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Predicting AI Adoption in Education: A Mixed-Methods Study in Israel

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Abstract:

This article explores the nuanced landscape of Artificial Intelligence (AI) adoption in education within Israel, with a specific focus on the psychological, cultural, and technological determinants influencing educators' intentions to integrate AI technologies. The study leverages a distinctive mixed-methods approach, strategically integrating both quantitative and qualitative questionnaire data. In the quantitative phase, validated psychometric scales-the Technology Acceptance Model (TAM), Sense of Coherence (SOC), and Technological Self-Efficacy (TSE) were employed alongside closed-ended questions. Data from 248 Jewish and Arab educators revealed a significant positive association between TSE and SOC and AI adoption intentions, with TAM constructs mediating these relationships. Independent samples t-tests further highlighted significant ethnic disparities in both AI adoption intentions and TSE. In the qualitative phase, responses to embedded open-ended questions within the questionnaire were analyzed to deepen understanding of educators' experiences and perceptions. Triangulation with quantitative findings via thematic analysis unveiled nuanced insights regarding perceived AI utility, differential access to knowledge and training resources, and a salient tension between technological enthusiasm and ethical-pedagogical concerns. This research offers a theoretical contribution by underscoring the complex interplay of psychological, cultural, and systemic factors in shaping technology adoption and provides actionable guidelines for policy development and professional learning initiatives promoting equitable and effective AI integration within multicultural educational systems on a global scale.

Keywords: Artificial Intelligence, Technology Adoption, Technology Acceptance Model (TAM), Sense of Coherence (SOC), Technological Self-Efficacy (TSE), Cultural Context

Introduction

In an era of rapid technological advancement, Artificial Intelligence (AI) has emerged as a transformative yet ethically complex force in education, reshaping pedagogical paradigms and challenging traditional administrative structures (Holmes et al., 2022; Williamson, 2020). AI-driven technologies, including machine learning algorithms and natural language processing models such as ChatGPT, are increasingly used to facilitate personalized learning, automate administrative tasks, and create dynamic instructional content, potentially enhancing student engagement and educational outcomes (Kumar et al., 2023). However, scholars caution that AI's benefits may exacerbate existing inequities if cultural context, institutional readiness, and ethical considerations are not carefully addressed (Giroux, 2024; Selwyn, 2022, 2024; Viberg et al., 2024; Williamson, 2020).

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Successful AI integration depends not only on adoption by educators but also on fostering their ability to critically engage with AI's underlying assumptions, ethical frameworks, and socio-political implications (Giroux, 2024). This study investigates the psychological, cultural, and demographic factors influencing educators' AI adoption intentions within Israel's diverse educational landscape. It explores how socio-cultural contexts, individual agency, and key psychological constructs—Sense of Coherence (SOC) and Technological Self-Efficacy (TSE)—predict AI adoption. It also examines mediating variables from the Technology Acceptance Model (TAM): Perceived Usefulness (PU), Perceived Ease of Use (PEOU) (Davis, 1989), and Perceived Enjoyment (PE) (Venkatesh et al., 2003). A mixed-methods approach integrating quantitative psychometric assessments with qualitative insights provides a holistic understanding of AI adoption beyond technologically deterministic perspectives.

Given the complexities of AI integration in culturally diverse environments, expanding TAM to incorporate psychological constructs is essential. TAM alone does not account for factors such as resilience, confidence, and sociocultural influences, all critical in shaping educators' readiness for AI adoption. SOC, derived from Antonovsky's (1987) salutogenic model, provides a valuable lens for understanding how individuals perceive their environment as comprehensible, manageable, and meaningful factors that help educators navigate technological change (Takeuchi et al., 2024). Similarly, TSE, based on Bandura's (1997) self-efficacy theory, reflects educators' confidence in using advanced technologies for teaching innovation (Guo et al., 2024).

The Israeli education system presents a compelling case for study due to its cultural and demographic diversity. Jewish and Arab educators operate within distinct socio-cultural and institutional contexts influenced by historical tensions, policy variations, and differing levels of autonomy (Masry-Herzallah & Dor-haim, 2024). Research suggests that Arab educational institutions often adhere to more collectivist, hierarchical, and traditional pedagogical models, whereas Jewish-sector schools exhibit greater openness to individualistic and innovation-oriented approaches (Hofstede, 2011; Masry-Herzallah & Da`as, 2021). However, these broad distinctions may oversimplify reality; educators' lived experiences likely reflect hybrid professional identities, diverse pedagogical beliefs, and complex socio-political pressures (Masry-Herzallah &Cohen, 2023). These cultural factors may shape teachers' perceptions of AI's usefulness, ease of use, and enjoyment, ultimately influencing adoption intentions (Zhou et al., 2024).

Conducted in early 2024, amid an ongoing global discourse on AI in education and the absence of comprehensive policies, this study frames AI adoption as a culturally negotiated process driven by local leadership rather than top-down mandates. Hofstede's (1980) Cultural Dimensions Model provides a framework for understanding cultural disparities while avoiding deterministic interpretations.

By situating AI integration within this socio-cultural and pedagogical context, this study addresses critical gaps in research on AI adoption in education. It pursues three key objectives: (1) to examine the relationships between SOC, TSE, and teachers' AI adoption intentions; (2) to assess the mediating influence of TAM constructs (PU, PEOU, Enjoyment) on these

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relationships; and (3) to investigate differences in AI adoption perceptions between Jewish and Arab educators.

This study advances the TAM by integrating SOC and TSE, providing a more comprehensive framework for understanding educators' AI adoption. By examining the interplay of psychological and cultural factors within a diverse educational landscape, it highlights how systemic influences, such as institutional climate and collective identity, shape technology adoption. Practically, the findings offer actionable insights for policymakers and educational leaders, emphasizing culturally responsive strategies, ethical considerations, and professional development initiatives to promote equitable and effective AI integration. This research contributes to the global discourse on AI in education, underscoring the need for inclusive, context-sensitive, and equity-driven technological innovations.

