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Technological self-efficacy and sense of coherence: Key drivers in teachers' AI acceptance and adoption

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ABSTRACT

This study investigates the factors influencing teachers within the Israeli education system toward the adaptations of artificial intelligence (AI) in teaching by examining the roles of technological self-efficacy (TSE) and a sense of coherence (SOC). Drawing on the Technology Acceptance Model (TAM), a sample of 200 Arab and Jewish teachers in Israel completed online questionnaires. The findings indicated a positive attitude towards AI among teachers. We found a significant positive correlation between perceived usefulness, perceived ease of use, and positive attitude towards AI. TSE fully mediated the relationship between attitude towards AI and adoption intentions AI, while a SOC partially mediated the relationship between TSE and teachers' attitude towards AI. The findings underscore the importance of developing TSE and fostering a SOC among teachers as part of the AI implementation process in the education system.

The findings offer a new understanding of AI technology adoption processes in education by incorporating psychological variables into the TAM framework and providing practical insights for decision-makers in the Israeli education system and beyond.

1. Introduction

The integration of artificial intelligence (AI) into educational frameworks represents a transformative paradigm shift that has accelerated significantly in the wake of the COVID-19 pandemic (Al Darayseh, 2023; Masry-Herzallah & Watted, 2024; Panagoulias et al., 2023; Sămărescu et al., 2024). Contemporary AI applications in education encompass three primary domains: adaptive learning platforms, AI-driven assessment tools, and generative AI technologies such as GPT-4 and OpenAI's Voice Engine (Lim et al., 2023; Zhang et al., 2023). These technological innovations offer unprecedented opportunities for enhancing pedagogical practices while simultaneously presenting complex implementation challenges that warrant systematic investigation (Cukurova et al., 2023; Vorm & Combs, 2022).

Meta-analyses and systematic reviews reveal a significant disparity between AI's theoretical potential and its practical adoption rates across international educational contexts (Choi et al., 2023; Guo, Shi, & Zhai, 2024a, 2024b). This implementation gap persists despite robust empirical evidence demonstrating AI's capacity to enhance learning outcomes, particularly in areas of personalized instruction and automated assessment (Asiri & El Aasar, 2022; Holmes et al., 2019). Recent research highlights the necessity of developing teachers' AI digital competencies as part of the broader transformation of 21st-century skills (Ng, Leung, & Xie, 2023). Understanding this disparity necessitates examination of both technological and psychological factors influencing AI integration processes.

The technology acceptance model (TAM) provides a well-established theoretical foundation for examining AI adoption patterns, identifying perceived usefulness (and perceived ease of use as primary predictors of technology acceptance decisions (Davis, 1989; Venkatesh et al., 2003). However, recent theoretical advances emphasize the necessity of incorporating psychological constructs to enhance the explanatory power of the TAM framework (Aburbeian et al., 2022; Geddam et al., 2024). This research extends the TAM by integrating two critical psychological constructs: Technological Self-Efficacy (TSE), reflecting educators' confidence in their ability to utilize technology effectively (Bandura, 2006; Kent & Giles, 2017; Masry-Herzallah & Dor-Haim, 2021), and Sense of Coherence (SOC), representing individuals' capacity to manage, comprehend, and find meaning in complex situations (Antonovsky, 1979; Moksnes, 2021).

The integration of these psychological constructs into the TAM framework addresses significant gaps in current understanding. TSE

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serves as a crucial mediator between attitude towards AI and adoption intentions for AI, with empirical evidence demonstrating its influence on implementation behaviors (Ma et al., 2021; Schiavo et al., 2024). Concurrently, SOC functions as a psychological resource enhancing resilience and adaptability during technological transitions, thereby influencing the relationship between TSE and AI acceptance (Ramberg et al., 2022; Vorm & Combs, 2022).

While this research employs the Israeli educational system as a case study, the theoretical framework and findings offer broader implications for understanding AI adoption processes internationally. The Israeli context exemplifies universal challenges in AI integration, including professional development needs, infrastructure requirements, and policy implementation concerns (Ramiel, 2023; Masry-Herzallah, 2024). Studies on South Korean teachers' AI competencies highlight similar challenges, emphasizing the need for structured professional development programs to bridge the digital skills gap (Kim & Kwon, 2023). This parallel with global educational systems enhances the generalizability of the findings while providing specific insights for addressing common implementation barriers.

The present study examines four critical research questions that address significant gaps in current understanding.

1. What is teachers' attitude towards AI in their teaching according to the TAM model?
2. Is there a correlation between teachers' attitudes towards AI and their adoption intentions for AI?
3. What role does teachers' TSE play in the correlation between attitude towards AI and their adoption intentions for AI?
4. What role does SOC play in the relationship between TSE and teachers' attitudes towards AI?

This investigation advances the international literature in three significant ways. First, it extends the TAM by empirically validating the integration of psychological mediators (TSE and SOC), addressing calls for more sophisticated models of technology acceptance (Korte et al., 2024). Second, it elucidates the mediating mechanisms through which psychological factors influence AI adoption, providing insights into the complex interplay between individual characteristics and implementation behaviors (Chiu, 2023; Kong et al., 2024). Third, it offers actionable insights for enhancing professional development initiatives globally, particularly in contexts facing similar challenges in technological integration (Sămărescu et al., 2024).

The findings hold significant implications for educational policy, professional development programs, and theoretical understanding of AI adoption processes. As educational systems worldwide navigate the integration of AI technologies, understanding the psychological mechanisms underlying successful adoption becomes increasingly critical (Chan & Hu, 2023). This research provides both theoretical advancement and practical insights for enhancing technology integration initiatives in educational contexts globally.

2. Literature review

2.1. Artificial intelligence (AI) in education

The integration of AI into educational frameworks represents a paradigmatic transformation that has evolved systematically since its inception in the 1980s, fundamentally reconceptualizing pedagogical approaches and learning outcomes (Williamson et al., 2020). Contemporary educational AI applications manifest through three distinct yet synergistic domains, each warranting systematic examination for its unique contribution to pedagogical innovation (Guo, Zheng, & Zhai, 2024).

