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Research Article

AI beyond the feed: Social media competency as predictors of self-efficacy in artificial intelligence learning

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ABSTRACT

This study examines the relationship between social media competence (SMC) and self-efficacy for artificial intelligence (AI) learning in university students on the basis of social cognitive theory. A quantitative and cross-sectional survey design was used in the study. In the data collection process, SMC scale and AI learning self-efficacy measures were used. The data obtained from 451 undergraduate students studying at Sechenov University in Russia were analyzed using partial least squares structural equation modeling (PLS-SEM). The findings showed that the content generation dimension (beta = .302, $p < .001$) and the technical usability dimension (beta = .273, $p < .001$) were the strongest positive predictors of AI learning self-efficacy. The anticipatory reflection dimension showed a weak but statistically significant negative effect (beta = -0.094, $p = .034$). The content interpretation dimension was found to have a weakly positive but statistically insignificant effect (beta = .073, $p = .151$). The model explained approximately 25 percent of the variance in AI learning self-efficacy ($R^2 = .251$). These findings suggest that competencies developed through active content production and technical use on social media platforms can increase students' confidence in learning AI. This result is in line with social cognitive theory's approach that emphasizes direct experience of success as the main source of self-efficacy. The study contributes to understanding how digital competencies transfer to learning confidence in new technological domains and provides practical implications for how social media-based strategies can be integrated into AI education.

Keywords: social media competency, artificial intelligence education, self-efficacy, PLS-SEM

INTRODUCTION

In recent years, social media has become an integral part of the everyday life and educational experience of students in higher education (Alalwan, 2022; Al-Rahmi et al., 2022). Students are increasingly using social media platforms to communicate, share information, and participate in collaborative learning processes. Therefore, the competencies they develop through these interactions are increasingly gaining interest in the academic literature. At the same time, artificial intelligence (AI) stands out as a fundamental field of knowledge and practice in different disciplines. This has led to the fact that the elements that enable students to learn AI effectively have become important both in theoretical and practical terms. This study examines the relationship between social media competence (SMC) and self-efficacy for AI learning in university students.

SMC refers to the knowledge, skills, and trends necessary to use social media platforms effectively and consciously. This concept has been discussed in various ways in different disciplines (Alber et al., 2015; Polanco-Levicán & Salvo-Garrido, 2022; Walsh et al., 2016). However, one of the most appropriate frameworks in terms of a higher education context was developed by S. Zhu et al. (2020). This framework consists of four basic dimensions: technical availability, content interpretation, content production, and anticipatory reflection. These dimensions cover a range of competencies, from the ability to navigate digital interfaces to the capacity to critically and reflectively evaluate online behavior. According to research, social media platforms are used for educational purposes. These platforms help students collaborate, share knowledge, and participate actively (Ansari & Khan, 2020; Bukhari et al., 2020; Sivakumar et al., 2023). The use of social media in higher education; it has been associated with positive outcomes such as strengthening student interaction, increasing engagement, and developing professional competencies (Chowdhury, 2025; Sun et al., 2023). These findings suggest that the competencies students develop during social media use may not be limited to social media environments alone.

According to Bandura (1977), self-efficacy is the individual's belief in the capacity to organize and implement the actions necessary to achieve certain goals. Self-efficacy plays an important role in shaping learning outcomes. Self-efficacy in the context of AI education affects how students approach tasks related to AI, how much effort they make, and to what extent they persist when faced with challenges (Du et al., 2024). Students with high self-efficacy in AI learning are more likely to engage more effectively with AI technologies and achieve more successful learning outcomes (Rodríguez-Ruiz et al., 2025; Rui & Badarch, 2022).

Various studies have examined the relationship between social media engagement and self-efficacy in different contexts. Jia et al. (2024) showed that regular social media use increased self-efficacy through the social support mechanism. X. Zhu et al. (2021) reported that nursing students actively engaged in social media exhibited higher levels of self-regulated learning and self-efficacy. These findings provide leading-edge evidence that the skills and confidence developed in the social media use process can also be transferred to other areas of learning. However, it is not yet clear what mechanisms the different dimensions of SMC are related to AI learning through self-efficacy. The current literature has revealed that SMC and self-efficacy are important in terms of technology-based education. However, it has not yet been examined how and to what extent the different components of SMC fatigue students' confidence in AI learning. This gap is important. Because different dimensions of SMC, such as technical use, critical evaluation, and reflective thinking, can be processed through different psychological mechanisms and have different effects on self-efficacy.

This study addresses the gap by making use of social cognitive theory (Bandura, 1986). Social cognitive theory provides a comprehensive framework that explains the mutual impact of environmental, behavioral, and personal factors on learning outcomes. In this context, social media competencies are treated as behavioral factors that develop through interaction with digital environments. Self-efficacy related to AI learning is considered as a personal factor that can be affected by these competencies. This work has the following purposes:

(1) to examine the effects of the four dimensions of SMC, namely technical availability, content interpretation, content production, and anticipatory reflection, on the self-efficiencies of students' learning of AI, using partial least squares structural equality modeling (PLS-SEM) and

(2) to determine, among the dimensions of SMC, which is the most powerful predictor of self-efficacy for AI learning.

By examining these relationships, the study aims to contribute to the literature at the intersection of digital competencies, self-efficacy, and AI education. The findings may provide useful information for educators and instructional designers who want to increase their confidence and effectiveness in learning AI-related concepts and skills by leveraging their existing social media competencies.

LITERATURE REVIEW

Theoretical Framework

This study adopted social cognitive theory as the fundamental theoretical framework. In particular, the study focuses on the concept of self-efficacy, which is central to the theory. Social cognitive theory provides an appropriate framework to explain how SMC can impact students' self-efficacy in AI learning. The theory emphasizes the interaction between individual beliefs, behaviors and environmental conditions (Bandura, 1986; Schunk & DiBenedetto, 2020).

Social cognitive theory and triple reciprocal determinism

According to Bandura (1986), human behavior is shaped by the interaction of three basic factors. These are personal factors, behavioral factors and environmental factors. Personal factors include cognitive, affective and biological features. Behavioral factors include the actions exhibited by the person. Environmental factors refer to the social and physical context in which the individual exists. According to this model, the person is neither solely the product of internal forces nor a passive recipient of external stimuli. The individual actively participates in his/her own learning and behavior processes (Bandura, 1986). Studies in the field of education also show that learning outcomes are formed by the interaction between students' beliefs, actions and learning environments (Schunk & DiBenedetto, 2020).

