

Article

Analyzing the Foundations of Social Sustainability in Teacher Education: A Study of Self-Regulation, Social-Emotional Expertise, and AI-TPACK

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Abstract

The integration of artificial intelligence (AI) into education is a defining challenge for achieving a sustainable digital future. This study addresses this challenge by exploring the psychological foundations necessary for teacher readiness, framing this preparation as a matter of social sustainability for the teaching profession. Employing a correlational research design, this study investigates the relationships among key psychological constructs as perceived by pre-service educators. Specifically, it examines how pre-service preschool teachers' self-reported levels of self-regulation and social-emotional expertise relate to their self-assessed AI—Technological Pedagogical Content Knowledge (AI-TPACK). The findings were revealing: multiple linear regression analyses confirmed perceived self-regulation as a robust predictor of the self-assessed core and composite knowledge elements of AI-TPACK. Counterintuitively, social-emotional expertise did not show a significant correlation with any aspect of AI-TPACK. This suggests that the metacognitive skills inherent in self-regulation are fundamental for empowering educators to engage in the lifelong learning required for a sustainable career. Therefore, teacher education programs must strategically cultivate these skills to foster a resilient teaching workforce, capable of ethically shaping the future of AI in inclusive and sustainable learning environments.



Academic Editor: David González Gómez

Received: 22 August 2025

Revised: 19 September 2025

Accepted: 23 September 2025

Published: 25 September 2025

Citation: Şahin, M. Analyzing the Foundations of Social Sustainability in Teacher Education: A Study of Self-Regulation, Social-Emotional Expertise, and AI-TPACK. *Sustainability* **2025**, *17*, 8613. <https://doi.org/10.3390/su17198613>

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Keywords: AI-TPACK; preschool teacher education; self-regulation; social-emotional expertise; social sustainability; sustainable pedagogy

1. Introduction

Since technology has been integrated into every sphere of our lives, early education teachers are supposed to know how to use it appropriately in the classrooms in order to meet the new challenges. Efficient technology implementation in early childhood education can be done in many ways, such as strengthening the teaching and learning process, fostering digital literacy, and getting little ones ready for technological bullying, which is definitely going to be a part of their lives when they grow up [1]. The use of information and communication technology (ICT) in the early childhood education field is being studied more and more by researchers and educators [2]. Successful technology integration in early childhood education is contingent upon several key factors, including the availability of technological resources, the quality of school infrastructure, and class size [3]. Beyond these structural elements, pre-service teachers' personal beliefs and attitudes toward technology are pivotal, as they significantly influence the development of their technological skills and their subsequent application in future professional practice [4]. Thus, leading organizations

in the field emphasize the need for robust guidance and support to ensure preschool teachers are proficient in using technology effectively in their classrooms [5].

The continuous development of pre-service teachers, especially in the integration of technology into the classroom, is a challenge that necessitates an approach with various features [6,7]. Effective teacher education programs must extend beyond technical skill acquisition to cultivate a foundational positive mindset toward technology integration. This mindset encompasses more than just enthusiasm and confidence; it involves fostering a critical and adaptive disposition that enables future educators to thoughtfully navigate the rapidly evolving digital world [4]. Therefore, curricula should be designed to build both the practical confidence for using technology and the deeper pedagogical understanding required to manage its integration sustainably and ethically. This challenge of managing the digital world is now rapidly evolving with the advent of artificial intelligence (AI). The integration of AI into education represents more than a technological upgrade; it is a profound socio-technical transition that carries significant implications for social sustainability. Ensuring that this transition is managed effectively is crucial for fostering a sustainable digital future, one where technology serves to enhance human-centric pedagogy rather than detract from it. This perspective reframes the discourse from merely adopting new tools to the ethical and pedagogical stewardship of powerful systems that will shape future learning environments. Consequently, preparing educators for this reality is a cornerstone of achieving long-term, sustainable educational quality. With the increasing adoption of artificial intelligence in education, particularly in preschools, educators are now called to participate in this emerging phenomenon. In order to make use of the benefits of AI for students, teachers should be AI competent [8]. Such integration calls for re-evaluating teachers' skills in the 21st century [9]. However, the integration of AI also raises critical ethical questions about the restructuring of educational labor and the professional identity of educators. Thus, AI must be understood not merely as a pedagogical tool but as a powerful socio-technical system that can significantly impact teachers' professional autonomy, creativity, and ethical roles. This calls for a balanced approach to sustainable AI integration that prioritizes teacher empowerment and ethical governance [10].

Recent literature confirms that the integration of AI in early childhood education (ECE) is no longer a futuristic concept but a burgeoning reality, primarily manifested through interactive and child-appropriate technologies [11,12]. The focus of current applications is on enhancing learning through tools tailored to children's developmental stages, such as smart toys, educational robots like KIERO, and chatbots, which are used to improve literacy and foundational concepts in an engaging manner [11,13]. This trend underscores a pedagogical shift towards leveraging AI to create active and personalized learning interventions [14]. However, this rapid integration brings significant ethical challenges to the forefront. Key concerns highlighted in recent scoping reviews include the safeguarding of children's sensitive data, the risk of algorithmic bias perpetuating social inequities, and the potential for AI tools to undermine relational learning if not designed with developmental needs in mind [15]. The discourse has therefore moved towards defining and promoting "AI literacy" for young children, which involves not only using AI tools but also understanding their basic principles, limitations, and ethical implications [11,13]. This imperative places a significant new responsibility on educators, who must be prepared to navigate both the pedagogical opportunities and the ethical complexities of AI-mediated learning environments [14,16].

This need for a balanced approach is also evident in studies focusing on specific educational contexts, such as rural elementary schools, where teachers perceive AI as a valuable tool to reduce their workload and facilitate teaching in multigrade classrooms without viewing it as a job threat. These teachers, however, emphasize the need for techno-

