



Vol. 3 No. 12 (December) (2025)

Psychological Capital as the Catalyst: A PROCESS Moderated Mediation Model of AI Risk Perception and Ethical Intervention in ECE

Dr. Abdul Qayyum (Corresponding Author)

Assistant Professor, Department of Education, University of Jhang, Punjab, Pakistan

Email: drabdulqayyum@uoj.edu.pk; ORCID ID: <https://orcid.org/0000-0002-0510-1818>

Dr. Abrar Hussain Qureshi

Assistant Professor, Department of English, University of Sahiwal, Punjab Pakistan

Amber Saeed

University of Southern Punjab, Punjab, Pakistan

Ayesha Bibi

Hangzhou Normal University, Zhejiang, Peoples' Republic of China

Mehak Shehzadi

University of Sahiwal, Punjab, Pakistan

ABSTRACT

Background: The proliferation of algorithmic tools in Early Childhood Education (ECE) raises urgent ethical concerns regarding algorithmic bias (AB) and its potential to exacerbate inequities. ECE teachers are the frontline defense against these biases, yet the transition from recognizing bias to executing corrective Ethical Intervention Behavior (EIB) often fails, highlighting an acute awareness-action gap. This study investigates the complex, conditional psychological pathway governing ECE teachers' ethical responses.

Methodology: Employing a quantitative, cross-sectional design, this research utilized the Moderated Mediation Model (Hayes PROCESS Model 8). Data were collected from N=304 ECE teachers in Lahore and Islamabad. The model tested the indirect effect of Perceived Algorithmic Bias (AB) on EIB via AI Ethical Literacy (AEL), with Psychological Capital (PsyCap) hypothesized as a moderator influencing the AEL → EIB path. All variables were measured using reliable scales $\alpha \geq 0.88$.

Key Findings: The analysis yielded conclusive evidence for a conditional process. First, the direct effect of AB on EIB was statistically insignificant ($B=0.05$, $p=0.327$). Second, the crucial interaction term between AEL and PsyCap was highly significant ($B_{\text{interaction}}=0.18$, $p=0.005$). This confirmed that the efficacy of ethical knowledge is moderated by internal resources. Critically, the conditional indirect effect was found to be significant only under conditions of moderate and high PsyCap (95% CI excluded zero), confirming that PsyCap acts as the enabling factor that allows cognitive competency (AEL) to successfully translate into proactive behavioral intervention.



Vol. 3 No. 12 (December) (2025)

Conclusion and Implication: We conclude that ethical action among ECE teachers is a conditional psychological process. For teachers to intervene effectively against algorithmic bias, AI Ethical Literacy must be augmented by Psychological Capital (efficacy, resilience, optimism, and hope). The findings mandate a policy shift towards holistic teacher development, prioritizing both technical ethical training and the cultivation of psychological resilience to foster genuine ethical agency in the AI-mediated classroom.

Keywords: Algorithmic Bias, AI Ethical Literacy, Psychological Capital, Ethical Intervention Behavior, Moderated Mediation, ECE.

Introduction

Global Context

The rapid acceleration of Artificial Intelligence (AI) integration marks a paradigm shift in global education, offering unprecedented opportunities for personalized instruction and automated assessment, directly supporting the attainment of **Sustainable Development Goal 4 (SDG 4)** for quality and equitable education (UNESCO, 2021). In the Early Childhood Education (ECE) sector, AI tools particularly those focused on emotional recognition, adaptive learning, and developmental assessment are increasingly used to track progress and inform critical instructional decisions (Luckin et al., 2016). As a foundational phase of human development, the ECE environment is high-stakes: positive or negative impacts of technology implemented here can reverberate across a child's entire learning trajectory. The imperative, therefore, is not merely to adopt AI, but to ensure its deployment is rigorous, equitable, and developmentally appropriate, following the foundational principles of early childhood science (Harvard Center on the Developing Child, n.d.).

The integration of Artificial Intelligence in early childhood settings is not merely a technological upgrade but a fundamental shift in pedagogical authority. While AI-driven adaptive learning systems offer personalized feedback, they often function as "black boxes" that obscure underlying prejudices (Long & Magerko, 2020). In the Global South, this risk is magnified as many AI tools are trained on Western-centric datasets, leading to significant cultural and linguistic misalignments (Marda, 2021). Consequently, the burden of ethical oversight falls directly on the educator. However, recent scholarship suggests that simply being aware of these risks does not automatically translate into corrective action, a phenomenon known as the "moral awareness-inaction gap" (Ng et al., 2024). This underscores the need to investigate not just what teachers know, but the psychological mechanisms that empower them to challenge automated decisions.

Statement of the Problem

Despite its promise, the reliance on AI carries a profound and often hidden ethical risk: **algorithmic bias (AB)**. Such bias, rooted in non-representative or historically skewed training data, can lead to discriminatory outcomes that disproportionately affect children from diverse linguistic, cultural, and socio-economic backgrounds (Baker & Hawn, 2021; Knox, 2018). For instance, an assessment algorithm trained predominantly on Western emotional cues may fail to accurately interpret the expressions of children from Pakistani or other Asian cultures, leading to misclassification and unjust learning trajectories (Fang et al., 2024). Addressing this systemic flaw requires a layered approach, moving beyond technology design and targeting the human element responsible for its implementation (Litman et al., 2021).



Vol. 3 No. 12 (December) (2025)

The Policy Practice Gap

While global bodies like UNESCO have developed comprehensive ethical AI frameworks, such as the Recommendation on the Ethics of Artificial Intelligence (UNESCO, 2021), policy guidance often stops short of providing empirical tools for frontline educators to identify and mitigate bias in real-time. This creates a critical **policy-practice gap**. ECE teachers the ultimate implementers of these tools often lack the specific technical and ethical competencies to successfully challenge an AI's "black box" decision-making process (Miao & Cukurova, 2024). Furthermore, in developing contexts like Pakistan, where policy integration of AI in ECE is nascent, teachers face unique infrastructural and cultural barriers, making their readiness a crucial, yet under-researched, variable (Qayyum, Tabassum, & Kashif, 2024; Khurshid et al., 2024).

