

## Understanding the Relationship Between Usage of Generative Artificial Intelligence Tools and Learning Performance: A Dual-Path Perspective

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### ABSTRACT

With the rapid advancement of generative artificial intelligence (GAI) technologies, tools such as ChatGPT have become prevalent in educational settings, enhancing the efficiency and convenience of learning tasks. However, concerns about their potential negative impacts have emerged within the academic community. To solve the debate, this study aims to conduct a comprehensive analysis of how GAI tools influence the learning process and outcomes. Drawing upon the Adaptive Structuration Theory (AST), this study investigates the impacts of two types of GAI usage namely exploitative and explorative use on two kinds of learning performance (e.g., routine and innovative learning performance) through two opposite mechanisms. On the one hand, through positive reinforcement process, GAI use can improve learning performance by increasing students' routine and creative self-efficacy. On the other hand, through the negative reinforcement process, GAI use may reduce learning performance by increasing technology dependence and deskilling. A survey of 306 GAI users was conducted to test the proposed hypotheses, and the results suggest that (1) both explorative and exploitative use positively influence routine and creative self-efficacy which in turn have positive impacts on routine and innovative performance, (2) both explorative and exploitative use positively influence technology dependence which positively affects routine and innovative performance, and (3) GAI use has no significant direct effect on deskilling but an indirect effect on deskilling through technology dependence and deskilling negatively influences innovative performance.

**Keywords:** Generative artificial intelligence tools, exploitative use, explorative use, deskilling, learning performance.

### INTRODUCTION

In 2022, OpenAI's release of ChatGPT (Chat Generative Pre-trained Transformer) marked a milestone in the field of generative artificial intelligence (GAI). ChatGPT excels at engaging in human-like conversations, providing instant responses, and assisting users in various tasks such as writing emails, articles, and generating software code (Ortiz, 2023). Upon its release, it garnered widespread attention and a large user base. Major internet companies in China quickly followed suit, introducing their own GAI products, such as ERNIE Bot, Kimi Chat, and Tongyi Qianwen. The success of ChatGPT has ushered AI tools into the era of GAI, characterized by creativity and adaptability, enabling them to perform complex tasks, generate diverse outputs, and continuously learn and improve.

GAI tools like ChatGPT have been widely applied across various fields to enhance efficiency and create value, significantly impacting the ecosystem and working patterns in numerous industries. In education, the use of GAI has profoundly influenced various aspects of higher education (Karakose, 2023). These tools can generate coherent and contextually appropriate responses based on students' queries, aiding in coding, text organization, mathematical calculations, statistical analysis, and document translation (Mhlanga, 2023). They are used to assist in research, homework, papers, and academic projects (Bahroun, Anane, Ahmed, & Zacca, 2023), providing effective support for learning tasks and academic work (Wadhawan, Jain, & Galhotra, 2023).

Current research has demonstrated that using GAI tools like ChatGPT to complete learning tasks can significantly enhance the learning experience (Firat, 2023), promote engagement and collaboration, and effectively support remote learning (Cotton, Cotton, & Shipway, 2024). A global survey across five countries revealed that 61% of students believe ChatGPT should be used to assist with homework (Ibrahim et al., 2023).

However, despite the undeniable benefits and conveniences provided by GAI tools in learning tasks, there are concerns about their potential misuse (Smolansky et al., 2023). Completing a learning task involves multiple deep strategy processes such as analysis, interpretation, application, and comprehension (Scouller, 1998). Outsourcing these tasks to ChatGPT, which can generate contextually coherent text based on a set of parameters and prompts almost indistinguishable from human writing, undermines the need for complex cognitive processing and higher-order thinking, thus potentially leading to over-reliance on technology, hindering the development of fundamental skills, and threatening traditional educational assessment methods

(Mohammadkarimi, 2023). Additionally, its use may lead to academic integrity violations and weaken students' achievement motivation (Krou, Fong, & Hoff, 2021; Petricini, Wu, & Zipf, 2023).

Understanding the potential benefits and issues of using GAI tools like ChatGPT can help develop effective usage strategies to integrate these technologies into the learning process while controlling their misuse in higher education (Meyer et al., 2023). This is crucial for educators, policymakers, and students. Therefore, scholars call for future research to delve deeper into the pros and cons of ChatGPT in higher education (Bahroun et al., 2023; Chaudhry, Sarwary, El Refae, & Chabchoub, 2023).

However, there are several key gaps in existing research to understand the impact of GAI use on academic performance. First, a unified theory has not been developed to consider both the positive and negative impacts of GAI use. Second, there remains a lack of distinction between explorative and exploitative uses of GAI, each potentially impacting learning differently. Third, previous studies have not distinguished the different roles of explorative and exploitative GAI use. Finally, previous studies have not distinguished innovative learning performance from routine learning performance and examined their different formation mechanisms. To address the problems of the current research, this study examines the dual effects (positive or negative) of using GAI tools such as ChatGPT on students' routine performance and innovative performance in the process of completing a learning task in terms of two types of use: exploratory and utilized use. It aims to dialectically examine the impact of GAI technology on education, clarify the intrinsic logic and theoretical mechanisms by which GAI technology promotes or hinders the learning process, and leverage the advantages of ChatGPT and other GAI tools while minimizing their negative impacts.

## THEORETICAL BACKGROUND

### GAI Use in Education

GAI tools, such as ChatGPT, are rapidly expanding their applications in education, primarily in four areas: natural language processing, problem-solving, virtual learning, and learning process optimization. These tools leverage advanced language models to enhance text translation and interpretation (Burger, Kanbach, Kraus, Breier, & Corvello, 2023; Strzelecki, 2023), improve students' problem-solving and logical reasoning abilities (Paschen, Wilson, & Ferreira, 2020), provide personalized experiences in virtual learning environments (G. Cooper, 2023; Kasneci et al., 2023), and increase information retrieval efficiency, thereby optimizing the learning process (Dwivedi et al., 2023; Sweller, 2020).

One major category of research on GAI tools in education focuses on exploring the key factors influencing user adoption of GAI tools and providing strategies for GAI in education. Strzelecki based on the Technology Acceptance Model, identified habit, performance expectancy, and hedonic motivation as the main drivers for Polish students using ChatGPT (Strzelecki, 2023). Yilmaz et al. using the UTAUT model in India, pointed out that perceived usefulness, trust, social influence, privacy, security, and ease of use positively influence students' attitudes (H. Yilmaz, Maxutov, Baitekov, & Balta, 2023). Tribikram's comparative study showed that performance expectancy and social influence significantly impact ChatGPT adoption intentions among students in the UK and Nepal, though the impact of anxiety varies by country (Budhathoki, Zirar, Njoya, & Timsina, 2024). Akhmad's research in Indonesia found that facilitating conditions and behavioral intention are key predictors of ChatGPT usage (Habibi et al., 2023). These findings provide data support for educational decision-makers to develop strategies for effectively applying GAI tools in education.