The first domain encompasses intelligent tutoring systems (ITS), exemplified by platforms such as DreamBox and Carnegie Learning, which employ sophisticated adaptive algorithms to create personalized learning trajectories based on granular analysis of individual student progress patterns (Anderson et al., 2024). Complementing these adaptive systems, automated assessment platforms constitute the second domain, with systems like Gradescope enhancing pedagogical efficiency through instantaneous feedback mechanisms and data-driven reflective practices (Ranga et al., 2024). The third domain comprises generative AI technologies, including ChatGPT and DALL-E, which demonstrate particular efficacy in specialized educational contexts, revolutionizing instruction in domains ranging from software engineering to creative arts education (Vierhauser et al., 2024).

The implementation of these advanced algorithmic systems illustrates AI's capacity to enhance learning efficiency through systematic content customization and sophisticated learning analytics integration. Notable implementations such as Squirrel AI exemplify this approach, facilitating equitable learning experiences while promoting enhanced engagement and self-regulated learning behaviors (Green et al., 2023; Holmes et al., 2019; Kumar et al., 2023). Recent research highlights the necessity of developing teachers' AI digital competencies as part of the broader transformation of 21st-century skills (Ng, Leung, & Xie, 2023).

A comprehensive theoretical foundation emerges from the UNESCO AI Competency Framework for Educators (2024), which emphasizes the critical dimensions of ethical awareness, contextual adaptability, and professional development. This framework systematically aligns with contemporary educational objectives while addressing social, ethical, and legal dimensions alongside technical applications (Mutawa & Sruthi, 2024; Tenório & Romeike, 2023). However, significant implementation challenges persist, particularly concerning data privacy, algorithmic bias, and ethical implications (Pokrivcakova, 2024; Cukurova et al., 2023).

2.2. Theoretical framework for AI acceptance in education

The examination of teachers' acceptance of AI technologies necessitates a sophisticated theoretical framework that synthesizes multiple theoretical constructs and empirical findings. Contemporary research emphasizes the complex interplay between individual cognitive factors, psychological resources, and technological perceptions in shaping AI adoption patterns in educational contexts (Anderson et al., 2024; Williamson et al., 2020).

Empirical investigations have identified three fundamental theoretical constructs that warrant systematic examination. The TAM provides foundational insights into the cognitive mechanisms underlying technology adoption decisions, establishing perceived usefulness and perceived ease of use as primary predictors (Davis, 1989; Wicaksono & Maharani, 2020). Building upon this foundation, TSE emerges as a critical mediating variable, influencing both initial acceptance and sustained implementation of AI technologies (Choi et al., 2023; Wang et al., 2021). Additionally, psychological resources demonstrate significant importance in facilitating successful technology integration, particularly in challenging implementation contexts (Collie et al., 2024; Kong et al., 2024).

Contemporary research reveals sophisticated interrelationships between these theoretical constructs. Choi et al.'s (2023) comprehensive investigation demonstrates TSE's significant mediating role between traditional TAM variables and adoption intentions for AI. Complementarily, Panagoulias et al. (2023) establish that psychological resources moderate the impact of environmental challenges on implementation success, while institutional support structures influence both cognitive and affective aspects of AI acceptance. A study on elementary school teachers in South Korea highlights similar challenges, emphasizing the need for structured professional development programs to bridge the digital skills gap (Kim & Kwon, 2023).

The UNESCO AI Competency Framework for Educators (2024) further reinforces this integrated theoretical approach by emphasizing three critical dimensions of AI acceptance.

1. *Cognitive dimensions*: encompassing technological understanding and perceived utility
2. *Affective dimensions*: including self-efficacy and emotional responses
3. *Contextual dimensions*: considering institutional support and environmental factors

This theoretical synthesis aligns with recent findings from the Israeli educational context, where research reveals complex interactions between individual capabilities, institutional support, and implementation outcomes (Debowy et al., 2024). These investigations underscore the importance of examining AI acceptance through multiple theoretical lenses while considering context-specific characteristics (see Fig. 1).

2.3. Technology acceptance model (TAM) and teachers' attitudes toward AI integration

The TAM model (Davis, 1989) provides a well-established theoretical framework for systematically examining the cognitive mechanisms underlying teachers' decision-making processes regarding the adoption of AI technologies in educational contexts. Contemporary research has demonstrated the continued relevance and applicability of this model while underscoring the necessity of contextual adaptations to account for the nuanced dynamics of AI implementation in educational settings (Wicaksono & Maharani, 2020).

Recent empirical investigations have extended the TAM's application to the specific domain of AI adoption in education, revealing complex and multifaceted patterns of acceptance and implementation. For instance, Al Darayseh's (2023) study documented significant correlations between traditional TAM variables, such as perceived usefulness and perceived ease of use, and the attitudes of science teachers toward the integration of AI. Similarly, Wang et al. (2021) identified five key factors influencing behavioral intentions: self-efficacy, anxiety, projected benefit, perceived ease of use, and attitude towards AI. These findings collectively demonstrate the robust applicability of the TAM framework while suggesting the need for domain-specific adaptations to account for the unique characteristics of educational AI implementation.

Notably, the relationship between perceived usefulness and perceived ease of use manifests in a distinctive manner within educational AI contexts. Studies reveal that teachers' evaluations of AI utility extend beyond considerations of individual task efficiency, encompassing broader pedagogical implications and the potential to enhance student learning outcomes (Kong et al., 2024). This expanded conceptualization of perceived usefulness aligns with findings from international research contexts, wherein this variable consistently emerges as a primary determinant of adoption intentions for AI (Choi et al., 2023; Panagoulias et al., 2023).

Further insights are provided by research conducted in the Israeli educational context, which offers a nuanced understanding of the application of TAM variables in this specific setting. Findings indicate that perceived usefulness correlates strongly with teachers' intentions to integrate AI technologies into their pedagogical practices, while perceived ease of use exerts a significant influence on initial adoption decisions. Importantly, institutional support has been found to moderate both of these relationships (Debowy et al., 2024). These contextual findings align with the UNESCO AI Competency Framework's emphasis on the importance of addressing both technical and pedagogical aspects of AI integration (Tenório & Romeike, 2023). Furthermore, they provide empirical support for the hypothesis that teachers' attitudes towards AI will demonstrate positive orientations when examined through the lens of the TAM framework:

Based on this comprehensive theoretical foundation, we hypothesize.