When SMC and AI learning are considered together, this triadic structure provides an explanatory basis. Social media platforms can be seen as an environmental factor. They give students the opportunity to observe, interact and engage with content. The skills that students develop in these environments, such as technical use, content production, critical interpretation and reflective thinking, can be considered as behavioral factors. These skills are shaped by the digital environment and affect the digital environment. Self-efficacy beliefs regarding AI learning, which is included in personal factors, can also be affected by this process. In other words, as students become more competent in social media environments, they may become more confident in new and complex technological fields such as AI. Recent studies also show that there are significant and positive relationships between digital efficacy and academic self-efficacy (González-Prida et al., 2024; Zakir et al., 2025).

Self-efficacy as a fundamental mechanism

Self-efficacy is one of the most important concepts in social cognitive theory. Bandura (1977) sees self-efficacy as an individual's belief in his/her capacity to organize and implement the actions necessary to perform a certain performance. This belief does not only reflect what the individual can do. It also indicates which tasks the individual is oriented towards, how much effort he/she makes and how persistent he/she is in the face of difficulty (Bandura, 1997).

According to Bandura (1997), self-efficacy beliefs are based on four main sources. The first source is direct experiences, that is, experiences of success. Repeated success in a field strengthens self-efficacy. Failures, especially in the early period, may weaken self-efficacy. The second source is indirect experiences. When individuals see others successfully accomplishing a task, they are more likely to believe that they too can be successful. The third source is verbal reinforcement. Supportive feedback and encouragement from others can increase a self-efficacy. The fourth source is physiological and emotional states. Positive emotional states support self-efficacy, while states such as anxiety and stress may decrease this perception.

These four sources provide a strong basis for explaining why SMC can influence AI learning self-efficacy. Students who create and share content on social media platforms get direct experience in digital environments. Although these experiences are not directly related to AI, they may strengthen their overall perception of digital competence.

This general competency can then be transferred to AI learning. Similarly, technical usability skills can be considered as a kind of success experience. Students who are comfortable with complex digital interfaces may approach AI tools and applications with less anxiety. Recent studies show that digital competence, digital literacy and AI literacy are closely related to self-efficacy (Asio, 2024; Bećirović et al., 2025).

The interactive nature of social media also creates favorable conditions for indirect experiences and verbal persuasion. Students can observe their peers as they interact with technology-related content. They can also receive feedback on their own digital contributions. These two processes can strengthen students' beliefs that they can cope with new technologies. Content interpretation skill is more important in the cognitive evaluation dimension. Students who can critically evaluate the information encountered in social media may be better prepared to learn in technically challenging areas. Indeed, recent findings showed that the technical understanding and practical application dimensions of AI literacy support AI self-efficacy (Bećirović et al., 2025; Bewersdorff et al., 2025).

The dimension of anticipatory reflection refers to the student's thinking in advance about the possible consequences of their actions in digital environments. This characteristic is related to self-regulation. Self-regulation often supports effective learning. However, an overly cautious or overly questioning approach may in some cases decrease self-efficacy rather than increase it. This point is particularly important in the context of AI. Some recent studies showed that overly critical or risk-oriented evaluation of AI tools can have negative effects on self-efficacy (Bećirović et al., 2025).

Relating social cognitive theory to the research model

In line with this theoretical foundation, the current study examined the relationship between the four social media competency dimensions conceptualized by S. Zhu et al. (2020) and AI learning self-efficacy. In terms of social cognitive theory, technical usability and content production dimensions are expected to be more effective through direct experience of success. Students who demonstrate competence in these areas have repeated successful experiences in digital environments. This may develop a broader perception of technological self-efficacy. The content interpretation dimension may contribute to self-efficacy through indirect learning and cognitive evaluation processes as it supports the processing and evaluation of digital information. The anticipatory reflection dimension offers a more complex structure related to self-regulation. This dimension can support learning. However, an overly cautious approach to technology may limit the level of confidence in some students.

Therefore, in this study, technical usability, content generation and content interpretation dimensions are expected to show positive relationships with AI learning self-efficacy. The anticipatory reflection dimension, on the other hand, may show a more complex, even weak or negative relationship depending on the context. This expectation is in line with both social cognitive theory's explanations of self-efficacy and recent findings in the field of digital efficacy and AI self-efficacy (Asio, 2024; Bećirović et al., 2025; Bewersdorff et al., 2025; González-Prida et al., 2024; Zakir et al., 2025).

Social Media Competence: Conceptualizations and Frameworks

SMC is a multidimensional structure defined in different forms in different disciplines. In its most general sense, this concept refers to the knowledge, skills, and trends necessary to use social media platforms effectively, consciously, and responsibly. However, which dimensions are highlighted varies according to the theoretical approach and application area of the study. Recent studies have also shown that SMC is not limited to technical use-only skills, but also includes dimensions such as critical evaluation, ethical awareness, engagement, and self-regulation (Cho et al., 2024; Polanco-Levicán & Salvo-Garrido, 2022)

Various theoretical frameworks have been developed to explain SMC. One of the early and comprehensive models was proposed by Walsh et al. (2016). This model defines five key components in the context of corporate reputation management: technical skills, knowledge of visibility mechanisms, awareness of the impact of online behavior, communication skills, and understanding the social media ecosystem. This approach treats SMC as a professional capacity associated with strategic communication. Similarly, but in a different field of practice, Alber et al. (2015) have developed a SMC inventory for health education professionals. Within this framework, the ability to effectively disseminate health information through digital environments and promote positive behavior change is prominent.

Table 1. Comparison of social media competence framework

Framework	Dimensions	Context	Key focus
Walsh et al. (2016)	Technical skill, visibility awareness, impact assessment, communication, knowledge	Organizational/ corporate	Reputation management
Alber et al. (2015)	Health information dissemination, behavioral influence	Health education	Professional competence
Polanco-Levicán and Salvo-Garrido (2022)	Participation, ethical awareness, communication, education	Social media literacy	Citizenship and ethics
Pagnotta et al. (2018)	Knowledge, skill, awareness of digital life	Psychotherapy	Client-therapist relations
S. Zhu et al. (2020)	Technical usability, content interpretation, content generation, anticipatory reflection	Higher education	Student digital competence

From a broader literacy perspective, Polanco-Levicán and Salvo-Garrido (2022) collected social media literacy in four key areas: engagement, ethical awareness, communication, and education. This approach shows that SMC goes beyond technical competence. Subsequent theoretical studies also supported this view. Cho et al. (2024), for example, proposed a more holistic framework that handles social media literacy in conjunction with the user's message choices, network relationships, values, and platform features. Similarly, Valle et al. (2025) emphasized purpose, context, inquiry, reflection, and action dimensions in the critical social media literacy approach. These current approaches demonstrate that SMC is not only the ability to drive, but also the capacity for critical and ethical decision-making.