logical resources that align with their specific contexts, such as offline tools and adaptable curricula, highlighting the critical role of accessible resources and professional development in successful AI integration in these settings. Therefore, exploring the factors that contribute to teachers' readiness and expertise in integrating AI is crucial for developing effective and equitable educational practices [17]. Indeed, leveraging AI to its full potential in educational settings requires a structured and systematic approach. For instance, recent studies propose multi-stage modeling methodologies to integrate generative AI tools into STEM education, demonstrating that such a systematic pathway not only enhances problem-solving skills but also supports personalized and inquiry-based learning, which is crucial for sustainable educational development [18]. In this regard, recent literature also highlights the importance of AI-supported STEM education in fostering 21st-century skills and contributing to sustainable development goals [19]. In addition, the powerful role of AI in higher education, in its ability to improve students' decision-making through support for the use of digital tools such as e-books, immersive experiences via simulations, and virtual execution [20], has gradually been recognized. The introduction of AI technologies in the learning process is being pursued by preschool centers, especially those located in coastal areas [21]. The application of AI in preschool education, through tools like interactive toys and personalized learning platforms, offers significant potential to enhance children's engagement and motivation [22]. These technologies can tailor educational content to individual learning paces and needs by providing customized feedback and guidance, thereby creating more effective and empowering learning experiences [23–28]. For instance, intelligent tutoring systems can offer real-time support, helping children navigate complex concepts in a personalized manner [29]. The foremost consideration in training preschool teachers for the incorporation of AI technology is that they must take a key role in the development of AI-based educational activities in a way that the early childhood programs run with the help of this technology will be brought to perfection by preschool teachers. Studies in further education recommend that preschool teachers should be included. The list of AI knowledge and skills that preschool teachers must have to enrich the educational experiences of children via the use of AI is long. To begin with, teachers need to be conversant with the basic principles and applications of AI, including its advantages and limitations [25,30]. This will enable them to select appropriate AI technologies and resources for their pupils, and thus ensure the application of technology will be best suited to educational practices. Teachers then need to develop the necessary skills to include artificial intelligence appropriately in their lessons [31]. Such experience can be implemented by incorporating a hybrid model as well as tutorials to engage the maximum students and obtain their suggestions, remarks, and other comments derived from the use of these technologies [32]. Additionally, preschool teachers should have a positive attitude towards the implementation of AI in their classrooms [33–35]. Research shows that the acknowledgment of teachers' trust in AI is an integral part of its acceptance, as their doubt can be an obstacle to using those technologies effectively [36]. Teachers, moreover, must understand the paramount importance of constructing a proper balance between the technology and the social contacts through which the early and emotional learning of children is done, and the uniting of both should be done with the stress on personal and social learning. The successful integration of technology with a good focus on the overall technology as well as the educational and emotional aspects of such technology means that AI should blend well with both the relevant technology and the educational and emotional needs of the users. In order to reach the desired individualization of preschool education where the use of technology like AI will go far beyond the application of any other existing mainstream educational tool while being encouraged by the educator in a way that is entertaining and of the maximum amount of engagement, literature suggests that inclusive

training programs and professional development for preschool teachers should be at the center of this process [22,36]. In their research, Bernstein, Haagen-Schützenhöfer, and Schubatzky [37] highlighted the urgent need to promote digital skills across all educational levels, from primary to higher education.

Artificial Intelligence Technological Pedagogical Content Knowledge (AI-TPACK) is a new umbrella concept that outlines the three important domains of knowledge and know-how that teachers ought to have for the effective integration of AI in schools [38]. Interest in AI-TPACK has grown, particularly concerning how psychological factors such as self-regulation and social-emotional abilities can significantly influence its successful implementation. While these abilities are vital for all educators, their role is especially critical for preschool teachers, who must navigate the unique developmental needs of young children during technology integration. Self-regulation refers to a person's ability to detect and control his or her thoughts, feelings, and behaviors [39–42]. Self-regulation is among the factors that genuinely affect the success of AI-TPACK implementation as it is noted for positive outcomes. Preschool educators that exhibit self-regulation skills can efficiently navigate the often-confusing paths of AI integration and differentiate their instruction to the specific aspects of the children they are teaching and the technology they have access to. Also, the capacity to connect and build relationships with others, understand empathically, and be emotionally present for others is the area of social-emotional skills that is found to be crucial for the effective use of the AI-TPACK framework [43,44]. Competencies such as empathy, sympathy, and emotional understanding among preschool education personnel can also be said to be necessary for integrating innovative technologies such as AI-TPACK. The other benefit of high-level social-emotional expertise in preschool teachers is that it empowers them to proactively recognize and address potential challenges and concerns related to the use of such innovative technology in the classroom, which ensures a seamless and consistent transition for all involved [33]. Self-regulation and social-emotional capabilities among preschool teachers show a developmental state that is sometimes overlooked in educating and preparing preschool teachers to integrate emerging technologies in their classrooms. It is essential to understand the psychological, behavioral, and emotional aspects of teachers so as to enhance the positive impact of the AI-TPACK framework and realize the full potential of AI in enhancing the teaching and learning process.

In the domain of preschool education, self-regulation and social-emotional expertise combined with technological pedagogical content knowledge (TPACK) have a significant role to play [38]. Since young children often need a special kind of attention and support, AI technology's seamless integration into the classroom requires a fine mixture of pedagogical and technical skills and the ability to ensure the efficiency of social-emotional relationships. Among preschool educators, those who are capable of interweaving self-regulation and social-emotional expertise into their TPACK will be in a better position to navigate the changing education landscape and provide their students with a rich and engaging learning experience that captures the potential of AI while preserving the essential human aspects of teaching and learning [36,38].

1.1. Research Gap

This research gap extends beyond mere technical skills to encompass the psychological dispositions of teachers, which are critical for the sustainable adoption of AI. The successful integration of technology is not solely dependent on teachers' ability to use digital tools, but is profoundly shaped by their professional knowledge, pedagogical beliefs, and attitudes. A systematic review of AI professional development programs highlights that effective teacher learning requires a fusion of technological and pedagogical knowledge, framed within models like TPACK [45]. Indeed, studies show that teachers' underlying pedagogical

beliefs—whether constructivist or transmissive—significantly predict their acceptance and use of AI tools in the classroom [46]. This underscores the necessity of investigating the internal, cognitive, and affective attributes of pre-service teachers to understand their readiness for an AI-driven educational landscape.

In this context, cognitive and metacognitive skills have emerged as significant predictors of techno-pedagogical competence. For instance, recent research has established a strong positive correlation between teachers' cognitive flexibility—the ability to adapt thinking and adjust strategies in response to new demands—and their capacity to integrate technology and pedagogy [47,48]. This mental agility is considered fundamental for navigating the complexities of emerging educational technologies. Closely related to this is the role of teacher self-efficacy, defined as an individual's belief in their capability to perform specific teaching tasks (Dellinger et al., 2008, as cited in [49]). A substantial body of evidence demonstrates that teacher self-efficacy is a powerful determinant of AI-TPACK development and the intention to use AI tools [49–51]. This aligns with social cognitive theory, which posits that self-efficacy beliefs are central to human agency and the capacity for self-regulation (Bandura, 1997, as cited in [50]). Therefore, examining self-regulation as a predictor of AI-TPACK represents a logical and well-supported line of inquiry.

While the role of cognitive skills like cognitive flexibility and self-efficacy is increasingly well-documented, the influence of teachers' social-emotional competencies on their AI-TPACK remains a significant and underexplored area. The existing literature, as synthesized above, predominantly links technology readiness to cognitive and metacognitive attributes rather than interpersonal or affective skills. This creates a critical research gap, as social-emotional skills are fundamental to teaching effectiveness, yet their connection to the specific demands of AI integration is not clearly understood. Compounding this gap is the rise of negative psychological factors such as technostress—stress induced by the inability to adapt to new technologies—and AI anxiety, which can act as significant barriers to technology adoption [52–54]. Given these countervailing psychological forces, it is imperative to investigate a broader range of teacher attributes. This study, therefore, aims to address this gap by concurrently investigating the established relationship between self-regulation and AI-TPACK and the largely unexamined role of social-emotional expertise, providing a more holistic understanding of pre-service teacher readiness for the AI era.