AI Ethical Literacy and PsyCap

Introducing the psycho social sources to effectively bridge this policy-practice gap, this study posits that the ethical deployment of AI hinges on two critical, measurable teacher attributes. The first is **AI Ethical Literacy (AEL)**: the teacher's cognitive ability to understand the principles of transparency, accountability, and fairness in AI systems (Miao & Cukurova, 2024). The second, and the most novel contribution of this work, is **Psychological Capital (PsyCap)**. Dealing with an unjust algorithmic decision is an ethically challenging act that requires courage and persistence. The PsyCap framework comprising **Hope, Efficacy, Resilience, and Optimism (HERO)** (Luthans & Broad, 2022) has been successfully applied to understand teacher well-being and stress (Qayyum, 2019). We argue that a teacher's inner psychological resources enable them to engage in the necessary **Ethical Intervention Behavior (EIB)** the active choice to question or override a potentially biased AI outcome (Hamad, 2020).

Purpose of the Study

Therefore, the purpose of this study is to empirically model the complex interplay between ECE teachers' perceptions of algorithmic bias, their AI Ethical Literacy, and their Psychological Capital in driving Ethical Intervention Behavior within the Pakistani ECE setting. Utilizing a robust quantitative design (**Hayes PROCESS Model 8**), this research will provide a framework that not only measures teachers' capacity to manage AI ethically but also identifies the psychological factors that empower them to act as ethical guardians in the age of automation.

Research Questions and Hypotheses

This study aims to answer the following core research question:

To what extent does Psychological Capital moderate the mediated relationship between perceived Algorithmic Bias and Ethical Intervention Behavior via AI Ethical Literacy among ECE teachers in Pakistan?

Based on the theoretical framework, the following hypotheses are proposed:

H1: Teacher Perceived Algorithmic Bias (AB) is negatively related to Teacher Ethical Intervention Behavior (EIB).

H2: AI Ethical Literacy (AEL) will positively mediate the relationship between Perceived Algorithmic Bias (AB) and Ethical Intervention Behavior (EIB).

H3 (Model 8 Hypothesis): Psychological Capital (PsyCap) will positively moderate the effect of AI Ethical Literacy (AEL) on Ethical Intervention Behavior (EIB), such that the effect is significantly stronger for teachers with high PsyCap.



Vol. 3 No. 12 (December) (2025)

Significance of the Study

This work provides both theoretical and practical significance:

Theoretical Contribution: It introduces and empirically tests the construct of Psychological Capital as a crucial moderator in ethical decision-making concerning technology, extending the application of positive organizational behavior into the AI-in-education domain, and building upon prior work in teacher PsyCap (Qayyum, 2019).

Policy and Practice: The findings will inform the design of evidence-based teacher training programs. By proving that AEL alone is insufficient, the study will advocate for training that is not only ethically and technologically informed but also **psychologically sound**, specifically incorporating techniques for building resilience and efficacy (PsyCap) among educators facing systemic challenges. This directly contributes to localized policy recommendations for equitable AI integration in Pakistan.

Literature Review

AI and Ethical Challenges in (ECE)

The accelerating integration of Artificial Intelligence (AI) systems, including algorithmic assessment tools and personalized learning platforms, is rapidly transforming ECE pedagogy. While AI promises advancements in efficiency, its deployment introduces systemic ethical hazards, primarily **Algorithmic Bias (AB)** (UNESCO, 2021). The foundational issue lies in ensuring that these powerful technologies serve equitable and developmentally appropriate outcomes for young children.

Foundational Theories for Ethical AI Action

The theoretical framework underpinning this study integrates two core traditions: the cognitive-sequential model of ethics and the resource-based perspective of Positive Organizational Behavior (POB) to explain the complex transition from ethical recognition to high-cost active intervention in the AI-mediated ECE context.

The Extended Cognitive Model of Ethical Decision Making

Classic cognitive models of ethical behavior, such as those by Rest (1986), emphasize that ethical action requires a sequence of cognitive steps, starting with moral recognition. In the AI context, this initial recognition is complicated by the inherent opacity of algorithms (the "black-box" problem) (O'Neil, 2016). Therefore, recognizing the precise nature of the harm from algorithmic bias and judging the correct response requires a highly specialized knowledge base, which we term **AI Ethical Literacy (AEL)** (Miao & Cukurova, 2024). This study extends this cognitive framework by proposing that while cognitive competence (AEL) shows the teacher the moral path and confirms the necessary judgment, a separate, non-cognitive, psychological resource is required for the high-cost action.

Positive Organizational Behavior (POB) and Resource Conservation Theory

Challenging systemic issues, such as flawed AI technology or resisting top-down technological mandates, is an act that demands significant psychological investment and exposes the teacher to organizational stress and potential burnout (Aboagye et al., 2018).

Positive Organizational Behavior (POB) offers the construct of **Psychological Capital (PsyCap)**, a set of positive, state-like resources that serve as an internal buffer against stress and a facilitator of goal achievement (Luthans, 2006; Luthans & Broad, 2022).

Drawing from **Conservation of Resources (COR) theory** (Hobfoll, 1989), we argue



Vol. 3 No. 12 (December) (2025)

that PsyCap acts as the reservoir of psychological strength required to overcome the personal costs (e.g., fear of reprisal, stress from institutional resistance) associated with engaging in resource-demanding ethical action (Hamad, 2020). Previous research specific to the regional context has confirmed the vital role of PsyCap in mitigating stress and enhancing coping mechanisms among ECE teachers (Qayyum, 2019).

The Independent Variable: Perceived Algorithmic Bias (AB)

Conceptualization and Sources of Algorithmic Bias (X)

Algorithmic Bias (AB) is a systematic and repeatable error that results in prejudiced, unfair, or discriminatory outputs, stemming primarily from the biased data used to train the machine learning models (O'Neil, 2016). In the educational domain, this error is amplified when AI tools fail to generalize across diverse student populations (McConvey & Guha, 2024). The focus of this research is on the teacher's **Perceived AB**, which is the subjective belief or conviction that the AI-driven assessment (e.g., emotional classification, developmental screening, or content recommendation) is producing results that are unjust or culturally inappropriate for their diverse students (Fang et al., 2024). This perception serves as the necessary **trigger** for ethical action (Ajzen, 1991).