Pagnotta et al. (2018), on the other hand, explained the competence of social media in the field of psychotherapy through the knowledge of digital culture, the ability to find directions on online platforms, and the awareness of the digital lives of the clients. These models come from different disciplines. But they have something in common. All agree that SMC includes both functional skills and high-level cognitive and ethical capacity.

The framework most directly related to this work is the SMC scale, developed and validated by S. Zhu et al. (2020) in the context of higher education. This model consists of four dimensions. Technical usability refers to the ability of students to navigate social media environments and manage their own assets. Content interpretation covers the capacity to analyze and critically evaluate information encountered on social media. Content generation focuses on the ability to produce meaningful content and create an authentic online identity. Anticipatory reflection measures the ability to think ahead of the possible consequences of behavior in digital environments. **Table 1** provides a comparative summary of these frameworks. The scale developed by S. Zhu et al. (2020) is particularly suitable for this study, as it has been developed for higher education students and offers a balanced, functional and reflective competency structure. The validity and reliability findings of the scale were also supported in previous research (S. Zhu et al., 2020).

There are several reasons why the SMCS framework was preferred in this study. First, the scale was developed directly for higher education students. This is in line with the sample of the research. Secondly, the four-dimensional structure of the scale evaluates both functional skills and intellectual and reflective dimensions together. This makes it possible to examine the social media capacities of students in a more balanced way. Thirdly, current theoretical debates about social media literacy suggest that technical use and critical and ethical awareness should be considered together. Therefore, the structure of SMCS is also compatible with current literature (Cho et al., 2024; Valle et al., 2025).

Social media competence in educational settings

The role of social media in higher education has long been explored. The findings suggest that these platforms have more than one educational function. Previous studies have shown that social media supports collaborative learning and knowledge sharing among students (Ansari & Khan, 2020; Bukhari et al., 2020). More recent reviews and empirical studies also offer similar results. Social media-based learning environments in particular are reported to be able to increase engagement, resource sharing, discussion and engagement (Perez et al., 2023; Wang et al., 2025). This suggests that social media can function as a tool that takes learning out of the classroom.

The cognitive dimension of social media use also holds an important place in educational research. Liu et al. (2022) showed that students with stronger cognitive skills were more successful in social media-based collaborative learning tasks. This finding is important. Because it suggests that the educational opportunities offered by social media do not produce the same level of benefit for all students. What knowledge and skills students come to social media with can affect how much they can benefit from these platforms. Current research also shows that digital competence, quality of interaction, and collaborative learning processes are associated with learning outcomes (Bach et al., 2024; Shabur & Siddiki, 2024). This point is especially important for learning in complex areas such as AI.

In the post-COVID-19 period, the importance of social media and more general digital platforms in education has become more visible. Pandemic accelerated digital transformation in higher education and significantly increased the use of online tools in teaching and learning processes (Findyartini et al., 2024). Recent systematic reviews also confirmed this transformation. According to these studies, pandemic has accelerated the adoption of online learning systems, digital platforms and technology-enabled teaching practices in higher education (Matsieli et al., 2024; Pardo-Jaramillo et al., 2025). The greater inclusion of tools such as YouTube, WhatsApp, and learning management systems in the course processes has increased the importance of social media and digital competencies so that students can benefit effectively from these environments.

There also seems to be a correlation between student engagement and motivation and the use of social media. Previous studies have shown that peer interaction and common problem-solving can support learning, especially in challenging lessons (Almagro & Edig, 2024; Dwi Kurniati et al., 2020; Sivakumar et al., 2023). More recent research also reports that student interaction, engagement quality, and social media-based learning experiences are associated with academic performance (Perez et al., 2023; Zhang & Huang, 2025). These findings suggest that SMC is not only a technical skill set, but also a capacity that shapes participation in learning.

When all these findings are evaluated together, it can be said that SMC is a multidimensional structure that affects the way students learn, interact and cope with complex content. However, how these competencies are transferred to students' confidence in learning emerging technologies is still not adequately explained. Especially in the context of the self-efficacy of learning AI, it is seen that this relationship is examined limited. This study addresses the gap in question and examines the different effects of different dimensions of SMC on AI learning self-efficacy. The fact that AI is becoming increasingly visible in higher education also makes this question more important (Kovari, 2025; Long et al., 2026).

Self-Efficacy in Artificial Intelligence Learning

With the increasing inclusion of AI in teaching programs at different educational levels and contexts, it has become an important research topic in how students interact more confidently with these technologies (Karampelas, 2025; Nikolopoulou, 2025; Samara & Kotsis, 2024). Within the framework of the previously announced social cognitive theory, self-efficacy is one of the main personal factors affecting the learning process of the individual. Self-efficacy plays an important role in determining how students approach learning tasks, how much effort they put in, how persistent they are in the face of the challenges they face, and ultimately how successful they are. This is especially important for AI learning, a technically complex and fast-changing field.

The role of self-efficacy in technology-based learning

The importance of self-efficacy in learning processes has long been recognized in the educational literature. Research shows that self-efficacy is closely related to learning motivation, emotional regulation, and resilience in challenging learning environments (Andriani et al., 2022; Cong & Li, 2022; Görgülü & Törün, 2025; Hashemi & Ghanizadeh, 2011). Students with high self-efficacy often set more ambitious goals, put more effort into it, and are more resistant to recovery after failure. These characteristics are particularly important in the context of AI training. Because topics related to AI often include abstract concepts, technical operations, and new tools. These features can create significant learning disabilities for students.

The application of self-efficacy to the context of AI learning has started to attract more attention in recent years. Morales-García et al. (2024) adapted the general self-efficacy scale to the context of AI and developed a short tool to measure university students' confidence in interacting with AI technologies. This work is important. Because the overall self-efficacy scales may not always adequately reflect the perception of trust in new and specialized technologies. Therefore, field-specific measurements are needed. Similarly, Lee et al. (2024) emphasized that self-efficacy associated with AI should be measured in conjunction with larger structures such as AI literacy.