The other major research category of research on GAI tools in education explores the potential advantages and problems of using GAI tools such as ChatGPT, which helps to identify the mechanisms of action and accordingly develop effective strategies for users. Osorio et al. found that ChatGPT enhances students' written communication skills by providing grammar corrections and writing feedback (Osorio, 2023). Ali et al. suggested that ChatGPT motivates learners to develop reading and writing skills (Ali, Shamsan, Hezam, & Mohammed, 2023). Qadir et al. confirmed ChatGPT's potential in fostering teamwork (Qadir, 2023), while Yilmaz et al. found it significantly improves students' computational thinking and programming self-efficacy (R. Yilmaz & Yilmaz, 2023b). Studies indicated that ChatGPT positively influences learning motivation (Salmaan, 2023), although Siregar found this effect might vary by age and gender (Siregar, Hasmayni, & Lubis, 2023). Despite the apparent benefits of ChatGPT, concerns about its potential misuse have also arisen. Shrivastava and Susnjak worry that it may threaten the development of students' basic skills and the security of examinations (Shrivastava, 2022; Susnjak, 2022). Meckler and Verma have expressed concerns about the potential for academic misconduct associated with ChatGPT usage (Meckler & Verma, 2022).

Through a review of existing literature, it is evident that current research tends to emphasize the positive aspects of GAI tools like ChatGPT, such as improved learning efficiency, motivation, and language skills, while paying less attention to potential negative impacts. This has led to a biased understanding of its comprehensive effects. Additionally, research often focuses on unilateral effects, overlooking the complexity and duality of technology usage and lacking exploration of the interaction between positive and negative effects. Moreover, the classification of tool usage is overly generalized, lacking detailed segmentation of usage behaviors, which limits in-depth understanding of usage motivations, processes, and outcomes. Therefore, this study focuses on detailed types of tool usage and the dual impact of different usage methods on learning outcomes and educational practices.

### **Two types of GAI use: exploitative use and explorative use**

The diverse and robust capabilities of Generative Artificial Intelligence (GAI) tools offer users a plethora of applications. However, the extent of engagement with GAI tools varies among users. While some restrict their utilization to elementary tasks, others embrace a more expansive approach, exploring a wider array of functionalities. To delineate these distinct usage patterns, March's theoretical framework of exploitation and exploration innovation is pertinent. Within this framework, exploration encompasses the activities of "searching, discovering, and innovating," in contrast to exploitation, which is linked to notions of "production, efficiency, implementation, and execution" (March, 1991). March succinctly describes the difference between exploration and exploitation as the contrast between "exploring new possibilities" and "utilizing old certainties" (March, 1991).

Although the concepts of exploration and exploitation are commonly applied to the realms of organizational learning and knowledge management, they have been extended to the domain of information systems usage (Burton-Jones & Straub, 2006; Subramani, 2004). Subramani introduces the constructs of exploitative use and explorative use within the context of information system usage behavior, where the former pertains to the systematic, repetitive employment of systems to augment efficiency, and the latter involves the utilization of systems for the innovative execution of unstructured or existing tasks (Subramani, 2004).

In light of these definitions, this study categorizes the utilization of generative AI tools within the scope of generative AI-assisted learning tasks into two behavioral modalities: exploitative use and explorative use. Exploitative use refers to the systematic or repetitive use of GAI tools to enhance efficiency, while explorative use involves using these tools in novel or innovative ways to achieve innovative task execution. These classifications facilitate a nuanced examination of how individuals engage with GAI tools, whether through the optimization of existing processes or the pursuit of innovative applications.

### **Adaptive Structuration Theory**

The introduction of GAI tools in the education field is a technological innovation that provides new functions and introduces new ways of thinking, potentially triggering structural adjustments in learning behaviors and educational practices (Romanow, Rai, & Keil, 2018). These tools offer efficient solutions for students' information acquisition and organization while challenging traditional learning processes and knowledge absorption models. These changes align with AST's theory on how technology influences organizations, indicating that the AST framework is suitable for analyzing the impact of GAI tools on learning behaviors and performance. Therefore, this study chooses AST as the overall theoretical framework to explore how GAI tools assist in completing learning tasks and analyze their potential impact on learning behavior transformation and learning performance.

DeSancti and Poole, based on Giddens' "structuration theory," developed the Adaptive Structuration Theory (AST). AST emphasizes that technology possesses both functional and mental characteristics, capable of interacting with existing organizational structures to induce social change. Individuals adjust organizational roles, norms, behaviors, and decision-making mechanisms through technology use, allowing organizations to adapt to new environments and technological changes (R. B. Cooper & Zmud, 1990; DeSanctis & Poole, 1994). AST reveals the interaction mechanism between technological structures and organizational structures, providing theoretical support for understanding how technology influences organizations and society.

In summary, the basic form of the AST framework is "technological features → adaptation process → transformation impact" (Zhang, Liu, Cheng, Wang, & Wang, 2023). In this study, we will take exploitative use and explorative use as the technological features variables, and classify the reinforcement effects in the adaptation process into positive and negative reinforcement effects, in which the enhancement of routine self-efficacy and creative self-efficacy as the positive reinforcement effects, leading to technology dependence and deskilling as the negative reinforcement effects. The transformational impact of technology characteristics in the adaptation process will be measured by routine learning performance and innovative learning performance. As a result, an overall modelling framework based on AST was constructed.

### **Affordance Actualization Theory**

This study employs Affordance Actualization Theory to explain how different usage methods of technology empower learning behaviors in the research model. Participants take usage actions based on learning goals by utilizing the affordances of technology, thereby achieving enhancing or inhibiting learning behavior results.

Affordance Actualization Theory emphasizes that actors take action by utilizing the affordances provided by technology to achieve immediate specific outcomes that support organizational goals (Kumar, Rajan, Venkatesan, & Lecinski, 2019). This theory not only focuses on the functional characteristics of technology but also considers the interaction process between users and technology (Markus & Silver, 2008). The realization process is iterative, with the outcomes of actions serving as feedback to influence subsequent actions, forming a continuous interaction between actions and outcomes.

On one hand, the affordance actualization perspective has been successfully applied to study the use of technology and its impact, providing a solid foundation for researching other forms of technology usage, consistent with this study's context of GAI tool usage (Anderson & Robey, 2017). On the other hand, this theoretical perspective includes the influence of technological characteristics on user behavior and outcomes, meeting the need to understand the impact of GAI tools on students' learning behaviors and outcomes in this study's context. GAI tools possess affordances that support routine learning tasks and exploring new knowledge, enabling users to achieve different affordances through exploitative and explorative usage. Based on affordance actualization, enhancing routine and creative self-efficacy, technology dependence, and deskilling as immediate specific outcomes, acting as intermediate variables between use and performance.

### RESEARCH MODEL AND HYPOTHESES

This study is based on the Adaptive Structuration Theory and the Affordance Theory, and combines the theory of exploitation and exploration innovation with the characteristics of GAI tools to assist in completing learning tasks, distinguishing between exploitative use and explorative use as technological features. Through the positive reinforcement (enhancement of routine self-efficacy, creative self-efficacy) and negative reinforcement (technology dependence, deskilling) of the technology adaptation process, it explores the impact on routine learning performance and innovation learning performance. The theoretical model constructed is shown in Figure 1.