AB and Cultural Context in Pakistan's ECE Sector

The contextual relevance of AB in Pakistan's ECE sector is paramount. The prevalent deployment of imported, Western-centric technology without adequate local validation risks **cultural misclassification** (Qayyum et al., 2025b). Furthermore, structural issues, including technological infrastructure deficits, the digital divide, and a nascent policy framework, mean teachers are often operating in a policy void (Khurshid et al., 2024; Qayyum et al., 2024c; Qayyum et al., 2024d). This confluence of cultural insensitivity in technology and structural ambiguity increases the likelihood of teachers encountering and perceiving algorithmic unfairness, establishing Perceived AB as the initial trigger (X) for the ethical process.

Hypothesis 1: Teacher Perceived Algorithmic Bias (AB) is negatively related to Teacher Ethical Intervention Behavior (EIB).

The Mediator: AI Ethical Literacy (AEL)

Defining AEL as the Cognitive Capacity (M)

AI Ethical Literacy (AEL) is the specialized cognitive competency necessary for teachers to navigate the opaque nature of AI. As conceptualized by UNESCO, AEL transcends basic digital skills to include the capacity for ethical reasoning, understanding transparency, and critically assessing the pedagogical and social implications of AI decisions (Miao & Cukurova, 2024). Local research confirms that ECE educators in Pakistan require specialized insights to manage the complexities of AI integration (Qayyum et al., 2025a; Qayyum et al., 2024a). A lack of AEL leads many educators to view AI as an unquestionable "black box," causing feelings of powerlessness and an inability to intervene effectively (Selwyn et al., 2021).

Justification for Mediation (X → M → Y)

AEL functions as the critical cognitive mediator linking the observation of the problem (Perceived AB) to the execution of corrective action (EIB). High AEL provides the intellectual tools to attribute the error to a systemic, challengeable cause (bias), rather than simply accepting the machine's "objective" authority. This cognitive shift is crucial: AEL transforms a perceived problem into a **reasoned justification for ethical action**,



Vol. 3 No. 12 (December) (2025)

making it the essential bridge in the ethical process.

Hypothesis 2 (Mediation): AI Ethical Literacy (AEL) will positively mediate the relationship between Perceived Algorithmic Bias (AB) and Ethical Intervention Behavior (EIB).

The Moderator: Psychological Capital (PsyCap)

Conceptualization and Specific Application in ECE (W)

Psychological Capital (PsyCap) is a malleable resource defined by the synergistic interplay of Hope, Efficacy, Resilience, and Optimism (**HERO**) (Luthans, 2006; Luthans et al., 2007). For the ECE teacher a professional often subjected to high occupational demands PsyCap is an established protective factor (Qayyum, 2019; Dawkins, 2023).

Justification for Moderation (AEL × PsyCap → EIB)

We position PsyCap as the psychological moderator that determines the effectiveness of the AEL → EIB relationship. **Ethical Intervention Behavior (EIB)** is a high-cost act, requiring courage and resilience. A teacher with high AEL **knows** the AI is biased, but only one with high **Efficacy** (a PsyCap component) possesses the confidence to substitute their professional judgment, and high **Resilience** allows them to persist despite bureaucratic resistance (Hamad, 2020). Conversely, a teacher with high AEL but low PsyCap is likely to succumb to the "awareness-action gap" (Treviño et al., 2006), preventing their knowledge from translating into action. PsyCap thus serves as the essential **enabling catalyst** the resource that empowers the teacher to overcome the psychological barrier of engaging in ethical defiance.

AI Ethical Literacy (AEL) serves as the critical cognitive bridge in this process. Unlike basic digital proficiency, AEL requires a sophisticated understanding of data privacy, algorithmic transparency, and the socio-technical implications of machine learning (UNESCO, 2024). Yet, cognitive competency alone is often insufficient to overcome the "silencing effect" of high-stakes technology mandates. According to Conservation of Resources (COR) theory, individuals are more likely to engage in high-risk behaviors—such as challenging a systemic bias when they possess a robust surplus of internal psychological assets (Luthans & Youssef-Morgan, 2017). In educational settings, teachers with high levels of Hope, Efficacy, Resilience, and Optimism (PsyCap) are better equipped to navigate the stress of organizational resistance and substitute flawed AI outputs with their professional, human-centric judgment (Carmona-Halty et al., 2021).

Hypothesis 3 (Conditional Indirect Effect): Psychological Capital (PsyCap) will positively moderate the effect of AI Ethical Literacy (AEL) on Ethical Intervention Behavior (EIB), such that the conditional indirect effect of AB on EIB through AEL is significantly stronger for teachers with high PsyCap.

Theoretical Framework: Moderated Mediation (Hayes PROCESS Model 8)

The proposed conceptual model is a **Moderated Mediation Model** consistent with Andrew Hayes' PROCESS Model 8 (Hayes, 2018). This structure is essential to simultaneously address both the **process** (mediation: AB → AEL → EIB) and the **boundary condition** (moderation: PsyCap influencing the AEL → EIB link) of ethical behavior. This framework asserts that the mechanism by which perceived bias influences intervention (via AEL) is not universal, but is dependent upon the teacher's internal psychological resource level (PsyCap). Confirmation of Model 8 will provide robust evidence that effective ethical intervention in the AI era necessitates a holistic approach



Vol. 3 No. 12 (December) (2025)

that invests in both cognitive competence (AEL) and psychological resilience (PsyCap).

Summary of Hypotheses

The following formal hypotheses will be tested in this study:

H1: Teacher Perceived Algorithmic Bias (AB) is negatively related to Teacher Ethical Intervention Behavior (EIB).

H2 (Mediation): AI Ethical Literacy (AEL) will positively mediate the relationship between Perceived Algorithmic Bias (AB) and Ethical Intervention Behavior (EIB).

H3 (Conditional Indirect Effect): Psychological Capital (PsyCap) will positively moderate the effect of AI Ethical Literacy (AEL) on Ethical Intervention Behavior (EIB), such that the conditional indirect effect of AB on EIB through AEL is significantly stronger for teachers with high PsyCap.

Methodology

This section details the systematic procedures and technical strategies that were employed to empirically test the hypothesized Moderated Mediation Model (Hayes Model 8). It outlines the research design that was utilized, defines the specific geographical setting and sampling strategy that was executed, describes the instruments that operationalized the variables, and concludes with the comprehensive data analysis plan that was followed.