Literature Review

Artificial Intelligence in Education: Promises and Perils

AI is rapidly transforming education, offering data-driven solutions to address diverse learning needs, improve student engagement, and enhance assessment practices (Kong et al., 2024). Since the 1980s, AI in education (AIEd) has evolved, bridging computer science and pedagogical innovation (Holmes et al., 2022; Kumar et al., 2023; Williamson et al., 2020). Generative AI (GenAI), a type of AI that can create new content such as text, images, and code, offers particularly transformative potential, enabling autonomous content creation and adaptation, and tailoring learning experiences to individual student needs (Pahi et al., 2024; Zhai et al., 2024). This could alleviate teacher workloads and foster higher-order cognitive skills.

AI-driven learning platforms, such as Smart Sparrow and Carnegie Learning, demonstrate how data analytics can personalize instruction and automate time-intensive tasks like assessment (Holmes et al., 2019; Nazaretsky et al., 2022; Sharma et al., 2024). However, the potential benefits of AI in education must be carefully weighed against significant ethical considerations. These include data privacy, algorithmic bias potentially leading to inequitable learning experiences, transparent data utilization, and the risk of over-reliance on AI leading to deskilling of teachers (Farooqi et al., 2024; Fu & Weng, 2024; Williamson, 2020).

Successful AI integration hinges on teacher preparedness, including AI literacy, access to training, and strong institutional support (Debowy et al., 2024; Masry-Herzallah, 2023; Masry-Herzallah & Watted, 2024). Many educators worldwide report insufficient institutional support and limited access to culturally sensitive professional development (Bezjak, 2024; Vazhayil et al., 2019), impeding effective AI adoption.

Beyond technical skills, teachers' perceptions and acceptance of AI are shaped by socio-cultural norms, institutional power dynamics, and community values (Giroux, 2024). Sector-based variations, particularly in dual-structured systems like Israel's, highlight the influence of leadership, resource allocation, and historical inequities on technology adoption (Masry-Herzallah et al., 2025). AI implementation strategies must be culturally responsive and equity-focused, addressing systemic biases and promoting teacher agency (Dao et al., 2023; Nyaaba et al., 2024; Tang et al., 2024).

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Technology Acceptance Model (TAM) in the Era of AI

The TAM (Davis, 1989) is a cornerstone framework for understanding technology adoption. TAM posits that users' intentions to adopt new technologies are primarily driven by PU and PEOU, often augmented by PE (Venkatesh et al., 2003). In AIEd, PU reflects educators' perceptions of AI's capacity to streamline tasks and enhance learning outcomes (Zhai, 2024), while PEOU emphasizes the importance of user-friendly AI systems (Holmes et al., 2022). PE adds an intrinsic motivational dimension, recognizing that enjoyment from technology use can bolster acceptance (Ramírez-Correa et al., 2019).

However, a culturally informed application of TAM acknowledges that AI integration extends beyond individual perceptions. It encompasses broader factors, including institutional trust, algorithmic transparency, fairness, and alignment with pedagogical values (Barnes et al., 2024; Jagannathan et al., 2025; Zhou et al., 2024). Educators' openness to AI is shaped by organizational culture, leadership, collaboration opportunities, and congruence with established pedagogical norms. Research shows that when AI is perceived as accessible (high PEOU), educators are more likely to explore its capabilities for enhancing teaching and learning (Long & Magerko, 2020; Wang et al., 2021).

In Israel's dual-structured educational system, PU and PEOU are likely differentially influenced by cultural and organizational factors for Jewish and Arab educators (Masry-Herzallah & Dor-Haim, 2024). Arab schools, characterized by collectivist norms and hierarchical structures, may face systemic barriers like unequal resource allocation and constraints on teacher autonomy (Masry-Herzallah & Da`as, 2021; see also Hofstede, 2011, for a broader discussion of cultural dimensions). Jewish schools, more individualistic and innovation-oriented, may have different adoption patterns. These historical, cultural, and organizational dynamics shape educators' professional identities and responses to technological reforms (Giroux, 2024). It is therefore hypothesized that these factors will influence educators' perceptions of AI's usefulness and ease of use, ultimately affecting their adoption intentions.

Therefore, TAM is a crucial lens for understanding teachers' perceptions of AI. However, applying it in the AI era requires incorporating psychological variables, particularly TSE. Drawing from Bandura's (1997) self-efficacy theory, TSE reflects teachers' confidence in their ability to use advanced technologies effectively. This is expected to significantly influence PU, PEOU, and PE regarding AI and provides a foundation for deeper analysis. Furthermore, integrating SOC may offer additional insights, as educators with a higher SOC may perceive AI as more manageable and meaningful, thus impacting their PU and PEOU assessments.

The Role of Technological Self-Efficacy (TSE) in AI Adoption: Expanding TAM

TSE, reflecting confidence in using technology effectively (Bandura, 1997; Kent & Giles, 2017), is crucial for understanding teachers' readiness to integrate AI into education. TSE encompasses not only basic technical skills but also proactive adaptation and resilience to technological change (Choi et al., 2023; Patil & Pramod, 2024; Wang et al., 2021). It is shaped by personal experiences, environmental support, and technological factors (Masry-Herzallah et al., 2025; Pan et al., 2020; Zainab et al., 2017). Higher TSE is associated with greater exploration of AI tools (Guo et al., 2024; Masry-Herzallah & Dor-Haim, 2022; Yang & Lou,

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2024) and stronger perceptions of ease of use. Teachers with high TSE also engage more in professional development and may assume leadership roles in technology initiatives (Phan et al., 2020). Recent research highlights the cognitive and behavioral aspects of TSE: higher TSE correlates with improved decision-making, enhanced information processing, and greater persistence in AI adoption (Rajapakse et al., 2024). Teachers with high TSE also report reduced anxiety, contributing to emotional resilience and willingness to implement AI (Hsu et al., 2023). Thus, TSE strongly influences both attitudinal and behavioral dimensions of AI integration.

H 1: TSE will be positively associated with AI adoption intentions.

