Journal of Artificial Intelligence and Technology, 2025, 5, 475-486
https://doi.org/10.37965/jait.2025.0812

RESEARCH ARTICLE

Artificial Intelligence in Second Language Acquisition: Enhancing Teacher Self-Efficacy Through Tacit and Explicit Knowledge Sharing

Shulin Yu,[1,2] Bee Eng Wong,[1] and Petra Poulova[3]

[1]Faculty of Social Sciences and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia

[2]School of Management, Chengdu Aeronautic Polytechnic, Chengdu, China

[3]Department of Informatics and Quantitative Methods, Faculty of Informatics and Management, University of Hradec Kralove, Hradec Kralove, Czech Republic

(Received 09 May 2025; Revised 16 July 2025; Accepted 04 August 2025; Published online 05 September 2025)

Abstract: This research delves into the ways artificial intelligence (AI) may improve oral English instruction for second language acquisition (SLA) by boosting both explicit and tacit knowledge. We use social cognitive theory and broaden-and-build theory to design a comprehensive model that includes knowledge-sharing behaviors, academic self-efficacy, and AI-driven language learning. Despite the growing interest in AI-assisted education, the literature has paid little attention to the link between teachers' emotional intelligence (EI), knowledge-sharing behaviors, and self-efficacy in language instruction. To fill this informational void, we surveyed 347 faculty members from Chinese public and private institutions, including lecturer, senior lecturer, associate professor, and professor levels. Our results show that instructors' self-efficacy is much improved by both tacit and explicit knowledge, according to a quantitative method based on partial least squares structural equation modeling. In addition, self-efficacy and knowledge-sharing behaviors are moderated by EI in a favorable way. Lastly, when it comes to oral English instruction, instructors' self-efficacy is crucial in helping students acquire the language. For educators and policymakers in poor nations, this research offers useful insights by suggesting an AI-integrated framework to enhance knowledge-sharing, self-efficacy, and language learning. It also adds to the literature by addressing this issue.

Keywords: academic self-efficacy; artificial intelligence; emotional intelligence; explicit knowledge; second language acquisition; tacit knowledge

I. INTRODUCTION

Teaching a second language is an exciting and challenging endeavor that calls for enthusiasm, imagination, and an in-depth knowledge of how students' minds and hearts work [1,2]. Research increasingly supports the idea that emotional intelligence (EI) plays a vital role in foreign language acquisition (FLA), enabling learners to engage more effectively in communication and comprehension tasks [3–5]. Emotional regulation facilitates academic persistence and the development of positive attitudes toward second language learning [6]. Therefore, emotionally intelligent teachers are more likely to inspire enthusiasm, build sustainable academic performance, and maintain long-term motivation among learners [7]. Recognizing that learners differ in their emotional responses, learning strategies, and confidence, second language acquisition (SLA) is considered a multifaceted and dynamic process [8]. Scholars have long highlighted the influence of learner perceptions, attitudes, expectations, and emotions on successful language acquisition [9,10].

Simultaneously, global educational discourse is increasingly centered around sustainable development, where knowledge acquisition is viewed as a key catalyst for economic, social, and environmental transformation [11,12]. Here, artificial intelligence (AI) has been shown to be a potent facilitator of new ways of sharing information, which improves classroom instruction and student achievement. Learning has become more efficient, accessible, and emotionally flexible because of AI-driven technologies, including adaptive learning platforms, intelligent tutoring systems, virtual teaching assistants, and natural language processing (NLP) apps.

According to [13], knowledge is generally categorized into two main forms: tacit and explicit. Tacit knowledge is inherently experiential, intuitive, and personal, often developed through individual reflection and interaction [14]. This type of knowledge is notoriously difficult to codify or transfer. However, emerging AI technologies are now helping bridge this gap. For instance, AI-powered learning analytics, facial recognition for emotion tracking, and behavior prediction systems can capture and interpret tacit signals, making the invisible visible for educators and learners alike. On the other hand, explicit knowledge—structured, codified, and formal—can be directly transferred via AI-enhanced knowledge repositories, intelligent content delivery systems, and collaborative digital platforms [15].

In knowledge-intensive environments like higher education, both tacit and explicit knowledge are critical for sustained performance and competitive advantage [16–20]. Explicit knowledge becomes even more valuable when complemented by experience, intuition, and emotional input—areas where AI systems can now offer cognitive and affective scaffolding to enhance the learning process [21]. Despite

Corresponding author: Shulin Yu (e-mail: 1002164130@ucsiuniversity.edu.my).

the promise of AI in education, previous research has primarily focused on organizational-level knowledge-sharing dynamics [16], with limited attention given to individual-level knowledge-sharing behaviors—especially in language learning contexts [22,23]. This study addresses that gap by analyzing how AI-supported explicit and tacit knowledge-sharing behaviors influence academic self-efficacy among teachers engaged in SLA.

Tacit knowledge, due to its unstructured nature, remains difficult to externalize and communicate. However, recent developments in AI-driven systems such as real-time emotional feedback tools, sentiment analysis, and adaptive content delivery have made it increasingly possible to identify and disseminate tacit knowledge effectively [24]. These technologies also enable the creation of personalized learning experiences based on emotional and cognitive inputs, further supporting teachers in their instructional roles. Research has linked successful tacit knowledge sharing with supportive environments [25], transformational leadership [26], and positive interpersonal relationships [24]. A person's academic self-efficacy, or confidence in their own abilities to study and succeed, is very important when it comes to acquiring a second language. One's emotional state, one's social input, and one's personal experiences all come together to form one's self-efficacy [27,28]. Academically self-confident educators are better able to overcome pedagogical and language barriers, and they are also more likely to try out new technologies, such as AI [29].

Knowledge resides in individuals who generate, apply, and disseminate it. Yet, in a digital age, the mechanisms of knowledge transfer are evolving. AI-powered platforms facilitate the transformation of individual knowledge into shared organizational intelligence [30,31]. Nevertheless, theoretical understanding is still limited regarding how AI-enhanced explicit and tacit knowledge-sharing behaviors influence self-efficacy in language education. Most current studies highlight obstacles and incentives to knowledge-sharing [22], but few examine how these behaviors—amplified by AI tools—enhance individual sustainable performance in areas such as second language teaching. This research builds upon the broaden-and-build theory, suggesting that emotionally intelligent teachers generate positive emotions that enhance learning. Additionally, it applies social cognitive theory to show how feedback mechanisms, reinforced by AI systems, shape behaviors and build confidence in knowledge acquisition. In AI-assisted learning environments, motivation and self-efficacy are dynamically constructed through real-time feedback, emotional support, and adaptive learning paths.

Second language acquisition (SLA) is deeply influenced by psychological and motivational constructs such as EI, interest, and perceived value. Earlier research has emphasized the predictive power of constructs like self-efficacy, job values, self-regulated learning, and commitment [32–35]. Yet, there is a notable gap in understanding how these variables interact within AI-supported environments, particularly in Asian language education contexts [36,37]. Finally, our limited study indicates that the examined factors have not been examined in conjunction, and that Chinese instructors suffer from a lack of expertise in this area. By investigating the role of EI as a mediator between academic self-efficacy, practices of explicit and tacit information sharing, and lesson effectiveness in an AI-integrated language learning environment, this research aims to fill a substantial gap in the literature. Using concepts from social cognitive theory and broad and build theory, we created an all-encompassing model that takes into account two types of knowledge sharing: academic self-efficacy and second language learning.

II. REVIEW OF LITERATURE AND DEVELOPMENT OF HYPOTHESES

A. THEORETICAL UNDERPINNINGS

Our approach was grounded on two theories: social cognitive theory and the broaden-and-build theory [38]. Positive emotions, according to the broaden-and-build hypothesis, encourage people to develop social resources by expanding their thought-action repertoires, while negative emotions limit this capacity. Highly emotionally intelligent learners who experience positive emotions are more likely to acquire knowledge and enrich themselves with resources that support SLA [39]. In contrast, less emotionally intelligent learners, governed by negative emotional states, may limit their cognitive engagement and reduce their focus on language learning tasks. Emotionally intelligent positive emotions thus play a vital role in enhancing sustainable academic performance [40] by building learners' confidence in achieving academic and linguistic goals. In recent years, AI has emerged as a catalyst in amplifying the mechanisms described by the broaden-and-build theory. Artificial intelligence (AI)-driven learning environments, such as adaptive language platforms and virtual assistants, can generate personalized feedback, simulate interactive dialogues, and foster emotionally engaging experiences. These AI features not only improve learners' academic outcomes but also induce positive affect, which can expand learners' openness to acquiring social and cognitive resources essential for language acquisition.