Factors affecting self-efficacy in artificial intelligence learning

There are several factors that affect the self-efficacy of students with regard to AI learning. One of these factors is AI literacy. Du et al. (2024) found that the level of AI literacy significantly compares the students' self-efficiencies of understanding, interacting with, and thinking about the ethical dimensions of AI. This finding is in line with social cognitive theory. Because knowledge and skill acquisition is one of the main sources of success experiences. As individuals gain knowledge and skills in a particular field, their belief in competence in that field also grows stronger.

The opportunity to encounter AI tools in educational settings and to use these tools is also associated with self-efficacy. Ng and Chu (2021) reported that providing students with access to AI applications and providing examples of how AI works increased their confidence in working with these technologies. In terms of social cognitive theory, this can be explained in several ways. Direct interaction with AI tools provides an experience of success. To observe that peers and lecturers use these tools constitutes indirect life. Rodríguez-Ruiz et al. (2025) also showed that self-efficacy in the process of interacting with AI applications plays a critical role in the active learning and problem-solving behavior of students. This finding suggests that successful interaction with AI strengthens self-sufficiency.

Students' attitudes towards AI are also associated with self-efficacy. Research showed that students are generally positive about generative AI tools and are willing to incorporate them into their learning processes (Abualrob, 2025; Aldossary et al., 2024). Wang et al. (2023) showed that students have significant differences in literacy levels and that self-efficacy is one of the main variables associated with these differences. Students with high self-efficacy also performed more strongly in skills associated with AI. This shows that competence and trust are not independent of each other, but mutually evolving structures.

However, the less explained topic in the existing literature is how competencies that have developed outside the field of AI contribute to the self-efficacy of learning AI. The extent to which digital competencies acquired, especially through the use of social media, are transferred to self-confidence in AI learning, has not yet been adequately investigated. Current studies have focused more on factors directly linked to AI training. In contrast, transmission effects from neighboring digital domains have been studied at a limited level.

Relationship Between Social Media Competence and Self-Efficacy of Learning Artificial Intelligence

In the previous sections, it was revealed that SMC is a multidimensional structure and is associated with educational results. It has also been shown that self-efficacy is a fundamental determinant that influences students' participation in AI learning. In this section, these two lines of research are put together and the possible relationship between SMC and AI learning self-efficacy is addressed from a theoretical and empirical point of view.

Empirical findings towards relationship

To date, there is no study that directly examines the relationship between SMC dimensions and AI learning self-efficacy. But different lines of research offer findings that indirectly support this relationship. Jia et al. (2024) showed that regular social media use increased self-efficacy through the social support mechanism. It has been found that individuals who receive positive feedback and encouragement from their online networks have stronger self-efficacy beliefs. This finding is in line with the assumption of social cognitive theory that verbal persuasion can strengthen self-efficacy. Similarly, X. Zhu et al. (2021) has shown that nursing students who are actively involved in social media exhibit higher levels of self-regulated learning and self-efficacy. This result suggests that the skills developed during the social media use process can be transferred to other areas of learning.

The relationship between digital competencies and attitudes towards technology-based learning is also included in the literature. Bozkurt et al. (2023) reported that individuals with high social media self-efficacy had greater confidence in the content on digital platforms and interacted with them more willingly. This suggests a positive relationship between trust in social media use and openness to digital learning opportunities. Du et al. (2024) found that AI literacy compares both self-efficacy and ethical reasoning in the context of AI. There is a conceptual likeness between AI literacy and more general digital competencies. Therefore, it can be thought that the skills students develop through their social media experience can serve as a foundation for more specialized technological fields.

The influence of the media on the attitudes and behavioral responses of individuals is also important in understanding this relationship. Choi et al. (2017) has shown that the self-efficacy levels of individuals influence how they process and respond to information encountered through the media. Ng and Chu (2021) found that social networking sites can be used effectively to motivate students in AI learning. This study establishes a more open link between social media environments and AI learning. When evaluated together, these studies show that SMC can contribute to AI learning self-efficacy in several ways. First, the social media experience can boost overall digital confidence. Second, social media environments can provide social support and encouragement. Third, these environments can enhance students' knowledge processing, critical assessment, and online interaction skills. All of these can support the cognitive and affective preparation required for AI learning.

Research Gap

Although SMC and self-efficacy are becoming increasingly important in technology-related educational research, the specific relationship between the different dimensions of SMC and the self-efficacy of AI learning has not yet been empirically adequately studied. Most of the available studies treat SMC as a one-dimensional structure or focus more on general social media use than on specific competencies. Similarly, research on AI self-efficacy focuses more on AI literacy, attitudes toward AI, and the use of AI directly. In contrast, how competencies developed in other digital environments, such as social media, are transferred to AI learning, has been addressed at a limited level.

This study addresses this gap using the multidimensional framework developed by S. Zhu et al. (2020). The study examines how the dimensions of technical availability, content interpretation, content production, and anticipatory reflection relate to the self-efficacy of students with regard to AI learning in different ways. This approach is in line with the social cognitive theory. Accordingly, different competency dimensions can affect self-sufficiency through different mechanisms. Technical availability and content production can be more effective than direct success experiences. Content interpretation may be related to cognitive assessment and indirect learning processes. Anticipatory reflection is linked to self-regulation processes and therefore its relationship to self-efficacy can be more complex. The empirical testing of these relationships will help to further explain how social media competencies are transferred to learning confidence in new technological areas such as AI.

The theoretical rationale outlined above leads to the following hypotheses:

1. **H1.** Technical usability has a positive and significant effect on self-efficacy in learning AI.
2. **H2.** Content interpretation has a positive and significant effect on self-efficacy in learning AI.
3. **H3.** Content generation has a positive and significant effect on self-efficacy in learning AI.
4. **H4.** Anticipatory reflection has a significant effect on self-efficacy in learning AI.

It should be noted that **H4** is stated as non-directional, as the theoretical reasoning suggests that the relationship between reflective thinking and self-efficacy may not be straightforwardly positive. Excessive reflection on risks and consequences in digital environments could, in principle, either enhance self-efficacy through better preparation or diminish it through heightened awareness of potential difficulties.

METHOD

Research Design

This study was conducted by quantitative research within the positivist paradigm. Cross-sectional and relational screening pattern was used in the research. This pattern was estimated appropriate to examine the predictive relationships between dimensions of SMC and self-efficacy related to AI learning (Creswell & Creswell, 2017). The survey-based data collection approach has enabled data to be obtained from a group of students with relatively broad and distinct characteristics. This supports the generalization of the findings (Fowler, 2014). The relational nature of the research allowed to examine the direction and strength of the relationship between variables without any experimental intervention.