H1. *According to the TAM model, teachers'* attitude towards AI *integration in teaching will be positive.*

H2. *A significant positive correlation will be found between* perceived usefulness *and* perceived ease of use *of AI in teaching and teachers' positive* attitude towards AI *integration.*

Importantly, contemporary investigations also reveal the necessity of examining TAM variables in conjunction with psychological and contextual factors to gain a more comprehensive understanding of AI adoption in educational settings. For instance, Green et al. (2023) demonstrated that while traditional TAM constructs are necessary, they may not sufficiently explain the complex dynamics of AI integration in educational contexts. This finding underscores the importance of examining additional mediating and moderating variables that may influence the relationship between basic TAM constructs and adoption outcomes. The subsequent sections of this review will delve deeper into the role of specific mediating variables, starting with the crucial factor of teachers' self-efficacy beliefs.

2.4. The mediating role of technological self-efficacy (TSE)

TSE represents teachers' self-assessed capability to effectively utilize and integrate technological tools within professional practice (Bandura, 1997). In educational contexts, TSE encompasses teachers' confidence in their ability to implement, adapt, and leverage technological innovations, particularly AI systems, to enhance pedagogical outcomes (Choi et al., 2023; Masry-Herzallah & Watted, 2024; Wang et al., 2021). This construct extends beyond basic technological competence to include adaptive capabilities, problem-solving orientation, and resilience in facing technological challenges (Patil & Pramod, 2024).

Contemporary research firmly establishes TSE as a critical mediating variable in the relationship between teachers' attitudes towards AI and their subsequent adoption intentions of AI. Empirical investigations reveal TSE's multifaceted influence on AI acceptance patterns, with

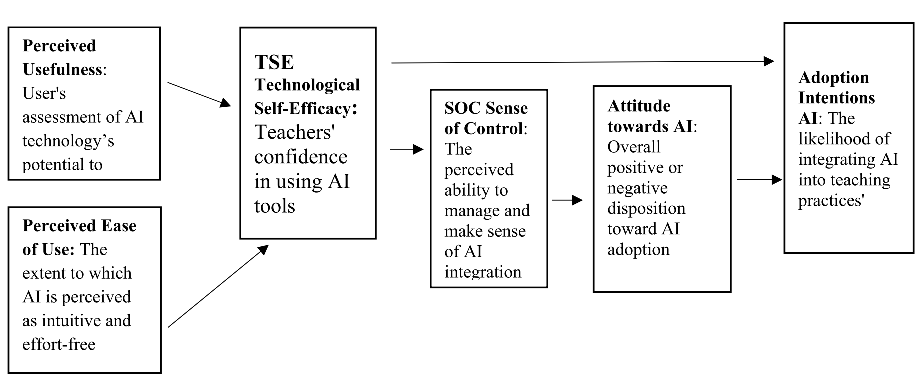

Fig. 1. Research model: AI adoption in education.
The Research Model illustrates the relationships between Attitudes Toward AI Integration, TSE (Technological Self-Efficacy), SOC (Sense of Coherence), and AI Adoption Intentions. The model highlights mediating effects and influencing pathways in AI adoption among educators.

Basri (2024) demonstrating significant mediation effects between information source quality and AI adaptability. Kong et al. (2024) further establish the crucial role of structured professional development in enhancing teachers' self-efficacy, while Suardewa et al. (2024) document strong correlations between high self-efficacy levels and increased propensity for AI integration in instructional practices.

The mediating function of TSE manifests through three primary mechanisms: (1) Cognitive Processing—TSE influences how teachers interpret and evaluate AI technologies, shaping their perception of technological affordances and constraints; (2) Behavioral Intentions—Higher TSE levels correlate with increased willingness to implement AI tools and explore innovative pedagogical applications; and (3) Implementation Persistence—TSE affects sustained engagement with AI integration efforts, particularly when facing technological or pedagogical challenges.

Shao, Zhang, Zhang, and Benitez (2024) integrative model provides crucial insights into the interaction between TSE and ethical considerations in shaping AI adoption patterns. Their framework demonstrates that ethical perceptions mediate the relationship between self-efficacy and technological factors, highlighting the complexity of psychological processes underlying AI acceptance. This theoretical advancement aligns with contemporary understanding of technology integration as a multifaceted process involving both technical and ethical dimensions.

Massaty, Budiyanto, Tamrin, and Fahrurozi (2024) research expands understanding of TSE's role in fostering computational thinking and adaptive feedback implementation. Their findings demonstrate that TSE serves as a crucial mediating factor between AI's transformative potential and its practical realization in educational contexts. Yang and Lou's (2024) investigation of language teaching applications further supports this relationship, particularly in specialized instructional domains.

Recent research by Rajapakse et al. (2024) illuminates the impact of emotional and physiological states on TSE development. Their findings emphasize the necessity of adopting a holistic approach to self-efficacy enhancement, addressing cognitive, emotional, and social dimensions simultaneously. This perspective aligns with Hsu and Lin's (2023) observations regarding anxiety levels among teachers during AI integration processes.

Based on this comprehensive empirical foundation, this study proposes.

H3. *TSE will mediate the relationship between teachers'* attitudes towards AI *and their* adoption intentions of AI.

These relationships highlight the importance of examining TSE within broader theoretical frameworks that consider both individual and institutional factors affecting AI adoption. The subsequent section explores how SOC interacts with TSE to influence teachers' attitudes towards AI and implementation behaviors.

2.5. Sense of coherence (SOC) in teachers' AI acceptance: A mediating framework

The salutogenic approach, developed by Antonovsky (1979, 1987), provides a robust theoretical foundation for understanding how individuals maintain functionality and well-being despite encountering significant stressors. Central to this framework is the concept of SOC, which represents a global orientation reflecting an individual's confidence in managing environmental challenges. SOC comprises three interrelated components: comprehensibility (the cognitive ability to understand and predict environmental stimuli), manageability (the perceived availability of resources to meet demands), and meaningfulness (the emotional investment in addressing challenges) (Antonovsky, 1987; Eriksson & Lindström, 2006).