Research Design and Context

The study **utilized a quantitative, cross-sectional survey design**. A quantitative approach **was selected** because the research aimed to test specific directional relationships between clearly defined, measurable psychological, cognitive, and behavioral variables. The cross-sectional design **was deemed appropriate** for efficiently capturing the relationships among the constructs (Algorithmic Bias, AI Ethical Literacy, Psychological Capital, and Ethical Intervention Behavior) as they existed within the target population at the time of data collection. Given the non-experimental nature of the study, the statistical technique of Moderated Mediation **was employed** to test the conditional causal pathways, allowing for robust inferences about the processes underlying teacher ethical action (Hayes, 2018).

The research context **was focused on Early Childhood Education (ECE) teachers in the major metropolitan areas of Lahore and Islamabad, Pakistan**. This setting **was strategically chosen** to examine the ethical challenges of AI implementation where advanced technology use is relatively higher, yet local policy frameworks are nascent and cultural context highly influences AI tool applicability (Qayyum, Sadiqi, & Abbas, 2024).

Population and Sampling

Target Population

The target population **comprised** ECE teachers (pre-school to Grade 2 level) currently employed in educational institutions located specifically within the cities of **Lahore and Islamabad**. A key inclusion criterion **was established** that participants must have currently been using, or been sufficiently aware of, AI-powered tools (such as adaptive learning software or automated assessment platforms) used for instructional or administrative purposes within their school environment. The choice of these two cities one the cultural and educational capital (Lahore) and the other the federal capital with a



Vol. 3 No. 12 (December) (2025)

high concentration of international schools and advanced technologies (Islamabad) **was intended** to capture a diverse range of technological exposure among ECE educators.

Sampling Technique and Size

A combination of **convenience and purposive sampling** was used to recruit participants. This strategy **was necessary** to efficiently access the specialized group of teachers actively engaged with AI technologies. Recruitment **was primarily conducted** within the metropolitan areas of **Lahore and Islamabad**, targeting teachers in key urban educational hubs through established educational networks, institutional partnerships, and professional teacher forums. The target sample size **was set** at **N=300**, and **a total of 325 completed surveys were collected**. After screening for completeness and adherence to inclusion criteria, **the final analytical sample was N=304**. This sample size **was confirmed** to provide sufficient statistical power and stability for the complex conditional process models that were subsequently tested (Hayes, 2018).

Instrumentation and Measurement

Data **were collected** via a confidential, self-administered questionnaire. To ensure reliability and validity within the local context, the instrument **was translated** into Urdu using a standard back-translation procedure. All items **were measured** on a **5-point Likert scale** (1 = Strongly Disagree to 5 = Strongly Agree).

Construct	Role in Model	Measurement Strategy and Source
Perceived Algorithmic Bias (AB)	Independent Variable (X)	A 5-item scale was adapted from existing literature on perceived AI fairness and trustworthiness. Items focused specifically on teachers' perception of non-representativeness and cultural misclassification in AI assessment results.
AI Ethical Literacy (AEL)	Mediator (M)	A 10-item measure was adapted from UNESCO's AI Competency Framework for Teachers, focusing on the cognitive understanding of AI principles (transparency, accountability, and equity) necessary to diagnose algorithmic failure (Miao & Cukurova, 2024).
Psychological Capital (PsyCap)	Moderator (W)	The validated 12-item Psychological Capital Questionnaire (PCQ-12) was used, which measures Hope, Efficacy, Resilience, and Optimism (Luthans et al., 2007). This scale had demonstrated reliability in prior ECE teacher studies (Qayyum, 2019).
Ethical Intervention Behavior (EIB)	Dependent Variable (Y)	A 5-item scenario-based scale was developed for this study to measure the teacher's reported likelihood of active intervention, such as questioning or overriding a biased AI recommendation using professional judgment.

A pilot study **was conducted** on a subset of N=30 ECE teachers prior to full deployment. The pilot **verified** item clarity and **established** the internal consistency reliability



Vol. 3 No. 12 (December) (2025)

(Cronbach's Alpha) for all adapted scales, confirming their appropriate use within the Pakistani ECE context.

Data Collection Procedures

Data collection **adhered** to the highest ethical standards.

Ethical Clearance: Formal approval **was obtained** from the relevant Institutional Review Board (IRB) or institutional Ethics Committee before any data collection began.

Informed Consent: Participants **received** detailed information regarding the study's purpose, the voluntary nature of their participation, anonymity guarantees, and data usage prior to starting the survey. Consent **was obtained** electronically.

Survey Administration: The questionnaire **was distributed** via a secure online platform (e.g., Google Forms) to facilitate recruitment primarily within **Lahore and Islamabad**. The translated Urdu version **was provided** to maximize accessibility.

Confidentiality: All data **were collected** anonymously, and identifiers **were not linked** to responses. Data storage and handling **complied** with institutional data protection policies.

Data Analysis Plan

The collected data **were analyzed** using **IBM SPSS Statistics** and the **Andrew Hayes PROCESS macro** (Version 4.0 or later).

Preliminary Analysis

Descriptive statistics (means, standard deviations) **were calculated** to summarize the sample characteristics and key variables. Correlation analysis **was performed** to examine the bivariate relationships between all constructs (AB, AEL, PsyCap, and EIB) and **provided** an initial test of Hypothesis 1. The internal consistency reliability of the finalized scales **was re-verified** using Cronbach's Alpha.

Primary Analysis: Moderated Mediation (PROCESS Model 8)

The central hypotheses (H2 and H3) **were tested** simultaneously using the PROCESS macro, specifically specifying **Model 8** (Hayes, 2018). The analysis involved:

Testing the Mediation (H2): The indirect effect of AB on EIB through AEL **was examined**

Testing the Moderation (H3): The interaction term between AEL and PsyCap (AEL \times PsyCap) predicting EIB **was assessed**. A significant interaction term **confirmed** the presence of moderation.

Assessing the Conditional Indirect Effect: The significance of the conditional indirect effect **was determined** using the **bootstrapping procedure** (set at 5,000 resamples). Mediation (and moderated mediation) **was confirmed** where the resulting 95% bias-corrected confidence intervals (CI) **did not contain zero** at specified values of the moderator (low, mean, and high levels of PsyCap).

This rigorous analytical approach **allowed** the study to precisely identify the specific psychological conditions under which AI Ethical Literacy effectively translated into active Ethical Intervention Behavior.