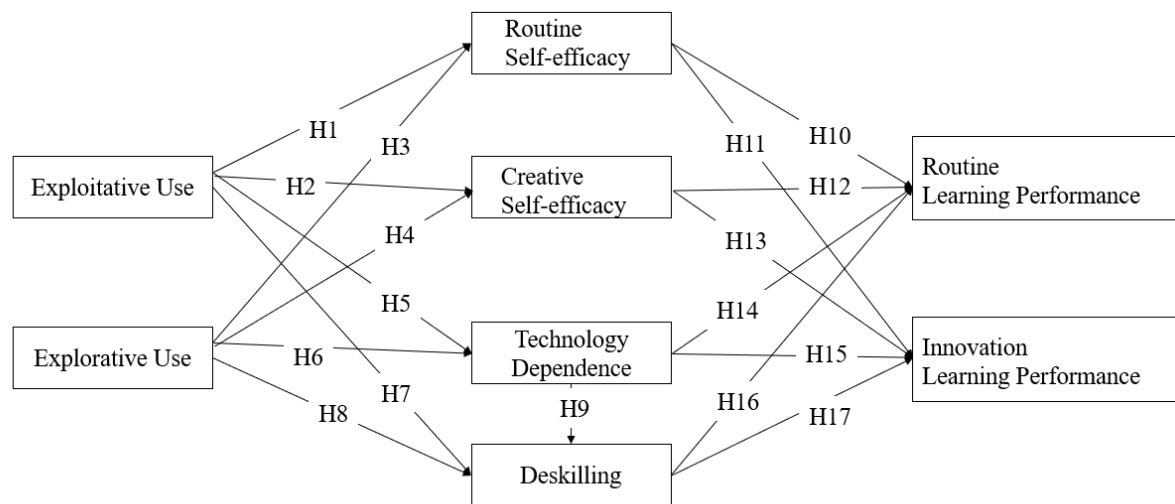


Figure 1: Theoretical model and hypotheses

#### GAI Tool Usage and Self-Efficacy

##### *Concepts of Routine Self-Efficacy and Creative Self-Efficacy*

Self-efficacy originates from social cognitive theory and refers to an individual's belief in their ability to complete specific tasks or job duties (Bandura, 1997). Individuals with high self-efficacy tend to perform actions they believe they can master and exhibit confidence in their abilities across various activities and contexts (Zander, Brouwer, Jansen, Crayen, & Hannover, 2018). Bandura identified four main sources of self-efficacy: successful practice, vicarious experiences, social persuasion, and overcoming emotional barriers (Bandura, 1997). In this study we distinguish between routine self-efficacy and creative self-efficacy.

In this study, routine self-efficacy refers to an individual's confidence in their ability to perform necessary actions to achieve predetermined outcomes in routine learning tasks. Conversely, creative self-efficacy refers to an individual's belief in their ability to use innovative methods, develop creative thinking, and flexibly utilize resources to achieve innovative outcomes in learning tasks.

##### *Exploitative Use and Self-Efficacy*

Exploitative use of GAI tools implies that the learner utilizes the tool functions in a known and routine way to accomplish a given learning task, e.g., college students are able to efficiently complete learning tasks such as academic surveys, academic assignments, etc., through a series of commands utilizing GAI tools (Roose, 2022). It can be seen that the utilization-based use of GAI tools can enhance their routine self-efficacy from the perspective of successful practice of self-efficacy sources. At the same time, the utilization-based use of GAI tools attenuates negative emotions such as anxiety or stress in the process of completing routine tasks, which can enhance their routine self-efficacy from the perspective of overcoming emotional barriers (Kavanagh & Bower, 1985). March concluded that rapid routines of exploitative activities enhance exploratory activities such as variation and innovation (March, 1991). Exploitative use, on the other hand, solves the procedural tasks involved in innovative behavior, which can underpin and liberate the ability to innovate, and may thus enhance the user's creative self-efficacy.

Therefore, the following hypotheses are proposed:

H1: Exploitative use positively influences routine self-efficacy.

H2: Exploitative use positively influences creative self-efficacy.

### ***Explorative Use and Self-Efficacy***

The explorative use focus on describing the user's exploration and experimentation in using a GAI tool to discover new possibilities and functions that may go beyond the original intent and predefined functions of the task set. In the context of this study, explorative use solves problems in learning tasks in a more varied and flexible way, enhancing students' sense of control (S. Y. Cooper & Lucas, 2007), which in turn boosts confidence and leads to increased routine self-efficacy. At the same time, explorative use has the behavioral characteristics of innovation, and the increase in the degree of explorative use enhances the practice of innovation. Therefore, explorative use as a category of innovative behaviors can positively influence their innovative attitudes and strengthen the perception of self-innovation ability (Coeurderoy, Guilmot, & Vas, 2014), which can enhance creative self-efficacy in terms of behavioral practices.

Therefore, the following hypothesis is proposed:

H3: Explorative use positively affects routine self-efficacy.

H4: Explorative use positively influences innovative self-efficacy.

### **GAI Tool Use and Technology Dependence**

Technology dependence is defined as "the extent to which a user relies on technology to solve a problem or perform a specific function" (Fan, Liu, Wang, & Wang, 2017). Accordingly, this study defines technology dependence as the extent to which a user relies on generative GAI tools such as ChatGPT to solve a problem or perform a specific function in the process of accomplishing a learning task.

Exploitative use of GAI tools can replace users to quickly complete many routine tasks, including writing, computing, coding, etc. Explorative use of GAI tools can help users to develop new functions and play styles, and generate novel ideas and creativity. The two uses of GAI tools cover the basic realization of the learning task to the exploration of the extension, which can effectively assist users in the whole process of completing the learning task. Technology availability directly affects technology dependence (Fan et al., 2017), so the convenient, efficient, and comprehensive features of GAI tools are likely to increase the degree of users' dependence on them in the process of completing learning tasks.

Therefore, the following hypothesis is proposed:

H5: Exploitative use positively influences technology dependence.

H6: Explorative use positively influences technology dependence.

### **GAI Tool Usage and Deskilling**

Long-term disuse of skills leads to their decay, i.e., deskilling (Arthur Jr, Bennett Jr, Stanush, & McNelly, 1998). Exploitative use of GAI tools can replace users' regular task skills (Chan, Wong, Yau, & Lam, 2023), and explorative use reduce users' cognitive skill practice. Therefore, continuous exploitative use or explorative use of ChatGPT for learning tasks may reduce students' academic training during learning tasks, foster laziness, and weaken their task-related skills (R. Yilmaz & Yilmaz, 2023a).

Therefore, the following hypothesis is proposed:

H7: Exploitative use positively influences deskilling.

H8: Explorative use positively influences deskilling.

### **Technology Dependence and Deskilling**

Over time, the over-reliance on GAI tools such as ChatGPT for learning tasks rather than critical thinking and brainstorming may impair memory retention, cognitive functioning, and critical thinking skills (Dwivedi et al., 2023), ultimately leading to deskilling. In addition, technology dependence refers to the tendency of users to rely on technology to solve problems or perform specific operations in place of human implementation (Fan et al., 2017). This may lead to long-term idleness of task-relevant skills, and it can be inferred that technology dependence may contribute to the phenomenon of deskilling.

Therefore, the following hypothesis is proposed:

H9: Technology dependence positively affects deskilling.