The Role of Sense of Coherence (SOC) in Navigating AI Uncertainty

Complementing TSE, SOC, derived from Antonovsky's (1987) salutogenic model, provides another key psychological dimension to AI adoption. SOC, encompassing comprehensibility, manageability, and meaningfulness, equips individuals to handle uncertainty and embrace new technologies (Antonovsky, 1987; Ramberg et al., 2022). High SOC fosters a proactive perspective on AI, framing it as an opportunity rather than a threat (Takeuchi et al., 2024). While TAM emphasizes technological attributes like PU and PEOU (Davis, 1989), SOC enhances emotional and cognitive readiness (Juliana et al., 2024). Teachers with elevated SOC often view AI implementation challenges as opportunities for professional growth, leading to higher engagement with training and innovation (Aurangzeb et al., 2024; Goldrat et al., 2023; Joseph & Thomas, 2022). Studies link SOC to greater willingness to collaborate and invest in AI-based pedagogies (Aurangzeb et al., 2024). In multicultural contexts like Israel's Jewish and Arab communities, SOC can mediate tensions by aligning AI adoption with local values and collaborative cultures (Goldrat et al., 2023).

H 2: SOC will be positively associated with AI adoption intentions.

Mediating Role of TAM Constructs in AI Adoption

The TAM posits that PU, PEOU, and PE mediate users' intentions to adopt new technologies, including AI in education. These constructs are socially situated, reflecting institutional power dynamics, teacher identity, and the broader pedagogical context (Giroux, 2024).

Usefulness and Cultural Relevance: PU extends beyond general usefulness to encompass the extent to which AI aligns with teachers' pedagogical goals, ethical values, and student needs (Guo et al., 2024; Zhang et al., 2023). Educators with high SOC and TSE may see AI as extending their pedagogical agency, particularly when AI tools address student diversity and counteract biases (Lockwood, 2024). In STEM education, PU mediates the link between personal competencies and inquiry-based technologies (Chiriacescu et al., 2023). However, in low-resource settings, teachers may need additional support to realize AI's full utility without exacerbating inequities (Widiar et al., 2023). Culturally responsive AI can enhance value and prevent perpetuating inequalities (Dao et al., 2023; Tang et al., 2024). Teachers with high SOC may find AI more meaningful (higher PU) because they see it as a way to address challenges and improve outcomes.

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H 3: PU mediates the relationship between SOC, TSE, and AI adoption intentions.

Ease of Use and Context: PEOU emphasizes the perceived effort required to use AI. Culturally, 'ease of use' depends on local norms, language support, and collective experiences (Bilgin Şimşek & Balta, 2022). Educators with high SOC and TSE often view AI's complexity as manageable, but under-resourced or hierarchical institutions may struggle to provide adequate training (Aurangzeb et al., 2024). Teachers with high TSE may perceive AI as easier to use (higher PEOU) due to confidence in their ability to learn. Equitable professional development, tailored to diverse teachers, enhances PEOU by fostering shared ownership (Bilgin Şimşek & Balta, 2022), acknowledging that AI's "ease" is co-constructed and shaped by institutional trust and cultural relevance (Nyaaba et al., 2024).

H 4: PEOU mediates the relationship between SOC, TSE, and AI adoption intentions.

Enjoyment and Collaboration: PE adds an emotional dimension, deepening engagement with AI. Educators with high SOC or TSE are more likely to enjoy exploring new technologies, especially when AI supports creative pedagogies and celebrates diversity (Chiriacescu et al., 2023). In diverse classrooms, engaging AI applications can empower teachers to co-create inclusive learning experiences with students (Rahmi, 2016). Teachers with high TSE and SOC may experience greater enjoyment (higher PE) when using AI due to feelings of competence and purpose. However, ethical concerns, such as perceiving AI as surveillance or reinforcing hierarchies, can undermine this (Fu & Weng, 2024). Thus, designing AI for "enjoyment" must consider teacher autonomy and context.

Hypothesis 5: PE mediates the relationship between SOC, TSE, and AI adoption intentions.

PU, PEOU, and PE are hypothesized to mediate the relationship between teachers' psychological readiness (SOC/TSE) and their culturally and ethically informed AI adoption. A teacher with strong SOC/TSE might use AI to promote inclusion, but only if TAM constructs align with institutional values and student-centered goals (Bilgin Şimşek & Balta, 2022). Successful AI adoption involves addressing ethical, cultural, and communal dimensions of teaching.

Cultural Influences on AI Adoption

AI integration in education is shaped by institutional norms, power dynamics, and socio-political contexts, impacting educators' sense of agency (Giroux, 2024; Masry-Herzallah&Watted, 2024). Hofstede's (1980) cultural dimensions model provides a framework but should be applied critically to avoid oversimplifying culture. It helps examine historically constructed frameworks shaping AI adoption at multiple levels (Nyaaba et al., 2024).

In Israel, Jewish schools often prioritize teacher autonomy and innovation, potentially leading Jewish educators to see AI as empowering (Hofstede, 2011). Arab schools, with more centralized structures and collectivist norms (Masry-Herzallah et al., 2025), may experience AI adoption as externally imposed. This, combined with an emphasis on group conformity (Hofstede, 2011), might lead to hesitations, not from resistance to technology, but from different contexts and a perceived lack of agency. These distinctions reflect broader inequities

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in policy, resources, and professional development (Tang et al., 2024). Viberg et al. (2024) also found cultural variations in teachers' views of AI.

Understanding these dimensions is crucial for equitable AI adoption, preventing digital colonialism (Selwyn, 2022, 2024), and technology access inequities. For Arab schools, effective integration requires collaborative decision-making, culturally embedded professional development (e.g., Arabic workshops, incorporating traditional methods), and AI tools aligned with community priorities (Masry-Herzallah et al., 2025). In Jewish schools, leveraging teacher-led innovation while being aware of AI's impact on teacher agency is key (Giroux, 2024).

Hypothesis 6: Significant differences are expected between Jewish and Arab teachers in TSE and AI adoption intentions, with Jewish teachers reporting higher levels on these variables. The pattern for SOC may differ, reflecting distinct cultural and institutional contexts.

Methods

Research Context

The Israeli education system, overseen by the Ministry of Education, serves approximately 2 million students, with 73% in Hebrew-sector and 27% in Arabic-sector schools (Central Bureau of Statistics, 2023; Israel Democracy Institute, 2023). This centralized system, with a standardized curriculum and assessments, provides a unique context for studying educational technology adoption.