Ethical Declaration

Necessary permission was obtained from the university administration before the data collection process. The survey was conducted online. At the beginning of the survey, informed consent process was presented to the participants. A preliminary question was posed asking participants whether they agreed to participate in the study voluntarily. In the introduction part of the survey, the purpose of the research is clearly stated that the participation is voluntary and that the participants can leave the study without encountering any negative results at any time. In addition, the contact information of the researcher was shared so that the participants could submit their questions or opinions. Students who stated that they did not want to participate in the research were not directed at the survey items. Instead, they were thanked and the questionnaire was terminated. No data was collected that could reveal personal identity at any stage of the research. Thus, participant anonymity is preserved throughout the entire research process.

Data Collection Tools

Two measuring instruments were used in this study. The first tool is the SMC scale developed by S. Zhu et al. (2020). This scale was developed to measure the SMC levels of university students. The scale consists of 28 items collected in four dimensions. These dimensions are technical usability (TK; 5 items), content interpretation (good; 7 items), content production (IU; 7 items), and anticipatory reflection (PIE; 9 items). Technical availability measures students' ability to navigate social media platforms and manage their digital assets. Content interpretation focuses on the capacity to analyze, understand and critically evaluate social media content. Content production evaluates the skills of creating meaningful content and establishing an authentic online identity. Anticipatory reflection measures the capacity to reflect on the possible consequences of behavior in digital environments. All items are scored with the five Likert type scale, which extends from 1' to 5'. On the scale 1 "definitely do not agree", while 5 "means absolutely agree".

The second measurement tool is the self-efficacy dimension of the AI literacy scale developed by Wang et al. (2023). This dimension has been used to measure students' confidence in understanding AI and interacting with AI technologies. The scale consists of four items of this size.

Sampling

The data of the study were collected from undergraduate students studying at the University of Sechenov in Russia. Ten observation criteria per item proposed by Hair et al. (2017) were used to determine the minimum sample size required. Since there are a total of 32 items in both measuring instruments, the lowest number of participants required was calculated as 320. A total of 500 surveys were sent to students through the online survey platform. After the data cleaning process, 451 valid surveys were found to be suitable for analysis. This number is above the minimum sample size required. Demographic information was not collected in the study. This is because the study focuses only on the relationships between the structures being measured. This preference has resulted in complete anonymity. But it also constitutes a limitation. Because demographic variables such as age, gender and previous AI experience have not been controlled in the analysis.

Data Analysis

Data were analyzed using SmartPLS 4 software using PLS-SEM (Ringle et al., 2022). There are two main reasons why PLS-SEM is preferred. First, this method does not mandate the multivariate assumption of normal distribution. It is therefore also suitable for data that is not normally distributed (Hair et al., 2017). Secondly, PLS-SEM allows to evaluate the contribution of each substance to its structure through factor loads. This feature was seen as important in terms of improving the measurement model in the current study. In

Table 2. Factor loading and reliability coefficients

Dimension	Items	Factor loading	Cronbach's alpha	Composite reliability		AVE
				rho_a)	rho_c	
Self-efficacy of AI	01	0.792	.770	.771	.853	.592
	02	0.753				
	03	0.801				
	04	0.729				
Technical usability	02	0.751	.744	.780	.851	.656
	03	0.857				
	04	0.820				
Content interpretation	06	0.761	.748	.765	.856	.665
	08	0.874				
	09	0.809				
Content generation	15	0.730	.751	.765	.842	.572
	17	0.702				
	18	0.816				
	19	0.772				
Anticipatory reflection	23	0.810	.833	.886	.874	.582
	24	0.751				
	25	0.709				
	26	0.751				
	27	0.789				

addition, PLS-SEM is considered a particularly useful method in exploratory research into procedure and theory development (Hair et al., 2019). This is in line with the aims of the study.

The two-stage approach proposed by Anderson and Gerbing (1988) was followed. Accordingly, the measurement model was evaluated first, then the structural model. In the first stage, the contribution of each substance to the structure to which it belongs is examined through factor loads. Substances with a factor load below .70 were removed one by one. After each item was removed, the model was retested and the stability of the model was checked. At the end of this iterative process, all four items belonging to the self-efficacy dimension were preserved. Because none of these substances are below the threshold value. On the SMC scale, 13 items were removed due to insufficient factor load. These substances are 02, 05, 07, 10, 11, 12, 13, 14, 16, 20, 21, 22, and 28. During this process, at least three items of any dimension are left. Thus, attention was paid to the preservation of the representative power of the structures. As a result, the final measurement model consists of 15 items from the SMC scale and 4 items from the self-efficacy dimension, totaling 19 items.

The internal consistency reliability of the corrected measurement model was assessed by Cronbach's alpha and composite reliability coefficients. Convergent validity was examined using the average described variance value. For this criterion, values of .50 and above were considered acceptable. The divergent validity has been tested by two different methods. These are the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. After the measurement model was determined to provide reliability and validity conditions, the structural model was analyzed. At this stage, the hypothetical relationships between the dimensions of SMC and the self-efficacy related to AI learning have been tested. The statistical significance of the path coefficients was assessed by the bootstrap method, which included 5,000 resamples (Hair et al., 2017). The effect sizes of the exogenous structures on the endogenous structure were examined with f-square (f^2) values. The effect size of the model was assessed using the Stone-Geisserin Q-square (Q^2) value (Eom & Ashill, 2016).

FINDINGS

Following the iterative item elimination process described before, the final measurement model comprised 19 items: 4 items for self-efficacy of AI, 3 items for technical usability, 3 items for content interpretation, 4 items for content generation, and 5 items for anticipatory reflection. **Table 2** presents the factor loadings and reliability coefficients for the refined model.

As presented in **Table 2**, all factor loadings in the final model are above the threshold value of .70. Factor loadings ranged between .702 and .874. This finding indicates that each item adequately represents the

Table 3. HTMT ratio matrix

Dimensions	Anticipatory reflection	Content generation	Content interpretation	Technical usability	Self-efficacy of AI
Anticipatory reflection					
Content generation	.548				
Content interpretation	.674	.699			
Technical usability	.540	.681	.704		
Self-efficacy of AI	.210	.560	.411	.537	

Table 4. Fornell-Larcker criterion

Dimensions	Anticipatory reflection	Content generation	Content interpretation	Technical usability	Self-efficacy of AI
Anticipatory reflection	.763				
Content generation	.452	.756			
Content interpretation	.528	.507	.816		
Technical usability	.410	.496	.511	.810	
Self-efficacy of AI	.193	.432	.316	.422	.769

construct to which it belongs. Internal consistency reliability was evaluated with Cronbach's alpha and composite reliability coefficients. Cronbach's alpha values ranged between .744 and .833. The lowest value was seen in the technical usability dimension, and the highest value was seen in the anticipatory reflection dimension. The composite reliability (rho_c) values ranged between .842 and .874. All these values are above the recommended limit of .70 (Hair et al., 2017). These results indicate that the internal consistency reliability for all dimensions is adequate. Convergent validity was examined with the average variance explained (AVE) value. All AVE values were above the threshold value of .50 and ranged between .572 and .665. The lowest value was obtained in the content generation dimension, and the highest value was obtained in the content interpretation dimension. This result shows that each construct explains more than half of the variance in its indicators. Overall, it can be said that the measurement model provides sufficient reliability and convergent validity.