In educational technology contexts, SOC demonstrates particular relevance for understanding teachers' adaptation to AI integration. Research indicates that SOC influences educators' readiness to adopt and effectively utilize AI technologies through multiple mechanisms (Aurangzeb et al., 2024). Teachers with robust SOC demonstrate enhanced ability to perceive technological changes as comprehensible and manageable, thereby reducing technology-related anxiety and fostering positive adoption attitudes (Takeuchi et al., 2024).

The relationship between SOC and technology acceptance manifests through several pathways. Naseri and Abdullah (2024) demonstrate that SOC complements traditional TAM constructs by enhancing emotional and cognitive readiness, which mediates perceptions of technological PE and perceived ease of use. This mediation effect is particularly evident in AI-driven educational environments, where SOC fosters resilience and adaptability among teachers encountering implementation challenges (Juliana et al., 2024).

Recent empirical investigations reveal SOC's crucial role in mediating the relationship between TSE and attitude towards AI. Guo et al. (2024a, 2024b) establish that SOC enhances individuals' ability to comprehend and manage complex systems, thereby strengthening TSE's influence on positive AI perceptions. This relationship is further supported by findings from Joseph and Thomas (2022), who demonstrate SOC's effectiveness in reducing technology anxiety and perceived complexity barriers.

In the Israeli educational context, Goldrat et al.'s (2023) study highlights the significance of SOC in supporting teachers' resilience during the COVID-19 pandemic. Their research demonstrates SOC's role in enabling educators to perceive technological integration as an opportunity for professional growth and development. Additionally, their findings underscore how SOC empowers educators to effectively utilize institutional resources and foster collaborative learning environments. These contextual insights are consistent with broader international research that emphasizes SOC's contribution to promoting professional growth and innovation in technological integration (Matić & Vuletić, 2023).

Based on this robust theoretical foundation and empirical evidence, this study proposes the following hypothesis.

H4. *SOC will mediate the relationship between TSE and teachers'* attitudes towards AI *in teaching.*

This hypothesis reflects the complex interplay between psychological resources, TSE, and attitude towards AI in educational contexts. The subsequent methodological section delineates the empirical approach for examining these relationships within the Israeli educational system.

The Research Model illustrates the relationships between Attitudes Toward AI Integration, TSE (Technological Self-Efficacy), SOC (Sense of Coherence), and AI Adoption Intentions. The model highlights mediating effects and influencing pathways in AI adoption among educators.

3. Method

The methodological framework of this study was designed to investigate the complex interplay of factors influencing AI adoption among teachers in the Israeli education system. This section delineates the research context, sample characteristics, instrumentation, procedural elements, and analytical approaches employed.

3.1. Research context

The Israeli education system operates within a complex, multilingual environment serving approximately 2 million students, with 73% in Hebrew-sector schools and 27% in Arabic-sector schools (Central Bureau of Statistics, 2023; Israel Democracy Institute, 2023). This bifurcated structure functions under the centralized oversight of the Ministry of Education, which governs curriculum development, standards, assessment, and personnel management.

Amidst global advancements in AI, the Israeli Ministry of Education has recently initiated significant measures to develop a policy for integrating AI technologies into the education system. In August 2023, the

Ministry issued initial guidelines promoting the prudent and responsible use of generative AI applications in educational institutions (Ministry of Education, 2023a, 2023b). The policy aims to harness the potential of AI to optimize teaching and learning processes and foster personalized learning while addressing challenges such as privacy protection, ethics, and critical thinking. These efforts reflect a broader commitment to positioning Israel as a leader in educational technology innovation (Debowy et al., 2024).

The Ministry's approach underscores the complexity of integrating AI in education, necessitating a balance between technological innovation and the preservation of the core values of the education system while addressing the diverse needs of learners and educators in Israel (Masry-Herzallah & Watted, 2024). This contextual framing provides essential background for understanding the environmental factors shaping AI adoption patterns within the Israeli educational landscape.

3.2. Sample description

The study employed a stratified convenience and snowball sampling approach to recruit participants, ensuring representation across diverse pedagogical contexts in the Israeli education system (Heckathorn & Cameron, 2017). The final sample comprised 200 educators (N = 200), drawn from multiple educational districts, reflecting a broad spectrum of teaching experiences and institutional affiliations.

During the data collection period (November 2023–May 2024), a substantial 82% of participants reported no prior experience with AI integration in their teaching practices, while 18% indicated minimal exposure to basic AI tools. This predominant lack of direct AI engagement underscores the study's emphasis on adoption intentions rather than current usage behaviors, ensuring that findings primarily capture teachers' attitudes toward AI rather than their practical implementation experiences.

The sample's ethnic composition (68.5% Arab teachers and 31.5% Jewish teachers) deviates from the national distribution of educators in Israel, a disparity influenced by both methodological and contextual factors. First, the researchers' institutional affiliations and professional networks facilitated enhanced recruitment among Arab educators, leveraging accessibility and trust within these communities. Second, the national crisis following the October 7th events significantly impacted participation rates, potentially leading to an overrepresentation of Arab educators in the sample. While these factors may limit generalizability, they also provide valuable insights into AI adoption within the Arab education sector, a historically underrepresented group in educational technology research.

Beyond ethnic composition, the sample encompassed a diverse range of genders, educational backgrounds, and teaching levels, offering a comprehensive foundation for examining key factors influencing technological self-efficacy (TSE) and AI adoption in education. Table 1 provides a detailed summary of the sample characteristics.

Table 1
Sample characteristics (N = 200).

Category	Details
Total Participants	200 teachers from across Israel
Ethnicity	137 Arab teachers (68.5%) and 63 Jewish teachers (31.5%)
Gender	162 female teachers (81%) and 38 male teachers (19%)
Educational Districts	75 from Haifa District (37.5%), 57 from Central District (28.5%), 47 from Northern District (23.5%), 15 from Southern District (7.5%), and 6 from Jerusalem District (3%)
Education	122 with master's degrees (61%), 78 with bachelor's degrees (39%)
School Level	109 in elementary schools (54.5%), 91 in middle and high schools (45.5%)
AI Experience	164 with no prior AI integration experience (82%), 36 with minimal AI tool exposure (18%)

Note: AI experience refers to self-reported integration of AI tools in teaching practices at the time of data collection.