Given the global advancements in AI, the Israeli Ministry of Education has initiated policies for AI integration. In August 2023, guidelines were introduced to promote responsible generative AI use in schools (Ministry of Education, 2023a, 2023b). These policies aim to optimize pedagogy, personalize learning, and address ethical considerations, including data privacy and critical thinking. This initiative aligns with international trends, positioning Israel as an active player in this evolving domain (Debowy et al., 2024). Ministry strategies emphasize AI for enhanced learning and adaptive assessment while promoting cautious deployment. The Ministry acknowledges that these policies are still evolving, requiring ongoing collaboration with stakeholders (Ramiel, 2023). This approach reflects the complexities of AI adoption in education, balancing innovation with educational values and addressing the diverse needs of students and educators across sectors (Masry-Herzallah & Watted,, 2024). Understanding this context is crucial for interpreting AI adoption patterns within Israeli educational settings and for generalizing findings to other culturally diverse centralized systems.

Participant Profile and AI Exposure

Educators' AI exposure varied, reflecting differences in access to training and resources. Professional AI training initiatives were reported by 46.8% of participants; 39.5% engaged in private AI courses, while 57.3% participated in peer learning. Self-directed learning through digital platforms (e.g., online courses, educational websites) was prevalent (66.1%); however, formal AI training was limited to 26.6%.

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Significant sectoral differences emerged. Jewish sector educators reported greater participation in structured, institutionally organized training. Arab sector educators relied more on self-directed digital learning and peer networks. Jewish educators reported a more gradual adoption process, contrasting with Arab educators' more recent yet accelerated engagement.

Sample Description

A stratified convenience and snowball sampling approach was employed (Heckathorn & Cameron, 2017), resulting in a sample of 248 educators (N = 248) from diverse educational contexts within Israel. Data collection spanned November 2023–June 2024. Snowball sampling was used due to the challenges of accessing the Arab educator population through traditional methods, leveraging existing networks to reach this underrepresented group.

The sample's ethnic composition (66.9% Arab, 33.1% Jewish) differed from national teacher demographics. The over-representation of Arab educators is attributed to the researchers' institutional affiliations and professional networks, which facilitated access within Arab educational communities, and the use of snowball sampling. The national crisis that began on October 7th, 2023, also impacted recruitment, making it more difficult to recruit Jewish educators due to heightened security concerns and restrictions.

While these factors limit the generalizability of quantitative findings to all Israeli educators, they provide valuable insights into AI adoption within the Arab education sector—a population often underrepresented in research. The sample's heterogeneity across ethnicity, gender, educational qualifications, and professional roles provides a robust foundation for analyzing the interplay of SOC, TSE, and factors influencing AI adoption. Table 1 provides a summary of participant characteristics.

Table 1 Sample Characteristics

Variable	Category	*N*	%
Gender	Female	206	83.1
	Male	42	16.9
Regional Distribution	Haifa	92	37.1
	Central	60	24.2
	Northern	50	20.2
	Jerusalem	30	12.1
	Southern	16	6.4
Educational Qualifications	Bachelor's Degree	77	31.0
	Master's Degree	150	60.5
	Doctoral Degree	7	2.8
	Teaching Certificate	14	5.6

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Socioeconomic Status of Schools	High	50	20.2
	Medium	170	68.5
	Low	28	11.3
Ethnic Composition	Arab	166	66.9
	Jewish	82	33.1

Note. N = 248

Research Instruments: Mixed-Methods Approach

This study employed a mixed-methods approach, integrating quantitative and qualitative data to achieve a comprehensive understanding of educators' AI adoption intentions. This design recognizes that while quantitative measures can delineate prevalence and predictive relationships, qualitative methods are essential for exploring lived experiences and contextual nuances shaping technology acceptance, especially in diverse settings.

Quantitative Instruments

The quantitative phase employed validated psychometric instruments, detailed in Table 2. The SOC scale (Antonovsky, 1987) was chosen for its established validity and reliability in measuring individuals' ability to cope with stress and uncertainty. The TSE scale was adapted from Bandura (2006) and Masry-Herzallah and Dor-Haim (2022), based on its proven effectiveness in assessing technology-related self-efficacy. TAM constructs (PU, PEOU, PE, and Adoption Intentions) were evaluated using scales adapted from Davis et al. (1989) and Guo et al. (2024), chosen for their widespread use and established validity in technology adoption research.

Qualitative Exploration through Open-Ended Questions

To complement the quantitative data, the survey incorporated open-ended questions (detailed in Table 2). These questions explored educators' familiarity and usage of AI tools, their sources of AI knowledge, and their perceptions of AI adoption, providing qualitative context for the quantitative findings on TSE, SOC, and TAM constructs.

Table 2 Research Instruments and Descriptions

Questionnaire	Source and Year	Description	Example Items	Cronbach's Alpha (α)
Demographic Questionnaire	Study-Designed	13 items assessing personal and professional characteristics.	-	-
SOC Scale	Antonovsky (1987)	13 items measuring global coherence (comprehensibility,	"Do you often have feelings that you're not sure	α = 0.75

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		manageability, meaningfulness).	you can keep under control?"	
TSE	Bandura (2006); Masry-Herzallah &, 2022	6 items assessing perceived self-efficacy in using technology.	"New technology does not intimidate me."	α = 0.87
TAM	Davis et al. (1989); Guo et al. (2024)	19 items evaluating attitudes toward and intentions to adopt AI, encompassing: PU; PEOU PE; Adoption Intentions	PU: "Integrating AI into my teaching will improve my effectiveness." PEOU: "Learning to use AI in teaching would be easy for me." PE: "I would find using AI in teaching to be enjoyable." AIAI: "I intend to integrate AI into my teaching in the near future."	PU: α = 0.93; PEOU: α = 0.91; PE: α = 0.88; Adoption Intentions: α = 0.95
Prior Knowledge of AI	Study-Designed	3 items assessing prior experience and familiarity with AI. **(Multiple Choice)**	"When did you first hear about AI?" (Options: More than a year ago, Six months ago, Three months ago, One month ago, Less than a month ago, I haven't heard about it)	-
AI Training Experience	Study-Designed	1 item assessing formal/informal professional development training related to AI.	"Have you received professional training in AI?" (Yes/No; with a space to specify source)	-

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First Exposure to AI	Study-Designed	1 item assessing the timeframe of initial exposure to AI.	"When did you first hear about AI?" (Same options as above)	-
First Source of AI Knowledge	Study-Designed	1 item assessing the primary source of initial AI knowledge.	"Where did you first hear about AI?" (Examples: School principal, social media, news media)	-
Use of AI-Based Tools	Study-Designed	2 items evaluating familiarity with and usage of AI tools across contexts (educational, professional, leisure).	"Which AI tools do you use, and for what purposes?" (Categories: Education, Work, Leisure).	-

Procedure

This study commenced in November 2023 following ethical approval from the College Review Board. A contextually appropriate survey instrument, available in both Arabic and Hebrew, was administered to educators. Prior to broad dissemination, a pilot study with 35 educators, representing sector and teaching level diversity, was conducted to enhance clarity and content validity; minor revisions were implemented based on pilot feedback. The finalized questionnaire was distributed to educators enrolled in advanced degree programs at three randomly selected Israeli higher education institutions, chosen for geographic and demographic representativeness. Dissemination employed email and WhatsApp (via secure Google Forms), supplemented by snowball sampling via educator professional networks on Facebook and WhatsApp, maximizing sample reach (N=248). Data collection concluded in May 2024.