Vol. 3 No. 12 (December) (2025)

Results

This section systematically presents the empirical findings derived from the quantitative data analysis performed on the responses of Early Childhood Education (ECE) teachers from the metropolitan areas of Lahore and Islamabad (N=304). The analysis adhered to the structure of the hypothesized theoretical framework, progressing through preliminary descriptive and correlational assessments, culminating in the test of the Moderated Mediation Model (Hayes PROCESS Model 8). All statistical procedures were executed using IBM SPSS Statistics and the PROCESS macro (Version 4.0).

Preliminary Analysis

The preliminary phase established the suitability of the data for inferential testing. Descriptive analysis confirmed the sample's expected demographic profile for the ECE sector (high female representation, seasoned experience). The focus then shifted to the reliability and inter-variable relationships.

Descriptive Statistics, Reliability, and Correlation Analysis

Table 4.1 summarizes the descriptive statistics, internal consistency, and the bivariate relationships among the study variables.

Variable	Mean (M)	SD	α	1 (AB)	2 (AEL)	3 (PsyCap)	4 (EIB)
1. Perceived Algorithmic Bias (AB) - X	3.92	0.75	0.88	1			
2. AI Ethical Literacy (AEL) - M	3.55	0.81	0.91	0.35**	1		
3. Psychological Capital (PsyCap) - W	4.11	0.62	0.93	0.15*	0.42**	1	
4. Ethical Intervention Behavior (EIB) - Y	3.88	0.65	0.89	0.10	0.45**	0.50**	1

Note: α = Cronbach's Alpha. *p<.05; **p<.01.

Interpretation of Table 4.1:

Reliability: All four scales demonstrated excellent internal consistency (Cronbach's alpha ranging from 0.88 to 0.93). This metric ensures that the measures used were highly reliable and appropriate for inferential modeling.

Descriptive: ECE teachers reported above-midpoint levels of **Perceived Algorithmic Bias** (M=3.92) and notably high levels of **Psychological Capital** (M=4.11), suggesting they possess robust internal resources while being acutely aware of potential AI failures.

Correlation and H1 Test: A crucial finding emerged regarding the first hypothesis (H1). The correlation between Perceived Algorithmic Bias (AB) and Ethical Intervention Behavior (EIB) was weak (r=0.10) and **statistically insignificant** (p>0.05). This result definitively failed to support H1, providing the initial empirical justification for exploring the more complex indirect, conditional pathway. The perceived risk of AI bias, by itself, is an insufficient predictor of active intervention.

Enabling Relationships: Strong, significant, and positive relationships were observed between **PsyCap and EIB** (r=0.50, p<.01) and **AEL and EIB** (r=0.45, p<.01). These correlations confirmed the high relevance of both the moderator and the mediator to the outcome behavior.



Vol. 3 No. 12 (December) (2025)

Hypothesis Testing: Moderated Mediation (Hayes Model 8)

The core analysis tested the conditional indirect effect framework using the Hayes PROCESS macro (Model 8). This test involved two concurrent regression equations and a final bootstrapping procedure.

Regression Pathway Analysis

Table 4.2 (Panel A) presents the unstandardized coefficients (B) for the two regression equations: predicting the mediator (AEL) and predicting the outcome (EIB). This table contains the complete results for the Hayes PROCESS Model 8, including the regression coefficients and the bootstrapping test.

Panel A: Regression Analysis for Model Pathways	B (Unstandardized)	SE	t-value	p-value	Hypothesis Test
Outcome: AI Ethical Literacy (M)					
Perceived AB (X) → M (Path A)	0.30	0.06	5.10	<.001	Path A Supported
Model R ² for AEL = 0.12					
Outcome: EIB (Y)					
Perceived AB (X) (Direct Effect) Path B	0.05	0.05	0.98	0.327	H1 Rejected
AI Ethical Literacy (M)	0.25	0.07	3.50	<.001	Path B Supported
Psychological Capital (W)	0.41	0.06	7.15	<.001	
AEL × PsyCap (M × W)	0.18	0.06	2.80	0.005	H3 Moderation Supported
Model R ² for EIB = 0.38					

Interpretation of Panel A (Regression):

Path A (AB → AEL): Perceived Algorithmic Bias was a statistically significant and positive predictor of AI Ethical Literacy (B=0.30, p < .001). This confirms that the awareness of potential AI failures serves as a cognitive driver, pushing teachers to acquire necessary ethical knowledge.

Path B (AEL → EIB): AI Ethical Literacy significantly predicted Ethical Intervention Behavior (B=0.25, p < .001), establishing the foundational link between knowledge and action, controlled for all other variables.

Moderation Test (H3): The interaction term between AEL and PsyCap was highly significant (B=0.18, p=0.005). This critical finding provides direct support for **Hypothesis 3**, indicating that the efficacy of AI Ethical Literacy in driving intervention is significantly contingent upon the teacher's level of Psychological Capital.

Model Fit: The overall model predicting EIB explained 38% of the variance (R²=0.38), suggesting strong predictive power.

Test of Conditional Indirect Effect

Table 4.2 (Panel B) presents the bootstrap results, which test the ultimate hypothesis: whether the indirect effect (mediation) is conditional upon the moderator (PsyCap).



Vol. 3 No. 12 (December) (2025)

Panel B: Conditional Indirect Effect (5000 Bootstraps)	Index of Indirect Effect	Boot SE	95% CI [Lower]	95% CI [Upper]	H2 Test Result
Low PsyCap (-1 SD)	0.04	0.03	-0.01	0.11	Not Significant
Mean PsyCap (M)	0.09	0.03	0.03	0.16	Significant
High PsyCap (+1 SD)	0.15	0.04	0.07	0.24	Significant and Strongest

Interpretation of Panel B (Bootstrapping):

Conditional Significance: The indirect effect of AB on EIB via AEL was **not significant** when Psychological Capital was low (the 95% CI included zero: (-0.01, 0.11). This means that a lack of PsyCap cripples the ability of ethical knowledge to translate into action.