3.3. Research tools

The study utilized several validated tools to collect data. Table 2 summarizes the research tools used. The complete questionnaire items are provided in Appendix A.

Prior to survey administration, participants viewed a standardized 5-min video introduction to AI in education, available in both Arabic and Hebrew. This multimedia primer encompassed fundamental AI concepts, educational applications, implementation scenarios, and ethical considerations, ensuring participants possessed requisite baseline knowledge for meaningful survey engagement despite limited direct experience.

Translation and Validation: The measures used in this study were initially developed in English and translated into Hebrew and Arabic using Brislin's (1980) back-translation method to ensure linguistic and conceptual equivalence. This rigorous process involved independent forward and backward translations, followed by expert review to resolve discrepancies, ensuring the validity and reliability of the translated items. This step was crucial to maintain the comparability of results across cultural groups and to ensure that the findings accurately reflect the intended constructs.

Cronbach's Alpha for SOC: The SOC scale yielded a Cronbach's alpha value of 0.60, which is slightly below the conventional threshold for acceptable reliability. This result aligns with findings in cross-cultural studies where the brevity of the SOC scale and its use across diverse contexts can contribute to lower reliability (Antonovsky, 1993; Eriksson & Lindström, 2006; Zonp & Arnault, 2023). Sensitivity analyses excluding SOC produced consistent results, indicating the robustness of the overall measurement approach. While this value indicates potential limitations in internal consistency, it highlights the importance of further validation and refinement. Specifically, future research could benefit from expanding the SOC scale to include additional items or adapting it to specific cultural contexts to enhance reliability. This finding underscores the necessity of integrating culturally appropriate measures in cross-cultural studies to ensure both validity and reliability across diverse populations.

3.4. Procedure

The research commenced following approval from the college's ethics committee in early November 2023. We specifically tailored both Arabic and Hebrew versions of the questionnaire to the study's context. Arab teachers responded to the Arabic version, while Jewish teachers answered the Hebrew version. Initially, we conducted a pilot study with 35 participants to assess the efficacy of the questionnaire. Insights from this phase were critical for refining the questionnaire, improving its clarity and relevance, and minimizing biases in question phrasing.

The revised questionnaire was first distributed to teachers pursuing advanced degrees at three randomly selected higher education institutions in Israel via email and WhatsApp using a Google Form. Subsequently, the snowball method was employed to distribute the questionnaire to more teachers via Facebook and WhatsApp teacher groups.

Responses were collected until May 2024. Teachers were informed about the research's purpose and the researchers' contact details, and their informed consent to participate in the study was requested. Full anonymity of the questionnaire was assured, and it was explained that there were no right or wrong answers. Participants were informed that the collected data would be used solely for research purposes, thereby reducing common method variance (Podsakoff et al., 2000).

3.5. Data processing

Following data collection, SPSS software (version 29) was employed to conduct a multi-stage analysis designed to address the study's objectives while maintaining statistical rigor within the constraints of the

Table 2
Research tools and descriptions.

Questionnaire	Source and Year	Description	Example Items	Cronbach's Alpha
Demographic	Study-Designed	13 items on personal and professional characteristics	See Table 1	–
SOC: Sense of Coherence	Antonovsky (1987)	13 items measuring SOC	"Do you often feel like you don't know what to do?"	α = 0.60
TSE: Technological Self-efficacy	Bandura (2006); Masry-Herzallah & Dor-Haim	6 items assessing TSE	"New technology does not intimidate me."	α = 0.88
TAM: Technology Acceptance Model	Davis et al. (1989); Guo et al. (2024a, 2024b)	19 items evaluating AI attitudes and intentions	See Appendix A	perceived usefulness: α = 0.93; perceived ease of use: α = 0.91; attitude towards AI: α = 0.88; adoption intentions AI: α = 0.95

sample size (n = 200):

Descriptive Statistics: We calculated means, standard deviations, and confidence intervals to characterize the distribution of quantitative variables, ensuring comprehensive preliminary data examination (Hayes, 2022).

Correlation Analysis: Pearson correlation coefficients were computed with bootstrapped confidence intervals (5000 iterations) to examine relationships between variables and test study hypotheses, providing robust estimates of association strength (Preacher & Hayes, 2008).

Mediation Analysis: Independent variables were introduced in a hierarchical sequence to test mediation effects, particularly the role of TSE and SOC in shaping adoption intentions AI. Changes in regression coefficients and their statistical significance were carefully examined to validate the hypothesized relationships and to elucidate the mechanisms underpinning the adoption process (Hayes, 2022).

Stepwise Linear Regression: Stepwise regression was selected as the primary analytical approach for its efficiency in identifying significant predictors within an exploratory framework. We considered structural equation modeling (SEM) to be inappropriate owing to its elevated parameter-to-sample ratio stipulations and the extensively recorded difficulties pertaining to limited sample sizes, particularly in light of the study's sample size of 200. As highlighted in the literature (Bentler & Yuan, 1999; Boomsma, 1985; Nevitt & Hancock, 2004; Rosseel, 2020), SEM often encounters issues such as non-convergence, inadmissible solutions (e.g., negative variances), and biased parameter estimates when applied to small samples. These challenges are exacerbated by the reliance of SEM on large sample asymptotics to ensure reliable estimation and hypothesis testing. For this reason, stepwise linear regression was employed to balance statistical rigor with practical constraints, enabling the exploration of incremental contributions of predictors while avoiding the pitfalls of SEM under these conditions.

This methodological framework facilitated the attainment of findings that are both resilient and indicative of the attributes inherent within the dataset, concurrently harmonizing with the exploratory essence of the research design.

4. Findings

The findings of this study are presented in two parts: descriptive statistics and inferential statistics, which address the research hypotheses.

4.1. Descriptive statistics

To address the first research question and test the first hypothesis, means and standard deviations were calculated for the quantitative research variables, as shown in Table 3.