According to social cognitive theory, people make deliberate efforts to develop themselves because they believe their actions can lead to meaningful outcomes, such as acquiring new knowledge. The central theme of this theory is the belief that individuals' thoughts, emotions, and behaviors are interrelated: what people think, believe, and feel significantly shapes how they behave [41] (p. 25). Reference [56] offered a consolidated view of human psychology, emphasizing that individuals' self-perceptions guide their motivation and behavior. For language learners, the belief that effort leads to proficiency motivates them to regulate their behavior in alignment with learning objectives. Accordingly, self-efficacy—an individual's belief in their capacity to perform academic tasks—emerges as a critical predictor of success in SLA [42]. The integration of AI aligns with social cognitive theory by enhancing learners' self-regulatory capabilities. AI-based feedback systems, automated assessments, and intelligent tutoring platforms offer real-time insights into learners' performance, enabling them to reflect on their progress and make informed adjustments. These affordances promote metacognitive awareness, reinforce self-beliefs, and strengthen academic self-efficacy. Furthermore, AI applications allow for personalized learning paths, which empower learners to feel more in control of their educational experience—a key tenet of social cognitive theory. By reinforcing both emotional and cognitive dimensions of learning, AI technologies serve as instrumental tools that support the theoretical premises of broaden-and-build and social cognitive frameworks. Their integration into educational settings may not only enhance knowledge acquisition but also foster the self-efficacy and emotional resilience necessary for sustainable second language performance.

B. TACIT KNOWLEDGE SHARING AND ACADEMIC SELF-EFFICACY

Self-efficacy provides a theoretically solid foundation for analyzing cognition-based knowledge, commonly referred to as tacit knowledge. This construct supports the prediction of actions and attitudes across diverse contexts and populations [43–46]. Self-efficacy beliefs are formed through a self-reflective judgment process, whereby individuals assess whether and how they can perform a specific action, based on a combination of subjective and cognitive factors [27]. Physiological arousal, verbal persuasion, vicarious experience, and enactive mastery are the four main data points used in this assessment [1,13].

- Enactive Mastery is developed primarily through hands-on practice and personal execution of tasks. It is shaped by cognitive, behavioral, and self-regulatory mechanisms, which alter how individuals perceive themselves and their surrounding environments [2].
- Vicarious Experience involves observational learning and social comparison—individuals can acquire skills by observing peers in action, regardless of whether knowledge transfer is intentional [3].
- Verbal Persuasion includes encouragement or feedback received from others, reinforcing one's belief in their capabilities [4].
- Physiological Arousal encompasses emotional states and physical responses that influence confidence and motivation.

These mechanisms represent deeply embedded cognitive and behavioral competencies, which are often unspoken and situational —thus aligning closely with the concept of tacit knowledge [47]. Tacit knowledge encompasses both cognitive components (e.g., beliefs, paradigms, and mental models) and technical components (e.g., task-specific know-how) [13]. Individuals form self-efficacy beliefs through engaging in tasks, reflecting on past experiences, leveraging personal and contextual resources, and managing constraints. As these beliefs develop, they shape future goal setting, effort expenditure, and adaptive learning behaviors. In this setting, AI is becoming more important in easing the process of acquiring, strengthening, and sharing tacit knowledge. By simulating mastery experiences, modeling peer behaviors, and providing real-time, tailored feedback, AI-powered technologies may imitate important sources of self-efficacy. These tools include intelligent tutoring systems, emotion-aware learning platforms, and collaborative virtual environments. For instance, AI-driven avatars or agents can guide learners through challenging scenarios, allowing them to observe successful task completion (vicarious experience) and receive targeted encouragement (verbal persuasion).

Furthermore, AI technologies can analyze behavioral patterns, emotional responses, and learning trajectories to adapt instructional support in real time. This creates an individualized, data-informed learning environment that enhances self-regulation and cognitive reflection, both critical elements of tacit knowledge development. By augmenting how learners internalize and share unspoken expertise, AI not only supports self-efficacy formation but also promotes more effective knowledge-sharing behaviors in academic contexts. Thus, academic knowledge-sharing results may be strongly predicted by self-efficacy in transmitting complicated tacit information, which may be aided by AI-supported learning ecosystems. The following hypothesis is formulated using the current literature (as presented in Fig. 1):

H1: Tacit knowledge is positively associated with academic self-efficacy.

C. EXPLICIT KNOWLEDGE SHARING AND ACADEMIC SELF-EFFICACY

There are two main ways in which people share what they know: explicitly and implicitly. Documents, manuals, databases, and group efforts like brainstorming sessions with colleagues are all good places to find explicit knowledge since it is codified, organized, and easy to express [48,49]. In contrast, tacit knowledge is personal, context-specific, and inherently more difficult to transfer due to its non-verbal, experiential nature. It is often communicated through nuanced expressions such as attitudes, gestures, intuition, or mental models, and is demonstrated through practice rather than formal instruction [50,51]. Sharing explicit knowledge plays a critical role in fostering academic self-efficacy, as it equips individuals with clearly defined frameworks and information that promote task clarity and encourage self-evaluation. By accessing organized knowledge, learners can better assess their capabilities, plan effectively, and gain the confidence required to complete academic tasks. Self-efficacy, being a key motivational construct, enhances learners' persistence, engagement, and adaptability when facing academic challenges [52–54].

Educators and learners with higher confidence in their task performance abilities are more inclined to share structured knowledge and collaborate, based on the belief that such interactions will

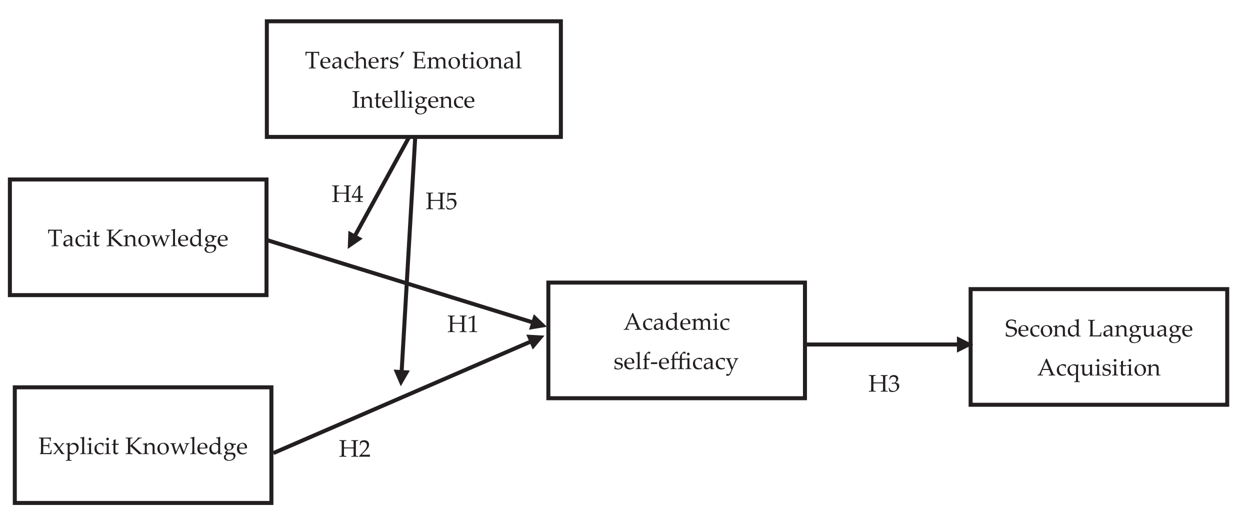

Fig. 1. Research model.

contribute to improved outcomes [55]. Empirical studies support a positive association between knowledge-sharing behaviors and enhanced self-efficacy, particularly in contexts requiring task-oriented collaboration and goal setting [52]. In the era of AI, the process of explicit knowledge-sharing is being fundamentally transformed and amplified. Artificial intelligence (AI) systems—ranging from intelligent learning platforms and digital content curators to AI-powered chatbots and collaborative tools—can capture, store, retrieve, and disseminate explicit knowledge at scale and in real time. These technologies facilitate more efficient access to structured information, allowing students and educators to engage in on-demand knowledge retrieval, automated content summarization, and guided decision-making.