All participants provided electronic informed consent after receiving detailed information regarding study objectives, anonymity, data confidentiality, and researcher contact details. Assurances were provided regarding data usage solely for research purposes, mitigating potential evaluation bias (Podsakoff et al., 2000).

It is important to note that the use of Large Language Models (LLMs) was employed in this study to assist in the editing, refinement, and enhancement of the manuscript's language and presentation. The LLM was used as a tool to improve clarity, conciseness, and overall academic rigor, but all research design, data collection, analysis, interpretation, and core writing were performed by the human author.

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Data Processing and Analysis

Data were analyzed using SPSS (version 29) with a multi-stage mixed-methods approach.

Quantitative Data Analysis

Quantitative data analysis included:

- Descriptive statistics: Calculation of means, standard deviations, and frequencies for participant demographics and key variables.
- Correlation analysis: Examination of bivariate relationships using Pearson's *r* coefficients, with bootstrapped confidence intervals (5,000 iterations) (Preacher & Hayes, 2008).
- Hierarchical regression and mediation analysis: Assessment of predictive power and mediating effects using hierarchical multiple regression with sequential variable entry (Hayes, 2018). Demographic variables were entered in Step 1, followed by SOC and TSE in Step 2, and the TAM constructs in Step 3, to examine their incremental predictive validity.
- Group comparisons: Independent samples *t*-tests to identify ethnic group differences on key variables.

Qualitative Data Analysis

Qualitative data (open-ended survey responses) were analyzed using inductive thematic analysis (Braun & Clarke, 2006).

- Familiarization and Initial Coding: Repeated readings of the data to identify initial patterns and generate inductive codes reflecting semantic content.
- Theme Development and Refinement: Codes were iteratively reviewed and refined into broader themes, ensuring internal homogeneity, external heterogeneity, and conceptual coherence (Braun & Clarke, 2006).
- Theme Quantitization and Reporting: While primarily qualitative, theme frequencies were tallied to provide supplementary quantitative description and facilitate intergroup comparisons. Illustrative quotes are presented in the findings tables.

Findings

This study examined the relationships among SOC, TSE, and AI adoption intentions within the TAM framework. The results reveal significant psychological, technological, and cultural factors shaping AI adoption among educators in Israel's diverse educational sectors.

Descriptive Statistics and Correlation Analysis

Table 3 presents descriptive statistics and Pearson correlation coefficients for key study variables.

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Table 3 Descriptive Statistics and Pearson Correlations Among Study Variables

Variable	M	SD	1	2	3	4	5	6
1. SOC	4.34	0.83	—					
2. TSE	3.83	0.86	.29**	—				
3. PU	3.57	0.92	.21**	.43**	—			
4. PEOU	3.32	0.94	.29**	.56**	.65**	—		
5. PE	3.63	1.05	.22**	.53**	.72**	.70**	—	
6. Adoption Intentions	3.55	1.06	.22**	.49**	.80**	.74**	.79**	—

Note. N = 248. ** $p < .01$.

Descriptive statistics (Table 3) revealed moderate to high mean scores across all constructs, suggesting generally positive attitudes toward AI: SOC (M = 4.34, SD = 0.83), TSE (M = 3.83, SD = 0.86), PU (M = 3.57, SD = 0.92), PEOU (M = 3.32, SD = 0.94), PE (M = 3.63, SD = 1.05), and Adoption Intentions (M = 3.55, SD = 1.06).

Pearson correlation analysis showed significant, positive, but small to moderate correlations between SOC and PU ($r = .21$, $p < .01$), PEOU ($r = .29$, $p < .01$), AI adoption intentions ($r = .22$, $p < .01$), PE ($r = .22$, $p < .01$), and TSE ($r = .29$, $p < .01$). Stronger positive correlations were found between adoption intentions and TAM constructs: PU ($r = .80$, $p < .01$), PEOU ($r = .74$, $p < .01$), PE ($r = .79$, $p < .01$), and TSE ($r = .49$, $p < .01$), consistent with prior research (Davis, 1989). Moderate positive correlations were also found between TSE and PU ($r = .43$, $p < .01$), PEOU ($r = .56$, $p < .01$), and PE ($r = .53$, $p < .01$). These findings support Hypotheses 1 and 2, indicating positive associations between SOC and TSE with AI adoption intentions. They also highlight the importance of TAM constructs and technological competence.

Mediation Analysis: TAM Constructs as Mediators

To test Hypotheses 3-5 regarding the mediating roles of TAM constructs (PU, PEOU, PE), hierarchical multiple regression was used.

Table 4 Hierarchical Multiple Regression Analysis Predicting Adoption Intentions

Model	Predictors	B	SE	β	R^2	ΔR^2
1	SOC	0.28	0.07	.23**	0.05**	0.05**
2	SOC	0.11	0.07	.09	0.24**	0.19**
	TSE	0.57	0.07	.46**		
3	SOC	0.007	0.04	.005	0.76**	0.52**
	TSE	0.001	0.04	.001		
	PEOU	0.28	0.05	.26**		
	PU	0.46	0.05	.40**		

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	PE	0.32	0.05	.32**		

Note: p < 0.01.

In Model 1, SOC significantly predicted adoption intentions, explaining 5% of the variance (B = 0.28, SE = 0.07, β = .23, $p < .01$). Model 2, incorporating TSE, significantly increased explained variance to 24% ($\Delta R^2 = .19$, $p < .01$), with TSE emerging as a significant predictor (B = 0.57, SE = 0.07, β = .46, $p < .01$), while the independent contribution of SOC became non-significant ($p > .05$).

