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Bridging the digital divide: analyzing educational inequality in technology access between urban and rural schools in China

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ABSTRACT

Introduction. Technological innovations have introduced numerous changes to the education environment, providing scope for improved learning experiences and academic outcomes. The application of sophisticated tools, including artificial intelligence, virtual reality, and learning management systems in a classroom, can easily convert conventional teaching methods into dynamic and interactive ones. *The purpose of this research* is to examine the interplay of technological self-efficacy, chatbot acceptance, and task-technology fit, investigating their effects on students' academic performance and learning outcomes. Additionally, the study explores the mediating role of technology use in learning and the moderating effects of chatbot acceptance and task-technology fit on the relationship between technological self-efficacy and academic performance.

Study participants and methods. A sample of 302 students from various Chinese schools participated in the study. Data were gathered using validated scales for technological self-efficacy, chatbot acceptance, task-technology fit, and learning outcomes. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to analyze the relationships between these constructs.

The results. Technological self-efficacy did not significantly influence academic performance directly ($T = 1.011$, $p = 0.156$). However, technology use in learning significantly mediated this relationship ($\beta = 0.170$, $T = 2.140$, $p = 0.016$). Both chatbot acceptance ($\beta = 0.161$, $T = 1.92$, $p = 0.028$) and task-technology fit ($\beta = 0.090$, $T = 1.748$, $p = 0.041$) were significant moderators, highlighting their critical role in enhancing technology adoption and learning outcomes.

Conclusions. This research highlights the significance of aligning technology with educational tasks and boosting students' confidence in technology use. The findings shows that technological self-efficacy, chatbot acceptance, and task-technology fit, significantly effects students' academic performance and learning outcomes. The findings offer valuable insights for educators and policymakers to design effective, technology-driven, student-centered learning environments.

KEYWORDS

technological self-efficacy, use of technology in learning, chatbot acceptance, task technology fit, performance impact

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INTRODUCTION

United Nations (UN) international initiatives in education, spearheaded by institutions like UNESCO, the Council of Europe, and the International Association of Universities (IAU), have placed greater focus on integrating digital technologies to promote learning globally. Technology and education have been a major focus of attention over the past century, as the ever-changing nature of digital tools has revolutionized learning paradigms to a large extent. These efforts focus on enhancing learning accessibility, engagement, and effectiveness through innovative tools. The adoption of AI-driven technologies, including chatbots, plays a crucial role in transforming modern educational practices[1].These innovations have not only enhanced the accessibility of education but have also enabled the delivery of personalized learning experiences tailored to the unique needs and capabilities of individual learners. For instance, the integration of AI-driven tools, such as chatbots, has been shown to facilitate adaptive learning environments, thereby supporting diverse learning styles and improving engagement [2]. Studies have demonstrated that when technology aligns with learners' needs, it can significantly enhance their ability to process information and achieve better academic outcomes. This growing reliance on technology in education reflects broader societal trends, where digital literacy has become an indispensable skill for navigating the modern economy [3]. In fact, the ability to effectively use digital tools is increasingly seen as a critical determinant of success in both academic and professional settings, underscoring the need for educational systems to prioritize digital competency.

Central to these developments is the concept of technological self-efficacy defined as an individual's belief in their ability to effectively utilize technology which plays a pivotal role in shaping how students interact with and benefit from digital tools [4]. Research has consistently shown that students with higher levels of technological self-efficacy are more likely to embrace new technologies, engage deeply with digital learning platforms, and achieve superior learning outcomes. However, the relationship between technological self-efficacy and academic performance is often mediated by factors such as the perceived usefulness of the technology and its alignment with specific educational tasks. Understanding these dynamics is crucial, as they directly influence the adoption and effectiveness of technology in educational settings, particularly in bridging gaps between urban and rural schools. Technological self-efficacy is best understood in the educational world, where students' confidence while using digital tools can actually influence their learning outcomes [5]. Technologies such as chatbots and learning management systems further augment this impact by providing on-demand support and enhancing students' engagement [6]. However, the effectiveness of these tools depends upon the fit with task requirements, so that task technology fit is critical in educational contexts [7]. Even though such tools are widely adopted, significant questions remain about their effects on student performance [8], especially when mediated or moderated by factors.