For example, AI algorithms can personalize the delivery of learning materials based on user preferences and performance data, enabling adaptive learning paths that reinforce self-efficacy through timely, relevant, and structured feedback. Similarly, AI-driven knowledge management systems within academic institutions can foster a culture of open knowledge exchange, allowing learners and faculty to collaborate across disciplines and bridge knowledge silos. By enabling streamlined access to explicit knowledge, AI not only supports academic performance but also strengthens learners' perceived competence, leading to enhanced academic self-efficacy. Consequently, the integration of AI technologies into educational contexts amplifies the effectiveness of explicit knowledge-sharing behaviors, further reinforcing their positive impact on learners' beliefs in their own academic capabilities. Based on the existing literature and the transformative potential of AI in educational knowledge-sharing, we formulate the following hypothesis:

H2: Explicit knowledge is positively associated with academic self-efficacy.

D. ACADEMIC SELF-EFFICACY AND SECOND LANGUAGE ACQUISITION

As a task-specific construct, self-efficacy is shaped by contextual factors. According to [56], the evaluation of self-efficacy varies with the nature of the task, making academic self-efficacy a domain-specific measure rather than a generalized trait. As noted by [57], linguistic competencies are distinct from other knowledge types, requiring a nuanced understanding of learners' confidence and motivational states in second language learning contexts. Although the construct of self-efficacy has been widely examined in relation to general academic performance, relatively few studies have focused on its role in FLA. Earlier research typically explored self-efficacy through limited dimensions such as language learning strategies, language anxiety, attributions, and sustainable performance. Scholars have lately come to acknowledge that self-efficacy plays a vital role in determining how well second language learners do in various settings [58–61]. Learners' levels of engagement, perseverance, effort, and dependence on self-regulatory learning strategies are significantly impacted by their self-efficacy, according to empirical research. While there is some evidence that students' self-efficacy mediates the connection between their aptitudes and their long-term performance outcomes, the vast bulk of this research has only looked at correlations [62]. Vocabulary retention, reading comprehension, and speaking fluency are just a few areas where students' self-efficacy has been shown to have a lasting influence [63–67].

Given the growing importance of personalized learning environments, further exploration is needed into how academic self-efficacy can be fostered within educational institutions, particularly in the context of SLA. Academic self-efficacy, viewed through a cognitive-motivational lens, involves learners assessing their ability to successfully perform specific academic tasks [27]. Learners with low self-efficacy often doubt their capacity to learn, leading to avoidance or withdrawal from cognitively demanding activities [68]. Conversely, high self-efficacy promotes adaptive learning behaviors, including proactive help-seeking, sustained effort, and the ability to persist through academic challenges [60,69]. These learners are also more likely to engage emotionally and intellectually with their academic tasks, exhibiting higher levels of academic engagement and cognitive strategy use [70–72]. Artificial Intelligence (AI) offers powerful tools to enhance academic self-efficacy among language learners. AI-driven language learning platforms such as Duolingo, Rosetta Stone, and GPT-based conversational agents can provide personalized, adaptive feedback that supports learners in identifying their strengths and targeting areas of improvement. By dynamically adjusting task difficulty and offering real-time encouragement, AI systems foster a sense of progression, which is critical for reinforcing learners' self-beliefs.

Moreover, AI-powered analytics can track learning behaviors and provide visual dashboards that help learners self-monitor their progress, increasing their metacognitive awareness and self-regulation capabilities—both of which are central to academic self-efficacy. Additionally, immersive AI technologies such as virtual reality and NLP enable learners to practice in simulated environments that reduce performance anxiety while providing meaningful interaction, which contributes to increased confidence and skill mastery. By tailoring learning pathways and enabling instant feedback loops, AI significantly contributes to the development of self-efficacy in language learners, especially in asynchronous or self-directed learning environments. As learners perceive that their actions—guided and informed by AI tools—lead to measurable improvements in performance, their belief in their ability to acquire a new language is strengthened. Based on the existing literature and the expanding role of AI in enhancing learner confidence and engagement, we propose the following hypothesis:

H3: Academic self-efficacy is positively associated with SLA.

E. MODERATING ROLE OF TEACHER'S EI

Academic and professional interest in studying the function of EI in classrooms has increased since Goleman's publication of "Emotional Intelligence" [73]. While aspects like emotional and social abilities form 80% of what contributes to life achievement, conventional intelligence quotient or academic intelligence only accounts for a portion, about 20%, according to Goleman's research [74]. In response to this realization, educational goals have shifted to place a greater emphasis on developing students' EI in addition to their cognitive abilities [75,76]. There is a lot of research that looks at how EI relates to teachers' self-efficacy, especially in educational and language learning settings. In one study, researchers in Shiraz, Iran, found that EI and self-efficacy were positively and statistically correlated among secondary school teachers. The intrapersonal EI component also offered the most convincing explanation for teachers' self-perceptions of effectiveness out of 169 Italian educators questioned [78]. Studying 89 EFL (English as a Foreign Language) instructors from various schools, researchers also found substantial relationships between EI and self-efficacy [79]. Additionally, research involving EFL teachers revealed a positive association between EI and teacher effectiveness, independent of demographic variables such as gender, age, or years of experience.

Despite these insights, most studies have been conducted in pre-university settings, with limited exploration of these dynamics among university-level educators. Given the different structural, pedagogical, and cultural dynamics in higher education, as noted by [80], it is critical to investigate how EI shapes teacher efficacy within university contexts—particularly in areas involving complex knowledge transfer, such as tacit and explicit knowledge sharing. In this light, AI offers a transformative lens through which the moderating role of EI can be better understood and operationalized. Intelligent systems powered by machine learning and NLP now enable the assessment and support of EI competencies among educators. For instance, AI-based platforms can analyze classroom interactions, voice tone, and facial expressions to provide real-time feedback to educators on their emotional responsiveness, interpersonal communication, and engagement with students.

Additionally, emotion-aware AI tools, such as affective computing systems, can assist teachers in adapting their knowledge-sharing strategies (both tacit and explicit) based on students' emotional and cognitive states. These systems can foster more emotionally intelligent pedagogical approaches by alerting teachers to signs of student frustration, disengagement, or confusion—factors directly linked to academic self-efficacy. This AI-assisted awareness helps educators modulate their responses, provide timely encouragement, and tailor explanations, thereby increasing students' confidence and learning outcomes. Moreover, AI can serve as a professional development tool, helping university teachers build their EI through personalized training modules, simulated classroom scenarios, and emotion recognition feedback. Such training, when combined with AI-driven performance analytics, can enhance teachers' abilities to share knowledge effectively and empathetically—key elements in boosting students' self-efficacy. In sum, the integration of AI into educational environments enriches the interplay between EI and knowledge-sharing practices. It provides a data-informed, personalized, and scalable means to strengthen the emotional and instructional competencies of educators, particularly in higher education settings where autonomous learning, self-efficacy, and knowledge transfer are vital. Based on the literature and the evolving educational landscape augmented by AI, we propose the following hypotheses:

H4: Tacit knowledge and academic self-efficacy are moderated by teachers' EI.

H5: Explicit knowledge and academic self-efficacy are moderated by teachers' EI.

III. RESEARCH METHODOLOGY

A cross-sectional design is used to test the theoretical framework [81]. Members of the teaching staff at both public and private universities in China were surveyed. From October 2022 through December 2022, data were gathered using a combination of convenience and selective sampling methods. A research assistant personally sent self-administered questionnaires to each department's faculty members in addition to a letter seeking their involvement and support in this study. The total number of surveys sent out was 460. After removing surveys with missing or partial information, 347 were retained for further research out of 460 that were originally disseminated. The encouraging thing is that 73.26 percent of people responded. According to structural equation modeling (SEM), which was used in this investigation, the sample size seems to be appropriate [82]. Male instructors made up 47.3% of the sample, while female students made up 52.7%. Of the instructors surveyed, 55.3% were in the 31–40 age bracket, 23.1% were in the 41–50 age bracket, and 21.1% were in the 20–30 age bracket. Numerous instructors have positions such as senior lecturer or associate professor, and the vast majority of them have doctoral degrees. Their years of expertise in the field range from five to eight and nine to eleven. In Table I, you can see the mentioned statistics.