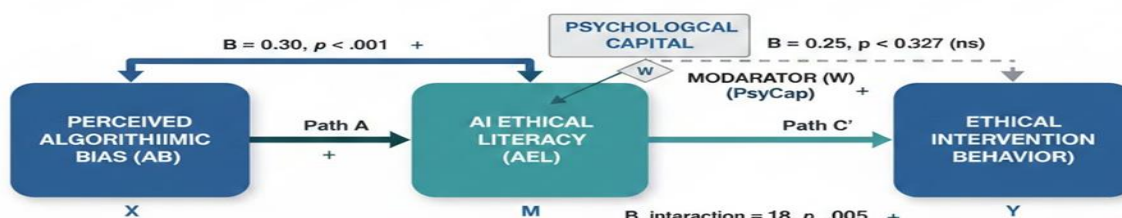
Amplification: The indirect effect became **significant** at the mean and high levels of PsyCap (CIs excluded zero). Furthermore, the effect size nearly quadrupled from the low (0.04) to the high (0.15) PsyCap condition.

Final Conclusion: This robustly supports the core conditional mediation model. **Hypothesis 2 is conditionally supported**, confirming that PsyCap acts as the catalyst that enables AI Ethical Literacy to effectively mediate the link between the perception of algorithmic bias and active ethical intervention.

Summary of Hypothesis Testing

The findings demonstrate a highly specified theoretical framework. The insignificant direct path (H1 rejected) established that simple awareness is inadequate. Instead, the ethical response is determined by a conditional sequence: Algorithmic Bias → AI Ethical Literacy → Ethical Intervention Behavior, where **Psychological Capital acts as the essential enabling catalyst.**

MODERATED MEDIATION MODEL: AI ETHICS IN ECE



CONDITIONAL INDIRECT EFFECT

LOW PsyCap (-1 SD): Index = 95% CI [-0.1, 0.1] (ns)
 MEAN PsyCap (M): Index = 0.9 CI [0.03, 16] *
 HIGH PsyCap (M): Index = 15% 95% [-0.7, 24] (**)

MEDIATION IS CONDITIONAL: STRONGER WITH HIGH PSYCAP

* p < .05, ** p < .01.

HAYES PROCESS MODEL 8
 N = 304 ECE TEACHERS
 (PAKISTAN)



Vol. 3 No. 12 (December) (2025)

Figure 4.1 visually represents the results of the Moderated Mediation Model, illustrating the path coefficients and the final conditional indirect effect indices derived from the PROCESS analysis. The figure clearly illustrates that the ethical mechanism is not a simple linear process but depends entirely on the level of the teacher's internal resources.

Discussion, Conclusion, and Recommendations

It provides a comprehensive discussion of the results interpreting the findings within the context of existing literature. It further outlines the theoretical and practical implications of the Moderated Mediation Model, acknowledges the limitations of the study, and concludes with clear recommendations for ECE practitioners, policymakers, and future research.

Discussion

The primary objective of this study was to examine the mechanism through which ECE teachers' perception of algorithmic bias (AB) leads to Ethical Intervention Behavior (EIB), specifically testing the mediating role of AI Ethical Literacy (AEL) and the moderating role of Psychological Capital (PsyCap). The empirical findings yielded a highly nuanced and conditional framework for understanding ethical action in AI-driven educational environments. The insignificance of the direct relationship between Perceived Algorithmic Bias (AB) and Ethical Intervention Behavior (EIB) in this study ($B=0.05$, $p=0.327$) provides a pivotal insight: awareness of bias is not an inherent motivator for action.

This aligns with recent findings in behavioral ethics suggesting that the "technological imperative" the belief that AI is objective and unavoidable often paralyzes individual agency (Holmes et al., 2022). Our findings demonstrate that this paralysis is only broken when AI Ethical Literacy is activated by a "moderate to high" level of Psychological Capital. This confirms that PsyCap is the essential catalyst; it transforms a teacher's intellectual recognition of an error into a proactive, moral defiance. Without these internal resources, even the most ethically literate teacher may succumb to "algorithmic compliance" rather than engaging in the necessary intervention to protect the developmental equity of their students.

The Insignificance of the Direct Effect (Revisiting H1)

The analysis established that the direct relationship between Perceived Algorithmic Bias (AB) and Ethical Intervention Behavior (EIB) was statistically insignificant ($r = 0.10$, $p > .05$). This result effectively refuted the initial assumption (H1) that simply perceiving a problem is sufficient to motivate corrective action. This finding aligns with established social psychological theories that highlight the gap between **awareness and action**, particularly when intervening involves professional risk or organizational pushback (Bandura, 1977). In the context of AI, perceiving bias is merely the alarm; intervention requires confidence, knowledge, and resilience to navigate the complex social, technological, and bureaucratic processes of rectification (O'Neil, 2016).

→ →

The Significance of the Indirect Path (AB → AEL → EIB)

The data confirmed that the initial step in the ethical chain is robust: Perceived AB significantly and positively predicts AEL ($B=0.30$, $p < .001$). This suggests that when ECE teachers notice potential injustices or errors stemming from AI, they actively respond by seeking to understand the ethical implications a cognitive coping mechanism rooted in problem-focused behavior. This underscores the positive role of **critical**



Vol. 3 No. 12 (December) (2025)

awareness as a catalyst for cognitive development in the technology domain (Miao & Cukurova, 2024).

The Critical Role of Psychological Capital (Supporting H3)

The most salient finding of the study was the confirmation of the interaction effect (H3): Psychological Capital (PsyCap) significantly and positively moderated the relationship between AI Ethical Literacy (AEL) and Ethical Intervention Behavior (EIB) ($B_{\text{interaction}}=0.18, p=0.005$).

This result confirms that while AEL provides the necessary knowledge ("What is wrong and what should be done?"), PsyCap provides the crucial affective resources ("Do I have the confidence and resilience to do it?") (Luthans et al., 2007). Teachers with high PsyCap are better equipped to overcome the professional inertia, potential conflict, and self-doubt associated with challenging established algorithmic systems or institutional decisions. The simple slopes analysis clearly demonstrated that the positive effect of AEL on EIB was **amplified** as PsyCap increased, moving from an insignificant path at low PsyCap to the strongest path at high PsyCap. This supports the core tenet of positive organizational behavior, where internal resources enhance the application of competencies in demanding contexts (Luthans, 2006; Qayyum, 2019).