Empirical studies up to date have established that significant relationships exist between technological self-efficacy and academic results, indicating self-efficacy as a solid foundation for increasing the ability of students to manage different digital tools [9]. For instance, several studies indicate that subjects with high technological self-efficacy are more likely to embrace and use e-learning programs effectively, which leads to better academic results [10]. Researchers have also looked into the way technological self-efficacy affects other educational behaviors like self-regulated learning and goal-setting. For instance, Al-Mamary, Alfalah [11] showed that students who were more confident in their use of technology tended to manage their time and resources more effectively than others, which was directly related to academic achievement. The role of technology use as a mediator has also been studied extensively [12]. Akram, Buono [13] further argue that self-efficacy itself might not be directly positively related to performance unless it is translated into meaningful interaction with the technological tools. The empirical study in this area shows that effective and frequent usage of education technologies, virtual classrooms, and digital simulations amplifies the positive relationship between self-efficacy and academic performance [14]. These findings are corroborated by evidence coming from blended learning environments, where integration of online and offline tools enhances cognitive engagement and retention. The moderating role of chatbot acceptance is also another important area of research as studies suggest that the more a student accepts conversational agents, the better the outcomes will be in learning [15]. Research by Shao, Nah [16]demonstrates that chatbots enable personalized support and immediate feedback, so they are beneficial for students with high technological self-efficacy. Similarly, the role of task-technology fit has been highlighted in studies examining to what extent the alignment between digital tools and learning goals affects performance [17]. Since the fit is high, the students are more likely to experience improved outcomes because of better resource utilization and task efficiency [18].

Existing studies do indeed help make clear the role of technology in education; however, certain gaps still exist [19]. Indeed, most of these studies were rather focused on the direct relationship that existed between technological self-efficacy and performance, whereas mediating and moderating factors that could have an effect on the former have been omitted [20]. For instance, the mediating role of technology has been studied mostly in specific contexts, such as in e-learning platforms, while its general implications in various educational settings have not been taken into consideration [21]. Moreover, the connection between self-efficacy and technological tools, such as chatbots, is not very clear, particularly in terms of how acceptance impacts their performance [22]. Another critical area is the deficiency in task technology fit knowledge. Despite its wide exploitation in organizational studies, this topic remains a little-explored arena in educational settings [23]. There exist few research studies on the moderation of technology-task requirement alignment on how self-efficacy affects performance by the ability to use the underlying technological capability [24]. Besides, existing studies tend to miss the dynamic nature of this fit. They fail to explain how changes in educational needs or technological changes might affect the effectiveness of the fit [25]. Also, longitudinal studies that determine the sustained impact of technological tools on student performance are not many. Most of the studies in this field are based on cross-sectional data, which fails to capture the dynamic nature of how students interact with technology over time [26]. Furthermore, very few studies account for cultural and contextual factors, such as the difference in digital literacy or access to technology, which lowers the generalizability of the findings [27]. It is also important in how it can further develop a better understanding of how technological self-efficacy could influence educational outcomes based on interactions with other variables.

This study is theoretically underpinned by social cognitive theory, where the role of self-efficacy in shaping behavior and outcomes is highlighted [28]. Zhang and Wang [29] argue that those with high self-efficacy are likely to be involved in challenging tasks and will be persistent in the face of difficulty and produce better results. This theory offers a comprehensive framework for understanding how technological self-efficacy affects students' performance by encouraging active engagement in digital tools and adaptive learning behaviors [30]. The Technology Acceptance Model further supports these proposed relationships by highlighting the significance of perceived usefulness and ease of use as factors in technology acceptance. According to Peng, Xu [31], the perceived value and friendliness of technological tools boost their adoption in work processes. The model supports the moderation of chatbot acceptance through students' intentions to use conversational agents, which might significantly improve their learning outcomes [29]. Similarly, the TTF theory also supports the findings by underlining the alignment of task requirements with technological capabilities as critical [32]. This study attempts to investigate how the complex interplay of technological self-efficacy, technology use, chatbot acceptance, and task technology fit affects students' performance impact. This study will fill identified research gaps by providing a more in-depth understanding of these relations, hence offering practical implications to educators and policymakers who may wish to optimize the utilization of technology in education. The expected contribution to theoretical advancement will be made in educational technology and self-efficacy, thereby enriching the academic discourse around these critical topics.

LITERATURE REVIEW

Technological advancements have brought many changes to the education scenario, offering opportunities for better learning experiences and academic results [33]. The use of advanced tools, such as artificial intelligence, virtual reality, and learning management systems in a classroom, can easily transform traditional teaching approaches into dynamic and interactive ones [34]. These technologies allow personalized learning, where educators can tailor the content to the needs of different students [35]. In addition, education technological innovations ensure more accessible and just learning fields since most resources are easy to access. For instance, online learning platforms and virtual libraries give equal opportunity to access high-quality content from students who otherwise would be marginalized within or in underserved areas [36]. More benefits of such innovations involve the promotion of teamwork, where easy interaction by either students or teachers is facilitated within distant geographical areas using virtual classrooms, discussion forums, and shared working environments [37]. Further, technology-based learning tools increased the thinking, problem-solving, and adaptability skills of the students. The gamification in schools is seen to increase the level of engagement and retention to an unprecedented high as technology advances, according to evidence-based research[38]. On the other hand, learning analytics in data-driven technology allow educators to track live performance and identify areas to intervene for optimizing the teaching approach [39]. It comes, however, with its own share of problems- technical integration requires strong infrastructural support, adequate training for the teachers, and cautious attention to matters of data privacy and digital equity [40]. Still, inappropriate implementation nurtures both the instructors and students and renders the system far more responsive to a world that's rapidly changing.