### **Self-Efficacy and Learning Performance**

#### ***Concepts of Routine and Innovation Learning Performance***

The field of learning performance has been divided into two categories: routine learning performance and innovation learning performance. Routine learning performance is the learning performance that is commonly defined in learning-related research, which refers to the level of academic excellence demonstrated by students in their pursuit of academic achievement (Abbas, Jam, & Khan, 2024). In contrast to innovation learning performance, routine learning performance, as defined in this study, specifically emphasizes student performance in foundational or universal learning tasks. This performance typically involves mastery and application of existing knowledge, as well as engagement and achievement in standardized learning

activities. In contrast to routine learning performance, innovation learning performance in this study refers to the level of performance in which an individual proposes and implements novel and effective solutions to accomplish a learning task.

### ***Routine Self-Efficacy and Learning Performance***

Academic self-efficacy is widely recognized as a key factor in promoting academic performance (Lane & Lane, 2001; Meng & Zhang, 2023). It can be postulated that routine self-efficacy in this study may have a positive impact on routine learning performance enhancement. The realization of innovation learning performance is believed to be based on the deepening and generalization of existing knowledge systems or skills (Yildiz, Murtic, Klofsten, Zander, & Richtnér, 2021). Routine self-efficacy serves to reinforce individuals' confidence in their ability to complete a range of basic learning tasks. This, in turn, facilitates the development of innovative behaviors in learning tasks and ultimately contributes to the enhancement of innovation learning performance.

Therefore, the following hypothesis is proposed:

H10: Routine self-efficacy positively influences routine learning performance.

H11: Routine self-efficacy positively influences innovation learning performance.

### ***Creative Self-Efficacy and Performance***

Numerous studies have demonstrated the positive impact of creative self-efficacy on innovation learning performance (Park, Jang, Thomas, & Smith, 2021). In addition, students with high creative self-efficacy tend to adopt diverse learning approaches (S. Y. Cooper & Lucas, 2007), suggesting that they demonstrate greater flexibility and adaptability in the learning process. Such intrinsic motivation and diverse learning strategies not only play a role in innovative activities, but also stimulate higher engagement and enthusiasm for learning in routine learning tasks, push students to think innovatively when faced with problems, and make the processing of routine learning tasks more efficient.

Therefore, the following hypothesis is proposed:

H12: Creative self-efficacy positively influences routine learning performance.

H13: Creative self-efficacy positively influences innovation learning performance.

### ***Technology Dependence and Learning Performance***

Relying on external resources without personal engagement and active learning may hinder the development of necessary learning-related skills and diminish the depth of knowledge needed to acquire academic success (Chan et al., 2023). GAI tools may reduce the opportunities for students to solve problems on their own by providing automated solutions (Baidoo-Anu & Ansah, 2023). Prolonged reliance on GAI tools may change students' learning habits and strategies, making them more inclined to find quick solutions rather than develop long-term learning skills (Dron, 2023). This change may cause students to have difficulty completing regular learning tasks without these tools, thus affecting their routine learning performance. If students become accustomed to relying on GAI tools to provide immediate feedback and answers, they may not learn or understand concepts in depth, but rather remain at the surface of knowledge, gradually losing the ability to analyse independently and form autonomous judgements. Such superficial learning and weakened analytical skills have a particularly negative impact on innovation learning performance, as innovation often requires critical analysis and synthesis of existing knowledge (Hoidn & Kärkkäinen, 2014). At the same time the habit of following the solutions provided by GAI tools may diminish the willingness to explore new approaches or solve problems creatively. In summary, technology dependence may impair innovation learning performance.

Therefore, the following hypothesis is proposed:

H14: Technology dependence negatively affects routine learning performance.

H15: Technology dependence negatively affects innovation learning performance.

### ***Deskilling And Learning Performance***

Deskilling refers to the phenomenon where the proficiency in certain skills diminishes due to prolonged disuse or lack of practice, often as a consequence of technological advancements that reduce the necessity for manual intervention or specialized knowledge in specific tasks (Dornelles, Ayala, & Frank, 2023). This process can lead to the atrophy of once-required competencies as technology assumes roles previously performed by individuals, thereby altering the skill set demanded in a given field or occupation. Empirical studies have consistently demonstrated a robust positive link between task skills and task performance (E. R. Bravo, Santana, & Rodon, 2015). This relationship implies that any degradation in task skills directly correlates with a decline in task performance. Within the context of learning tasks, the erosion of skills pertinent to learning impedes users from executing routine academic activities with the same level of proficiency or precision they once possessed, thus causing a decline in routine learning performance. Innovative learning performance requires expanding and applying on existing knowledge or skills (Yildiz et al., 2021). If pre-existing skills are deskilling, individuals may experience difficulties in attempting to innovate because they are unable to effectively utilize or integrate their existing knowledge and skills, thus limiting the generation of innovative thinking and creative solutions.

Therefore, the following hypothesis is proposed:

H16: Deskilling negatively affects routine learning performance.

H17: Deskilling negatively affects innovation learning performance.

## METHODOLOGY

### Research Setting

To validate the proposed model, a thorough online survey was executed. The survey targeted school students in China who had engaged with generative AI tools like ChatGPT and ERNIE Bot for educational purposes. ChatGPT, an AI-powered conversational agent crafted by OpenAI, offers prompt and precise answers to inquiries posed in natural language, as documented by van Dis et al. (Van Dis, Bollen, Zuidema, Van Rooij, & Bockting, 2023). By the close of 2023, it had nearly reached a user base of one billion per month, underscoring its global ubiquity. ERNIE Bot, developed by Baidu, mirrors this popularity and is a widely used generative AI tool within China. Consequently, examining ChatGPT and ERNIE Bot serves as a fitting context for investigating the impacts of generative AI on learning.

### Measurement Development

With the exception of the deskilling scale, all measures were derived from existing research and adapted slightly to the context of the GAI-supported learning task. Participants rated their agreement with the constructs using a seven-point Likert scale, ranging from "completely disagree" to "completely agree."

Specifically, exploitative and explorative uses were gauged using the scale developed by Koo, Chung, & Kim (2015). Besides, the items measuring routine self-efficacy were adapted from Wang, Liang, & Tsai (2018), while creative self-efficacy was evaluated with items modified from T. W. Ng & Lucianetti (2016). Additionally, technology dependence was measured according to the study by Shu, Tu, & Wang (2011). Routine performance was assessed with items adapted from P. M. Ng, Chan, & Lit (2022). Furthermore, innovation performance was similarly measured with three items derived from Janssen (2000), ensuring a concise yet comprehensive evaluation of the constructs of interest. Besides, the assessment of routine self-efficacy incorporated items adapted from Wang, Liang, & Tsai (2018), while creative self-efficacy was evaluated with items modified from T. W. Ng & Lucianetti (2016). Additionally, technology dependence was measured according to the study by Shu, Tu, & Wang (2011). Routine learning performance was assessed with items adapted from P. M. Ng, Chan, & Lit (2022). Furthermore, the items measuring innovation learning performance were adapted from Janssen (2000).