Including the TAM mediators (PEOU, PU, and PE) in Model 3 dramatically increased the explained variance to 76% ($\Delta R^2 = .52$, $p < .01$). In this fully mediated model, the direct effects of both SOC and TSE became non-significant (*p*s > .05). All three TAM mediators—PEOU (B = 0.28, SE = 0.05, β = .26, $p < .01$), PU (B = 0.46, SE = 0.05, β = .40, $p < .01$), and PE (B = 0.32, SE = 0.05, β = .32, $p < .01$)—emerged as significant predictors of adoption intentions. These findings support Hypotheses 3-5, showing that PU, PEOU, and PE fully mediate the relationship between SOC, TSE, and AI adoption intentions, consistent with cross-national findings (Viberg et al., 2024). TAM constructs are critical mediators in understanding how SOC and TSE influence AI adoption.

Differences Between Jewish and Arab Teachers: Ethnic Variations in Adoption Intentions and TSE

To examine ethnic group differences (Hypothesis 6), independent samples *t*-tests were conducted (Table 5).

Table 5 Independent Samples *t*-Test for Group Differences Between Jewish and Arab Teachers

Variable	Jewish Teachers (M, SD)	Arab Teachers (M, SD)	*t*	*p*	Cohen's *d*
SOC	4.39 (0.80)	4.32 (0.85)	0.57	.570	0.08
PU	3.69 (0.99)	3.51 (0.88)	1.48	.140	0.19
PEOU	3.41 (1.02)	3.28 (0.90)	1.01	.314	0.14
Adoption Intentions	3.76 (1.22)	3.45 (0.96)	2.12	.035*	0.29
PE	3.73 (1.18)	3.58 (0.98)	1.07	.287	0.14
TSE	3.97 (0.85)	3.77 (0.86)	2.10	.037*	0.23

Note. N = 248. $p < .05$.

Table 5 reveals significant differences between Jewish and Arab educators in adoption intentions and TSE. Jewish teachers reported significantly higher adoption intentions (M = 3.76, SD = 1.22) than Arab teachers (M = 3.45, SD = 0.96), $t(246) = 2.12$, $p = .035$, Cohen's $d = 0.29$. Similarly, TSE was significantly higher among Jewish educators (M = 3.97, SD = 0.85) than Arab educators (M = 3.77, SD = 0.86), $t(246) = 2.10$, $p = .037$, Cohen's $d = 0.23$.

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No significant differences were found for SOC, PU, PE, or PEOU. These results suggest that while perceptions of AI's utility, usability, and enjoyment are relatively consistent across ethnic groups, disparities emerge in technological competence and readiness to adopt AI, indicating potential cultural and/or institutional factors, consistent with prior research (Viberg et al., 2024).

Qualitative Findings: Key Themes from Open-Ended Responses

To provide context and nuance to the quantitative findings, thematic analysis of educators' open-ended survey responses was conducted. This section presents key themes, highlighting educators' perspectives on AI use cases and information sources.

Perceived Uses of AI in Teaching: Focus on Pedagogy and Efficiency

Table 6 summarizes thematic categories related to perceived AI uses in teaching, by sector.

Table 6 Central Themes in Perceptions of AI Uses in Teaching, by Sector

Theme Category	Jewish Educators (N = 82)	Arab Educators (N = 166)
Educational Purpose	n: 35	n: 58
	Illustrative Quotes:	*Illustrative Quotes:*
	Lesson enrichment	Improving teaching quality
	Personalization	Experiential learning
	Worksheet preparation	Classroom activities
Work Efficiency	n: 22	n: 30
	Illustrative Quotes:	*Illustrative Quotes:*
	Saving prep time	Efficient material organization
	Task automation	Efficient time management
	Report writing	Improved parent communication
Personal Enrichment	n: 15	n: 25
	Illustrative Quotes:	*Illustrative Quotes:*
	Personal brainstorming	Creative writing
	Idea development	Self-learning enrichment
	-	AI-generated images
Specific AI Tools	n: 52	n: 95
	Illustrative Quotes:	*Illustrative Quotes:*

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	Chat GPT, Canva, Magic School	Chat GPT, Canva
Not Using AI	n: 10	n: 18
	Illustrative Quotes:	*Illustrative Quotes:*
	Unfamiliar with tools	Not currently using
	Not relevant to the subject	Haven't tried
	Not yet using	New topic for me
Ethical/Pedagogical Concerns	n: 8	n: 14
	Illustrative Quotes:	*Illustrative Quotes:*
	Loss of human touch	Impaired critical thinking
	Ethical concerns	Teacher replacement
	Privacy worries	Unreliable information
Training Needs	n: 12	n: 20
	Illustrative Quotes:	*Illustrative Quotes:*
	Tailored PD	Institutional training
	Practical workshops	Technical support
	In-depth course	Training in teacher ed
Positive View	n: 18	n:32
	Illustrative Quotes:	*Illustrative Quotes:*
	Improves learning	Efficient tool

Note. N = 248. The table summarizes responses to "Which AI tools are you familiar with and use, and for what purposes?". Example responses are shortened.

Educators, regardless of sector, predominantly perceive AI pragmatically, emphasizing its instrumental value for education. Educational Purpose emerged as the most frequent theme, with educators highlighting AI's potential to enrich pedagogy and enhance student learning. Examples included enhancing lesson engagement, personalizing materials, facilitating collaboration, and generating content. Many educators, particularly in the Arab sector, also emphasized Work Efficiency, recognizing AI's potential to streamline tasks and improve efficiency. This dual emphasis aligns with TAM's PU construct, highlighting AI's instrumental value for educators.

Sources of Initial AI Knowledge: Sectoral Differences in Access

Table 7 shows sectoral differences in educators' initial AI knowledge sources.