Table 3 indicates high means (above the midpoint) for the variables: SOC (M = 4.04), perceived usefulness (M = 3.56), adoption intentions AI (M = 3.51), TSE (M = 3.59), and teachers' attitude towards AI (M = 3.80). This suggests that teachers have a positive attitude towards AI and intend to adopt the technology, and they also reported high TSE. However, the perceived ease of use had a moderate mean (M = 3.30). These findings support the first research hypothesis, indicating that teachers' attitude towards AI integration in teaching is generally positive.

Table 3
Descriptive statistics.

Variable	M	SD
SOC	4.04	0.66
Perceived Usefulness	3.56	0.94
Perceived Ease of Use	3.30	0.98
Adoption Intentions AI	3.51	1.07
TSE	3.59	1.06
Teachers' Attitude towards AI	3.80	0.88

4.2. Inferential statistics: hypothesis testing

To test the second research hypothesis, the Pearson correlation was first calculated between the variables as described in Table 4.

Table 4 reveals a statistically significant positive correlation of moderate strength between teachers' attitude towards AI and both perceived usefulness ($r = 0.48$, $p < 0.01$) and perceived ease of use ($r = 0.59$, $p < 0.01$). This suggests that the more teachers perceive AI as useful and easy to use, the more favorable their attitude towards AI becomes, and vice versa. These findings confirm the second research hypothesis.

To examine the third research hypothesis, which explores the mediating role of TSE, Pearson correlations between the relevant variables were calculated, as presented in Table 5.

The results in Table 5 show a statistically significant positive correlation of medium strength between teachers' attitude towards AI and adoption intentions AI ($r = 0.51$, $p < 0.01$) and a strong correlation between teachers' attitude towards AI and TSE ($r = 0.81$, $p < 0.01$). This suggests that the more positive teachers' attitude towards AI and the higher their TSE, the greater their intentions to adopt technology.

To examine whether TSE mediates the relationship between attitude towards AI and adoption intentions AI, we performed a stepwise linear regression, as described in Table 6.

The results in Table 6 indicate that in the first step of the regression with a single independent variable, there was a significant correlation between teachers' attitude towards AI and adoption intentions AI ($\beta = 0.51$, $p < 0.01$). However, in the second step of the multiple regression, the contribution of the variable teachers' attitude towards AI was not significant ($\beta = 0.09$, $p > 0.05$), while the contribution of the variable

Table 4
Pearson Correlations between TAM and Teachers' attitude towards AI.

Variable	Teachers' Attitude towards AI
Perceived Usefulness	0.48**
Perceived Ease of Use	0.59**

**$p < 0.01$.

Table 5
Pearson Correlations between attitude towards AI, TSE, and adoption intentions AI.

Variable	Adoption intentions AI
Teachers' attitudes towards AI	0.51**
TSE	0.81**

**p < 0.01.

Table 6
Stepwise linear regression for predicting adoption intentions AI.

Step	Predictor Variable	R^2	β	t
1	Teachers' Attitude towards AI	0.51**	0.51**	8.36**
2	Teachers' Attitude towards AI	0.81**	0.09	1.89
	TSE		0.75**	15.15**

**p < 0.01.

TSE was significant (β = 0.75, $p < 0.01$). This indicates full mediation, where TSE mediates the relationship between teachers' attitude towards AI and their adoption intentions AI, confirming the third research hypothesis.

To test the fourth research hypothesis regarding the mediating role of SOC, Pearson correlation was initially calculated between the variables, as shown in Table 7.

The results in Table 7 reveal a statistically significant positive correlation of medium strength between TSE and teachers' attitude towards AI ($r = 0.55$, $p < 0.01$) and a relatively weak correlation between SOC and teachers' attitude towards AI ($r = 0.26$, $p < 0.01$). This suggests that higher levels of TSE and a SOC are associated with more positive attitude towards AI among teachers.

To determine whether SOC serves as a mediating variable, a stepwise linear regression analysis was conducted, as detailed in Table 8.

The results presented in Table 8 reveal a significant relationship between TSE and teachers' attitude towards AI in the initial step of the regression analysis, where TSE was the sole independent variable (β = 0.55, $p < 0.01$). In the subsequent step of the multiple regression analysis, TSE continued to have a significant and substantial impact on teachers' attitude towards AI (β = 0.52, $p < 0.01$), while SOC also emerged as a significant, albeit smaller, contributor (β = 0.14, $p < 0.01$).

These findings indicate that SOC partially mediates the relationship between TSE and teachers' attitude towards AI, thereby providing support for the fourth research hypothesis. This pattern of results suggests that while TSE is the strongest psychological predictor of teachers' positive attitude towards AI, SOC also plays an important complementary role in shaping these attitudinal orientations.

The comprehensive examination of the relationships between SOC, TSE, attitude towards AI, and adoption intentions AI underscores the complex interplay of personal and contextual factors in influencing teachers' acceptance of AI technologies in educational settings. While TSE emerged as the dominant mediator, the partial mediating effect of SOC reflects the importance of considering both individual psychological resources and broader salutogenic factors in understanding the dynamics of AI adoption.

Table 7
Pearson Correlations between TSE, SOC, and Teachers' attitude towards AI.

Variable	Teachers' Attitude towards AI
TSE	0.55**
SOC	0.26**

**p < 0.01.

Table 8
Stepwise linear regression for predicting teachers' attitude towards AI.

Step	Predictor Variable	R^2	β	t
1	TSE	0.30**	0.55**	9.29**
2	TSE	0.32**	0.52**	8.64**
	SOC		0.14**	2.37**

**p < 0.01.

5. Discussion

This study provides a comprehensive examination of the factors influencing teachers in the Israeli education system to adopt AI in their teaching practices, with a focus on the mediating roles of Technological Self-Efficacy (TSE) and Sense of Coherence (SOC). The findings shed light on critical aspects of AI implementation and offer new insights into the psychological and contextual dynamics shaping technology adoption in educational settings.

Through rigorous analysis, the study advances the understanding of AI integration by exploring the complex mediating relationships between psychological constructs and technology acceptance variables. The results highlight intricate interaction patterns that contribute significantly to theoretical development, professional practice, and educational policy in the rapidly evolving domain of AI adoption.