The current studies exploring the association between preschool teacher candidates' perceived self-regulation, social-emotional expertise, and AI-TPACK are very limited [55–58]. The emphasis of the prior studies was on the relationship between primary TPACK, self-efficacy, and technology competencies in pre-service or in-service teachers using different educational levels [55,58]. On the other hand, the function of self-regulation and social-emotional expertise in developing AI-TPACK, especially in the context of early childhood education, has not received attention so far [56]. This research gap is not merely a question of technical skill acquisition; it touches upon the very foundation of sustainable professional development for educators in the 21st century. Teachers who possess strong self-regulation skills are better equipped to engage in lifelong learning, adapt to rapidly evolving technological landscapes, and maintain their professional agency. These competencies are critical for ensuring that the integration of AI in classrooms is thoughtful, ethical, and pedagogically sound over the long term, thereby contributing to the broader goal of inclusive and equitable quality education as outlined in the UN's 2030 Agenda for Sustainable Development. Understanding the role of these internal capacities is therefore essential for designing teacher education programs that cultivate a resilient and sustainable teaching workforce. The aim of this study is to fill this open area of research by analyzing the interrelations among preschool teacher candidates' perceived self-regulation, social-emotional expertise, and their knowledge and skills in using AI-based tools for

teaching. It is important to note that this study approaches these variables—self-regulation, social-emotional expertise, and AI-TPACK—as subjective constructs, measured through the self-perceptions and self-assessments of the participants rather than through objective performance metrics.

1.2. Research Aim and Research Questions

This research investigates the relationship between perceived self-regulation, social-emotional expertise, and AI-TPACK (Artificial Intelligence—Technological Pedagogical Content Knowledge) among preschool teacher candidates. The study aims to explore whether and how perceived self-regulation and social-emotional expertise predict AI-TPACK levels in this specific population. The research questions are as follows:

1. What are the perceived self-regulation levels of the participants?
2. What are the social-emotional expertise levels of the participants?
3. What are the AI-TPACK levels of the participants?
4. Is there a significant relationship between perceived self-regulation and AI-TPACK?
5. Is there a significant relationship between social-emotional expertise and AI-TPACK?
6. Do perceived self-regulation and social-emotional expertise predict AI-TPACK?

2. Methods

2.1. Research Design

The present research adopted a correlational research methodology to investigate the interrelationships between perceived self-regulation, social-emotional expertise, and AI-TPACK among preschool teacher candidates. Specifically, the study focused on the correlation between these variables and evaluated the predictive influence of perceived self-regulation and social-emotional expertise on AI-TPACK. In this respect, AI-TPACK was treated as the outcome variable, whereas perceived self-regulation and social-emotional expertise were taken as the predictor variables.

2.2. Population and Sample

This particular research project examines preschool teacher candidates as the unit of analysis. The original research sought to acquire a sample that would exceed one-half the number of candidates for teacher preschool in every one of three universities. This aim was successfully satisfied so that a total population of students was drawn in each institution. Random sampling was used for this research project, thereby giving participants a chance to participate voluntarily.

Table 1 provides an analysis of the demographic structure of the survey respondents, divided into gender, age, and university affiliation. The results are expressed in terms of absolute frequencies (*f*) and their corresponding percentages (%). The gender statistics indicated in the survey show a significant distribution of females at 89.0% (*n* = 356) and males at 11.0% (*n* = 44). This biased distribution corresponds with the respondent group being preschool teacher candidates, a field still now mostly dominated by the female gender. As a result, the study is expected to have a predominantly female sample, which is consistent with the targeted population's demographic. The gender structure reveals that the vast majority of respondents belong to the age group 18–23; hereof, 49.0% (*n* = 196) are aged 18–20 and 41.0% (*n* = 164) are aged 21–23. Participants aged 24 and above account for 10.0% (*n* = 40) of the total sample. The age distribution demonstrates that the focus is mainly on the young. The participants in the study are from three different universities: A (the most prominent at 42.0% (*n* = 168)), C (the second most common, representing 32.3% (*n* = 129)), and lastly, B (the least represented one with 25.8% (*n* = 103)). This distribution may suggest an impact of the universities' specific environments on the reactions to the

survey. According to the information provided in the table, it can be easily seen that the sample consisted mainly of female participants, most participants were from the age group of 18–23 years, and there was a diversified distribution across the three distinct universities.

Table 1. Participant demographics.

		F	%
Gender	Female	356	89.0
	Male	44	11.0
Age	18–20	196	49.0
	21–23	164	41.0
	24 and above	40	10.0
University	A	168	42.0
	B	103	25.8
	C	129	32.3

2.3. Data Collection Tools

To gather data on the primary variables of interest, this study utilized a set of established self-report questionnaires. This approach was chosen to capture the pre-service teachers' personal perceptions and assessments of their own competencies. Consequently, all data concerning self-regulation, social-emotional expertise, and the various dimensions of AI-TPACK reflect the subjective viewpoints of the participants. The data collection process for this study was conducted during the fall semester of the 2024–2025 academic year. Data were gathered through online forms.

Perceived Self-Regulation Scale: The Perceived Self-Regulation Scale, developed by Arslan and Gelisli [59], is a 5-point Likert-type scale (1 = Never, 5 = Always) that assesses individuals' self-regulation skills. The scale consists of 16 items and two factors: openness (8 items) and search (8 items). In this study, the Cronbach alpha coefficients were 0.84 for the openness subscale and 0.82 for the search subscale. The confirmatory factor analysis revealed that the two-factor structure of the scale was confirmed: $\chi^2 = 147.60$, $df = 95$, $p = 0.00$, RMSEA = 0.042, NFI = 0.98, CFI = 0.99, IFI = 0.99, RFI = 0.97, CFI = 0.99, GFI = 0.94, AGFI = 0.92, and SRMR = 0.035.

Social-Emotional Expertise Scale: To assess participants' perceptions of their own social-emotional expertise, the Social-Emotional Expertise Scale (SECS), developed by McBrien et al. [60], was used. This self-report instrument is designed to measure an individual's self-assessed social-emotional skills. The scale was adapted into Turkish in 2021 by Ay and Temel [61]. The scale is a 25-question, 5-point Likert-type self-assessment tool. The SECS consists of two factors: adaptability and expressiveness. The Cronbach alpha coefficient of the scale is 0.855, and the test-retest reliability coefficient is 0.838. The relationship between the original form of the Schutte Emotional Intelligence Test and the Social-Emotional Expertise Scale, which was used to examine criterion-dependent validity, was 0.615, $p < 0.01$.

Artificial Intelligence Technological Pedagogical Content Knowledge Scale (AI-TPACK): In this study, the Artificial Intelligence Technological Pedagogical Content Knowledge Scale (AI-TPACK) developed by Ning et al. [62] and adapted to Turkish by Canbazoglu Bilici et al. [63] was used to determine teachers' perceived levels of AI-TPACK. This scale aims to measure teachers' self-assessed knowledge, skills, and competencies in integrating artificial intelligence (AI) technologies into educational processes.