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Table 7 Central Themes in First Source of AI Knowledge, by Sector

Theme Category	Jewish Teachers (N = 82)	Arab Teachers (N = 166)
Academic/Institutional Sources	n: 45	n: 30
	Illustrative Quotes:	*Illustrative Quotes:*
	University lecturer	Lecturer in studies
	School-based PD	School tech center
	School principal	Principal
Media/News Sources	n: 18	n: 25
	Illustrative Quotes:	*Illustrative Quotes:*
	Newspaper article	Online article
	TV tech program	News report
Social Media/Digital Platforms	n: 10	n: 40
	Illustrative Quotes:	*Illustrative Quotes:*
	Facebook	Facebook
	YouTube	WhatsApp teacher groups
	Online posts	YouTube videos
Personal Connections	n: 5	n: 20
	Illustrative Quotes:	*Illustrative Quotes:*
	Work colleagues	Friends and acquaintances
	Peers	My children
	Family (children)	Family
Other/Don't Know/Not Relevant	n: 4	n: 51
	Illustrative Quotes:	*Illustrative Quotes:*
	Don't recall	Never heard before
	Not relevant	Not relevant
	-	Don't know

Note. N = 248. The table summarizes responses to "From whom did you first hear about artificial intelligence?". Example responses are shortened.

Jewish educators more often cited Academic/Institutional Sources (e.g., university lecturers, school-based PD), suggesting greater integration of AI within formal learning contexts. Arab educators more often reported Social Media/Digital Platforms and Personal Connections (e.g.,

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peer networks, family) as primary sources, suggesting greater reliance on informal learning. This disparity suggests unequal access to institutional AI knowledge, potentially contributing to the differences in TSE and adoption intentions (Table 5). These variations mirror international trends, where disparities in professional development and support contribute to the digital divide (Viberg et al., 2024).

Educator Sentiments: Navigating Enthusiasm and Ethical Concerns

Analysis of educators' additional notes (Table 8) revealed a range of sentiments, often characterized by both enthusiasm and apprehension.

Table 8 Central Themes in Additional Comments on AI Adoption, by Sector

Theme Category	Jewish Teachers (N = 82)	Arab Teachers (N = 166)
Ethical/Pedagogical Concerns	n: 15	n: 28
	Illustrative Quotes:	*Illustrative Quotes:*
	Loss of human touch	Impaired thinking
	Ethical questions	Teacher replacement
	Privacy concerns	Unreliable info
Need for Training/Support	n: 20	n: 35
	Illustrative Quotes:	*Illustrative Quotes:*
	Tailored PD	Institutional training
	In-depth courses	Technical support
	Practical workshops	Training in teacher ed
Positive Potential	n: 30	n: 32
	Illustrative Quotes:	*Illustrative Quotes:*
	Improves learning	Efficient aid
	High potential	Engaging instruction
	Enables personalization	Opens new possibilities

Note. N = 248. The table summarizes responses to "Additional notes/instructions on the topic you wish to add". Example responses are shortened.

Table 8 shows that while educators acknowledged AI's positive potential, many also voiced ethical and pedagogical concerns. Concerns included dehumanizing pedagogy, eroding critical thinking, algorithmic bias, and data privacy – highlighting apprehension about unintended consequences and the need for careful consideration. The emphasis on "Need for Training and Support," particularly among Arab educators, reinforces the importance of professional development to address anxieties and promote responsible adoption. Some Arab educators also mentioned a perceived "Generational Gap" in technology adoption attitudes, suggesting age

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and digital nativeness may play a role. These findings align with growing international concern regarding ethical considerations in AIEd (Viberg et al., 2024).

Integrating Quantitative and Qualitative Findings: A Holistic Picture

Quantitative and qualitative findings converge on the importance of TSE, PU, and PEOU. Qualitative themes amplify the quantitative findings. The qualitative themes of "Educational Purpose" and "Work Efficiency" (Table 6) reinforce the quantitative emphasis on PU. The "Need for Training and Support" theme (Table 8), particularly among Arab educators, highlights the importance of PEOU.

This integration also unveils critical nuances. The quantitative ethnic disparities in TSE (Table 5) gain deeper context through qualitative data. The thematic analysis of initial knowledge sources (Table 7) reveals Jewish educators' greater reliance on institutional/academic channels versus Arab educators' reliance on informal networks—a finding indicative of differential access to structured AI learning opportunities, potentially explaining quantitative TSE gaps. This underscores the importance of understanding the contextual antecedents of TSE, resonating with findings on the role of institutional support (Viberg et al., 2024).

Qualitative findings also highlight ethical dimensions. The "Ethical/Pedagogical Concerns" theme (Table 8) revealed concerns about dehumanizing pedagogy and eroding human connections. The recurring "fear of losing human touch" emphasizes a vital, value-laden dimension. This parallels the emphasis in recent literature on the need for ethical considerations in AIEd as core pedagogical and humanistic concerns (e.g., Holmes et al., 2022).

Triangulating findings provides a holistic picture: quantitative data identify key predictors and disparities, while qualitative data add context and ethical considerations. This integrated perspective provides a more holistic understanding of AI adoption in education, highlighting the limitations of relying solely on quantitative models like TAM.

Discussion

This study examined the multifaceted dynamics of AI adoption among educators in Israel, integrating the TAM with constructs of SOC and TSE to elucidate the interplay of psychological, contextual, and socio-cultural factors influencing adoption intentions. The findings contribute substantively to the theoretical understanding of technology integration in education and offer actionable implications for fostering equitable and ethically informed AI adoption within diverse educational systems.

Integrated Findings: Determinants of AI Adoption Intentions

The integration of TAM's core constructs—PU, PEOU, and PE—with SOC and TSE provides empirical validation of the model's applicability to the domain of AI in education (Davis, 1989; Venkatesh et al., 2003). Consistent with a growing body of international research (e.g., Viberg et al., 2024), our findings confirm that PU, PEOU, and PE mediate the relationship between SOC/TSE and educators' adoption intentions, underscoring the centrality of user perceptions in technology acceptance. The need for training and professional development, a recurring theme in the qualitative data, highlights the crucial role of perceived mastery and pedagogical adaptability in shaping PEOU, aligning with prior research emphasizing the importance of

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targeted interventions to enhance self-efficacy (Masry-Herzallah & Watted, 2024; Masry-Herzallah et al., 2025).