Discriminant Validity

Discriminant validity was assessed with two complementary methods. These methods are HTMT ratio and Fornell-Larcker criterion.

As seen in **Table 3**, all HTMT values were below the threshold value of 0.85. Most of the values ranged between .210 and 0.704. The highest HTMT value was observed between content interpretation and technical usability (.704). This indicates that there is a moderate relationship between these two constructs. The lowest value was obtained between anticipatory reflection and AI self-efficacy (.210). This finding shows that the common variance of these two constructs is quite limited. The fact that all HTMT values are below the recommended limit indicates that the constructs are empirically separated from each other.

According to the Fornell-Larcker criterion, the AVE square root of each construct should be greater than its correlations with other constructs. As seen in **Table 4**, this condition is met for all constructs. The values on the diagonal vary between .756 and .816. The lowest value belongs to the content generation dimension, and the highest value belongs to the content interpretation dimension. In each case, these values are higher than the other correlations in the same row and column. The highest correlation between the constructs was between content interpretation and anticipatory reflection (.528). The lowest correlation was between AI learning self-efficacy and anticipatory reflection (.193). The relatively low correlations between AI self-efficacy and SMC dimensions indicate that self-efficacy for AI learning is a separate construct within the model. When HTMT and Fornell-Larcker results are evaluated together, it can be said that discriminant validity is achieved for all constructs in the measurement model.

Structural Model and Hypothesis Testing

After the reliability and validity conditions of the measurement model were met, the structural model was examined to test the hypothetical relationships between the dimensions of SMC and self-efficacy for AI learning. The structural model and path coefficients are presented in **Figure 1**.

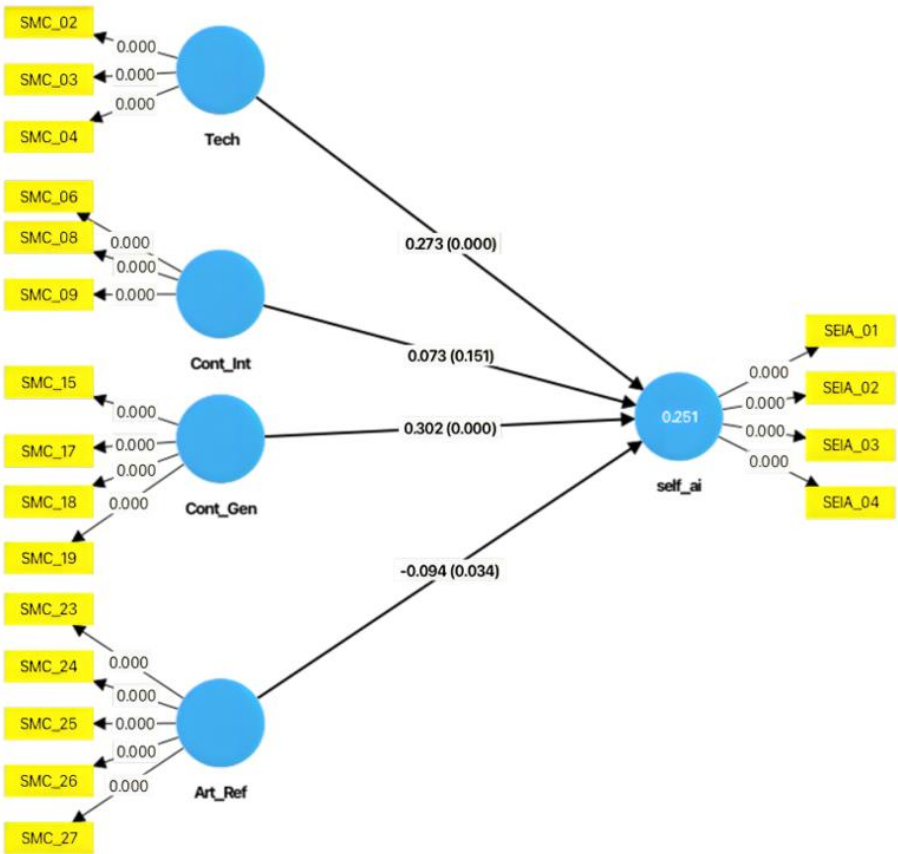

Figure 1. Structural model (Source: Created by the authors)

Table 5. Path coefficient for model

Path	O	M	SD	t-statistics (|O/SD|)	p
Anticipatory reflection -> Self-efficacy of AI	-.094	-.076	.052	1.824	.034
Content generation -> Self-efficacy of AI	.302	.304	.058	5.187	.000
Content interpretation -> Self-efficacy of AI	.073	.068	.071	1.033	.151
Technical usability -> Self-efficacy of AI	.273	.271	.065	4.219	.000

Note. O: Original sample; M: Sample mean; & SD: Standard deviation

The structural model results presented in **Table 5** show that two of the four dimensions of SMC have a statistically significant effect on AI self-efficacy. Content generation showed the strongest positive effect (beta = .302, t = 5.187, $p < 0.001$). This was followed by technical usability (beta = .273, t = 4.219, $p < 0.001$). These findings indicate that content generation and technical usability dimensions are the main predictors of self-efficacy for AI learning. Therefore, **H3** and **H1** were supported.

The anticipatory reflection dimension showed a weak but statistically significant negative effect on AI self-efficacy (beta = -0.094, t = 1.824, p = 0.034). This finding supports **H4**. The negative direction of the effect suggests that thinking more about possible outcomes in digital environments may be slightly inversely related to the level of confidence in AI learning. In contrast, the content interpretation dimension showed a weak positive effect (beta = 0.073, t = 1.033, p = 0.151). However, this relationship was not statistically significant. Therefore, **H2** hypothesis is not supported.