The original scale developed by Ning et al. [62] consists of 39 items. The scale assesses seven dimensions of AI-TPACK: content knowledge, pedagogical knowledge, AI—technological knowledge, pedagogical content knowledge, AI—technological content knowledge, AI—technological pedagogical knowledge, and AI-TPACK. The scale items are

answered on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The factors included in AI-TPACK are presented below:

Core Knowledge Score: The combined score of the core knowledge elements:

- Pedagogical Knowledge (PK);
- Content Knowledge (CK);
- AI—Technological Knowledge (AI-TK).

Composite Knowledge Score: This score represents the combined score of the composite knowledge elements:

- Pedagogical Content Knowledge (PCK);
- AI—Technological Content Knowledge (AI-TCK);
- AI—Technological Pedagogical Knowledge (AI-TPK).

AI-TPACK Score: This is the overall score reflecting the seventh factor, which represents the integrated knowledge of AI in pedagogical practices.

The scale was adapted to the Turkish context by Canbazoğlu Bilici et al. [63]. The adaptation study ensured both the linguistic equivalence and cultural relevance of the scale. Confirmatory factor analysis (CFA) evidenced that the 39-item scale could be presented through the original seven-factor structure. The overall Cronbach alpha reliability coefficient was 0.980. The Cronbach alpha reliability scores for the sub-dimensions varied between 0.873 and 0.973. The validity and reliability assessments, both for the original and the Turkish adaptation of the scale, demonstrated the scale's competence as a valid and reliable AI-TPACK measurement tool.

2.4. Data Analysis Techniques

The data from the participants were analyzed using descriptive and inferential statistics. The descriptive statistics methods utilized included mean, median, standard deviation, skewness, and kurtosis, in order to summarize the self-regulation, social-emotional expertise, and AI-TPACK levels. A Pearson correlation analysis was applied to check the associations between the aforementioned variables. In addition, a multiple linear regression analysis was employed to investigate how much the perceived self-regulation and social-emotional expertise can predict the AI-TPACK components.

3. Results

This section presents the findings of the study, beginning with descriptive statistics for the main variables: perceived self-regulation, social-emotional expertise, and AI-TPACK. Following the descriptive analysis, the results of the correlation and multiple linear regression analyses are provided to examine the relationships between these variables.

Table 2 presents descriptive statistics for the perceived self-regulation levels of the 400 participants. The total self-regulation perception score produced a mean of 3.04 (SD = 0.32), which indicates a moderate degree of self-regulation in the sample. In the analysis of the self-regulation sub-dimensions, the average score of one “openness” dimension was found to be higher than that of another “search” dimension, at 3.22 (SD = 0.40) compared to 2.86 (SD = 0.43), respectively. This implies that the participants are characterized by the fact that they consider themselves being more open to new experiences and information than actually looking for meaning in their experiences.

Table 3 presents a descriptive analysis of the participants' self-reported levels of social-emotional expertise. The aspects of adaptability and expressiveness were used to derive the total score on social-emotional expertise. The mean score for adaptability was 2.84 with a standard deviation of 0.40, indicating that participants reported lower scores in the area of adaptability. The scores were also slightly positively skewed at 1.08; this skewness indicated

that only a few of the participants were able to score higher than average, indicating their ability to adapt to changing situations and conditions. The average score for expressiveness was 3.43 with a standard deviation of 0.43. Therefore, the analysis indicated that the respondents in the study reported high amounts of expressiveness. A skewness of -1.17 was computed from the distribution of scores; precisely, this means that some, although few, participants indicated remarkably low levels of expressiveness. The overall average score on social-emotional expertise was 3.05 with a standard deviation of 0.34, which shows that most of the respondents were able to adhere to this skill set. The distribution of the scores was positively skewed with a score of 0.24 indicating that any attempt to measure social-emotional expertise could be limited, as only a few of them have high levels of expertise on the same. The scores show that the participants reported a moderate level of social-emotional expertise with a slight margin for a high degree of expressiveness compared to adaptability. This, however, could indicate the possibility that adaptability is an aspect of social and emotional intelligence that could hardly be developed unless over time, while expressiveness is more or less a generic and easy-to-develop technique or a skill. Adaptability is a more complicated concept that entails the ability to monitor personal emotions and audiences' reactions depending on the environment or surroundings, while expressiveness is more basic and mainly entails the articulation of one's needs to another. Thus, from the above-stated views, the present study implies that the respondents evoke a moderate degree of social and emotional intelligence competency with more expression than adaptation.

Table 2. Perceived self-regulation levels of participants.

	n	Mean	Median	Standard Deviation	Skewness	Kurtosis	Minimum	Maximum
Factor 1 Openness	400	3.22	3.25	0.40	0.72	1.75	2.00	4.75
Factor 2 Search	400	2.86	2.88	0.43	0.17	−0.04	1.75	4.25
Total Score Perceived Self-regulation	400	3.04	3.06	0.32	0.60	1.52	2.38	4.44

Table 3. Social-emotional expertise levels of participants.

	n	Mean	Median	Standard Deviation	Skewness	Kurtosis	Minimum	Maximum
Factor 1 Adaptability	400	2.84	2.81	0.40	1.08	2.59	1.81	4.69
Factor 2 Expressiveness	400	3.43	3.44	0.43	−1.17	3.15	1.44	4.33
Total Score Social-Emotional Expertise	400	3.05	3.04	0.34	0.24	2.09	1.76	4.48

Table 4 provides an overview depicting the descriptive statistics for the AI-TPACK framework, which mostly comprises core knowledge elements, composite knowledge elements, and an overall AI-TPACK score that encompasses all of them.

Table 4. AI-TPACK levels of participants.

		n	Mean	Median	Standard Deviation	Skewness	Kurtosis	Minimum	Maximum
Core Knowledge Elements	Content Knowledge (CK)	400	3.12	3.00	0.51	0.87	2.11	1.80	5.00
	Pedagogical Knowledge (PK)	400	2.89	3.00	0.53	−0.21	0.12	1.33	4.33
	AI—Technological Knowledge (AI-TK)	400	3.21	3.20	0.46	0.39	0.10	2.20	4.80
Core Knowledge Elements Score		400	3.07	3.06	0.31	0.75	1.69	2.36	4.47
Composite Knowledge Elements	Pedagogical Content Knowledge (PCK)	400	3.29	3.25	0.44	1.01	2.27	2.17	5.00
	AI—Technological Content Knowledge (AI-TCK)	400	2.96	3.00	0.41	−0.24	0.08	1.83	4.00
	AI—Technological Pedagogical Knowledge (AI-TPK)	400	2.94	3.00	0.43	0.06	0.10	1.67	4.17
Composite Knowledge Elements Score		400	3.06	3.06	0.31	0.34	1.30	2.11	4.28
Artificial Intelligence—Technological Pedagogical Content Knowledge, AI-TPACK		400	3.21	3.20	0.45	0.22	0.13	2.00	4.60

When considering the core knowledge elements, the AI—Technological Knowledge (AI-TK), Core Knowledge Score can be observed; this has the highest mean score of 3.21 (SD = 0.46), while the Content Knowledge (CK) scores have a mean of 3.12 (SD = 0.51). Pedagogical Knowledge (PK) ranked as the least true core knowledge element with a mean score of 2.89 (SD = 0.53). Thus, like previously presented composite scores from these three scores forming the Core Knowledge Score, which also takes into account the introductory averages from two great groups, the composite score reaches 3.07 (SD = 0.31), denoting a valid composition using these major building blocks.