To date, however, no research has developed an instrument that can quantify the extent of the impact of technology assistance on deskilling. Therefore, this study constructs its own scale for measuring deskilling based on the research context, definition, concepts and theories of deskilling. The concept of skill can be identified at three levels: knowledge, skills, and abilities (Arthur Jr et al., 1998; N. Wang, Schnipke, & Witt, 2005). Knowledge is the information, principles, and facts needed to understand and perform a specific task and is the internalisation of skills (Butler, 1978; A. D. Ritzhaupt & Martin, 2014). Skills are the outward manifestation of the ability to apply knowledge to perform a task on a specific task (A. D. Ritzhaupt & Martin, 2014). They are specific, observable behaviours or activities. Competencies are latent, intrinsic traits of an individual that allow the individual to apply knowledge and skills in different contexts (A. Ritzhaupt, Martin, & Daniels, 2010). In summary, in order to fully assess deskilling, this study argues that it is necessary to measure the extent of deskilling across the three dimensions of knowledge, skill, and competence in order to provide an accurate picture of the overall trend of skill change. The process of deskilling emphasises the degradation that occurs when an individual stops applying or mastering the knowledge, skills and abilities associated with a particular skill (Arthur Jr et al., 1998). This study concentrates on the degree of deskilling that may be induced by GAI tools. Specifically, it examines whether the robust capabilities of GAI tools might compensate for individuals' lack of skills to complete tasks, thereby hindering or halting the development of their own skills. Therefore, the scale developed in this study was designed to assess the risk and performance of deskilling caused by the process by which a GAI tool performs a task in place of the user so that the user no longer needs to directly acquire the relevant knowledge, skills, and abilities. Based on the above concepts, definitions, theories and research background the deskilling scale was completed and summarised into three question items, namely, "Some knowledge can be obtained through GAI tools, so that I no longer need to master this knowledge myself", "Some skills can be replaced through GAI tools, so that I no longer need to master these skills myself", "GAI tools make some abilities less important and eliminate the need for me to develop them".

Finally, in order to establish the face validity of the instrument, it underwent initial evaluation by five doctoral candidates proficient in GAI and experienced in its application. Their feedback prompted minor adjustments to the items, ensuring their suitability for the study's objectives. Details of the variables measured and their corresponding items, along with citations from relevant literature, are presented in the subsequent table.

Table 1: Constructs and measures

Constructs	Serial Number	Items	Sources
Exploitative use (IU)	IU1	I fully use the available GAI tools features to complete my tasks *	Koo et al. (2015)
	IU2	I use most of the available GAI tools features in performing my tasks	
	IU3	I make thorough use of the available GAI tools features to accommodate my tasks *	

	IU4	I use all the available GAI tools features to help me with my tasks	
Explorative use (RU)	RU1	I explore new uses of the GAI tools to support my tasks	Koo et al. (2015)
	RU2	I often experiment with new ways of using the GAI tools to accomplish my tasks	
	RU3	I often find new uses of the GAI tools in performing my tasks	
	RU4	I use the GAI tools in novel ways to complete my tasks	
Routine self-efficacy (RSE)	RSE1	I am certain I can understand the ideas taught in the course *	Wang et al. (2018)
	RSE2	Compared with others in class, I think I am a good student	
	RSE3	I think I will receive a good grade in class	
	RSE4	My study skills are excellent compared with others in class	
	RSE5	I know that I will be able to learn the material for class	
Creative self-efficacy (CSE)	CSE1	I have confidence in my ability to solve problems creatively	T. W. Ng & Lucianetti (2016)
	CSE2	I feel that I am good at generating novel ideas	
	CSE3	I have a knack for further developing ideas of others	
Technology dependence (TD)	TD1	GAI tools have replaced many traditional learning methods and devices, better assisting me in completing learning tasks*	Shu et al. (2011)
	TD2	Most of my learning tasks are done with the support of GAI tools	
	TD3	I would be difficult to image my learning without GAI tools	
	TD4	The conveyance and transformation of knowledge during learning tasks are achieved through GAI tools	
	TD5	GAI tools have become part of the daily routine in my learning life	
Routine learning performance (RP)	RP1	GAI tools help me to accomplish my tasks more quickly *	Ng et al. (2022)
	RP2	GAI tools improve my learning performance	
	RP3	GAI tools enhance my academic effectiveness *	
	RP4	GAI tools help reviews and eliminate errors in my work tasks *	
	RP5	GAI tools help me to realize my future target	
	RP6	GAI tools help me acquire new knowledge	
Innovation learning performance (IP)	IP1	GAI tools help me to create new ideas for difficult issues	Janssen (2000)
	IP2	GAI tools help me to search out new learning methods, techniques, or instruments	
	IP3	GAI tools help me to generate original solutions for problems	
Deskilling (DS)	DS1	Some knowledge can be obtained through GAI tools, so that I no longer need to master this knowledge myself	Self-developed
	DS2	Some skills can be replaced through GAI tools, so that I no longer need to master these skills myself	
	DS3	GAI tools make some abilities less important and eliminate the need for me to develop them	

Notes: Measurement items with factor loading values below the 0.6 criterion (labeled with \*) have been excluded from the measurement validity assessment.



## Sample and Procedure

Data collection was facilitated through the Wenjuanxing platform (www.wjx.com), renowned for its extensive respondent base, making it the platform of choice for numerous businesses and academic institutions. Following the questionnaire's formal release, the data collection phase spanned four days, during which 3127 questionnaires were dispatched. The questionnaire's initial page featured a mandatory inquiry: "Have you utilized generative artificial intelligence tools like ChatGPT during your learning activities?" Only respondents affirming this question were considered valid. Moreover, exclusions encompassed individuals outside the target demographic, failed attention checks, or those completing the questionnaire hastily. To mitigate potential disparities in usage patterns across various generative artificial intelligence tools and ensure the study's reliability and consistency, analysis was confined to the two most prevalent tools, namely ChatGPT and ERNIE Bot. Following data scrubbing, 306 valid responses were obtained, yielding an effective response rate of 9.79%. Tabulated in Table 2 are the fundamental demographics and statistical analyses derived from the questionnaires. Among the valid respondents, females comprised 62.42%, while males constituted 37.58%. The predominant age bracket fell between 19 and 22 years, constituting 83.66% of the sample. As for educational achievements, the vast majority held bachelor's degrees, representing 91.50% of respondents. Within academic disciplines, students in engineering and technology fields constituted the largest portion at 43.46%, followed by those in social sciences and management at 22.88%. ChatGPT emerged as the favored generative artificial intelligence tool, with 71.57% preference among respondents.

Table 2: Demographic statistics

Characteristics	Levels	Frequency	Percentage (%)
GAI tools	ChatGPT	219	71.57
	ERNIE Bot	87	28.43
Gender	Male	115	37.58
	Female	191	62.42
Age	18 or below	4	1.31
	19-22	256	83.66
	23-29	43	14.05
	30 or above	3	0.98
Education	Two-year college student	5	1.63
	Undergraduate	280	91.50
	Graduate	21	6.86
Major	Arts and humanities	50	16.34
	Engineering and technologies	133	43.46
	Life science and medicine	36	11.76
	Natural science	17	5.56
	Social science and management	70	22.88

## Data Analysis and Results

In order to deeply explore the measurement model and structural model of the research model, we used Partial Least Squares (PLS) to analyze. First, the goal of this study is to construct theories and explore the relationships and potential effects among variables, and PLS is more appropriate than the traditional Covariance-Based SEM (CB-SEM) for exploratory studies. Second, PLS does not force the data to conform to the properties of a normal distribution, and the method is particularly suitable for research contexts with small sample sizes, which is appropriate for the sample size of this study. Finally, PLS is able to simultaneously estimate factor loadings, cross loadings of the measures, and path coefficients between the study variables, which fulfills the need of this study for revealing the relationships between the predictor variables.