5.1. *Teacher attitudes towards AI and factors influencing adoption*

The empirical validation of positive teacher attitudes towards AI provides significant insights into the evolving theoretical understanding of this field. Recent international research underscores the need for AI digital competencies among teachers to ensure effective technology integration (Ng, Leung, & Xie, 2023). The favorable orientations documented in this study align with recent international findings, reflecting an accelerating acceptance of educational AI applications (Aghaziarati et al., 2023; Kong et al., 2024). Teachers exhibit a generally positive disposition toward AI adoption, indicating recognition of its transformative potential. However, this optimism is tempered by moderate perceptions of perceived ease of use, suggesting a nuanced awareness of both the benefits and the complexities involved in implementing AI in educational settings (Cukurova et al., 2023; Holmes et al., 2022). This nuanced perspective underscores the multifaceted nature of AI integration, where the allure of potential pedagogical enhancements is carefully weighed against the pragmatic realities of implementation challenges within resource-constrained educational environments.

A notable finding is the persistence of a positive attitude towards AI despite limited direct exposure, with 82% of participants reporting no prior experience with AI integration. This intriguing result contrasts with earlier technology adoption studies that often reported initial resistance from educators towards novel technologies (Kaplan-Rakowski & Grotewold, 2023). This attitudinal shift may be attributed to a confluence of factors, including the accelerated digitalization of education catalyzed by the COVID-19 pandemic and the increasingly prominent discourse surrounding AI's transformative potential in public spheres, shaping teacher perceptions even prior to direct engagement (Al Darayseh, 2023; Panagoulias et al., 2023). These findings point to a potential paradigm shift in educational technology acceptance, signaling a transformative moment in integrating AI into pedagogical practices.

The second hypothesis revealed several critical factors influencing AI adoption within the educational context. First, perceived usefulness demonstrated a significant positive correlation with teachers' attitudes, indicating that recognition of AI's pedagogical value strongly influences acceptance. Second, perceived ease of use showed an even stronger correlation, suggesting that implementation complexity may be a more crucial determinant than utility perceptions. Third, TSE emerged as a full mediator between attitudes and adoption intentions, while SOC demonstrated partial mediation between TSE and attitudes. These findings expand upon traditional TAM applications by illuminating the psychological mechanisms underlying successful AI integration in educational settings (Kong et al., 2024; Zhang et al., 2023). Specifically, our findings suggest that in the context of AI adoption in education, teachers' initial acceptance is more critically predicated on the perceived 'ease of integration' into existing pedagogical workflows and technological infrastructures, rather than solely on the 'perceived utility' of AI functionalities. This nuanced prioritization may stem from the inherent complexities associated with AI implementation in education, where teachers, often facing heavy workloads and limited technical support, prioritize tools that promise seamless integration and minimize disruption to established routines. Therefore, while the potential benefits of AI are acknowledged, the practical feasibility and manageability of implementation emerge as paramount determinants of adoption intention. A study on elementary school teachers in South Korea highlights similar challenges, emphasizing the need for structured professional development programs to bridge the digital skills gap (Kim & Kwon, 2023). This observation underscores that addressing the 'ease of use' barrier through targeted training and readily accessible support systems is crucial to facilitate broader AI adoption amongst educators, potentially even overshadowing the initial emphasis on showcasing AI's pedagogical usefulness.

5.2. The mediating roles of psychological constructs: technological self-efficacy (TSE) and sense of coherence (SOC) and factors influencing AI adoption

The investigation's third hypothesis yielded compelling evidence for TSE's full mediating function between attitude towards AI and adoption intentions for AI. This finding substantially extends current theoretical frameworks by demonstrating that TSE's influence transcends direct effects, fundamentally restructuring the relationship between attitudinal orientations and behavioral implementation intentions. The robust correlation between TSE and adoption intentions AI illuminates self-efficacy's critical function as a **pivotal psychological mechanism** bridging theoretical acceptance and practical implementation paradigms (Ma et al., 2021; Wang et al., 2021). **Specifically, this study identifies TSE as a primary factor influencing AI adoption intentions. Teachers with higher TSE are significantly more likely to intend to adopt AI in their teaching practices. Furthermore, SOC also emerges as an important, albeit partially mediating, factor. Teachers with a stronger sense of coherence exhibit more positive attitudes towards AI, which indirectly facilitates adoption.**

These results both align with and substantially extend previous findings regarding TSE's role in technology adoption processes. The identification of full mediation suggests that the pathway from attitude towards AI to adoption intentions AI operates predominantly through teachers' confidence in their technological capabilities, a finding that carries significant implications for professional development design and implementation strategies (Schiavo et al., 2024; Masry-Herzallah, 2023). **This underscores that enhancing teachers' TSE is a crucial strategy for promoting AI adoption. Professional development programs should therefore prioritize building teachers' confidence in using AI technologies.**

The fourth hypothesis, examining SOC's mediating role, revealed significant partial mediation between TSE and attitude towards AI integration. This finding represents a novel theoretical contribution by demonstrating the applicability of Antonovsky's (1987) salutogenic framework to educational technology contexts. The partial mediation effect illuminates how SOC enhances the relationship between technical confidence and adoption attitudes through three distinct mechanisms identified in previous research: comprehensibility of AI systems, manageability of implementation challenges, and meaningfulness of technological integration (Ramberg et al., 2022; Goldrat et al., 2023). Specifically, a stronger SOC empowers teachers to perceive the complexities of AI systems as comprehensible and implementation challenges as manageable, thereby bolstering their TSE and fostering a more positive overall attitude towards AI integration. Thus, fostering a SOC among teachers, through supportive school environments and resources, can indirectly but significantly contribute to AI acceptance and eventual adoption.