The next composite knowledge element was Pedagogical Content Knowledge (PCK), represented by a mean score of 3.29 (SD = 0.44). Many instructors accepted it as being the best of the three composites. Even though both AI—Technological Content Knowledge (AI-TCK) and AI—Technological Pedagogical Knowledge (AI-TPK) had similar mean scores, AI-TCK showed a little higher dominance with a mean of 2.96 (SD = 0.41) if compared to its counterpart. In comparison, AI-TPK had a mean of 2.94 and the standard deviation was 0.43. The average composite mean score for knowledge level, exposing these three dimensions calculated as composites, obtains a sufficiently gratifying level, which is 3.06 (SD = 0.31).

An overall AI-TPACK score symbolizing the integrated knowledge of artificial intelligence (AI) in pedagogical practices reached up to 3.21 (SD = 0.45). The relevant index denotes that the participants have an awareness of closely collaborating with artificial intelligence and existing pedagogical practices when modifying teaching/learning for twenty-first-century students. It can be concluded that teachers are able to connect their experience with each other and productive development if they practice. It also indicates for teachers and school leadership where there are areas for further development so they can ensure progressive students and innovative schools when using AI-paced pedagogy.

The results indicate a varied level of pedagogical competence across the different dimensions of the AI-TPACK framework. The higher mean scores in AI-TK and CK suggest that participants possess strong knowledge in these areas, while PK scores indicate a relative need for development in pedagogical knowledge. Similarly, within the composite knowledge elements, PCK was significantly higher, thus suggesting a better integration of pedagogy and content, whereas AI-TCK and AI-TPK might require more time and attention during the professional development activities despite being significant for AI integration.

Table 5 presents the correlation analysis between perceived self-regulation, social-emotional expertise, and AI-TPACK levels. It was revealed through the results that there was a strong positive correlation between perceived self-regulation and both core knowledge elements ($r = 0.836$, $p < 0.001$) and composite knowledge elements ($r = 0.843$, $p < 0.001$). This indicates that those who see themselves as more self-regulated also have more AI-TPACK-related core and composite knowledge. However, the correlation between perceived self-regulation and AI-TPACK score was moderate ($r = 0.550$, $p < 0.001$), indicating that while self-regulation is associated with overall AI-TPACK, the relationship is not as strong as with the individual knowledge components.

Table 5. Correlation analysis.

		Perceived Self-Regulation	Social-Emotional Expertise
Core Knowledge Elements	Pearson Correlation	0.836 *	0.046
	Sig. (2-tailed)	0.000	0.359
	N	400	400
Composite Knowledge Elements	Pearson Correlation	0.843 *	0.087
	Sig. (2-tailed)	0.000	0.082
	N	400	400
Artificial Intelligence—Technological Pedagogical Content Knowledge. AI-TPACK	Pearson Correlation	0.550 *	0.040
	Sig. (2-tailed)	0.000	0.426
	N	400	400

* Correlation is significant at the 0.01 level (two-tailed).

It was a disappointment that social-emotional expertise did not show any statistically significant link with any of the AI-TPACK aspects. The correlation that was obtained with core knowledge elements was weak and statistically insignificant ($r = 0.046$, $p = 0.359$). Likewise, the correlation with composite knowledge elements was trivial and not statistically significant ($r = 0.087$, $p = 0.082$). Additionally, social-emotional expertise exhibited a negligible and non-significant correlation with AI-TPACK score ($r = 0.040$, $p = 0.426$). It is revealed by these findings that, in the case of this sample in this study and these measures, social-emotional expertise does not have a significant direct relationship with AI-TPACK or its components.

The findings demonstrate the necessity of perceived self-regulation in the formulation of AI-TPACK competencies, particularly with regard to core and composite knowledge elements, which are the fundamental ones. The less strong correlation with AI-TPACK suggests that self-regulation might not be the only aspect that should be blamed for any relationship due perhaps to some other influential factors. Furthermore, the lack of a significant relationship between social-emotional expertise and AI-TPACK questions the precise character of its role in the framework.

Although Table 5 showed no considerable direct link between social-emotional expertise and AI-TPACK, we wanted to examine the possibility of an indirect effect or interaction with perceived self-regulation. It was predicted that social-emotional expertise could play a role in the interaction with perceived self-regulation affecting AI-TPACK results, although it might not be a robust independent predictive capability. To verify this, we completed extra regression analyses, displayed in Tables 6–8, with social-emotional expertise integrated as a possible moderator in the association between perceived self-regulation and AI-TPACK. The purpose of those analyses was to clarify whether the degree of influence that perceived self-regulation applies to AI-TPACK alters with social-emotional expertise level.

The general form of the equation to predict “core knowledge elements” from “perceived self-regulation” and “social-emotional expertise” is as follows:

According to Model 1,

Core knowledge elements = $0.616 + (0.807 \times \text{perceived self-regulation})$.

Table 6. The predictors of core knowledge elements—multiple linear regression analysis.

Core Knowledge Elements									
Model	Predictors	Unstandardized Coefficients		Standardized Coefficients		Correlations		Collinearity	
		B	Std. Error	β	t	p	Partial	Part	VIF
1	(Constant)	0.616	0.081		7579	0			
	Perceived Self-regulation	0.807	0.027	0.836	30,371	0.000 *	0.836	0.836	1000
2	(Constant)	0.717	0.106		6762	0.000			
	Perceived Self-regulation	0.812	0.027	0.840	30,407	0.000 *	0.836	0.836	1011
	Social-emotional Expertise	−0.037	0.025	−0.041	−1481	0.140	−0.074	−0.041	1011

Dependent variable: core knowledge elements ' $p < 0.05^*$ '.**Table 7.** The predictors of composite knowledge elements—multiple linear regression analysis.

Composite Knowledge Elements									
Model	Predictors	Unstandardized Coefficients		Standardized Coefficients		Correlations		Collinearity	
		B	Std. Error	β	t	p	Partial	Part	VIF
1	(Constant)	0.554	0.081		6857	0.000			
	Perceived Self-regulation	0.825	0.026	0.843	31,229	0.000 *	0.843	0.843	1000
2	(Constant)	0.554	0.106		5243	0.000			
	Perceived Self-regulation	0.825	0.027	0.843	31,023	0.000 *	0.841	0.838	1011
	Social-emotional Expertise	−6552	0.025	0.000	−0.003	0.998	0.000	0.000	1011

Dependent variable: composite knowledge elements ' $p < 0.05^*$ '.**Table 8.** The predictors of Artificial Intelligence—Technological Pedagogical Content Knowledge, AI-TPACK—multiple linear regression analysis.