## Measurement Model

To evaluate the measurement model's validity, we examined the constructs' reliability, convergent validity, and discriminant validity. Composite reliability (CR) and average variance extracted (AVE) were employed to assess construct reliability. Each construct in our study demonstrated CR values exceeding 0.7 and AVE values surpassing 0.5, meeting the established threshold criteria (refer to Table 3 for specifics).

Table 3: Construct reliability and correlations

	CR	AVE	Mean	SD	CSE	DS	IU	IP	RU	RP	RSE	TD
CSE	0.832	0.623	3.066	1.510	<b>0.789</b>							
DS	0.93	0.816	5.342	0.869	0.096	<b>0.903</b>						
IU	0.772	0.630	5.400	0.912	0.307	0.087	<b>0.794</b>					
IP	0.802	0.575	5.009	1.265	0.585	-0.024	0.406	<b>0.758</b>				
RU	0.801	0.574	5.484	0.773	0.418	0.091	0.506	0.476	<b>0.758</b>			
RP	0.765	0.523	5.709	0.724	0.449	0.067	0.440	0.620	0.499	<b>0.723</b>		
RSE	0.83	0.551	4.948	0.964	0.498	-0.007	0.305	0.479	0.387	0.475	<b>0.742</b>	
TD	0.84	0.568	5.698	0.848	0.295	0.318	0.461	0.332	0.451	0.432	0.230	<b>0.754</b>

Notes: CSE=creative self-efficacy, DS=deskilling, IU=exploitative use, IP=innovation learning performance, RU=explorative use, RP=routine learning performance, RSE=routine self-efficacy, TD=technology dependence. Diagonal elements are the square roots of AVEs.

In assessing convergent and discriminant validity, we first examined whether items loaded significantly higher on their respective constructs than on others. However, two exploitative use items (IU1 and IU3), one routine self-efficacy item (RSE1), one technology dependence item (TD1), and three routine learning performance items (RP1, RP3, and RP4) were excluded due to insufficient loadings. After this screening, all remaining items had loading values above 0.6, which showed that the convergent validity of the construct was satisfactory (see Table 4). In addition, the loading values of each item on this construct were higher than those of the other constructs and the square root of the average variance extracted (AVE) of all the constructs was greater than the correlation coefficient between them (cf. Table 3), which further confirms the discriminant validity of the constructs.

Table 4: Cross-loadings

	CSE	DS	IU	IP	RU	RP	RSE	TD
CSE1	<b>0.799</b>	0.116	0.257	0.448	0.38	0.356	0.399	0.233
CSE2	<b>0.817</b>	0.021	0.214	0.483	0.336	0.382	0.444	0.225
CSE3	<b>0.751</b>	0.092	0.258	0.453	0.269	0.323	0.332	0.243
DS1	0.149	<b>0.907</b>	0.123	0.023	0.105	0.074	0.019	0.319
DS2	0.031	<b>0.908</b>	0.066	-0.051	0.092	0.07	0.001	0.291
DS3	0.076	<b>0.895</b>	0.039	-0.041	0.044	0.033	-0.047	0.246
IU2	0.227	0.028	<b>0.726</b>	0.307	0.39	0.379	0.175	0.322
IU4	0.26	0.101	<b>0.856</b>	0.338	0.415	0.332	0.296	0.403
IP1	0.428	-0.024	0.304	<b>0.778</b>	0.367	0.474	0.326	0.295
IP2	0.423	-0.032	0.291	<b>0.715</b>	0.387	0.416	0.396	0.208
IP3	0.477	0.001	0.327	<b>0.78</b>	0.33	0.518	0.367	0.252
RU2	0.276	0.099	0.437	0.344	<b>0.727</b>	0.311	0.283	0.346
RU3	0.294	0.05	0.363	0.358	<b>0.732</b>	0.34	0.299	0.296
RU4	0.374	0.059	0.356	0.38	<b>0.811</b>	0.471	0.299	0.378
RP2	0.353	0.037	0.296	0.46	0.361	<b>0.807</b>	0.422	0.378
RP5	0.318	0.174	0.374	0.434	0.398	<b>0.708</b>	0.298	0.324
RP6	0.301	-0.074	0.299	0.465	0.33	<b>0.645</b>	0.294	0.216
RSE2	0.368	-0.012	0.228	0.333	0.258	0.332	<b>0.741</b>	0.15
RSE3	0.308	-0.037	0.173	0.321	0.267	0.33	<b>0.685</b>	0.06
RSE4	0.42	0.077	0.199	0.346	0.251	0.301	<b>0.787</b>	0.207
RSE5	0.38	-0.039	0.287	0.406	0.353	0.425	<b>0.753</b>	0.244
TD2	0.243	0.312	0.375	0.301	0.342	0.365	0.144	<b>0.766</b>
TD3	0.178	0.244	0.264	0.228	0.308	0.324	0.202	<b>0.749</b>
TD4	0.277	0.243	0.378	0.274	0.336	0.326	0.204	<b>0.789</b>
TD5	0.181	0.143	0.365	0.183	0.377	0.279	0.147	<b>0.71</b>

Notes: CSE=creative self-efficacy, DS=deskilling, IU=exploitative use, IP=innovation learning performance, RU=explorative use, RP=routine learning performance, RSE=routine self-efficacy, TD=technology dependence.

### Structural Model

The final result of the structural model is shown in Figure 2. Specifically, exploitative use has a significant positive effect on routine self-efficacy ( $\beta=0.147$ ,  $t=2.279$ ,  $p<0.05$ ) and creative self-efficacy ( $\beta=0.129$ ,  $t=2.066$ ,  $p<0.05$ ), and explorative use has a significant positive effect on routine self-efficacy ( $\beta=0.312$ ,  $t=5.440$ ,  $p<0.01$ ) and creative self-efficacy ( $\beta=0.353$ ,