Technological self-efficacy refers to a person's perception that they can use technology effectively to produce desired outcomes [41]. Other researchers have investigated self-efficacy in technology with respect to academic performance. Different research studies have established the positive relationship between technological self-efficacy and attainment [42]. Students who are self-assured in their technological capabilities are more engaged in the use of digital learning environments [43]. For example, in the social cognitive theory, the technological self-efficacy level is essential to behavior: students with higher technological self-efficacy are more inclined to try to use more educational technology [3]. The research of Esiyok et al. [1] confirms that this technological self-efficacy level not only enhances user interaction but also reduces the anxiety of using a new tool. Additionally, experimental studies in e-learning environments have shown that the greater the levels of technological self-efficacy of students, the greater their participation, completion, and performance [5]. Technological self-efficacy has been said to support self-regulated learning behaviors. For instance, [7] asserted that a student who believes in his technological capability can establish appropriate goals, time management, and the efficient use of resources. In addition, studies on blended learning report that technological self-efficacy facilitates the ease of adjustment of students to hybrid models of instruction [9]. They can easily shift between in-person and online settings without a problem. Collectively, these findings show the importance of technological self-efficacy as an important predictor of the performance impact of students [1].

Building on this hypothesis, which is based on robust theoretical and empirical support, maintains that students' performance impacts are significantly influenced by technological self-efficacy [19]. High technological self-efficacy students are those who will use digital tools in an enhanced manner so that they can source, process, and implement information in new ways; this kind of engagement with the technology increases the depth and retention of learning material as well as enhances performance [44]. Technological self-efficacy further provides the learner with the ability to overcome technical problems and tools in which they are not knowledgeable; thus, it reduces learning difficulties [16]. Besides, the empirical evidence demonstrates that technological self-efficacy interacts with motivational factors; thus, it enhances academic performance [18]. For instance, if a student is convinced of his or her abilities in technology, then that student is likely to feel intrinsic motivation because they see digital tools as opportunities instead of obstacles. Positive learning activities with the resultant outcomes in higher academic performance accrue from such perceptions [20]. By way of facilitating autonomy as well as self-managed learning, technological self-efficacy creates positive reinforcements for improving general performance for students [22]. In this regard, the proposed hypothesis that goes with the existing literature for sure would form a strong basis to conclude the significant performance impacts that technological self-efficacy makes among students.

H1. Technological self-efficacy significantly influences the students' performance impact.

A lot of attention has been given to mediating the effect of technology use in school settings in the literature [24]. This is because most studies report that the effect of self-efficacy on performance outcomes is mostly mediated through the actual use of technology in learning. The self-efficacy per se does not necessarily impact student outcomes unless the students also practice the use of technological means. Studies in higher education settings have shown that students with high self-efficacy are more likely to accept and use educational technologies, leading to better learning and performance [28]. For example, research on the use of learning management systems has shown that students who have a high self-efficacy about their technological ability tend to use the learning management systems more often and more effectively, resulting in better academic performance [30]. Additional empirical research indicates various means through which technology use facilitates learning [32]. Multimedia resources, for example, are reported to enhance cognitive involvement due to the visually and aurally stimulating character of the presentation formats employed, while group technologies like discussion boards and shared documents are reported to facilitate deeper understanding through peer-to-peer interaction [34]. E-learning research suggests that technology usage in a regular and meaningful manner enhances problem-solving ability, imagination, and general academic achievement [45]. It is this research that develops evidence that employing technology is a salient mediator by which technology self-efficacy is converted into outcomes of performance [38].

The examination of this relationship's mechanisms provides evidence to support the hypothesis that the use of technology mediates technological self-efficacy and the impact on performance [40]. The greater number of students with high technological self-efficacy are likely to look for and apply digital tools to their learning process as a means of bridging the gap between outcome and self-belief [17].This usage not only opens up a vast sea of learning resources but also empowers students to apply knowledge in practical and innovative ways, thereby directly affecting their performance [2]. Also, technology use often exposes students to adaptive learning features such as personalized feedback and progress tracking, which reinforce their self-efficacy and motivate continued engagement [4]. For instance, a technology-confident student will be able to know his or her strengths and weaknesses using data analytics in the learning platforms so as to focus on specific areas [14]. This cyclic interaction ensures that the mediating role of technology usage magnifies the overall effect of self-efficacy on performance [8]. This, then supports the proposed hypothesis, where the interplay among the constructs shows the position of technology usage as it applies to educational contexts.

H2. Use of technology in learning significantly mediates the relationship between technological self-efficacy and students’ performance impact.