The effect sizes of each predictor variable are presented in **Table 6**. According to Cohen's (1988) criteria, an f^2 value of .02 corresponds to a small effect size, .15 to a medium effect size and .35 to a large effect size. Considering these criteria, content generation (f^2 = .078) and technical usability (f^2 = .065) showed effect sizes that can be considered small to medium. Anticipatory reflection (f^2 = .008) and content interpretation (f^2 = .004) had negligible effect sizes.

Table 6. f^2, Q^2, R^2, and adjusted R^2 on self-efficacy of AI

Predictors	f^2	Q^2	R^2	Adjusted R^2
Anticipatory reflection	.008	.226	.251	.244
Content generation	.078			
Content interpretation	.004			
Technical usability	.065			

The predictive relevance of the model was evaluated with the Q^2 value. The Q^2 value obtained is .226. Values above zero indicate that the model has predictive relevance. This finding suggests that the structural model has moderate predictive power (Hair et al., 2017). The R^2 value was .251 and the adjusted R^2 value was .244. This result shows that the four dimensions of SMC together explain approximately 25 percent of the variance in AI self-efficacy. This rate indicates a moderate level of explanatory power. However, it suggests that there are other variables that affect students' self-efficacy for AI learning.

DISCUSSION

In this study, the relationships between four dimensions of SMC and university students' self-efficacy for learning AI were examined based on social cognitive theory. The findings showed that not all dimensions of SMC were related to AI learning self-efficacy in the same way. Content generation and technical usability raised out as significant and positive predictors, while anticipatory reflection had a weak but significant negative effect. Content interpretation had a positive but not statistically significant effect. These results suggest that SMC has a more complex and differentiated effect structure on self-efficacy in AI learning, rather than a single dimension.

The fact that the content generation dimension is the strongest predictor of AI learning self-efficacy can be explained by the concept of direct success experience, which Bandura (1997) defines as the most effective source of self-efficacy. Students who regularly produce and share content on social media platforms have repetitive experiences in digital environments such as completing tasks, creating visible products and receiving feedback. Although these experiences are not directly related to AI, they can create a general perception of digital competence in students. Such a perception of competence can then be expected to transfer to self-efficacy in AI learning. Indeed, Yaacob et al. (2024) showed that students with content production experience adapt to new technologies more easily. Similarly, skills such as critical thinking, problem solving and digital literacy developed during the content production process are also important for AI learning (Koehler & Vilarinho-Pereira, 2023; Liu et al., 2022). In this context, content creation is not only a social media activity, but also an experience that helps students develop confidence in more complex technological domains.

Similarly, the fact that the technical usability dimension had a significant and positive effect on AI learning self-efficacy suggests that functional competencies gained in digital environments can affect students' approach to new technologies. In terms of social cognitive theory, skills such as navigating social media platforms, managing settings, using tools effectively, and organizing online presence also constitute a type of success experience. Such skills can make students more comfortable with digital interfaces. As a natural consequence, students may approach AI tools, platforms and applications with less anxiety. This finding is in line with research emphasizing the role of technical competence in technology use (S. Zhu et al., 2020). It is also in line with studies that reveal the functions of social media in terms of learning, interaction and participation in higher education (Ansari & Khan, 2020; Bukhari et al., 2020; Sivakumar et al., 2023).

However, it is particularly significant that the content generation dimension shows a stronger effect than technical usability. One of the reasons for this difference may be that content generation requires more intensive cognitive engagement than technical usability skills. The process of content generation often involves stages such as planning, making sense, making choices, creative decision-making, and creating a targeted presentation. In this respect, it is more similar to the cognitive processes required by AI. There is a significant difference between simply being able to use an interface and being able to design and present digital content. In the latter case, the learner takes on a more active, productive and self-regulated role. The study conducted by X. Zhu et al. (2021) on nursing students also points to a similar point. The results showed that active social media engagement was more strongly associated with self-regulated learning and self-efficacy than passive social media use. This suggests that it is not only technical ease, but also the quality and depth of digital interaction that is decisive in building learning confidence in complex areas such as AI.

The finding regarding the anticipatory reflection dimension revealed a picture that should be interpreted more carefully. The weak but significant negative effect of this dimension on AI learning self-efficacy suggests that the relationship between reflective thinking and confidence may not always be linear and positive. Anticipatory reflection, as conceptualized by S. Zhu et al. (2020), refers to an individual's tendency to pre-evaluate the possible consequences of their behaviors in digital environments. In the context of social cognitive theory, this feature is associated with self-regulation and personal control capacity (Bandura, 1986). In general, self-regulation is considered a positive characteristic for learning. However, the present finding suggests that this relationship may be more complex, especially in new, uncertain and sometimes risky technological fields.

One possible explanation for this result is that students who think more about the risks and consequences in digital environments may be more cautious about technologies that they are not yet fully familiar with, such as AI. While such caution may increase critical awareness in some cases, it may not support confidence to the same extent. The physiological and affective states that Bandura (1997) includes among the sources of self-efficacy may be explanatory at this point. Increased sensitivity to possible errors, risks or negative consequences may cause anxiety or timidity in students. This may lead to some weakening of self-efficacy in AI learning. Bukhari et al. (2020) stated that active participation in social media in higher education supports knowledge sharing and engagement. However, when this engagement is coupled with a strong tendency towards risk assessment, students may become more aware of the opportunities offered by AI technologies as well as their complexities and potential drawbacks. Such awareness, while valuable for learning, may have had a slight dampening effect on self-efficacy. Nevertheless, it should be noted that the effect size of this relationship is extremely low ($f^2 = .008$). Therefore, it can be said that even though this result is statistically significant, its effect in practice is limited.

The weak positive but statistically insignificant effect of content interpretation dimension on AI learning self-efficacy is also an important finding. The ability to analyze, interpret and critically evaluate social media content can theoretically be expected to contribute to AI learning. Because the process of learning with AI often requires information selection, interpretation, verification and critical evaluation. However, the fact that this relationship did not reach a significant level in the current sample suggests that this effect may work through more indirect mechanisms. Choi et al. (2017) showed that media is effective in the formation of attitudes, and Ansari and Khan (2020) showed that educational social media use supports knowledge sharing. However, in terms of social cognitive theory, the content interpretation dimension seems to be related to indirect learning and cognitive evaluation processes rather than direct achievement experience. Therefore, it is not surprising that its effect is weaker. In addition, Liu et al. (2022) showed that students with higher cognitive capacity were more successful in social media-based collaborative learning processes. This finding suggests that the effect of content interpretation skill on AI learning self-efficacy may be mediated by other cognitive variables. In other words, the effect of this dimension may not be directly visible in the current model

These findings have some important theoretical implications. The results support Bandura's (1997) approach to self-efficacy resources in the context of technology education. The stronger effects of content generation and technical usability dimensions, which are directly related to achievement experience, are consistent with the theoretical expectation that the strongest source of self-efficacy is achievement experience. On the other hand, the fact that the dimensions that are more closely related to social learning and self-regulation show more limited effects reveals that not all dimensions of SMC affect self-efficacy with the same strength. Thus, the study shows that social cognitive theory can be applied in technology-based learning contexts in a more detailed way that considers the differences between dimensions.