Table I. Descriptive statistics

Categories	Items	Frequency	Percent
Gender	Female	183	52.7
	Male	164	47.3
Age	20–30	73	21.0
	31–40	192	55.3
	41–50	80	23.1
	>50	2	.6
Education	Bachelor	52	15.0
	MS/M.Phil.	84	24.2
	PhD	211	60.8
Working period as a teacher	<5	26	7.5
	5–8	124	35.7
	9–11	118	34.0
	>11	79	22.8
Position	Lecturer	53	15.3
	Senior lecturer	120	34.6
	Associate professor	115	33.1
	Professor	59	17.0

A. MEASUREMENT SCALE

Questionnaires were used to gather data, and all of the construct elements were taken from preexisting sources. In order to ensure that the questionnaire was legitimate, a pilot survey was conducted with 50 educators from a higher-education institution. The questionnaire's validity was enhanced by the implementation of revisions and refinement of the instrument based on the findings of the pilot survey. Then, after a quick pilot survey with randomly chosen participants, the process was repeated with 25 professors from other colleges to ensure the instrument was accurate. There are a total of seventy-three items in the survey. Two separate factors, tacit and explicit knowledge, were the subject of this study. Tacit knowledge sharing is defined in this research as an organizational or departmental norm of open communication and cooperation between workers that promotes the free flow of information and expertise amongst workers [30]. A 5-item scale that was created by [30] was used to assess tacit knowledge exchange. A total of five questions were modified from previous references in order to assess explicit knowledge exchange [83,84]. A 22-item scale developed by [85] was used to evaluate the dependent variable of second language learning. To evaluate the EI of the educators, Salovey and Mayer (1990) created a 33-item test. The last step in measuring academic self-efficacy was to modify 12 questions originally found in [86]. The items were analyzed using a 5-point Likert scale, where 1 indicates Strongly Disagree, 2 indicates Disagree, 3 indicates Neutral, 4 indicates Agree, and 5 indicates Strongly Agree. The study's instrument was chosen for its efficacy and convenience of use, making it suitable for data collection within a quantitative framework.

In this work, quantitative research was conducted using PLS-SEM (partially least squares SEM) [87]. Since the PLS-SEM approach does not undergo the typical assumption testing that is standard for this method, we used standard respondent data [82]. In addition, analysts have a flexible tool at their disposal with smart PLS to tackle issues with data normality and sample size limits. Because it can deal with different structural routes and many equations, the PLS approach was used [88]. Similarly, when numerous theories support a model, it is considered suitable. External variables that impacted academic self-efficacy included tacit and explicit knowledge. While learning a second language is an internal variable, academic self-efficacy is an external one that could affect it. One important moderating aspect is EI. After that, we ran the bootstrapping method after implementing the PLS algorithm. We used measurement modeling to evaluate the data, and then we moved on to structural modeling.

IV. RESULTS

Considerations of composite reliability, average variance extracted (AVE), and factor loading formed the basis of the assessment of the measurement model [82]. All study variables have Cronbach's alpha cutoff values of more than 0.70; an appropriate cutoff value is 0.8 or above [87]. Therefore, the statistics show that the scale is reliable enough to be used for future research. There are Cronbach's alpha values for every variable in Table II. Factor loadings for all items of the under-studied variables in the research were 0.70 or higher, as per the recommendation. Furthermore, every single

Table II. Assessment of the measurement model

Items	Factor loading	α	CR	AVE	Items	Factor loading	α	CR	AVE
Academic self-efficacy		0.892	0.917	0.540	*Emotional Intelligence*		0.943	0.947	0.560
ASE1	0.798				EI1	0.684			
ASE10	0.797				EI10	0.608			
ASE11	0.671				EI11	0.734			
ASE12	0.423				EI12	0.722			
ASE2	0.813				EI13	0.658			
ASE3	0.777				EI14	0.596			
ASE4	0.831				EI15	0.575			
ASE5	0.838				EI16	0.577			
ASE6	0.842				EI17	0.600			
ASE8	0.681				EI18	0.559			
ASE9	0.848				EI19	0.586			
Second Language Acquisition		0.813	0.763	0.515	EI2	0.683			
SLA1	0.754				EI20	0.590			
SLA10	0.824				EI21	0.566			
SLA11	0.752				EI22	0.493			
SLA12	0.822				EI23	0.523			
SLA13	0.873				EI24	0.555			
SLA14	0.500				EI25	0.505			
SLA15	0.469				EI26	0.523			
SLA16	0.595				EI27	0.779			
SLA17	0.524				EI8	0.701			
SLA18	0.532				EI29	0.724			
SLA19	0.494				EI3	0.710			
SLA2	0.418				EI30	0.528			
SLA9	0.892				EI31	0.701			
SLA21	0.654				EI32	0.753			
SLA22	0.677				EI33	0.887			
SLA3	0.894				EI4	0.729			
SLA4	0.539				EI9	0.695			
SLA5	0.779				EI6	0.671			
SLA6	0.756				EI7	0.746			
Tacit Knowledge		0.900	0.926	0.713	*Explicit Knowledge*		0.770	0.805	0.546
TK1	0.844				EK1	0.827			
TK2	0.845				EK2	0.862			
TK3	0.852				EK3	0.744			
TK4	0.833				EK4	0.840			
TK5	0.849				EK5	0.708			

Abbreviations: TK stands for tacit knowledge and EK for explicit knowledge, ASE for Academic self-efficacy, SLA for Second Language Acquisition, EI for Emotional Intelligence, α stands for Cronbach's alpha, CR stands for composite reliability, and AVE is for average variance extracted.

Table III. HTMT analysis

Constructs	*Academic Self-Efficacy*	*Emotional Intelligence*	*Explicit Knowledge*	*Second Language Acquisition*	*Tacit Knowledge*
Academic Self-Efficacy					
Emotional Intelligence	0.531				
Explicit Knowledge	0.770	0.526			
Second Language Acquisition	0.513	0.126	0.235		
Tacit Knowledge	0.377	0.410	0.661	0.596	

research variable's composite reliability (CR) value was greater than or equal to 0.70. 89 came up with a way to remove items from reflective scales that had loadings between 0.40 and 0.70, in order to see whether this improved the CR and AVE. Items measuring EI5 and self-efficacy in academics (ASE7), as well as SLA (SLA7, SLA8, and SLA20), were omitted. Factor loadings, CR, and AVE predictions will all be higher than the suggested cutoff values when some components are removed. We may now proceed with structural modeling analysis, since our study model has shown convergent validity.

Additionally, the heterotrait-monotrait (HTMT) method, as proposed by [90], was utilized. The assessment of the discriminant validity of the HTMT was conducted through two distinct methods. The initial phase involved establishing the threshold value through the application of HTMT. The presence of inadequate discriminating validity was suggested when the HTMT value exceeded a certain threshold. There exists ongoing discussion about the appropriate threshold value for HTMT when the correlation approaches one. Some studies have proposed a cutoff value of 0.85, whereas others have indicated a cutoff value of 0.90 [87]. Secondly, we established discriminant validity by examining the range of values for the HTMT, which was found to be less than 1. The removal of number 1 from the interval range illustrates that the variables are clearly defined from an empirical perspective. The findings presented in Table III indicate that the HTMT values between the constructs are all below 0.85. Therefore, it can be inferred that this study recognized discrimination validity.

After the measurement model was assessed to establish the reliability and validity of the constructs, the structural model was subsequently evaluated to examine the hypothesized relationships among the latent variables [89]. The structural models were evaluated using *t*-values and beta as key performance indicators. Table IV shows the results of using bootstrapping to find the direct hypotheses' route coefficients in Smart PLS 4. A comparison with predefined threshold values ($t > 1.645$, $P < 0.05$) was used to establish the hypothesis' validity. We used four criteria to examine the direct and indirect effects of SEM. By evaluating the R^2 values of the endogenous latent constructs, the first step was to determine the total variance explained by each variable. In accordance with [91], the significance level of an inquiry determines the value of R^2, with values of 0.13 indicating moderate significance, 0.26 representing strong significance, and 0.09 indicating poor significance. Further analysis using the direct effect model showed that academic self-efficacy was an endogenous variable with an R^2 of 0.394 in this study. This suggests that EI, tacit knowledge, and explicit knowledge may all predict a 93.1% shift in academic self-efficacy. Academic self-efficacy may explain 55.9% of the variance in second language learning, according to the coefficient of determination (R^2) values. Table IV demonstrates that the model's predicted accuracy was rather good (see Fig. 2).