The emergence of chatbots in education has brought new dimensions to the learning experience as research explores their acceptance and effectiveness in moderating various educational outcomes [19]. Acceptance of chatbots, defined as students' readiness to interact with AI-driven conversational agents, enhances learning support and access. Studies show that chatbots, like those integrated into learning management systems, help students answer their questions, access course resources, and receive tailored support [13]. According to research by Dahri, Yahaya [6], students who embraced the use of chatbot technology reported increased satisfaction and engagement in their learning activities. Perceived ease of use and perceived usefulness are also positively correlated with chatbot acceptance, according to empirical evidence, based on the TAM [15]. For instance, the fact that the chatbot is perceived as reliable and user-friendly enhances students' incorporation of the tool into their study routines, leading to better academic outcomes [17]. Second, the instant feedback ability of chatbots and the simulation of human interaction can make learning better in the case of highly techno-centric, self-efficacious students. These findings position acceptance of the chatbots as a potential moderator between the effects of self-efficacy on performance [19].

The moderating role of acceptance of chatbots in the relationship between technological self-efficacy and its impact on student's performance is based on its ability to bridge support and interaction gaps [21]. Students with a strong sense of technological self-efficacy are more likely to use chatbots, utilizing features and improving learning efficiency and productivity [23]. By providing instant help and personalized feedback, the empowerment of students to achieve higher utility from their technological capabilities, linking self-efficacy with performance, is strengthened. Acceptance of chatbots also increases the adaptability of technologically confident students toward a smooth and easily accessible interface for solving complex questions [27]. This dynamic interaction ensures that students can maintain their momentum in learning even in the face of challenging scenarios, thereby ensuring that the positive influence of self-efficacy on performance is maintained [29]. The moderating effect of chatbot acceptance thus amplifies the benefits of technological self-efficacy, providing empirical support for the proposed hypothesis.

H3. Chatbot acceptance significantly moderates the relationship of technological self-efficacy and students’ performance impact.

Task technology fit (TTF) is the degree to which the technological tools used to match the needs of specific tasks, and it has been widely discussed in educational and organizational contexts [31]. Consistent evidence indicates that technology fits with task demands and enhances user satisfaction and performance outcomes. Yang, Luo [33]defined TTF as a critical determinant of technology acceptance and use, pointing out its impact on efficiency and effectiveness. In education, research has proven that learning tools aligned with the needs and preferences of learners help them achieve better engagement and academic performance [36]. For example, an adaptive learning platform customized to match students' progress with content learned leads to high performance when compared to systems that do not customize content [3]. Empirical findings also highlight TTF's necessity to provide effective user experiences. Studies of e-learning environments reveal that students are more likely to meet their learning goals when tools used are effective in meeting the cognitive and functional requirements of tasks [4]. For example, shared whiteboards and online discussion forums work best for group projects, whereas interactive simulations help learners better understand sophisticated scientific concepts [7]. Research also indicates that the impact of technological self-efficacy on performance depends on the level of fit between task and technology since even self-assured users might perform poorly if the tools used do not properly support their learning goals [12].

The hypothesis that technological self-efficacy of students is substantially moderated by task technology fit, and performance depends on its ability to facilitate proper use of the technology [10]. Students with high levels of technological self-efficacy are likely to use more appropriate tools for their academic work, thus enhancing the positive effects of this confidence on performance [15]. When the fit is high, these students can use their technological skills to navigate challenges, access relevant resources, and apply learned concepts effectively, which leads to better outcomes [14]. Conversely, a poor task-technology fit may hinder even technologically capable students, as misaligned tools fail to meet the functional or cognitive demands of the tasks [11]. For instance, basic text editors for collaborative writing projects may reduce productivity, whereas advanced platforms like Google Docs offer real-time editing and commenting features that enhance group efficiency [8]. Therefore, task technology fit acts as a moderator, magnifying the influence of self-efficacy when the tools align with task requirements and mitigating its effects when the alignment is poor [5]. The interplay between task demands, technology capabilities, and the individual's skills would, in turn provide a strong basis for the hypothesis proposed here.

H4. Task technology fit significantly moderates the relationship of technological self-efficacy and students' performance impact.