Artificial Intelligence—Technological Pedagogical Content Knowledge, AI-TPACK									
Model	Predictors	Unstandardized Coefficients		Standardized Coefficients		Correlations		Collinearity	
		B	Std. Error	β	t	p	Partial	Part	VIF
1	(Constant)	0.818	0.183		4466	0.000			
	Perceived Self-regulation	0.787	0.060	0.550	13,146	0.000 *	0.550	0.550	1000
2	(Constant)	0.881	0.240		3677	0.000			
	Perceived Self-regulation	0.790	0.060	0.552	13,104	0.000 *	0.549	0.549	1011
	Social-emotional Expertise	−0.023	0.057	−0.017	−0.408	0.684	−0.020	−0.017	1011

Dependent variable: Artificial Intelligence—Technological Pedagogical Content Knowledge, AI-TPACK ' $p < 0.05^*$ '.

This variable statistically significantly predicted core knowledge elements, $F = 922,412$, $p < 0.05$, $R^2 = 0.699$.

According to Model 2,

Core knowledge elements = $0.717 + (0.812 \times \text{perceived self-regulation})$.

The perceived self-regulation variable statistically significantly predicted core knowledge elements, $F = 463,684$, $p < 0.05$, $R^2 = 0.700$.

The social-emotional expertise variable was not a significant predictor.

Table 6 shows the results of the multiple linear regression analysis that considered the predictors of the core knowledge elements. Model 1 suggested that perceived self-regulation was the only predictor that had a considerable impact, and 69.9% of the variance

in the core content was accounted for ($R^2 = 0.699$, $F = 922.412$, $p < 0.05$). This indicates that perceived self-regulation is the main predictor of core knowledge aligning with the correlation analysis in Table 5.

Perceived self-regulation was a determinant of core knowledge and Model 2 was developed to see if social-emotional expertise could be added to it. Model 2 was similar to Model 1 as it also presented a statistically significant relationship between perceived self-regulation and core knowledge elements ($F = 463.684$, $p < 0.05$) but its predictive power was not significantly enhanced by social-emotional expertise. Indeed, the addition of social-emotional expertise did not account for a significant predictor in this model ($\beta = -0.041$, $p = 0.140$). That supports the argument that when the effects of perceived self-regulation are excluded, social-emotional expertise is not responsible for unique variance in predicting core knowledge elements.

Based on these findings, in addition to the correlation analysis, we conclude that perceived self-regulation is a major factor in the evolution of core knowledge concerning AI-TPACK. It is stated that social-emotional expertise does not have a significant impact on AI-TPACK; it is possible that its function is more subtle or indirect, with its influence working through other unmeasured variables in this study.

The general form of the equation to predict “composite knowledge elements” from “perceived self-regulation” and “social-emotional expertise” is as follows:

According to Model 1,

Composite knowledge elements = $0.554 + (0.825 \times \text{perceived self-regulation})$.

This variable statistically significantly predicted composite knowledge elements, $F = 975,248$, $p < 0.05$, $R^2 = 0.710$.

According to Model 2,

Composite knowledge elements = $0.554 + (0.825 \times \text{perceived self-regulation})$.

The perceived self-regulation variable statistically significantly predicted composite knowledge elements, $F = 486,399$, $p < 0.05$, $R^2 = 0.700$.

The social-emotional expertise variable was not a significant predictor.

In addition, results in Table 7 also confirm the crucial part that perceived self-regulation plays in the prediction of composite knowledge elements within the AI-TPACK framework. Specifically, the R-squared value in Model 1 was high (0.710), which is indicative of the fact that perceived self-regulating, in particular, accounted for a large amount of the variance in composite knowledge scores. This indicates that students who are more skillful at their own learning and cognitive process management are more likely to show a highly integrated understanding of AI in pedagogical contexts.

Moreover, it is worth noting that even in the case of social-emotional intelligence being included in Model 2 as a variable, there are only slight changes in the predictive value of perceived self-regulation. This serves as further confirmation that the social-emotional aspect of expertise, in this study, is not the one that mainly drives AI-TPACK outcomes. Also, as the R-squared value is not changed and the effect size for social-emotional expertise is not significant, it appears that this factor is not unique in the prediction of composite knowledge elements but the same variance has been accounted for through the perceived self-regulation factor.

Theoretical implications of this finding might suggest that the cognition and metacognition aspects of self-regulation are more vital areas in order to develop integrated AI-TPACK knowledge than the skills in social and emotional areas, which are normally related to expertise in the educational field.

The general form of the equation to predict Artificial Intelligence—Technological Pedagogical Content Knowledge, AI-TPACK from “perceived self-regulation” and “social-emotional expertise” is as follows:

According to Model 1,

$$\text{AI-TPACK} = 0.818 + (0.787 \times \text{perceived self-regulation}).$$

This variable statistically significantly predicted AI-TPACK, $F = 172,809$, $p < 0.05$, $R^2 = 0.303$.

According to Model 2,

$$\text{AI-TPACK} = 0.881 + (0.790 \times \text{perceived self-regulation}).$$

The perceived self-regulation variable statistically significantly predicted AI-TPACK, $F = 86,307$, $p < 0.05$, $R^2 = 0.303$.

The social-emotional expertise variable was not a significant predictor.

The results presented in Table 8 corroborate the results of the correlation analysis. Model 1 shows a statistically significant predictive relationship between perceived self-regulation and AI-TPACK ($F = 172.809$, $p < 0.05$, $R^2 = 0.303$). The effect size, though, is moderate, indicating that there are other factors beyond self-regulation that influence AI-TPACK. In Model 2, which incorporates social-emotional expertise, there is no crucial improvement in the prediction of AI-TPACK. The F-statistic remains significant ($F = 86.307$, $p < 0.05$); however, the R-squared value is invariant $R^2 = 0.303$, and social-emotional expertise was not established as a significant predictor. This reaffirms the fact that social-emotional expertise, as was gauged by this study, does not have a significant direct effect on AI-TPACK, nor does it seem to be moderating the association between perceived self-regulation and AI-TPACK.

From all of these findings, it can be inferred that while perceived self-regulation is a major element in AI-TPACK development, it is not the only factor that counts. The unimportant contribution from social-emotional expertise implies the necessity of delving into other potential predictors and moderators of AI-TPACK, such as certain personality traits, previous engagements with technology, or situational factors within the educational context.

4. Discussion

This study aimed to investigate the relationships between perceived self-regulation, social-emotional expertise, and AI-TPACK among preschool teacher candidates. The findings of the study provide several insights into these relationships.

4.1. Perceived Self-Regulation Levels

The first research question that was investigated centered on the self-regulation perception levels among the research participants. From the findings, it was observed that the participants possessed a moderate level of self-regulation. The mean score under the “openness” subscale was higher than the “search” subscale, indicating that the participants viewed themselves to be more open to new experiences and information than having a more active meaning search in their knowledge experiences.

This moderate self-regulation perception aligns with several previous studies that reported differences in self-regulatory capacity among different demographics as demonstrated by Zimmerman [64]. However, the discrepancy between the “openness” and “search” indices deserves further investigation. The high “openness” scores represent a natural inclination to engage in intellectual curiosity and a positive attitude toward the exploration of new ideas, which are humanistic attributes that lead to favorable learning [65]. Similarly, this aligns with the idea of openness to experience as a positive attribute that enhances the capability for cognitive flexibility and flexibility.

