use deeper learning strategies, regulate their learning more effectively, and show stronger confidence in facing academic challenges (Hayat et al., 2020). Therefore, students with high self-efficacy are more likely to use these features actively and strategically. This allows smart learning to contribute more strongly to their mental well-being. In contrast, students with low self-efficacy may still have access to smart learning, but they may not be able to use it optimally. They may feel confused, less confident, or overwhelmed by the number of digital features, information sources, and AI-generated responses. Thus, academic self-efficacy can positioned as a psychological amplifier to improve mental well-being when students believe that they are capable of using digital technologies, managing learning tasks, and overcoming academic challenges (Liu et al., 2025).

Sixth implication, the result shows that perceived behavioral control significantly moderates the relationship between creepiness and mental well-being. The interaction effect between creepiness and perceived behavioral control is positive and significant, indicating that the relationship between creepiness and mental well-being becomes stronger when students have higher perceived behavioral control. However, the direction of the moderation suggests that perceived behavioral control does not simply weaken a negative effect. Rather, it changes how students psychologically respond to AI-related creepiness.

This finding can be explained through Consumer Vulnerability Theory. Baker et al. (2005) explain that consumer vulnerability may emerge when individuals experience powerlessness, limited control, or dependence on external factors in their interaction with a system. In the context of AI-supported learning, creepiness may reflect students' discomfort when AI is perceived as intrusive, overly human-like, or difficult to predict. Baek and Kim (2023) also show that creepiness in AI interaction is related negative perception in AI use.

Then, the significant moderating effect of perceived behavioral control indicates that students do not respond to AI-related creepiness in the same way. Individuals evaluate both their capability to perform a behavior and the extent to which the behavior is under their control (Ajzen, 2002). In this study, students with higher perceived behavioral control may feel more capable of managing AI use, verifying AI-generated answers, recognizing AI limitations, switching platforms, ignoring disturbing responses, or discontinuing AI use when necessary.

Therefore, AI-related creepiness may not necessarily reduce mental well-being when students feel that they can control their interaction with AI. Instead, among students with high perceived behavioral control, creepiness may reflect awareness of AI-related risks rather than psychological helplessness. Students who are aware that AI can be strange, intrusive, or unreliable may still maintain psychological comfort because they believe they can manage these risks.

This explanation is consistent with Dang and Li (2025), who emphasize the role of explainability and transparency in reducing uncertainty in AI interaction, and with Hu et al. (2025), who show that digital technostress can create reduced perceived control and technological helplessness, while self-control can reduce the harmful effect of digital stressors. On the other hand, students with lower perceived behavioral control may be less able to transform AI-related creepiness into manageable awareness. They may feel confused when evaluating AI-generated responses, uncertain about data privacy risks, or dependent on AI despite feeling uncomfortable. This condition may make them more psychologically vulnerable. the problematic AI chatbot use may occur when users become overly dependent on AI chatbots and experience a loss of self-reliance in solving problems (Klimova & Pikhart, 2025; Yao et al., 2025). Thus, this study contributes to the literature by showing that AI-related creepiness is not only relevant to technology acceptance outcomes (trust, resistance, or continuance intention), but it is also related to mental well-being when students' perceived behavioral control is considered.

CONCLUSION

Overall, the findings show that students' mental well-being is influenced by academic performance, smart learning, and AI-related experiences. Meanwhile, creepiness does not directly reduce mental well-being directly because the students may still view AI mainly as a practical academic tool rather than an immediate psychological threat. The results also highlight the role of psychological resources. Self-efficacy strengthens the positive effects of academic performance and smart learning on mental well-being, as students with higher self-efficacy are better able to transform academic success and digital learning support into confidence and psychological comfort. Perceived behavioral control also changes how students respond to AI-related creepiness. When students feel able to verify AI answers, understand AI limitations, manage risks, or stop using AI when needed, creepiness is less likely to become psychological distress. Thus, mental well-being in AI-supported learning depends not only on academic and technological factors, but also on students' ability to regulate and control their learning experiences.

Limitation

This study has not yet fully developed a coherent set of moderation hypotheses, although each part is supported by a strong conceptual basis. The variable of creepiness can also be considered relatively new in the proposed hypothesis framework, including its moderating mechanism. For future research, the number of buffer and amplifier variables could be expanded by including other relevant variables that

may provide richer findings. In addition, future studies may consider incorporating locus of control as an additional moderator to capture the phenomenon more comprehensively.

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Table 6. Indicators

Variables	Items
Smart learning Shahzad et al. (2024)	1. AI tools, such as ChatGPT, Gemini, DeepSeek, and others, help me learn various topics. 2. AI tools, such as ChatGPT, Gemini, DeepSeek, and others, help me in group work. 3. AI tools, such as ChatGPT, Gemini, DeepSeek, and others, help me perform better than others. 4. AI tools, such as ChatGPT, Gemini, DeepSeek, and others, help me learn new things.
Academic performance Youssef et al. (2024)	1. AI tools, such as ChatGPT, Gemini, DeepSeek, and others, provide innovative ideas for students. 2. Students can obtain comprehensive written content from AI tools, such as ChatGPT, Gemini, DeepSeek, and others. 3. AI tools, such as ChatGPT, Gemini, DeepSeek, and others, improve my academic achievement. 4. AI tools, such as ChatGPT, Gemini, DeepSeek, and others, accelerate my learning process.
Mental well-being Tennant et al. (2007)	1. By using AI tools, such as ChatGPT, Gemini, DeepSeek, and others, I feel that I become a more useful person. 2. By using AI tools, such as ChatGPT, Gemini, DeepSeek, and others, I feel more relaxed. 3. By using AI tools, such as ChatGPT, Gemini, DeepSeek, and others, I feel that I can handle problems better. 4. By using AI tools, such as ChatGPT, Gemini, DeepSeek, and others, I can think more clearly. 5. By using AI tools, such as ChatGPT, Gemini, DeepSeek, and others, I become interested in many new things.
Creepiness Wozniak et al. (2021)	1. I believe that AI designers are aware that unethical actions may occur in the future. 2. AI system design sometimes produces inaccurate outputs. 3. Sometimes, others underestimate me because I frequently use AI. 4. Sometimes, AI provides me with strange or inaccurate information.
Self-efficacy Carolus et al. (2023)	1. I can rely on AI tools, such as ChatGPT, Gemini, DeepSeek, and others, in difficult situations. 2. I am independently skilled in using AI tools, such as ChatGPT, Gemini, DeepSeek, and others. 3. I can complete difficult and complex tasks with the help of AI tools, such as ChatGPT, Gemini, DeepSeek, and others. 4. I can continuously keep up with the latest developments in AI.

Perceived behavior control Ivanov et al. (2024)	1. Based on my own decision, I use AI tools, such as ChatGPT, Gemini, DeepSeek, and others, in the learning process. 2. Based on my own beliefs, I use AI tools, such as ChatGPT, Gemini, DeepSeek, and others, during the learning process. 3. I have the skills, time, and opportunities to use AI tools, such as ChatGPT, Gemini, DeepSeek, and others, in the learning process.

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