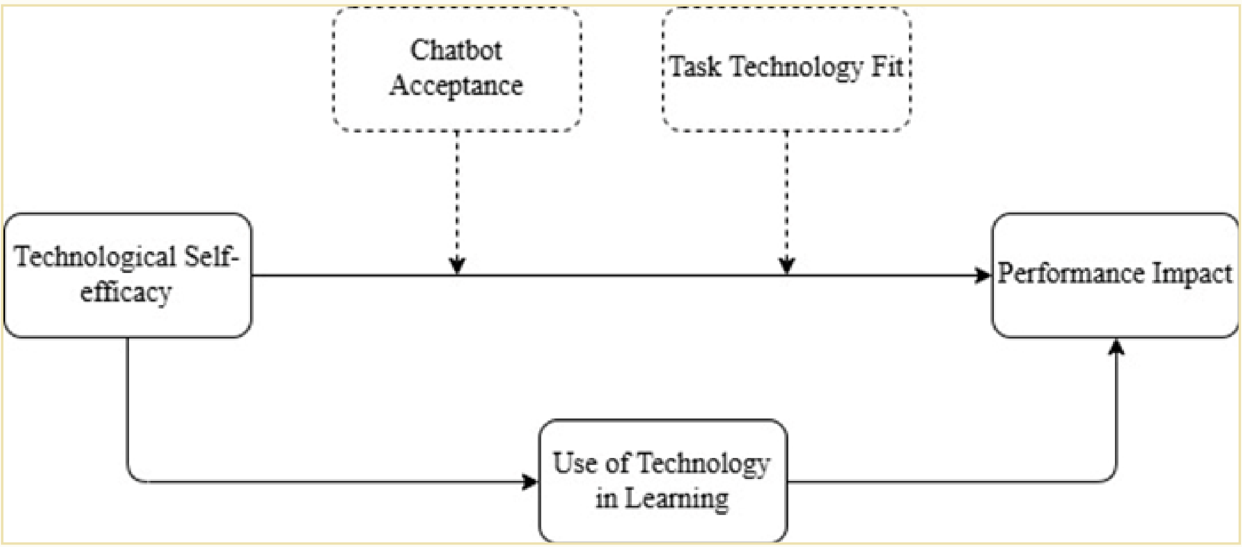

Figure 1 Theoretical Model

METHODOLOGY

This study employed a quantitative research design to examine the relationships between technological self-efficacy, chatbot acceptance, task-technology fit, and their combined effects on learning outcomes. It tested a structural model using data collected from school students in China. A cross-sectional design was used to collect information at one particular time point. The focus here was on the way different factors – individual and technological – may impact students' performance in learning technology settings. This study targeted different levels of school programs offered by several Chinese schools. In total, 302 students participated, forming a diverse and representative sample. The selection process adopted convenience sampling, which meant that students who were easily accessible and willing to participate were included. The sample comprised students from different academic disciplines and at various levels of exposure to technology, thereby ensuring that the phenomena under study were well understood. Participants were informed of the objectives of the study and then given informed consent before data collection began. The study utilized well-established scales adopted from previous research to measure the constructs. Technological self-efficacy was measured using items designed to assess individuals' confidence in effectively using technology in academic settings. Chatbot acceptance was measured through scales evaluating students' perceptions of the usability, effectiveness, and relevance of chatbot technology in learning. Task-technology fit was assessed by scales examining the alignment between the technological features and academic tasks. Lastly, measures of learning and performance impact of technology in use were gauged with validated scales which addressed each of their dimensions. All the items were scored on 5-point Likert scales ranging from 1 "strongly disagree" to 5 "strongly agree".

Table 1

Instrumentation of the study

Variable	No of items	Source
Technological self-efficacy	Seven	[44]
Use of technology in learning	Seven	[45]
Chatbot acceptance	Fourteen	[46]
Task technology fit	Three	[35]
Performance impact	Ten	

It is designed through a structured online questionnaire and distributed to students across schools through their e-mails and learning management portals. It contains sections regarding demographics, which are the constructs mainly investigated in the study. Therefore, clarity in the questionnaire was established as a pilot with a limited group of students prior to administering it, based on their suggestions, and necessary minimal corrections were made accordingly. The last survey took over four weeks to provide enough time for the students to respond. The gathered data were then analyzed with the help of PLS-SEM, a strong technique in exploring relationships between latent variables. It was chosen in this context because it supports non-normal distributions of data and relatively smaller sample sizes while being able to give insights into the predictability of the model. The analysis was conducted in two stages: first, by testing the reliability and validity of the measurement model and then by testing the structural model to test the hypotheses. Some of the key metrics that were used for validation of the model and testing of the hypotheses were Cronbach's alpha, composite reliability, Average Variance Extracted (AVE), and path coefficients. This methodological approach ensured a rigorous examination of the research model, leveraging a validated measurement framework and advanced statistical techniques to derive meaningful insights. Focusing on a diverse population of students and robust analytical tools, the study provides an accurate basis for understanding the role of technology in academic performance within Chinese schools.

RESULTS

Table 2 is used to measure the construct's reliability and validity used in this study by considering Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE). All Cronbach's alpha values are above 0.7, where the highest was Chatbot Acceptance, which equals 0.944 and is therefore good for high internal consistency. Composite reliability shows that the overall reliability for all latent constructs is attained at 0.7, thus providing further confidence in the constructs' reliability. AVE values capture the proportion of variance where the construct actually explains to measurement error. All such values are more than acceptable at 0.5, which shows convergent validity. However, constructs like "Use of Technology in Learning" and "Performance Impact" have relatively lower AVE values of 0.514 and 0.521, respectively, and thus call for the measurement items to be refined so that future research can better capture variance.

Table 2

Variables reliability and validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Chatbot acceptance	0.944	0.962	0.950	0.578
Performance impact	0.895	0.902	0.915	0.521
Task technology fit	0.716	0.775	0.839	0.636
Technological self-efficacy	0.764	0.766	0.836	0.546
Use of technology in learning	0.809	0.827	0.863	0.514

Table 3 provides the factor loadings of individual items on their constructs to test the validity of the measurement model. All items have loadings greater than the minimum threshold of 0.5, with many items having a loading of more than 0.7, which shows robust item reliability. For example, items like CA10 (0.885) and CA12 (0.894) for Chatbot Acceptance and TTF2 (0.889) for Task Technology Fit have strong relationships with their constructs. On the other hand, some items like CA4 (0.566) and PI6 (0.519) are relatively weak. These might be revisited for further improvement. Results indicate that the constructs capture the intended dimensions but may benefit from the refinement of lower-loading items to strengthen the model.