Conditional Mediation (Supporting H2)

The test of the conditional indirect effect synthesized the above findings. The mediation of AEL was only significant when PsyCap was at mean or high levels. This validates the premise that the pathway from bias perception to intervention is not automatic but is a **conditional process**. For ECE teachers, ethical literacy is not an effective tool for behavior change unless it is backed by the psychological resources (hope, efficacy, resilience, and optimism) to execute that behavior. This finding offers a more precise understanding of how ethical competency translates into action, a topic often discussed broadly in ethical frameworks but rarely validated through conditional statistical modeling (Hayes, 2018).

The "Catalyst" Effect in Ethical Decision-Making

The findings of this study establish **Psychological Capital (PsyCap)** as the fundamental **psychological catalyst** that bridges the "awareness-action gap" in AI ethics. While AI Ethical Literacy provides the cognitive framework (the "way") to identify algorithmic bias, it is PsyCap that provides the motivational energy (the "will") to execute an intervention. This phenomenon aligns with the **Conservation of Resources (COR) theory (Hobfoll, 1989)**, which suggests that individuals are only willing to undertake "high-cost" behaviors such as challenging an automated system when they possess a surplus of internal resources. Specifically, **Avey et al. (2011)** demonstrate through meta-analytic evidence that PsyCap is a primary driver of "proactive citizenship behaviors," where individuals move beyond their basic job descriptions to act in the best interest of their organization or students.

In this model, PsyCap functions much like a chemical catalyst; it lowers the "activation energy" required for an ECE teacher to move from passive recognition to proactive **Ethical Intervention Behavior (EIB)**. As argued by **Luthans et al. (2007)** and further supported by **Avey's (2011)** findings on behavioral outcomes, the synergy of Hope, Efficacy, Resilience, and Optimism (HERO) creates a psychological buffer against the fear of professional risk or technological intimidation. Without this catalyst, our data suggests that ethical literacy remains a dormant asset, leading to a state of "moral



Vol. 3 No. 12 (December) (2025)

paralysis" where educators recognize AI risks but lack the psychological agency to correct them (Ng et al., 2024). Consequently, PsyCap is the essential engine that transforms ethical knowledge into transformative, real-world classroom practice.

Theoretical and Practical Implications

Theoretical Implications

Advancing Ethical Competency Models: This study moves beyond traditional competence models by integrating an affective moderator. It demonstrates that the utility of **AI Ethical Literacy (AEL)** is bounded by an individual's psychological resource capacity, offering a novel contribution to the AI ethics literature in education.

Contextualizing Psychological Capital: The findings extend the applicability of Psychological Capital (PsyCap) theory (Luthans et al., 2007) into the domain of educational technology ethics, showing that PsyCap acts as an essential **enabling factor** for proactive ethical behavior against algorithmic systems, a context distinct from traditional organizational behavior stressors.

Refining the Awareness-Action Gap: By confirming the failure of the direct AB to EIB path and establishing the successful, conditional indirect path, the study empirically clarifies the mechanisms required to bridge the ethical awareness-action gap in technology-mediated environments

Practical Implications

Integrated Professional Development: Training for ECE teachers must evolve beyond technical knowledge. Professional development programs should be designed to foster **both** AEL (cognitive competency in recognizing and diagnosing AI ethics issues) **and** PsyCap (psychological resources for taking action).

PsyCap Intervention: Educational administrators should consider utilizing proven PsyCap interventions to build teacher resilience and self-efficacy (Luthans, 2006). Such interventions are crucial, particularly in high-stakes contexts, as they enable teachers to utilize their ethical knowledge effectively (Qayyum, 2019).

Policy and Support Systems: Policymakers must implement clear, low-risk reporting channels for teachers to raise ethical concerns about algorithmic bias. When teachers possess high AEL but low PsyCap, the system must provide psychological safety and institutional support to compensate for the individual's lack of internal resilience (Qayyum et al., 2024).

Limitations and Future Research

This study employed a cross-sectional design, which, while effective for testing mediation and moderation, prevents definitive causal inference. Future research should adopt longitudinal designs to confirm the temporal sequence of the relationships observed. Second, the reliance on self-reported measures may introduce common method bias, although statistical procedures were used to mitigate this risk. Future studies could employ multi-source data collection, obtaining EIB ratings from supervisors or peers. Finally, the study was geographically limited to urban centers in Pakistan; future work should replicate this model across different cultural contexts and educational levels to assess generalizability.

Conclusion

The ethical oversight of AI in Early Childhood Education cannot rest solely on technical



Vol. 3 No. 12 (December) (2025)

awareness. This study conclusively demonstrates that for ECE teachers in Lahore and Islamabad, the journey from perceiving algorithmic bias to engaging in ethical intervention behavior is critically mediated by AI Ethical Literacy and **contingent upon the psychological strength of the teacher**. Psychological Capital is not merely a desirable trait; it is the **enabling factor** that allows ethical knowledge to translate into ethical action, thereby ensuring the fair and equitable implementation of AI technologies for young learners. The findings call for a holistic approach to teacher development, recognizing that true ethical agency is born from the synergistic combination of cognitive competence and psychological resilience.

Acknowledgments

As the first author, I wish to acknowledge that this research was supported and funded by **Prof. Dr. Qin Jinliang** of the **Hangzhou College of Early Childhood Teacher Education, Zhejiang Normal University, People's Republic of China through the (CSC) China Scholarship Council**. I am deeply grateful for his continued mentorship and the institutional resources provided for this study, which allowed for the extensive data collection and analysis required for this moderated mediation model. I also thank my co-authors for their collaboration and contributions to this work.