Table IV. PLS determination coefficients

Variables	R^2	R^2 adjusted	Predictive Relevance (Q^2) Values
ASE	0.821	0.819	0.452
SLA	0.595	0.565	0.446

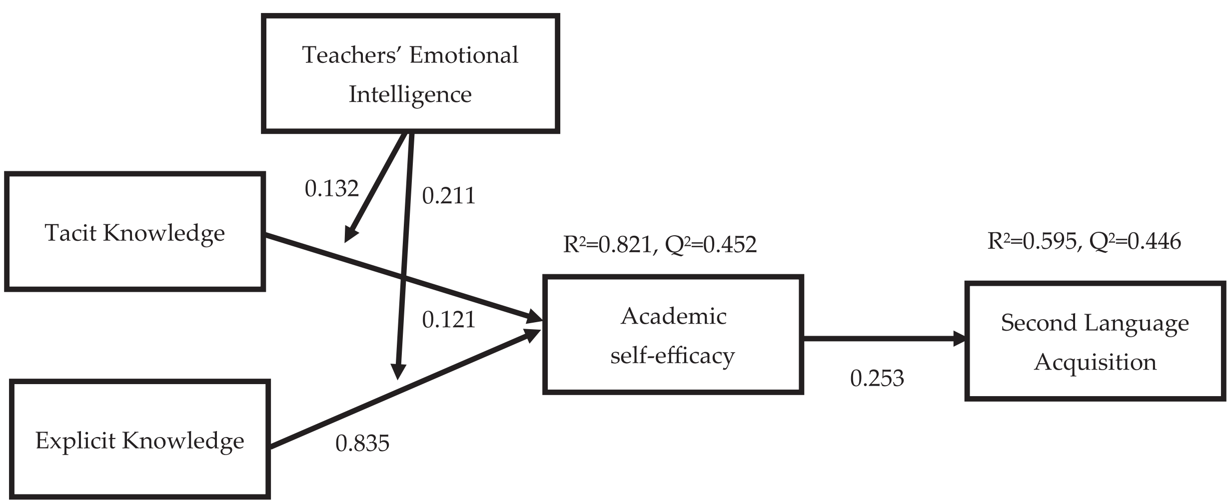

Fig. 2. Structural equations model.

Table V. Results of the structural equations model

Hypotheses	Relationship among Variables	β	Sample mean	S.D.	T Values	F square	P values	Remarks
	Direct Effect							
H1	TK -> ASE	0.121	0.122	0.024	5.001	1.151	0.000	Supported
H2	EK -> ASE	0.835	0.832	0.023	36.004	3.833	0.000	Supported
H3	ASE -> SLA	0.253	0.229	0.051	6.322	1.541	0.016	Supported
	Indirect Moderating effect							
H4	EI x TK -> ASE	0.132	0.133	0.053	2.880	1.148	0.018	Supported
H5	EI x EK -> ASE	0.211	0.212	0.064	3.463	1.194	0.033	Supported

The second step was to find the model's predictive relevance (Q2) values using the cross-validation redundancy technique [89]. The model's predictive relevance is deemed satisfactory when Q2 values are greater than zero, as seen in Table IV (also presented in Fig. 2). The number is 0.542 for the indirect influence of TK, EK, and EI on ASE, and 0.464 for the direct effect of ASE and SLA.

As indicated in the table, the findings reveal that tacit knowledge has a positive and substantial influence on ASE ($\beta = 0.121$, $P < 0.05$), explicit knowledge has an effect on ASE ($\beta = 0.8351$, $P < 0.05$), and ASE has an effect on SLA ($\beta = 0.253$, $P < 0.05$). This led to the acceptance of all three directed hypotheses (H1, H2, and H3). Furthermore, the amount of the exogenous (independent) variable's influence on the endogenous (dependent) variable is determined by effect size (f2), which is the impact of an independent variable on the dependent (f2). According to [91], effect sizes ranging from 0.02 to 0.25 are considered small, those between 0.25 and 0.35 are regarded as moderate, while values exceeding 0.35 are classified as high. The impact sizes for TK to ASE, EK to ASE, ASE to SLA, moderator EI to TK and ASE, and EK and ASE are 1.151, 3.833, 1.541, 1.148, and 1.194, respectively, as shown in Table V. A review of the literature reveals that these external variables impact endogenous variables in moderate to substantial ways. The findings indicated that H4 and H5 were both accepted because the association between TK and ASE ($\beta = 0.132$, $P < 0.05$) and EK and ASE ($\beta = 0.211$, $P < 0.05$) was positively and significantly affected by the moderating effect of EI.

V. DISCUSSION

It has been confirmed that knowledge acquisition is strongly related to sustainable development [92]. This study focused on the antecedents of acquiring a new language, particularly because the capacity to acquire and absorb knowledge can greatly influence the environmental, social, and economic dimensions of sustainability [93]. The current research aimed to examine whether tacit and explicit knowledge sharing among Chinese university teachers influences their academic self-efficacy, with EI acting as a moderator. Moreover, it investigated whether academic self-efficacy positively affects SLA. The findings revealed that both tacit and explicit knowledge significantly and positively impact academic self-efficacy among university teachers. These results align with the conclusions of [52,94], who confirmed that tacit knowledge-sharing is significantly associated with self-efficacy. This supports the argument that confidence and self-efficacy are prerequisites for engaging in effective tacit knowledge exchange. Furthermore, the results suggest that greater explicit knowledge sharing enhances teachers' academic self-efficacy, corroborating earlier studies such as [95].

The study's main takeaway is that EI is a powerful mediator between students' perceptions of their own academic competence and their level of tacit and explicit knowledge. Previous studies have shown a favorable correlation between EI and self-efficacy in the English teaching profession, and our results are in line with those studies [77,79]. Teachers in both elementary and secondary schools were shown to have a strong relationship between EI and self-efficacy in a study conducted by [96]. It is clear from comparing the results of this study with those of previous research that EI is crucial in enhancing academic self-efficacy across all levels of schooling and types of institutions. Importantly, the study also established that academic self-efficacy significantly contributes to SLA. As proposed by [97], teachers' belief in their own abilities motivates them to enhance their professional practices, which in turn positively influences students' academic performance in language learning. Teachers with high self-efficacy demonstrate greater commitment, utilize more engaging pedagogical methods, and create supportive learning environments. This finding is reinforced by [98], who noted that innovative and confident teachers employ creative strategies to make learning more enjoyable and impactful, thereby increasing students' motivation and knowledge retention.

As AI becomes more prevalent in educational settings, the results of this research become even more significant. An abundance of explicit and tacit information may be found in AI-powered products like intelligent tutoring systems, adaptive learning platforms, and language learning applications like Duolingo, ChatGPT, and Grammarly, among others. Educators with high levels of EI and self-efficacy are more likely to adopt these AI technologies, integrate them into their lessons, and help their students learn more successfully via individualized feedback and assistance. Moreover, AI can serve as a medium for tacit knowledge sharing by simulating expert behaviors, enabling vicarious learning, and offering verbal and non-verbal cues through interactive interfaces. Thus, fostering teachers' academic self-efficacy and EI not only enhances their capacity to share and apply knowledge but also empowers them to fully leverage AI innovations in second-language instruction. Ultimately, this leads to more sustainable and effective language acquisition outcomes in the modern digital age.

A. IMPLICATIONS FOR THEORY AND PRACTICE

Important theoretical advances are made by this work. To start with, it helps us comprehend more fully how both implicit and explicit forms of information sharing impact students' capacity to believe in their own abilities to succeed in school. Additionally, it delves into the ways in which knowledge-sharing impacts second language learning, taking into account social, cognitive, and contextual factors. By doing so, the study not only constructs a comprehensive theoretical framework but also offers practical evidence through empirical examination of these relationships. Additionally, it highlights how teachers' EI can amplify the positive effects of knowledge-sharing behaviors on self-efficacy. From a practical standpoint, the study provides valuable guidance for curriculum designers and educational policymakers. It underscores the importance of fostering teachers' confidence by promoting EI development—an essential factor that enhances the likelihood of successful knowledge exchange. The findings show that when teachers actively engage in sharing both tacit and explicit knowledge, their academic self-efficacy improves, particularly in environments that support collaboration and emotional awareness.

This research offers actionable insights for academic institutions. Training programs, workshops, and professional development seminars can be designed to cultivate EI and emphasize the importance of collaborative teaching practices. Hiring emotionally intelligent educators who value knowledge-sharing can lead to the creation of a supportive and confident teaching workforce. Institutions should also cultivate a strong knowledge-sharing culture through structured brainstorming sessions, communities of practice, and peer learning initiatives. Importantly, the integration of AI can enhance these processes. Artificial intelligence (AI)-driven tools—such as intelligent content recommendation systems, virtual mentoring platforms, and language acquisition apps—can serve as powerful facilitators of both explicit and tacit knowledge exchange. Teachers with strong self-efficacy and EI are more likely to engage with these AI tools effectively, leveraging them to enhance student learning outcomes and foster collaborative professional development. Moreover, AI can simulate expert behavior, offer adaptive feedback, and even track emotional cues, all of which support teachers in developing both their teaching competence and confidence.

Second language learning remains a challenging endeavor that requires empowered, confident educators. When teachers are emotionally intelligent and supported by AI technologies, they are better equipped to communicate effectively, foster engaging learning environments, and continuously enhance their own professional capabilities. Thus, integrating EI training and AI technologies within teacher development programs can be a transformative step toward improved second language education.

B. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Although this work used unique theoretical models and applied rigorous analytical techniques to guarantee the findings' robustness and dependability, it does have significant shortcomings that may be addressed in future research. Both the sample size and the intended audience are constrained by the first factor. The results may not be applied to a broader population since the research only used data from one region in China. To enhance external validity, future researchers are encouraged to increase the sample size and gather data from universities across multiple provinces, thereby providing a more diverse and representative understanding of the phenomenon. Secondly, the reliance on self-reported data from a single source raises the possibility of common method bias. To mitigate this in future studies, data should be collected from multiple sources, such as peer evaluations, supervisors, and department heads. This triangulation would strengthen the validity of the findings and provide a more comprehensive perspective on academic self-efficacy and knowledge-sharing behaviors.

Artificial Intelligence (AI) can also play a pivotal role in addressing some of these limitations. For instance, AI-based data collection tools can help automate and expand respondent reach, enabling real-time surveys and feedback from a broader population across various regions. Moreover, AI-driven analytics can detect and control for response biases, including social desirability and common method variance. Sentiment analysis and NLP techniques could also be employed to analyze open-ended responses and behavioral data from digital platforms used by teachers, offering more objective insights beyond self-reporting. Additionally, AI tools such as learning analytics dashboards can assist institutions in tracking and validating teacher engagement, knowledge-sharing behavior, and EI in real-time, offering a richer, multi-source data stream for future academic inquiries. Integrating AI into future research designs can thus not only improve data quality but also provide deeper, more nuanced insights into the factors affecting SLA and teacher development.

C. CONCLUSION

This study contributes significantly to the understanding of how EI, tacit and explicit knowledge-sharing behaviors, and academic self-efficacy interact to influence SLA in AI-supported environments. Drawing upon the broaden-and-build theory and social cognitive theory, we proposed and empirically tested a model that demonstrates the centrality of EI as a mediating factor in the relationship between knowledge sharing and academic self-efficacy. The findings affirm that both tacit and explicit knowledge-sharing behaviors positively impact teachers' academic self-efficacy, with emotionally intelligent educators being more effective in leveraging these knowledge forms to support their professional roles. Furthermore, academic self-efficacy emerged as a critical enabler of effective second language instruction, highlighting the importance of teacher confidence in achieving successful learning outcomes. The integration of AI technologies has added a transformative dimension to the second language teaching process. Artificial intelligence (AI) tools such as adaptive learning systems, intelligent tutoring platforms, and emotion-aware applications can facilitate the transfer of both explicit and tacit knowledge. These technologies provide teachers with real-time feedback, personalized instructional recommendations, and tools for emotional tracking, all of which contribute to the development of a more responsive and engaging teaching environment. Our results show that emotionally intelligent teachers with high self-efficacy are more willing and capable of integrating these AI tools into their pedagogy, leading to more sustainable and effective language learning experiences for students.

From a theoretical perspective, this research advances the literature by combining emotional, cognitive, and technological dimensions into a unified framework. It sheds light on the mechanisms through which knowledge-sharing behaviors and emotional capacities converge to shape teacher effectiveness in second language education. It also addresses an underexplored area in prior research by focusing on individual-level dynamics rather than organizational-level knowledge management in the context of AI integration. Importantly, this work underscores that teacher development must move beyond content mastery alone and focus on cultivating EI and collaborative practices to maximize the benefits of AI-enhanced learning environments. Practically, this study offers actionable recommendations for educators, administrators, and policymakers. Institutions should design professional development programs that emphasize EI training, promote collaborative knowledge-sharing practices, and support the integration of AI tools into the curriculum. Fostering a supportive learning environment where educators feel confident, valued, and technologically empowered can significantly enhance language learning outcomes.

By encouraging a culture of emotional awareness and knowledge exchange, educational institutions can prepare teachers not only to meet current challenges but also to drive innovation in second language instruction. In sum, as education continues to evolve in response to technological advancements and shifting pedagogical paradigms, the role of emotionally intelligent, self-efficacious teachers becomes increasingly pivotal. This study confirms that empowering teachers with the emotional and cognitive tools to navigate AI-integrated classrooms is essential for cultivating meaningful, effective, and sustainable SLA in the digital age.

DATA AVAILABILITY

The datasets used in this work are primary in origin and may be obtained from the author of the relevant section upon reasonable request.

ACKNOWLEDGMENTS

This research is supported by Excellence the Project 2205 at the Faculty of Informatics and Management, University of Hradec Králové, Czechia.

CONFLICT OF INTEREST STATEMENT

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

REFERENCES

[1] P. Macizo, A. Herrera, P. Román, and M. C. Martín, "Proficiency in a second language influences the processing of number words," *J. Cogn. Psychol.*, vol. 23, no. 8, pp. 915–921, 2011.

[2] G. H. Khajavy, P. D. MacIntyre, and E. Barabadi, "Role of the emotions and classroom environment in willingness to communicate: applying doubly latent multilevel analysis in second language acquisition research," *Stud. Second Lang. Acquis.*, vol. 40, no. 3, pp. 605–624, 2018.

[3] M. V. López-Pérez, M. C. Pérez-López, and L. Rodríguez-Ariza, "Blended learning in higher education: students' perceptions and their relation to outcomes," *Comput. Educ.*, vol. 56, no. 3, pp. 818–826, 2011.

[4] Z. Dornyei and S. Ryan, *The Psychology of the Language Learner Revisited*. London: Routledge, 2015.

[5] E. Mierzwa-Kamińska, "Enjoyment in the foreign language classroom: does gender matter? A review of selected empirical studies," In *Positive Psychology in Second and Foreign Language Education*. Cham: Springer, 2021, pp. 55–75.

[6] J. M. Dewaele, X. Chen, A. M. Padilla, and J. Lake, "The flowering of positive psychology in foreign language teaching and acquisition research," *Front. Psychol.*, vol. 10, p. 2128, 2019.

[7] N. I. Guslyakova and A. V. Guslyakova, "Emotional intelligence as a driving force in the study of foreign languages in higher education," *ARPHA Proc.*, vol. 3, p. 781, 2020.

[8] Y. Wang, A. Derakhshan, and L. J. Zhang, "Researching and practicing positive psychology in second/foreign language learning and teaching: the past, current status and future directions," *Front. Psychol.*, vol. 12, p. 731721, 2021.

[9] P. Román, J. González, N. Ventura-Campos, A. Rodríguez-Pujadas, A. Sanjuán, and C. Ávila, "Neural differences between monolinguals and early bilinguals in their native language during comprehension," *Brain Lang.*, vol. 150, pp. 80–89, 2015.

[10] Z. Afzali and S. Izadpanah, "The effect of the flipped classroom model on Iranian English foreign language learners: engagement and motivation in English language grammar," *Cogent Educ.*, vol. 8, no. 1, p. 1870801, 2021.

[11] A. J. C. Fernandes, R. G. Rodrigues, and J. J. Ferreira, "National innovation systems and sustainability: what is the role of the environmental dimension?," *J. Clean. Prod.*, vol. 347, p. 131164, 2022.

[12] M. Chopra et al., "Past, present, and future of knowledge management for business sustainability," *J. Clean. Prod.*, vol. 328, p. 129592, 2021.

[13] I. Nonaka, "A dynamic theory of organizational knowledge creation," *Organ. Sci.*, vol. 5, no. 1, pp. 14–37, 1994.

[14] M. L. Endres, S. P. Endres, S. K. Chowdhury, and I. Alam, "Tacit knowledge sharing, self-efficacy theory, and application to the open source community," *J. Knowl. Manag.*, vol. 11, no. 3, pp. 92–103, 2007.

[15] I. Nonaka, H. Takeuchi, and K. Umemoto, "A theory of organizational knowledge creation," *Int. J. Technol. Manag.*, vol. 11, no. 7–8, pp. 833–845, 1996.

[16] A. N. Chen and T. M. Edgington, "Assessing value in organizational knowledge creation: considerations for knowledge workers," *MIS Q.*, vol. 29, no. 2, pp. 279–309, 2005.

[17] R. M. Grant and C. Baden-Fuller, "A knowledge-based theory of inter-firm collaboration," *Acad. Manag. Proc.*, vol. 1995, no. 1, pp. 17–21, 1995.

[18] A. Jashapara, "Cognition, culture and competition: an empirical test of the learning organization," *Learn. Organ.*, vol. 10, no. 1, pp. 31–50, 2003.

[19] S. V. López, "Competitive advantage and strategy formulation: the key role of dynamic capabilities," *Manag. Decis.*, vol. 43, no. 5, pp. 661–669, 2005.