Table 3

Confirmatory Factor Analysis

	Chatbot acceptance	Performance impact	Task technology fit	Technological self-efficacy	Use of technology in learning
CA1	0.721				
CA10	0.885				
CA11	0.778				
CA12	0.894				
CA13	0.861				
CA14	0.759				
CA2	0.735				
CA3	0.703				
CA4	0.566				
CA5	0.674				
CA6	0.859				
CA7	0.604				
CA8	0.694				
CA9	0.823				
PI1		0.624			
PI10		0.758			
PI2		0.768			
PI3		0.685			
PI4		0.799			

PI5		0.686			
PI6		0.519			
PI7		0.826			
PI8		0.672			
PI9		0.822			
TSE1				0.671	
TSE2				0.618	
TSE3				0.666	
TSE5				0.647	
TSE6				0.739	
TSE7				0.721	
TTF1			0.763		
TTF2			0.889		
TTF3			0.730		
UTL2					0.717
UTL3					0.722
UTL4					0.859
UTL5					0.655
UTL6					0.717
UTL7					0.608

The Fornell-Larcker criterion (table 4) is used to assess discriminant validity by comparing the square root of AVE values (diagonal values) with inter-construct correlations (off-diagonal values). All constructs meet the Fornell-Larcker criterion, as their diagonal values are higher than corresponding inter-construct correlations. For example, the square root of AVE for Task Technology Fit (0.797) is greater than its correlations with Chatbot Acceptance (0.638) and Technological Self-Efficacy (0.349). This confirms that the constructs are unique and measure different aspects of the framework.

Table 4

Fornell-Larcker Criterion

	1	2	3	4	5
Chatbot acceptance	0.760				
Performance impact	0.174	0.722			
Task technology fit	0.638	0.388	0.797		
Technological self-efficacy	0.602	0.231	0.349	0.678	
Use of technology in learning	0.351	0.177	0.099	0.719	0.717

HTMT (table 5) values evaluate discriminant validity as the ratio of heterotrait-heteromethod correlations to monotrait-heteromethod correlations. All HTMT values are less than the threshold of 0.9, hence establishing adequate discriminant validity. For example, the HTMT value for Task Technology Fit and Chatbot Acceptance is 0.777 and between Task Technology Fit and Technological Self-Efficacy is 0.478. This further establishes the fact that the constructs are well different from each other.

Table 6 R-squared measures explained variance by independent variables for the dependent constructs. For "Use of Technology in Learning," the R-squared is at 0.517, indicating that 51.7% of its variance can be explained by predictors of the model, meaning a strong explanatory power. For "Performance Impact," however, the R-squared was only at 0.225, which means it explained variance at a relatively weaker level. The adjusted R-squared values, however, incorporate the number of predictors and closely resemble R-squared values, therefore approving the model's fit. Q² predict, RMSE, and MAE revealed predictive relevance for good predictive accuracy by the model, yielding a Q² predict of 0.542.

Table 5

Heterotrait-Monotrait Ratio (HTMT)

	1	2	3	4	5
Chatbot acceptance					
Performance impact	0.173				
Task technology fit	0.777	0.448			
Technological self-efficacy	0.707	0.305	0.478		
Use of technology in learning	0.408	0.251	0.156	0.896	

Table 6

R-square Statistics Model Goodness of Fit Statistics

	R Square	R Square Adjusted	Q²predict	RMSE	MAE
			0.542	0.061	0.079
Performance impact	0.225	0.213			
Use of technology in learning	0.517	0.515			

Table 7 presents the F-statistic for the contribution of each independent variable to the dependent variables. "Task Technology Fit" contributes the most to "Use of Technology in Learning" with an F-statistic of 1.069, indicating its critical contribution in explaining variance. The F-statistic for "Chatbot Acceptance" in explaining "Performance Impact" is only 0.022, indicating a very low contribution. These results indicate the relative contribution of certain predictors in the model and the implications for targeted interventions.

Table 7

F statistics

	Performance impact	Use of technology in learning
Chatbot acceptance	0.022	
Task technology fit	0.218	
Task technology fit Moderator	0.032	
Technological self-efficacy	0.006	1.069
Use of technology in learning	0.028	

This table (8) shows the path coefficients, standard errors, t-statistics, and p-values to describe the significance of hypothesized relationships. There is no direct influence on Performance Impact, as the relationship between Technological Self-Efficacy and Performance Impact is not significant ($p = 0.156$). However, the mediation effect of "Use of Technology in Learning" is significant at $p = 0.016$. Thus, it's crucial to fill the gap. Moderation effects are also significant in the case of

Chatbot Acceptance (p = 0.028) and Task Technology Fit (p = 0.041), which indicate these factors augment the relationship between Technological Self-Efficacy and Performance Impact. The results, therefore, reveal the subtle dynamics among the variables and the need to consider moderation and mediation effects in further studies.