The integration of SOC within technology acceptance frameworks addresses recent calls in the literature for more sophisticated models incorporating psychological resources. This theoretical advancement aligns with UNESCO's AI Competency Framework for Educators (2024), particularly in its emphasis on developing comprehensive psychological readiness for technological innovation. **By highlighting the mediating roles of both TSE and SOC, this study pinpoints key psychological factors that educational institutions should focus on to facilitate successful AI integration. These factors, TSE and SOC, are identified as critical levers for influencing teachers' attitudes and intentions towards AI adoption.**

5.3. Cross-cultural and theoretical contributions

While grounded in the Israeli educational system, this investigation's findings demonstrate significant parallels with international research on AI adoption, suggesting universal psychological mechanisms in technology acceptance processes. The observed mediation effects align with findings from diverse educational contexts, including East Asian studies emphasizing collective efficacy (Kong et al., 2024), European frameworks focusing on digital competence (European Commission, 2023), and North American research examining technological readiness (Vorm & Combs, 2022). **This convergence across diverse cultural and educational settings strengthens the generalizability of our findings, suggesting that the psychological constructs of TSE and SOC are not merely context-specific but represent fundamental determinants of technology adoption intentions across varied global educational landscapes.**

This investigation advances theoretical understanding of AI adoption in educational contexts through three significant contributions. First, the empirical validation of psychological mediators within the TAM addresses the theoretical gap identified in recent literature regarding the psychological dimensions of technology acceptance (Korte et al., 2024). This extension of TAM provides a more sophisticated theoretical framework for understanding the complex interplay between cognitive, affective, and behavioral dimensions in AI adoption processes. **Notably, by empirically integrating and validating TSE and SOC as key psychological mediators within the established TAM framework, this study directly responds to recent scholarly calls for more nuanced and psychologically informed models of technology acceptance in education (**Korte et al., 2024**). This move beyond purely cognitive models represents a significant theoretical advancement.**

Second, the identification of differential mediation effects—full mediation by TSE and partial mediation by SOC—illuminates specific pathways through which psychological resources influence technology acceptance behaviors. These findings extend current theoretical models by demonstrating how individual psychological characteristics interact with institutional and technological factors to shape adoption outcomes (Guo et al., 2024a, 2024b; Takeuchi et al., 2024). **Similar findings in South Korean education research highlight the role of teacher training and professional development in AI competency development (**Kim & Kwon, 2023**). Furthermore, by delineating the distinct mediating roles of TSE (full) and SOC (partial), our research offers a more granular and differentiated understanding of the psychological mechanisms at play. This nuanced perspective moves beyond simply asserting the importance of psychological factors and instead unpacks their specific modes of influence on AI adoption, offering a more refined theoretical contribution that differentiates itself from prior, more generalized studies.**

Third, the research contributes to theoretical understanding of cross-cultural technology adoption by examining these relationships within the specific context of the Israeli educational system while demonstrating parallels with international findings. **This contextual analysis** supports **recent theoretical work on the universality of certain psychological mechanisms in technology acceptance while acknowledging culture-specific implementation considerations (**Al Darayseh, 2023; Cukurova et al., 2023**). Finally, and distinct from many prior studies primarily focused on theoretical validation, this research translates its theoretical advancements into actionable insights by explicitly outlining practical implications for enhancing professional development initiatives globally. This translational focus, particularly addressing contexts facing similar challenges in technological integration (**Sămărescu et al., 2024**), constitutes a valuable and practically relevant contribution to the field.**

6. Limitations and conclusion

6.1. Methodological considerations and limitations

This investigation's methodological approach warrants careful examination through several critical lenses. The sample composition presents notable considerations regarding external validity, particularly given the disproportionate representation of Arab educators (68.5%) relative to national demographic distributions. While this sampling characteristic provides valuable insights into an understudied population within educational technology research, it necessitates careful consideration when generalizing findings to broader educational contexts (Podsakoff et al., 2000; European Commission, 2023). **However, it is important to reiterate that this sample provides unique insights into AI adoption attitudes within the Arab education sector—a historically underrepresented group in educational technology research.**

The temporal context of data collection, coinciding with significant societal disruption following October 2023, introduces potential confounding variables that merit careful consideration. Although statistical analyses revealed no systematic response bias, the unique circumstances may have influenced participants' psychological orientations toward technological innovation and institutional change (Holmes et al., 2022; Nazaretsky et al., 2022). **Despite this, the research took steps to mitigate potential impacts by ensuring participant anonymity and emphasizing the use of data for research purposes only.**

Moreover, the reliance on self-reported measures, while consistent with established practices in technology acceptance research, introduces potential common method variance concerns. The implementation of procedural remedies following contemporary methodological guidelines (Podsakoff et al., 2000) partially addresses these concerns, though the integration of objective behavioral measures in future research would strengthen empirical validation. **Additionally, the reliability of the SOC scale was slightly below the conventional threshold ($\alpha = 0.60$), suggesting a potential limitation in the internal consistency of this measure. Future studies should consider using longer or more culturally adapted SOC scales to enhance reliability.**

6.2. Conclusion

This investigation advances the understanding of AI adoption in educational contexts through the empirical validation of psychological mediating mechanisms. The differential mediation effects observed—full mediation by TSE and partial mediation by SOC—demonstrate that successful AI integration requires systematic attention to both technical competencies and psychological resources. These findings extend UNESCO's AI Competency Framework (2024) through empirical validation of psychological mediators' critical role in technology acceptance (Kong et al., 2024). The synthesis of these results suggests a transformative theoretical framework for understanding AI adoption in education, providing a foundation for future longitudinal investigations and cross-cultural validations (Guo et al., 2024a, 2024b; Cukurova et al., 2023). **Moving forward, we recommend a paradigm shift in AI integration strategies within educational systems. This shift necessitates a move beyond a purely technology-centric approach towards a more holistic model that prioritizes the psychological readiness and well-being of educators. Educational systems must invest in comprehensive, sustained professional development programs that not only equip teachers with the necessary technical skills but also actively cultivate their TSE and SOC. Furthermore, fostering supportive school environments that encourage collaboration, provide adequate resources, and promote a shared sense of purpose will be crucial for the successful and ethical integration of AI in education, ultimately maximizing its potential to enhance teaching and learning outcomes.**

CRediT authorship contribution statement

Asmahan Masry Herzallah: Writing – review & editing. **Rania Makaldy:** Writing – review & editing.

Disclosure statement

The authors report there are no competing interests to declare.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to improve readability and language in certain places of the text. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Appendix A. Supplementary data

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