[20] E. A. Chaparro, A. Yuksel, P. Romero, and S. Bryant, "Factors affecting the perceived effectiveness of pair programming in higher education," in *Proc. PPIG*, June 2005, p. 2.

[21] V. Dougherty, "Knowledge is about people, not databases," *Ind. Commer. Train.*, vol. 31, no. 7, pp. 262–266, 1999.

[22] M. R. Haas and M. T. Hansen, "When using knowledge can hurt performance: the value of organizational capabilities in a management consulting company," *Strateg. Manag. J.*, vol. 26, no. 1, pp. 1–24, 2005.

[23] M. T. Tsai and L.-L. Tung, "An empirical study of the knowledge transfer methods used by clinical instructors," *Int. J. Manag.*, vol. 22, no. 2, p. 273, 2005.

[24] S. Perumal and S. Sreekumaran Nair, "Impact of views about knowledge and workplace relationships on tacit knowledge sharing," *Knowl. Manag. Res. Pract.*, vol. 20, no. 3, pp. 410–421, 2022.

[25] D. Nakano, J. Muniz, and E. D. Batista, "Engaging environments: tacit knowledge sharing on the shop floor," *J. Knowl. Manag.*, vol. 17, no. 2, pp. 290–306, 2013.

[26] W. Kucharska and T. Rebelo, "Transformational leadership for researcher's innovativeness in the context of tacit knowledge and change adaptability," *Int. J. Leadersh. Educ.*, pp. 1–22, 2022, doi: 10.1080/13603124.2022.2068189.

[27] A. Bandura, *Self-Efficacy: The Exercise of Control*. New York, NY: Macmillan, 1997.

[28] M. E. Gist and T. R. Mitchell, "Self-efficacy: a theoretical analysis of its determinants and malleability," *Acad. Manage. Rev.*, vol. 17, no. 2, pp. 183–211, 1992.
[29] A. D. Stajkovic and F. Luthans, "Self-efficacy and work-related performance: a meta-analysis," *Psychol. Bull.*, vol. 124, no. 2, p. 240, 1998.
[30] G. W. Bock, R. W. Zmud, Y. G. Kim, and J. N. Lee, "Behavioral intention formation in knowledge sharing: examining the roles of extrinsic motivators, social-psychological forces, and organizational climate," *MIS Q.*, vol. 29, no. 1, pp. 87–111, 2005.
[31] U. F. Sahibzada, C. Jianfeng, K. F. Latif, Z. Shafait, and H. F. Sahibzada, "Interpreting the impact of knowledge management processes on organizational performance in Chinese higher education: mediating role of knowledge worker productivity," *Stud. High. Educ.*, vol. 47, no. 4, pp. 713–730, 2022.
[32] Y. Nie, S. Lau, and A. K. Liau, "Role of academic self-efficacy in moderating the relation between task importance and test anxiety," *Learn. Individ. Differ.*, vol. 21, no. 6, pp. 736–741, 2011.
[33] M. Seker, "The use of self-regulation strategies by foreign language learners and its role in language achievement," *Lang. Teach. Res.*, vol. 20, no. 5, pp. 600–618, 2016.
[34] N. S. Stubbs and D. M. B. Maynard, "Academic self-efficacy, school engagement and family functioning, among postsecondary students in the Caribbean," *J. Child Fam. Stud.*, vol. 26, no. 3, pp. 792–799, 2017.
[35] E. Alyahyan and D. Düştegör, "Predicting academic success in higher education: literature review and best practices," *Int. J. Educ. Technol. High. Educ.*, vol. 17, no. 1, pp. 1–21, 2020.
[36] A. Jashapara, "The emerging discourse of knowledge management: a new dawn for information science research?," *J. Inf. Sci.*, vol. 31, no. 2, pp. 136–148, 2005.
[37] D. G. Ko, L. J. Kirsch, and W. R. King, "Antecedents of knowledge transfer from consultants to clients in enterprise system implementations," *MIS Q.*, vol. 29, no. 1, pp. 59–85, 2005.
[38] B. L. Fredrickson, "The value of positive emotions. The emerging science of positive psychology is coming to understand why it's good to feel good," *Am. Sci.*, vol. 91, no. 4, pp. 330–335, 2003.
[39] K. Shao, L. J. Nicholson, G. Kutuk, and F. Lei, "Emotions and instructed language learning: proposing a second language emotions and positive psychology model," *Front. Psychol.*, vol. 11, p. 2142, 2020.
[40] B. L. Fredrickson, "The broaden–and–build theory of positive emotions," *Philos. Trans. R. Soc. Lond. B, Biol. Sci.*, vol. 359, no. 1449, pp. 1367–1377, 2004.
[41] A. Bandura, *Social Foundations of Thought and Action*. Englewood Cliffs, NJ: Prentice-Hall, 1986, pp. 23–28.
[42] M. Wyatt, "Self-efficacy," In *The Routledge Handbook of Second Language Acquisition and Individual Differences*. New York, NY: Routledge, 2022, pp. 207–219.
[43] D. N. Stone, "Overconfidence in initial self-efficacy judgments: effects on decision processes and performance," *Organ. Behav. Hum. Decis. Process.*, vol. 59, no. 3, pp. 452–474, 1994.
[44] M. A. Quinones, "Pretraining context effects: training assignment as feedback," *J. Appl. Psychol.*, vol. 80, no. 2, p. 226, 1995.
[45] J. H. Dulebohn, "An investigation of the determinants of investment risk behavior in employer-sponsored retirement plans," *J. Manag.*, vol. 28, no. 1, pp. 3–26, 2002.
[46] K. M. Kuhn and M. D. Yockey, "Variable pay as a risky choice: determinants of the relative attractiveness of incentive plans," *Organ. Behav. Hum. Decis. Process.*, vol. 90, no. 2, pp. 323–341, 2003.
[47] A. Das, "Knowledge and productivity in technical support work," *Manag. Sci.*, vol. 49, no. 4, pp. 416–431, 2003.
[48] M. Alavi and D. E. Leidner, "Knowledge management and knowledge management systems: conceptual foundations and research issues," *MIS Q.*, vol. 25, no. 1, pp. 107–136, 2001.
[49] M. H. Selamat and J. Choudrie, "The diffusion of tacit knowledge and its implications on information systems: the role of meta-abilities," *J. Knowl. Manag.*, vol. 8, no. 2, pp. 128–139, 2004.
[50] K. U. Koskinen, P. Pihlanto, and H. Vanharanta, "Tacit knowledge acquisition and sharing in a project work context," *Int. J. Proj. Manag.*, vol. 21, no. 4, pp. 281–290, 2003.
[51] I. Nonaka and G. Von Krogh, "Perspective—Tacit knowledge and knowledge conversion: controversy and advancement in organizational knowledge creation theory," *Organ. Sci.*, vol. 20, no. 3, pp. 635–652, 2009.
[52] H. F. Lin, "Knowledge sharing and firm innovation capability: an empirical study," *Int. J. Manpow.*, vol. 28, no. 3/4, pp. 315–332, 2007.
[53] H. Lu, X. Chen, and C. Qi, "Which is more predictive: domain- or task-specific self-efficacy in teaching and outcomes?," *Br. J. Educ. Psychol.*, vol. 92, no. 3, pp. 1141–1160, 2022.
[54] C. L. Witherspoon, J. Bergner, C. Cockrell, and D. N. Stone, "Antecedents of organizational knowledge sharing: a meta-analysis and critique," *J. Knowl. Manag.*, vol. 17, no. 2, pp. 250–277, 2013.
[55] A. Kankanhalli, B. C. Tan, and K. K. Wei, "Contributing knowledge to electronic knowledge repositories: an empirical investigation," *MIS Q.*, vol. 29, no. 1, pp. 113–143, 2005.
[56] A. Bandura, *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ: Prentice-Hall, 1986.
[57] B. Williams, "Nietzsche's minimalist moral psychology," In *Nietzsche, Genealogy, Morality*. Berkeley, CA: Univ. of California Press, 1994, pp. 237–248.
[58] F. Pajares, "Self-efficacy beliefs in academic settings," *Rev. Educ. Res.*, vol. 66, no. 4, pp. 543–578, 1996.
[59] D. H. Schunk, "Self-efficacy for reading and writing: influence of modeling, goal setting, and self-evaluation," *Read. Writ. Q.*, vol. 19, no. 2, pp. 159–172, 2003.
[60] E. A. Linnenbrink and P. R. Pintrich, "The role of self-efficacy beliefs in student engagement and learning in the classroom," *Read. Writ. Q.*, vol. 19, no. 2, pp. 119–137, 2003.
[61] J. Lane, A. M. Lane, and A. Kyprianou, "Self-efficacy, self-esteem and their impact on academic performance," *Soc. Behav. Personal. Int. J.*, vol. 32, no. 3, pp. 247–256, 2004.
[62] A. Bandura, "Adolescent development from an agentic perspective," In *Self-Efficacy Beliefs of Adolescents*. Greenwich, CT: Information Age Publishing, 2006, pp. 1–43.
[63] N. Mills, F. Pajares, and C. Herron, "A reevaluation of the role of anxiety: self-efficacy, anxiety, and their relation to reading and listening proficiency," *Foreign Lang. Ann.*, vol. 39, no. 2, pp. 276–295, 2006.
[64] N. Mills, F. Pajares, and C. Herron, "Self-efficacy of college intermediate French students: relation to achievement and motivation," *Lang. Learn.*, vol. 57, no. 3, pp. 417–442, 2007.
[65] P. H. Hsieh, "Why are college foreign language students' self-efficacy, attitude, and motivation so different?," *Int. Educ.*, vol. 38, no. 1, p. 11, 2008.
[66] S. Han, Y. Li, and S. A. Haider, "Impact of foreign language classroom anxiety on higher education students academic success: mediating role of emotional intelligence and moderating influence of classroom environment," *Front. Psychol.*, vol. 13, p. 945062, 2022.
[67] P. P. H. Hsieh and H. S. Kang, "Attribution and self-efficacy and their interrelationship in the Korean EFL context," *Lang. Learn.*, vol. 60, no. 3, pp. 606–627, 2010.