Disparities in AI adoption readiness, notably the lower TSE and adoption intentions observed among Arab educators (Table 5), illuminate systemic inequities within the Israeli educational context. These disparities are mirrored in the divergent sources of AI knowledge reported by each group (Table 7), with Jewish educators more frequently citing formal, institutional channels and Arab educators relying more heavily on informal, social networks. This pattern suggests differential access to structured AI learning opportunities, reflecting broader digital divide phenomena. While potentially aligning with aspects of Hofstede's (1980) cultural dimensions framework, these variations appear more directly attributable to systemic resource disparities than to essentialized cultural traits (Masry-Herzallah, 2024). Addressing these inequities necessitates targeted policy interventions that ensure equitable access to high-quality AI training and professional development, resonating with global calls for equitable technology access and training (Selwyn, 2024).

Beyond the cognitive and utilitarian dimensions of technology acceptance, the findings underscore the critical importance of affective and ethical considerations. Educators expressed concerns regarding the potential for AI-mediated instruction to diminish the "human touch" in teaching, reflecting broader ethical dilemmas associated with automation in education. These concerns align with critical pedagogical perspectives that prioritize the preservation of relational and humanistic dimensions in teaching and learning (Giroux, 2024). The implication is that effective AI adoption strategies must proactively integrate ethical AI literacy into professional development, equipping educators to critically evaluate the pedagogical implications of AI and to ensure that technology serves as an augmentation to, rather than a replacement for, essential human interaction. This resonates with emerging calls within the AIEd community for the development and implementation of ethical, human-centered AI frameworks that move beyond purely technology-driven approaches (Holmes et al., 2022).

Theoretical Contributions, Practical Implications, Limitations, and Future Research

Theoretical Contributions: Contextualizing and Extending TAM for AIEd

This study advances the theoretical understanding of technology adoption in education by extending the TAM framework through the integration of SOC and TSE as key psychological antecedents. By demonstrating the indirect influence of these constructs on AI adoption intentions, mediated through PU, PEOU, and PE, the findings offer a more holistic and psychologically nuanced model of technology acceptance. This contribution aligns with recent calls for refining technology adoption theories to more comprehensively account for socio-emotional and cognitive determinants (Vorm & Combs, 2022), and it extends prior work by incorporating psychological resilience (SOC) as a critical factor alongside the well-established role of self-efficacy (TSE). Furthermore, the empirical documentation of ethnic disparities in AI adoption readiness challenges the assumption of universal applicability inherent in traditional TAM formulations. These findings underscore the necessity of adapting technology acceptance models to account for cultural and institutional variations, contributing to the burgeoning literature advocating for culturally responsive technology adoption frameworks (Selwyn, 2024). This contextualized approach to TAM, encompassing both individual differences and systemic factors, aligns with calls for increased nuance in technology adoption research (e.g., Viberg et al., 2024).

Practical Implications: Towards Equitable and Ethically Informed AI Integration

The research yields several actionable implications for policy and practice:

- *Addressing Inequities:* Targeted policy interventions are essential to ensure equitable access to AI training, resources, and infrastructure across all educational sectors. This necessitates strategic resource allocation to under-resourced schools and the provision of comprehensive AI literacy programs tailored to the specific needs and contexts of diverse educator populations.
- *Culturally Responsive Training:* Professional development initiatives should be community-based, collaborative, and culturally sensitive. For Arab educators, this may involve leveraging existing peer networks and adapting programs to address their unique learning preferences and concerns, as indicated by the qualitative findings. This approach aligns with recommendations for culturally responsive technology integration in diverse educational settings (Masry-Herzallah, 2024).
- *Promoting User-Centered Design:* AIEd tools should be developed through participatory co-design processes that actively involve educators. This ensures that technological solutions are aligned with pedagogical needs and classroom realities, fostering greater teacher buy-in and enhancing the PU, usability, and enjoyment of AI systems.
- *Fostering Ethical AI Literacy:* Professional development programs must explicitly address the ethical dimensions of AI in education, incorporating modules on responsible AI use, data privacy, algorithmic transparency, and the potential for bias. This cultivates critical awareness and reinforces the role of AI as a tool to complement, rather than supplant, human pedagogical judgment and the essential relational aspects of teaching (Holmes et al., 2022).

Limitations

This study, while providing valuable insights, is subject to certain limitations. The reliance on self-reported data introduces the potential for response biases, and future research should incorporate observational and objective usage data to triangulate findings. The qualitative analysis, while insightful, is based on a relatively modest sample size, which may limit the generalizability of the thematic findings. Furthermore, the identified cultural and systemic disparities are context-specific to the Israeli educational landscape, and future research should examine these dynamics across a broader range of geopolitical and educational settings. Finally, the study's focus on teacher perspectives does not encompass student perceptions of AI, which represents a crucial area for future investigation.

Future Research Directions: Advancing the Field of AIEd

Building on the insights and limitations of this study, future research should pursue several key avenues:

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- *Longitudinal Studies:* Employ longitudinal designs to track AI adoption trajectories over time and to assess the sustained impact of professional development interventions on technology integration and pedagogical outcomes.
- *Cross-Cultural Comparisons:* Expand research across diverse national and educational contexts to refine culturally adaptive technology adoption models and enhance the generalizability of findings across different educational systems.
- *Qualitative Deep Dives:* Utilize ethnographic and phenomenological approaches to gain richer, more nuanced understandings of educators' lived experiences of navigating AI integration within authentic classroom settings.
- *Investigating Organizational and Leadership Factors:* Explore the influence of school leadership, institutional policies, and administrative support structures on educators' AI adoption readiness and integration processes.
- *Developing and Validating Ethical AI Frameworks:* Develop and empirically validate ethical AI integration frameworks that prioritize inclusivity, transparency, and human agency within educational contexts.

Conclusion

This research provides a theoretically grounded and contextually sensitive analysis of AI adoption among educators, illuminating the complex interplay of psychological readiness, user perceptions, socio-cultural factors, and ethical considerations. By extending the Technology Acceptance Model (TAM) with SOC and TSE and strategically integrating quantitative and qualitative methodologies, the study offers a more holistic and nuanced understanding of technology integration within a diverse educational system. The findings underscore the imperative of multidimensional AI adoption strategies that foster TSE, address systemic inequities, and critically engage with the ethical implications of AI in pedagogy. This study advocates for a human-centered and ethically informed approach to AI integration in education, ensuring that technology serves as an enabler of equitable and meaningful learning experiences while preserving the essential relational dimensions of teaching.

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