$t=5.932$ ,  $p<0.01$ ), supporting H1-4. Both exploitative use ( $\beta=0.313$ ,  $t=6.111$ ,  $p<0.01$ ) and explorative use ( $\beta=0.293$ ,  $t=5.187$ ,  $p<0.01$ ) have significant positive effects on technology dependence, thereby confirming H5 and H6, respectively. However, neither exploitative use ( $\beta=-0.059$ ,  $t=0.971$ ,  $p>0.1$ ) nor explorative use ( $\beta=-0.044$ ,  $t=0.9721$ ,  $p>0.1$ ) had a significant effect on deskilling, indicating that neither H7 nor H8 holds. Meanwhile, technological dependence enhances deskilling ( $\beta=0.365$ ,  $t=6.639$ ,  $p<0.01$ ), therefore H9 holds. Routine self-efficacy exerts a significant positive influence on both routine learning performance ( $\beta=0.296$ ,  $t=5.162$ ,  $p<0.01$ ) and innovative learning performance ( $\beta=0.219$ ,  $t=3.611$ ,  $p<0.01$ ), thereby validating hypotheses H10 and H11, respectively. Similarly, creative self-efficacy demonstrates a significant positive effect on routine learning performance ( $\beta=0.213$ ,  $t=3.540$ ,  $p<0.01$ ) as well as on innovative learning performance ( $\beta=0.430$ ,  $t=8.225$ ,  $p<0.01$ ), supporting hypotheses H12 and H13. The significant positive impact of technology dependence on routine ( $\beta=0.318$ ,  $t=6.019$ ,  $p<0.01$ ) and innovative learning performance ( $\beta=0.195$ ,  $t=3.452$ ,  $p<0.05$ ) contradicts the negative correlations hypothesized in H14 and H15, indicating that these hypotheses are unsupported. Deskilling does not significantly affect routine learning performance ( $\beta=-0.053$ ,  $t=1.051$ ,  $p>0.1$ ), thereby failing to support H16. However, it does reveal a significant negative impact on innovative learning performance ( $\beta=-0.125$ ,  $t=2.541$ ,  $p<0.05$ ), thus confirming the validity of H17. Additionally, the structural model results indicate that routine learning performance accounted for 37.0% of the variance ( $R^2=0.370$ ), while innovative learning performance explained 42.4% of the variance ( $R^2=0.424$ ). Routine self-efficacy was associated with 16.6% variance explained ( $R^2=0.166$ ), and creative self-efficacy explained 18.7% of the variance ( $R^2=0.187$ ). Deskilling showed a variance of 10.7% explained ( $R^2=0.107$ ), and technology dependence was linked to a 27.6% variance explained ( $R^2=0.276$ ).

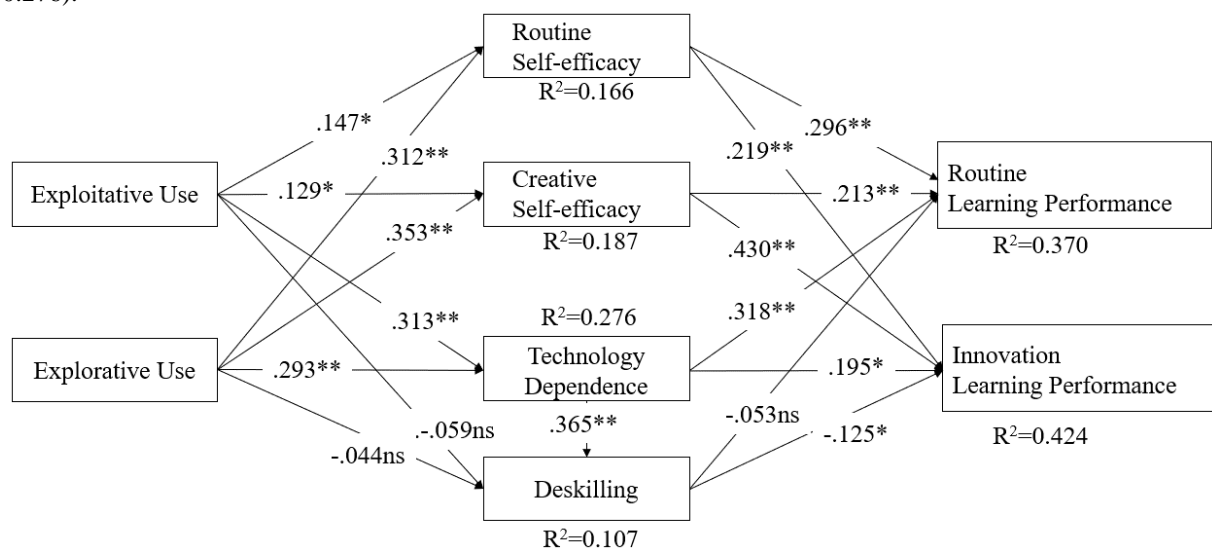


Figure 2: Results of structural modelling analysis

Notes: \*\*  $p<0.01$ , \*  $p<0.05$ , ns  $p>0.05$ .

### Post-hoc Analysis

Further analysis of the indirect effects has revealed significant positive mediation through creative self-efficacy in the relationship between exploitative use ( $\beta=0.055$ ,  $t=1.973$ ,  $p<0.05$ ) and explorative use ( $\beta=0.152$ ,  $t=4.648$ ,  $p<0.01$ ) with innovative learning performance. The indirect effect of exploitative use on routine learning performance through creative self-efficacy is marginally significant ( $\beta=0.027$ ,  $t=1.705$ ,  $p<0.1$ ), while the same effect for explorative use is significant ( $\beta=0.075$ ,  $t=2.849$ ,  $p<0.01$ ). Additionally, the indirect positive effect of exploitative use on both routine ( $\beta=0.044$ ,  $t=1.925$ ,  $p<0.1$ ) and innovative learning performance ( $\beta=0.032$ ,  $t=1.729$ ,  $p<0.1$ ) through routine self-efficacy is marginally significant. Similarly, the indirect positive effects of explorative use on routine learning performance ( $\beta=0.092$ ,  $t=3.571$ ,  $p<0.01$ ) and innovative learning performance ( $\beta=0.068$ ,  $t=2.747$ ,  $p<0.01$ ) through routine self-efficacy are significant.

The main effect analysis indicates no significant direct impact of exploitative use and explorative use on deskilling. However, in the examination of indirect effects, it was discovered that both exploitative use ( $\beta=0.114$ ,  $t=4.501$ ,  $p<0.01$ ) and explorative use ( $\beta=0.107$ ,  $t=4.076$ ,  $p<0.01$ ) have a significantly positive indirect effect on deskilling through technology dependence. Concurrently, the relationship between technology dependence and learning performance has been empirically confirmed as positive, contrary to the original hypothesis. Yet, further analysis uncovers that technology dependence indirectly exerts a significant negative impact on innovative learning performance through deskilling ( $\beta=-0.046$ ,  $t=2.200$ ,  $p<0.05$ ).

## DISCUSSION AND CONCLUSION

### Discussion

This study employs the theoretical foundation of adaptive structure theory to identify the technological features, positive and negative reinforcement of learning by technology use, and oriented performance outcomes in the context of GAI tool-assisted learning tasks. The study then constructs the basic framework of the model for this study. Among the identified features, technology was distinguished into two categories: exploitative use and explorative use. Performance outcomes were subdivided into two dimensions: routine learning performance and innovation learning performance. In conjunction with the theory of availability realization, the empowering effects of the independent variable of technology use on the intermediate

variable are described. Furthermore, the two main pathways of positive effects of technology use (routine self-efficacy and creative self-efficacy) and negative effects of technology use (deskilling and technology dependence) are identified.

Based on the research model and the proposed corresponding hypotheses, the data required for the study were collected by questionnaire survey method. The results of the data analysis confirmed some of the hypotheses, and the specific findings are as follows. First, both exploitative and explorative GAI use is found to positively affect routine and innovative learning performance through routine and creative self-efficacy.