[68] B. Dökmecioğlu, Y. Tas, and S. Yerdelen, "Predicting students' critical thinking dispositions in science through their perceptions of constructivist learning environments and metacognitive self-regulation strategies: a mediation analysis," *Educ. Stud.*, vol. 48, no. 6, pp. 809–826, 2022.
[69] R. Pekrun, T. Goetz, W. Titz, and R. P. Perry, "Academic emotions in students' self-regulated learning and achievement: a program of qualitative and quantitative research," *Educ. Psychol.*, vol. 37, no. 2, pp. 91–105, 2002.
[70] M. N. Mata, S. A. Haider, R. M. Dantas, J. X. Rita, and J. L. Lucas, "Blockchain technology system on student academic performance in higher education as perceived by students in Portugal," *Stud. High. Educ.*, vol. 50, no. 4, pp. 824–847, 2025.
[71] C. O. Walker, B. A. Greene, and R. A. Mansell, "Identification with academics, intrinsic/extrinsic motivation, and self-efficacy as predictors of cognitive engagement," *Learn. Individ. Differ.*, vol. 16, no. 1, pp. 1–12, 2006.
[72] R. M. Klassen and E. L. Usher, "Self-efficacy in educational settings: recent research and emerging directions," In *The Decade Ahead: Theoretical Perspectives on Motivation and Achievement*. Bingley, UK: Emerald Group Publishing, 2010.
[73] D. Goleman, "Emotional intelligence: issues in paradigm building," In *The Emotionally Intelligent Workplace*. San Francisco, CA: Jossey-Bass, 2001, pp. 13–26.
[74] D. Goleman, R. E. Boyatzis, and A. McKee, *Primal Leadership: Unleashing the Power of Emotional Intelligence*. Boston, MA: Harvard Business Press, 2013.
[75] S. Naz, C. Li, H. Khan, and M. Rafiq, "The impact of emotional intelligence on employee performance and engagement: the mediating role of job satisfaction," *Middle East J. Manag.*, vol. 6, no. 5, p. 574, 2019a.
[76] S. Naz, C. Li, Q. A. Nisar, and M. Rafiq, "Linking emotional intelligence to knowledge sharing behaviour: mediating role of job satisfaction and organisational commitment," *Middle East J. Manag.*, vol. 6, pp. 318–340, 2019b.
[77] Z. O. U. Ran, S. Zeb, F. Nisar, F. Yasmin, P. Poulova, and S. A. Haider, "The impact of emotional intelligence on career decision-making difficulties and generalized self-efficacy among university students in China," *Psychol. Res. Behav. Manag.*, vol. 15, pp. 865–874, 2022.
[78] S. Y. Toh, F. Yasmin, S. Tehseen, P. Poulova, S. A. Haider, E. Andrews, and R. Z. Mahendra, "Born this way or formed this way? Distal personality traits and proximal self-efficacy of Malaysian students and their academic performance," *Environ. Soc. Psychol.*, vol. 9, no. 5, p. 2282, 2024.
[79] F. Moafian and A. Ghanizadeh, "The relationship between Iranian EFL teachers' emotional intelligence and their self-efficacy in language institutes," *System*, vol. 37, no. 4, pp. 708–718, 2009.
[80] S. C. Tseng and C. C. Tsai, "Taiwan college students' self-efficacy and motivation of learning in online peer assessment environments," *Internet High. Educ.*, vol. 13, no. 3, pp. 164–169, 2010.
[81] M. K. Lindell and D. J. Whitney, "Accounting for common method variance in cross-sectional research designs," *J. Appl. Psychol.*, vol. 86, no. 1, p. 114, 2001.
[82] J. Hair and A. Alamer, "Partial least squares structural equation modeling (PLS-SEM) in second language and education research: guidelines using an applied example," *Res. Methods Appl. Linguist.*, vol. 1, no. 3, p. 100027, 2022.
[83] J. Liebowitz and Y. Chen, "Developing knowledge-sharing proficiencies," *Knowl. Manag. Rev.*, vol. 3, pp. 12–15, 2001.
[84] Z. Wang and N. Wang, "Knowledge sharing, innovation and firm performance," *Expert Syst. Appl.*, vol. 39, no. 10, pp. 8899–8908, 2012.
[85] H. Mohebbi and S. M. Alavi, "Teachers' first language use in second language learning classroom context: a questionnaire-based study," *Bellaterra J. Teach. Learn. Lang. Lit.*, vol. 7, no. 4, pp. 57–73, 2014.
[86] M. Tschannen-Moran and A. W. Hoy, "Teacher efficacy: capturing an elusive construct," *Teach. Teach. Educ.*, vol. 17, no. 7, pp. 783–805, 2001.
[87] M. Sarstedt, C. M. Ringle, and J. F. Hair, "Partial least squares structural equation modeling," In *Handbook of Market Research*. Cham: Springer International Publishing, 2021, pp. 587–632.
[88] J. Henseler, C. M. Ringle, and M. Sarstedt, "Using partial least squares path modeling in advertising research: basic concepts and recent issues," In *Handbook of Research on International Advertising*. Cheltenham, UK: Edward Elgar Publishing, 2012.
[89] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *Eur. Bus. Rev.*, vol. 31, no. 1, pp. 2–24, 2019.
[90] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *J. Acad. Mark. Sci.*, vol. 43, no. 1, pp. 115–135, 2015.
[91] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*. New York, NY: Routledge Academic, 1988, pp. 19–74.
[92] R. An, H. Zhang, A. Akbar, and S. A. Haider, "Exploring the influence of teacher-student relationships on Chinese language learning through the mediating role of student's self-efficacy: foreign language classroom anxiety as a moderator," *Acta Psychol.*, vol. 251, p. 104552, 2024.
[93] M. Shahzad, Q. Ying, S. Ur Rehman, A. Zafar, X. Ding, and J. Abbas, "Impact of knowledge absorptive capacity on corporate sustainability with mediating role of CSR: analysis from the Asian context," *J. Environ. Plan. Manag.*, vol. 63, no. 2, pp. 148–174, 2019.
[94] A. Cabrera, W. C. Collins, and J. F. Salgado, "Determinants of individual engagement in knowledge sharing," *Int. J. Hum. Resour. Manag.*, vol. 17, no. 2, pp. 245–264, 2006.
[95] A. Pérez-Luño, A. M. Bojica, and S. Golapakrishnan, "When more is less: the role of cross-functional integration, knowledge complexity and product innovation in firm performance," *Int. J. Oper. Prod. Manag.*, vol. 39, no. 1, pp. 94–115, 2018.
[96] A. Penrose, C. Perry, and I. Ball, "Emotional intelligence and teacher self-efficacy: the contribution of teacher status and length of experience," *Issues Educ. Res.*, vol. 17, no. 1, pp. 107–126, 2007.
[97] R. Akbari and N. K. Allvar, "L2 teacher characteristics as predictors of students' academic achievement," *TESL-EJ*, vol. 13, no. 4, p. n4, 2010.
[98] L. B. Nilson, *Teaching at Its Best: A Research-Based Resource for College Instructors*. Hoboken, NJ: John Wiley & Sons, 2016.