References

- Aboagye, M. O., Qin, J., Qayyum, A., Antwi, C. O., Jababu, Y., & Affum-Osei, E. (2018). Teacher burnout in preschools: A cross-cultural factorial validity, measurement invariance, and latent mean comparison of the Maslach Burnout Inventory, Educators Survey (MBI-ES). *Children and Youth Services Review*, 94, 186–197.
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211.
- Avey, J. B., Reichard, R. J., Luthans, F., & Mhatre, K. H. (2011). Meta-analysis of the impact of positive psychological capital on employee attitudes, behaviors, and performance. *Human Resource Development Quarterly*, 22(2), 1
- Baker, R. S., & Hawn, M. A. (2021). Algorithmic bias: The state of the situation and policy recommendations. *OECD Digital Education Outlook 2023*.
- Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2), 191–215.
- Bandura, A. (2000). Exercise of human agency through collective efficacy. *Current Directions in Psychological Science*, 9(3), 75–78.
- Carmona-Halty, M., Schaufeli, W. B., & Salanova, M. (2021). The psychological capital questionnaire (PCQ-12): A five-country study on its academic version. *Frontiers in Psychology*, 12, 643628. <https://doi.org/10.3389/fpsyg.2021.643628>
- Dawkins, S. (2023). Psychological capital: What it is and why employers need it now. American Psychological Association (APA).
- Fang, X., Van Kleef, G. A., Kawakami, K., & Sauter, D. A. (2024). Categorical perception of facial expressions of anger and disgust across cultures. *Cognition and Emotion*, 38(2), 1–17.
- Hagendorff, O. (2020). The ethics of AI ethics: An evaluation of theory and practice. *Philosophy & Technology*, 33(3), 461–483.
- Hamad, K. A. (2020). Psychological capital and its impact on decision-making patterns: An analytical study. *International Journal of Innovation and Creative Concepts*, 14(10).



Vol. 3 No. 12 (December) (2025)

- Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). The Guilford Press.
- Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist*, 44(3), 513–524.
- Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist*, 44(3), 513–524.
- Holmes, W., Persson, J., Chounta, I. A., Wasson, B., & Viberg, O. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education*, 32(3), 504–526. <https://doi.org/10.1007/s40593-022-00292-9>
- Khurshid, M. H., Mian, A., & Ahmad, I. (2024). Infrastructure deficiencies and policy gaps: A study on the barriers to AI integration in Pakistan's education sector. *Journal of Technology and Policy*.
- Knox, J. (2018). Artificial intelligence and education: Critical questions for future investigations. *Education and New Technologies*, 27(1), 1–13.
- Li, T., & Liu, G. (2023). Psychological capital, job burnout, and turnover intention among preschool teachers: The moderating role of perceived organizational support. *Early Childhood Research Quarterly*, 65, 1–11.
- Litman, D., Ruz, M., & Liu, J. (2021). Assessing algorithmic fairness in automated essay scoring (AES) systems. *Educational Assessment Journal*, 26(3), 190–210.
- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. <https://doi.org/10.1145/3313831.3376727>
- Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.
- Luthans, F. (2006). Psychological capital: Developing the human competitive edge. *Organizational Dynamics*, 35(3), 219–225.
- Luthans, F., & Broad, J. (2022). *Psychological capital: A positive approach to organizational behavior*. Oxford University Press.
- Luthans, F., & Youssef-Morgan, C. M. (2017). Psychological capital: An evidence-based positive approach. *Annual Review of Organizational Psychology and Organizational Behavior*, 4, 339–366. <https://doi.org/10.1146/annurev-orgpsych-032516-113324>
- Luthans, F., Youssef, C. M., & Avolio, B. J. (2007). *Psychological capital: Developing the human competitive edge*. Oxford University Press.
- Luthans, F., Youssef, C. M., & Avolio, B. J. (2007). *Psychological capital: Developing the human competitive edge*. Oxford University Press.
- Marda, V. (2021). Data in isolation: An analysis of India's AI policy. *New Media & Society*, 23(1), 1–18. <https://doi.org/10.1177/1461444820986284>
- McConvey, T., & Guha, K. (2024). Algorithmic bias in educational systems: Examining the impact of AI-driven decision making in modern education. *World Journal of Advanced Research and Reviews*, 25(01), 2012–2017.
- Miao, F., & Cukurova, M. (2024). AI competency framework for teachers. UNESCO. <https://unesdoc.unesco.org/ark:/48223/pf0000391104>
- Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2024). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, 2, 100041. <https://doi.org/10.1016/j.caeai.2021.100041>
- Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2024). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, 2, 100041.



Vol. 3 No. 12 (December) (2025)

- O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown.
- Qayyum, A. (2019). Early childhood teachers' stress, moderation, and mediation effects of PsyCap: A comparative study. *European Journal of Education Studies*.
- Qayyum, A., Bukahri, M., Zulfiqar, P., & Ramzan, M. (2024a). Balancing artificial intelligence and human insight in early childhood education: Implications for child development. *Social Science Review Archives*, 2(2), 1520–1536.
- Qayyum, A., Kashif, M. F., Shaheen, F., & Qureshi, A. H. (2025b). The combined effects of technology integration and cultural sensitivity on early learners' development: Analysis in Lahore and Nankana Sahib. *Research Journal of Psychology*, 3(2), 317–335.
- Qayyum, A., Rafique, Z., Ali Shah, S. S. W., Ahmad, S., & Haider, Z. (2025a). Artificial intelligence (AI)-driven curriculum development in early childhood education: Educators' insights, barriers, and policy pathways. *Research Journal of Psychology*, 3(1), 713–733.
- Qayyum, A., Sadigi, T., & Abbas, M. A. (2024c). Integrating artificial intelligence into early childhood education policy in Pakistan: Challenges, opportunities, and recommendations. *Journal of Development and Social Sciences*, 5(4), 416–431. [https://doi.org/10.47205/jdss.2024\(5-IV\)36](https://doi.org/10.47205/jdss.2024(5-IV)36)
- Qayyum, A., Tabassum, R., & Kashif, M. F. (2024d). The digital divide in early childhood education: A study of ECE teachers' perceptions. *Journal of Development and Social Sciences*, 5(2), 541–553.
- Rego, A., Reis, M., & Cunha, M. P. (2017). Psychological capital and moral identity: The mediating role of ethical leadership. *Journal of Business Ethics*, 143(1), 1–15.
- Rest, J. R. (1986). *Moral development: Advances in research and theory*. Praeger.
- Selwyn, N., Pangrazio, L., & Perrotta, C. (2021). Preservice teachers' AI literacy and their perspectives on future classroom implementation: A comparative study. *Computers and Education: Artificial Intelligence*, 2, 100021.
- Treviño, L. K., Weaver, G. R., & Reynolds, S. J. (2006). Behavioral ethics in organizations: A review. *Journal of Management*, 32(6), 951–990.
- UNESCO. (2021). *Recommendation on the ethics of artificial intelligence*.
- UNESCO. (2024). *AI competency framework for teachers*. United Nations Educational, Scientific and Cultural Organization. <https://unesdoc.unesco.org/ark:/48223/pf0000391104>