Second, both exploitative and explorative GAI use is found to positively affect technology dependence which in turn positively affect routine and innovative learning performance, contrary to our expectations. A plausible explanation is that there are two possible mechanisms for the role of technology dependence on learning performance. One is a direct positive mechanism: organisational dynamism leads to continuous adaptation of knowledge, i.e., performance-relevant learning skills in a given situation (e.g., without tool assistance) can be replaced by tool-use skills that are necessary for performance in another situation (e.g., with tool assistance) (Ilgen & Pulakos, 1999), thus dynamically adjusting performance. Research has shown that proficient use of GAI tools such as ChatGPT can have a positive impact on learning performance (Caratiquit & Caratiquit, 2023). The use of GAI tools increases the speed of information processing, assists in task manipulation, provides instant feedback, facilitates collaborative learning and knowledge integration (Baidoo-Anu & Ansah, 2023), compensates for the attenuation of individual learning-related skills, and ultimately demonstrates an increase in routine learning performance. Meanwhile, GAI tools can extend the learning boundary, support autonomous learning, and stimulate innovative thinking by generating a large amount of personalised content (Dai, Liu, & Lim, 2023; Su & Liu, 2023), so the use of GAI tools provides a powerful grip for users' innovative attempts, thus promoting innovative learning performance through technological dependence. Another mechanism is the negative indirect mechanism, which shows that technology dependence significantly promotes deskilling, while deskilling can significantly negatively affect innovation learning performance, i.e., technology dependence indirectly leads to the decline of innovation learning performance through deskilling.

Third, the relationship between GAI use and deskilling is found insignificant. a further analysis shows that this effect is mediated by technology dependence. That is, although exploitative use and explorative use do not directly induce deskilling, they indirectly contribute to the occurrence of deskilling through their positive effect on technology dependence. This may be due to the fact that exploitative use and explorative use are, in essence, positive applications of GAI tools. Exploitative use emphasises the efficiency and utility of the tool, whereas explorative use encourages innovation and knowledge discovery. In both modes of use, individuals are likely to extend their learning and problem-solving abilities more through technology rather than simply replacing their own skills. Therefore, if there is no over-reliance, these two modes of use do not directly lead to deskilling. However, when individuals frequently use GAI tools to assist in learning tasks, they may gradually become overly dependent on these tools. This dependence leads individuals to reduce the practice and application of their own skills as they become increasingly inclined to seek help from technology to solve problems. Over time, individuals' skills decline due to lack of practice and application. Thus, while exploitative use and explorative use may not directly cause deskilling, they indirectly create the conditions for deskilling by promoting technology dependence.

Finally, we found that deskilling significantly negatively affects innovative learning performance, but does not have a significant negative effect on routine learning performance. The reason for the non-significant negative effect of deskilling on routine learning performance is hypothesised to be that, although the reduction of task-relevant learning skills can lead to a decrease in routine learning performance, mastery of task-relevant learning skills may not be the only solution in enhancing routine learning performance, and that students may be able to compensate for degradation of skills through other means or skills to achieve a reconfiguration of the skills required for the learning task (E. Bravo, 2015). This means that students may rely on GAI tools to assist their learning, thus overcoming the negative effects of degradation of task-relevant learning skills. Even in the case of deskilling, students may still be able to sustain their learning performance in various ways.

### **Theoretical Contribution**

First, this study proposes a unified theory to shed light on the contrary impacts of GAI use on learning performance by considering both the positive and negative mechanisms. Specifically, previous studies have looked at only positive or negative aspects one-sidedly, failing to give a comprehensive and systematic analysis of the mechanism of action of GAI use, whereas the present study discusses both positive and negative perspectives in a comprehensive manner, integrating the dual effects of GAI use in the research model and giving a unified analytical framework.

Second, this study identifies the dark side of GAI use by exploring the role of technology dependence and deskilling. While existing studies have focused on the positive effects of GAI use and seldom addressed the negative effects, this paper combines the characteristics of the GAI context to extract two contextualised influences, technology dependence and deskilling, to explain the negative effects of GAI use; in addition, although existing studies have conceptually proposed a definition of deskilling, they have not provided empirical evidence of its mechanism. The present study remedies this shortcoming through the introduction of the deskilling variable, followed by the development of a scale based on the definition of deskilling and the situational characteristics of the study.

Third, this study carefully distinguished between different types of GAI use, self-efficacy, and academic performance, and investigates their differential mechanisms. Most of the existing studies treat technology use, self-efficacy, and academic performance as a general concept, failing to identify different categories of behaviours, processes, or outcomes, and failing to elaborate on their different mechanisms. This study further differentiates GAI usage into explorative and exploitative types, self-efficacy into routine and creative self-efficacy, and learning performance into routine and innovative learning performance, which can help to more accurately identify and assess the impact of different usage behaviours on targeted learning performances through specific learning processes, and to enrich the understanding of each pathway.

### Practical Contributions

First, the study underscores the importance of actively integrating GAI tools to augment learning performance. The findings reveal that the active use of GAI technologies positively influences both the routine and creative self-efficacy of learners, which in turn enhances their routine and innovation learning performance. Moreover, the study highlights the positive influence of technology dependence on learning outcomes, suggesting that when used judiciously, GAI tools can significantly enrich students' educational experiences and performance. Therefore, educational practitioners are encouraged to embrace these technologies and guide students in their use to bolster their future competitiveness.

Secondly, the study promotes the promotion of exploratory use to optimize the learning experience. The study showed that explorative use of GAI tools had a significant positive impact on learners' routine and creative self-efficacy, and the path coefficient of promoting self-efficacy was greater for explorative use than exploitative use, which indicates that explorative use is highly effective in improving learning experience and performance. At the same time, exploratory use of GAI tools had a smaller positive effect on technology dependence than exploitative use. This suggests that educators should create an environment that encourages students to explore and innovate, utilizing the functionality of various GAI tools and designing novel tasks to deepen their learning and broaden their capabilities.

Third, the study calls for protection against deskilling due to technology dependence. While the benefits of GAI tools are evident, the research also uncovers the potential negative consequences of overreliance on technology, which can lead to deskilling and adversely affect innovative learning performance. This serves as a cautionary note for educators and students to use GAI tools mindfully to avoid misuse and overdependence. It is imperative that educational strategies focus on nurturing critical thinking and independent problem-solving skills, ensuring that students maintain and develop their essential personal competencies alongside technological proficiency.

### Limitations

The current study, while providing significant findings, is subject to certain limitations that should be considered. The research was conducted with a student sample from China, and thus, the generalizability of the conclusions to other countries or populations remains to be further validated. Additionally, the study employed a cross-sectional survey with subjective measurements, which suggests that future research could enhance the findings by incorporating actual performance metrics and utilizing a longitudinal design to more precisely observe the long-term effects of technology use. Furthermore, although the model identified several influencing factors, the possibility of other unaccounted variables affecting the relationship between GAI use and learning performance suggests that the scope of this study can be expanded in subsequent research. Addressing these limitations will contribute to a more robust comprehension of the interplay between GAI tools and educational achievements.

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