In addition, the negative effect of the anticipatory reflection dimension provides an important contribution suggesting that self-regulation processes do not always increase self-efficacy. In the literature, reflection is often considered as a positive learning feature. However, the current finding suggests that excessive risk awareness may have a diminishing effect on confidence, especially in areas such as AI, which involves uncertainty, ethical debate and rapid change. In this respect, the study reveals that the effect of reflective thinking on learning outcomes should be considered in a context-sensitive manner.

On the other hand, the explanatory level of the model is also remarkable. The R^2 value of 0.251 indicates that the dimensions of SMC explain approximately one fourth of the variance in AI learning self-efficacy. This ratio reveals that SMC has a significant share on self-efficacy in AI learning. However, it is also clear that students' AI learning self-efficacy cannot be explained by SMC alone. It is thought that other variables such as previous AI experience, general academic self-efficacy, attitudes towards technology, instructional support and institutional learning environment may also play an important role in this process.

The practical implications of the study are also remarkable. The findings provide important clues especially for instructors and instructional designers designing AI education. The strong effect of the content generation dimension suggests that activities in which students can assume productive roles in AI courses may be useful. Students can be asked to produce short videos explaining AI concepts, write blog posts evaluating specific AI applications, or create infographics visualizing research findings. Such tasks allow students to use their already existing social media-based production skills for academic purposes. It can also contribute to a more confident approach to AI-related topics.

In parallel, the significant effect of the technical usability dimension suggests that it is also important to support students' general digital navigation and tool use skills. Before moving on to more complex AI-related content, it may be useful to support students with basic digital tools and AI platforms. Short workshops, guided practice and introductory activities, especially for introductory students, can support self-efficacy development by reducing technical uncertainty.

The result related to the anticipatory reflection dimension shows that a careful balance should be established in the teaching process. Discussing the ethical, social and risk dimensions of AI is undoubtedly important. However, if students encounter intense risk and responsibility discussions before they have developed a basic sense of competence in this field, this may lead to a loss of confidence in some students. Therefore, it would be appropriate to balance critical reflection activities with hands-on learning opportunities where students can have successful experiences. Guided tasks, small-scale practice and gradually challenging learning activities can allow students to first see what they can do and then consider more complex ethical and social dimensions.

Finally, the use of social media platforms as supplementary learning environments in teaching AI can also be useful. Sharing information, participating in discussions and offering support to each other in digital environments that students are already familiar with can make the learning process more accessible. Such interactions can contribute to the strengthening of self-efficacy through the social support mechanisms emphasized by Jia et al. (2024). Therefore, social media can be considered not only as a space for everyday communication but also as a pedagogical resource that supports confidence and engagement in AI learning.

CONCLUSION

Based on social cognitive theory, this study examined the relationship between SMC and AI learning self-efficacy of 451 university students. The findings showed that content generation dimension (beta = 0.302, $p < 0.001$) and technical usability dimension (beta = 0.273, $p < 0.001$) were the strongest predictors of AI learning self-efficacy. In contrast, the anticipatory reflection dimension was found to have a weak negative effect (beta = -0.094, $p = 0.034$). Although the content interpretation dimension showed a positive relationship, it was not statistically significant (beta = 0.073, $p = 0.151$). The model explained approximately 25 percent of the variance in AI learning self-efficacy ($R^2 = 0.251$).

The results support the social cognitive theory's assumption that direct experience of success is the strongest source of self-efficacy. It is understood that the competencies that students develop through active content production and technical use on social media platforms are transferred to their confidence in interacting with AI technologies. The negative effect of the anticipatory reflection dimension, although small, is noteworthy. This finding suggests that the relationship between reflective thinking and self-efficacy may not always be linear and positive, especially in new and uncertain technological fields. In other words, increased awareness of risks and possible consequences may limit, rather than support, confidence in some students.

The study contributes to the literature in several ways. First of all, it empirically demonstrates that not all dimensions of SMC contribute to AI learning self-efficacy to the same extent. In this respect, the study shows that digital competencies should not be considered as a unidimensional construct. In addition, by demonstrating that social cognitive theory can be applied at the intersection of social media and AI education, it shows that the sources of self-efficacy approach provide an explanatory framework for understanding digital competence transfer. The findings also provide practical tips for educators who want to utilize social media-based strategies in teaching AI.

However, the study has some limitations. First, the cross-sectional design of the study prevents causal interpretations about the direction of the relationship between SMC and AI learning self-efficacy. The fact that the data collected through self-report also brings the risk of social favoritism tendency or inaccurate self-evaluation. Although the validity and reliability levels of the measurement tools used are sufficient, this limitation is not eliminated. The fact that demographic data were not collected provided a significant advantage in terms of participant anonymity. However, this choice did not allow for the examination of the possible moderating effects of variables such as gender, age or previous AI experience. Moreover, the fact that the sample was selected only from Sechenov University in Russia limits the generalization of the findings to different educational settings and cultural contexts. Finally, the moderate level of explanatory power of the model suggests that a significant variance in AI learning self-efficacy is associated with variables other than the SMC dimensions considered in this study.

Future research may overcome these limitations in different ways. Longitudinal research patterns may offer the opportunity to examine how the relationship between SMC and AI learning self-efficacy has changed over time as students gain more experience with AI technologies. In addition, the inclusion of additional variables such as previous AI experience, general academic self-efficacy, and learning styles into the model can provide more comprehensive results. Qualitative research methods can also contribute to a deeper understanding of this relationship. In particular, interview and focus group work can detail how students perceive the connection between social media skills and their confidence in AI learning. Repetition studies to be carried out in different countries and cultural contexts are important in terms of testing the generalability of these findings. In addition, studies examining the impact of certain social media platforms and features specific to these platforms on AI learning self-efficacy can provide more concrete recommendations on how to integrate social media into AI education in a more targeted way.

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