However, the low “search” scores indicate a possible inadequacy in the active and metacognitive aspects that are critical in self-regulation. This finding can imply the presence of an exploratory tendency among participants with the corresponding limitations in the conscious efforts to critically analyze, integrate, and connect the newly acquired information

into their already existing knowledge structures. Hence, this suggests the existence of a gap as per research that uncovered the difficulties people undergo in monitoring and regulating their cognitive activity well, as noted by Flavell [66].

Additionally, this trend might signify an interim period in the development of a group's population whereby the individuals are more inclined to absorb the information they receive rather than engaging deeply in the process of learning. For example, self-regulation studies on adolescents have established that, though individuals are open to experience, they are still unable to develop highly advanced metacognitive strategies, thus, leaving them behind in the self-regulation continuum [67]. Apart from that, contextual features that may have affected the results must also be acknowledged. The environment or the actual cognitive task may have affected the learners' views regarding self-regulation in a hypothetical classroom that supported the results of the present study. Similar to the present investigation, the integration of modern instructional technology in learning may be said to be a phenomenon that depends on, among other variables, the readiness and attitude transformation of the pupils and tutors [68].

4.2. Social-Emotional Expertise Levels

The second research question that is part of the present study looked into the social-emotional expertise attained by the respondents. The results of this study showed that there were certain moderate levels of social and emotional expertise among the respondents. For instance, it was established that the mean score of the "expressiveness" domain was higher than that of the "adaptability" domain, which indicates that the respondents viewed themselves as being more expressive than adaptable.

This study thus went further into the level of social-emotional expertise possessed by the respondents and as the findings show, it was confirmed that the respondents possessed a fair or moderate level of social-emotional expertise. It was, for instance, worth noting that the mean score in the domain of 'expressiveness' was found to be higher when compared with that of the 'adaptability' domain and this indicates people's inner disposition, showing that the respondents were more expressive than adaptive.

This aspect of the findings goes to show that these contrasting aspects of the social skills of the pre-service teachers are likely to develop separately or independently and they certainly need more research on this issue. Social-emotional expertise refers to a combination of different competencies among which are the ability to understand and to manage one's own emotional expressions (known as expressiveness), and the ability to easily adapt one's behavior depending on changing contexts and social situations (adaptability) [69]. The higher mean scores for how the respondents perceive their expressiveness at school could indicate that a high percentage of the respondents have significant confidence in recognizing as well as communicating emotional expressions in class situations. The same research pointed to a low percentage of adaptability skills as a result of this, which may indicate that some interventions are needed to change the presently rigid ways of interacting in class and to understand the needs of students well throughout the course of study.

In the realm of teacher education, there exists an urgent and immediate need for pre-service teacher programs to adopt and implement teaching methods that increase teachers' social-emotional skills. In this sense, Zych and Llorent [70] have suggested that teachers be taught these essential competencies as a part of both their pre-service and in-service teacher training. Jennings and Greenberg [71] claim that teachers' social and emotional skills have immense and extremely powerful effects on how well classes are managed and how successful students become academically. This is coupled with the fact that the successful integration of ICT also requires improving the capacity of instructors and changing the mindset of practitioners in the education sector [68]. Thus,

teachers' education programs ought to expand their base and put much emphasis on improving teachers' social-emotional skills through teaching specific skills such as empathy, communication, and problem solving with a focus on their applicability. Brackett et al. [72] acknowledge that programs such as the RULER program, which teaches school children how to identify their feelings through emotional language and develop self-controllability, can substantially improve the academic performance of children and the social-emotional expertise of children.

4.3. AI-TPACK Levels

The third research question of study enabled us to analyze the AI-TPACK levels of the participants. The results from the analysis produced showed that the participants had a moderate level of AI-TPACK. Moreover, the mean scores for the core knowledge elements were considerably higher than the mean scores for the composite knowledge elements, implying that the participants had a more solid foundation in the core knowledge areas of AI-TPACK. This was because these knowledge areas included pedagogy, teacher development, technology use, and knowledge integration in any AI-TPACK endeavor. It was further observed that these core knowledge areas were still essential as regards AI-TPACK paradigms despite people being enthusiastic about incorporating AI in pedagogical elements.

This particular finding implies that the development of AI-TPACK in pre-service tutors happens progressively, with the core knowledge areas (i.e., technological knowledge, pedagogical knowledge, and content knowledge) emerging prior to the composite knowledge areas (i.e., technological pedagogical knowledge, pedagogical content knowledge, technological content knowledge, and technological pedagogical content knowledge). The TPACK model (technological, pedagogical, and content knowledge model) proposed by Mishra and Koehler in 2006 [73], in particular, provides strong theoretical underpinnings for the integration of pedagogy, technology, and content knowledge in teaching. However, it appears that the development of AI-TPACK follows the same pattern as it starts with: the strong construction of know-how concerning the core knowledge areas before engaging in the composite knowledge domains. The impressive mastery of the core knowledge aspects by pre-service teachers may indicate their naturally higher inclination to understand and use AI tools and concepts. However, the lower scores for the composite knowledge domains indicate that it is imperative to have proper and adequate support for pre-service teachers, to easily integrate AI tools, and improve the method of learning that incorporates such tools.

In this modern world of technology and advances in different aspects of life, teacher education programs should adopt a new orientation that incorporates certain practices in order to help future teachers develop the required AI-TPACK for teaching. These practices can include the incorporation of the ideas employed in the exploratory lessons, which would assist students by providing hands-on experiences in applying AI tools in the teaching process. It is also possible for the prospective teachers to engage in creating and implementing lesson plans that include AI tools, including various activities that foster student learning, engagement, and participation. However, the effort to properly train teachers on the newly emerged skills does not end here. There are more avenues of research that should be explored, including the factors that make prospective teachers different in terms of their abilities to develop AI-TPACK as well as the outstanding merits of some educational interventions as regards the AI-TPACK levels of pre-service teachers.

4.4. Relationship Between Perceived Self-Regulation and AI-TPACK

In the fourth research question, the relationship between AI-TPACK and perceived self-regulation was examined through the eyes of the respondents. There was a clear strong positive correlation between the construction of AI-TPACK and perceived self-regulation and both core and composite knowledge elements. Thus, we can state that individuals with a high level of perceived self-regulation will almost certainly possess AI-TPACK-related knowledge both core and composite. But still, the AI-TPACK score's correlation with perceived self-regulation was moderate. What this means is that even though self-regulation can be linked to the overall AI-TPACK score, the connection is weaker than with each component of knowledge independently.

This particular finding becomes coherent and consistent with the self-regulation theory put forth by Zimmerman [74] highlighting and emphasizing the significance of being able, as an individual, to plan, monitor, and evaluate, or better still, assess effectively their own individual learning processes and experiences. These learners who have developed and cultivated and even improved their individual self-regulation processes and skills like setting clear, achievable goals, collaboration, and risk-taking can very easily adapt to various new areas of learning, grasp ideas, and successfully master them completely [74]. This study demonstrates that self-regulation skills used by pre-service teachers are immensely vital and truly significant in the development and improvement of AI-TPACK competencies and abilities, which therefore indicates that the importance attached to the proper development of individual learning competencies goes a long way in ensuring individual goals are achieved.