Table 8

Path Analysis

	Original Sample	Sample Mean	Standard Deviation	T Statistics	P Values
Technological self-efficacy significantly influences the students' performance impact.	0.112	0.083	0.111	1.011	0.156
Use of technology in learning significantly mediates the relationship of technological self-efficacy and students' performance impact.	0.170	0.184	0.079	2.140	0.016
Chatbot acceptance significantly moderates the relationship of technological self-efficacy and students' performance impact.	0.161	0.153	0.084	1.92	0.028
Task technology fit significantly moderates the relationship of technological self-efficacy and students' performance impact.	0.090	0.099	0.052	1.748	0.041

DISCUSSION

Modern organizational complexity speaks towards the relevance of how digital and pedagogical competencies influence career satisfaction and self-efficacy. For, faculty members are central for educational quality; therefore, they need well-designed support schemes for professional growth and well-being. The empirical chapter brings to discussion the convergence or otherwise of DTC on teacher self-efficacy as well as PCKs in relation to shaping up faculty career well-being. By breaking down the relationships between these constructs through tested hypotheses, this discussion draws out key insights, theoretical contributions, and practical implications. While acknowledging the subtleties and the implications of the results, this chapter is an attempt to provide a roadmap for institutional decision-makers and educators toward creating a balanced, efficient, and innovative academic environment.

The first hypothesis was that DTC holds a significant impact on career well-being for faculty careers. This hypothesis, though, was not supported theoretically or by any prior research either. The result, on the other hand, sends a signal towards the idea that although DTC absolutely is a pre-requisite in today's educational geographies, it doesn't have to hold a gigantic impact on career well-being as perceived earlier. A whole lot of contextual factors are prompting introspection over this very result. For instance, the highly rapid digitalization of learning tools and practices, though revolutionary, may bring along the added burden of workload, stress caused by technology, and the steepness of the learning curve, thus reducing the direct positive effects on career well-being. Furthermore, faculty members may perceive DTC as a minimum standard rather than an enabler of career satisfaction, thereby reducing its independent effect [4]. These results require a holistic analysis, focusing on how DTC interacts with factors of institutional support, professional development, and collaborative environments to support enhanced well-being.

However, the second hypothesis held as it stated that the degree of digital teaching competency impacted teacher self-efficacy. The results conform with the theories that explain mastering digital tools boosts educator's confidence in their ability to ensure effective learning. This positive relationship underscores the transformative potential of digital competence in empowering teachers to navigate diverse instructional challenges. Equipped with adequate digital skills, educators can integrate technology into their pedagogy effectively, fostering innovation and engagement in the classroom [33]. The results emphasize the importance of structured training programs and technological infrastructure as critical enablers of teacher self-efficacy. By focusing on investments in digital competence development, the institutions can create a ripple effect where increased self-efficacy translates into enhanced teaching outcomes, greater adaptability, and sustained professional growth.

The third hypothesis postulated that teacher self-efficacy significantly mediates the relationship between digital teaching competence and faculty career well-being, and this was empirically confirmed. These results illuminate the crucial intermediary role of self-efficacy in bridging technical competence with broader career satisfaction. This outcome implies that digital teaching competence per se is not directly impactful on well-being but assumes importance when it gives educators a sense of mastery and control over their teaching practices. Self-efficacy serves as a psychological buffer, allowing educators to withstand the challenges of digital integration with resilience and optimism [28]. This mediation effect strengthens the call for comprehensive policies from institutions to embed building of self-efficacy within the broader frameworks through mentoring, peer learning opportunities, and feedback mechanisms with technical training in the most integrated approach for individual and institutional-level outcomes.

PCK will moderate the relationship between the faculty's digital teaching competence and the faculty's career well-being. Indeed, this research supports the idea of the interplay between technoperativeness and pedagogics' synergies in promoting good professional careers. PCK reflects teaching competencies that combine in various ways content knowledge with techniques of teaching, which leads to the successful practical application of digital teaching skills. Educators with high PCK would likely be better placed to contextualize digital tools in teaching; thereby, their adoption is likely intuitive and effective [20]. Moderation effects emphasize the holistic approach of professional development programs without isolating digital competence from pedagogical and content knowledge, creating a robust set of skills for faculty members. Institutions must, therefore, place great emphasis on interdisciplinary training modules that bridge these competencies so that educators are both technologically capable and pedagogically competent.