The strong correlation with core and composite knowledge elements indicates that self-regulation affects different dimensions of AI-TPACK. Self-regulation skills are fundamentally significant for pre-service teachers in their process of learning AI tools, using them not just for pedagogical purposes, but also for integrating them with the content. These necessary skills allow pre-service teachers to carry on their learning and become adept in using new learning and teaching technologies that are mostly employed in the present education system.

However, the moderate correlation with the overall AI-TPACK score suggests that self-regulation does not equally influence all dimensions of AI-TPACK, or that other factors might also play a vital role in the overall AI-TPACK development. One factor affecting AI-TPACK development might be the attitude of students themselves towards technology and the perceived importance thereof to academic performance, or they might lack a belief that the use of these tools is imperative, or they might have a belief that using such tools would not help them improve their results. Secondly, the other factors may include the context of the teacher education institution, in-service training activities, and support for self-regulation. Overall, it is significant that educators are encouraged towards a self-regulated process, which emphasizes mastering the AI-TPACK and thereby improving future teacher education.

In today's fast-paced educational world, it becomes very important to gear up teacher training programs with those interventions that are necessary to improve the self-regulation skills of student teachers. The main area of focus of the programs should supply pre-service teachers with necessary tools for developing skills in goal setting, managing time efficiently, and keeping track of and assessing their own performance. It is even possible to use techniques and instruments to help pre-service teachers remove the obstacles they face while including AI tools in teaching practice.

4.5. Relationship Between Social-Emotional Expertise and AI-TPACK

The fifth research question explored the connection between social-emotional expertise and AI-TPACK. Contrary to expectations, the results showed that social-emotional expertise was not significantly correlated with any facet of AI-TPACK. This result is in contrast to previous research, which posits that social-emotional capabilities significantly impact technology integration and teaching practices at school. For instance, Jennings and Greenberg [71] find that the teachers' social and emotional expertise can have a considerable influence on the students' classroom management and their academic achievement. In addition, Goleman [69] stated the significance of individuals' emotional intelligence and social-emotional skills. Thus, education is starting to see these social-emotional skills as essential. The research hypothesis was that social-emotional expertise would create more effective communication, empathy, and understanding of students' needs, especially in such complicated technological venues like AI integration claims. However, this study was not able to provide dependable empirical evidence that would support this declaration. Several factors might explain this unexpected outcome. First, the development of AI-TPACK may be a heavily cognitive and metacognitive task, where the skills involved in self-regulation—such as planning, monitoring, and adapting learning strategies—are more direct and dominant antecedents than the interpersonal skills associated with social-emotional expertise. Second, it is possible that the influence of social-emotional expertise on teaching practices becomes more apparent during the application of AI tools in a real classroom with students, rather than during the knowledge acquisition phase measured by the AI-TPACK scale in this study. This distinction suggests that while self-regulation is crucial for learning to use AI, social-emotional expertise may be more critical for using it effectively—a possibility that warrants future research.

4.6. Predictive Power of Perceived Self-Regulation and Social-Emotional Expertise on AI-TPACK

The multiple linear regression analysis further clarified these relationships by examining their predictive power. Results revealed that while perceived self-regulation emerged as a robust and significant predictor of AI-TPACK's core and composite elements, social-emotional expertise did not contribute significantly to the predictive model. This powerful predictive role of self-regulation is consistent with Zimmerman's [74] theory, which frames the ability to plan, monitor, and manage one's own learning as essential for mastering new and complex domains. The findings strongly suggest that these metacognitive skills are a foundational capacity for developing the integrated knowledge required by AI-TPACK. Educators with strong self-regulation are likely to be more proactive and adaptable, not only in their own professional learning but also in their future application of new technologies. This result has direct implications for teacher education, highlighting that interventions aimed at strengthening self-regulatory skills could be a highly effective strategy for preparing future teachers for the AI era.

5. Conclusions

The positive association found in this study between perceived self-regulation and self-assessed AI-TPACK suggests that self-regulation may be a key factor in how pre-service teachers build readiness for integrating advanced AI systems into their practice. The pre-service teachers, the ones who can, for example, plan, monitor, and evaluate their learning sufficiently, are also those who accumulated AI-TPACK faster and more efficiently. This observation fits well with the self-regulation theory by pointing out the role of metacognitive techniques in the process of adaptation to the innovation of the learning environment. At the same time, the regularity of the connection between self-regulation and

the overall AI-TPACK dimension indicates that other aspects such as technology attitudes, vocational support, or in-service training also enhance the development of AI-TPACK.

A counterintuitive finding of this study was the lack of a significant correlation between self-reported social-emotional expertise and AI-TPACK. This does not necessarily diminish the established importance of social-emotional skills in overall teaching effectiveness. Instead, it may indicate that within the specific context of developing technological pedagogical knowledge for AI, the metacognitive and self-directed learning skills associated with self-regulation are more direct antecedents. This distinction itself is a crucial finding, suggesting that different psychological competencies may be salient for different aspects of teacher development. Though social-emotional skills are crucial to all varying degrees of teaching efficacy and classroom management, their exertion towards the development of AI-TPACK has to be further studied. Ultimately, the strong predictive power of perceived self-regulation on self-assessed AI-TPACK repositions the discourse: preparing teachers for AI is not merely a technical training issue. Rather, it is a fundamental challenge for the social sustainability of the teaching profession, as the capacity for self-regulated, lifelong learning appears to be the bedrock of a sustainable career in an era of constant technological disruption. Educators equipped with these skills are not only more capable of integrating new tools like AI, but are also more resilient, adaptable, and better prepared to act as ethical stewards of technology in their classrooms. This stewardship is critical to ensuring that the digital future of education is inclusive, equitable, and human-centric.

The findings of this research provide strong support for the argument that self-regulation is a critical enabler for the development of perceived AI-TPACK in pre-service teachers. Therefore, teacher education programs must pivot towards a more holistic model that intentionally cultivates these metacognitive skills. By prioritizing self-regulation, these programs can empower a new generation of educators who are not just consumers of AI technology, but are also its critical and creative co-designers. While the direct role of social-emotional expertise in AI-TPACK development requires further investigation, its importance for overall teaching effectiveness and creating socially sustainable classroom environments remains undisputed. Ultimately, fostering self-regulated learners who can thoughtfully and ethically integrate AI into their pedagogy is a direct investment in the resilience and sustainability of our future educational landscapes.

Funding: This research received no external funding.

Institutional Review Board Statement: This study is waived for ethical review as the research consisting solely of anonymous surveys where participation was entirely voluntary and informed consent was obtained from all participants and the study presented no more than minimal risk to the subjects by Institution Committee.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data that support the findings of this study are available on request from the author.

Conflicts of Interest: The author declare no conflicts of interest.

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