The results of the study thus underpin complex dynamics forming faculty career well-being within an increasingly digitalized educational landscape. Though the direct effects of teaching competence with regard to digitalization on career satisfaction may be illusive, the indirect effects of teacher self-efficacy and its interaction with pedagogical content knowledge bring its multi-faceted significance into the limelight. It encourages professional development frameworks that shift away from isolated skill enhancement towards integrated competency building. These, however, can be made through the institutional environment that encourages confidence, flexibility, and pedagogic mastery to ensure educators prosper despite the changes in times. As the educational landscape enters the digital era, these findings lay the very essence of building academic excellence among supported and satisfied faculty.

THEORETICAL IMPLICATIONS

This research contributes significantly to the theoretical landscape by providing insight into the interplay between technological self-efficacy, chatbot acceptance, task-technology fit, and performance outcomes in learning environments. The results run contrary to traditional models of technology adoption, since a significant finding is that self-efficacy related to technology does not directly affect the performance outcome but is rather moderated by the effective use of technology in learning. This mediating relationship helps understand better that self-efficacy transforms to actual outcomes and that variables of complementary fit and technology adoption, through this, help emphasize its utility. This study expands available theoretical constructs by considering factors such as chatbot acceptance and task-technology fit as moderating influences such that the former, more than just a peripheral, holds central positions to augment technological self-efficacy and shape performance. These theoretical advances bridge gaps in previous literature and propose a more integrated model of technology use in learning environments.

The study also contributes more broadly to theories of human-computer interaction by demonstrating the extent to which perceptions of acceptance of a chatbot significantly moderate the relation between self-efficacy and performance. This is aligned with the task-technology fit theory in which the optimal fit between users and technologies positively influences outcomes. The alignment creates the potential for understanding deeper interactions of individual and contextual factors influencing performance in educational environments. Future theoretical frameworks will benefit from this study by integrating similar moderating and mediating mechanisms to provide a more holistic view of the factors involved in technology integration. Furthermore, the study supports the increasing acknowledgment of mediated learning environments as a crucial component of educational progress, thus prompting researchers to re-examine existing theories through the context of new technologies such as chatbots.

PRACTICAL IMPLICATIONS

This study holds profound practical implications for educational institutions and developers of technology who wish to enhance the learning experience. The key role of "Use of Technology in Learning" as a mediator calls for investments by institutions in training programs that nurture both technological self-efficacy and the effective use of tools in learning processes. This would, therefore, lead the educator to make best of technological advancements in schools as well as virtual teaching scenarios. In addition to these findings, acceptance research implies that chatbot developers should primarily concern themselves with creating user-friendly context-adaptable chatbots that are capable of relating to the needs as well as expectations of their students. It should not just enable knowledge delivery but also interaction between participants for an interactive fun-loving environment, which influences results favorably.

In addition, the demonstrated importance of task-technology fit provides practical guidance for policymakers and educational administrators. Aligning technology design and implementation with the specific tasks it supports can significantly improve learning outcomes. This entails rigorous needs assessments and usability testing during the adoption phase to ensure that technological solutions are relevant and effective. Institutions must also ensure continuous support for learners, emphasizing the need for accessible training and troubleshooting mechanisms. These strategies may enable the organization to develop an ecosystem in which technology totally integrates and supports learning with the advent of improved performance.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study has some weaknesses that are worth noting even though it has its merit. It is limited in geographic scope to one cultural and education setting that may not enable generalization of the results in other cultural settings. Therefore, further studies may use this study to take it into varied cultural settings in understanding how contextual aspects influence the relations studied. Thirdly, because the study employs a cross-sectional design, it limits inferring causal associations. Longitudinal studies would offer a stronger understanding of how technological self-efficacy and related constructs change over time and their long-term effects on performance outcomes. Another limitation is the reliance on self-reported measures, which are prone to biases such as social desirability and inaccuracies in self-perception. Future research could incorporate objective performance metrics or experimental designs to validate the findings. In addition, the research mainly deals with students in a learning environment and does not extend to other areas, such as professional or corporate training settings. Future studies need to look into how these constructs work in a wider context of learning, like workforce development and lifelong learning settings. Another avenue could be exploring emerging technologies such as AI-driven personalized learning tools that might offer a better insight into their interaction with constructs such as task-technology fit and chatbot acceptance.

CONCLUSION

This study provides valuable insight into the dynamic interactions among technological self-efficacy, chatbot acceptance, task-technology fit, and learning performance nuances of technology adoption. Because technological self-efficacy does not directly affect performances, its influence was considered to be mediated through better use of technology within an educational setting, so implying that structured and guided incorporation plays a critical role. In addition, the moderation effects of chatbot acceptance and task-technology fit indicate that contextually appropriate and user-friendly technological solutions are important. These results contribute to both theory and practice by providing a more nuanced understanding of the role of technology in education. The implications of this study go beyond the academic world as it provides actionable insights to educators, developers, and policymakers. By fostering environments that support the effective use and alignment of technology, stakeholders can influence meaningful advances in learning outcomes. The study's weaknesses also open up avenues for further research, especially regarding its generalizability to different contexts and changing technological environments. As technology continues to transform education, this research represents a foundational effort toward the full exploitation of its potential while mitigating the problems that come along with it.

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