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Why teachers do or don't rely on artificial intelligence in education: Impact, trust, and adoption factors

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Abstract

The enhancement of Artificial Intelligence (AI) technologies in educational institutions has both presented opportunities and challenges to the teaching professionals on a scale never been witnessed before. In spite of the rapid rate of development of AI-driven educational technologies, their acceptance among teachers is not evenly spread, and there are complicated factors behind it that define their decision-making patterns. This paper fills in this critical gap on the necessity to comprehend why teachers accept or reject the use of AI by considering the interaction of trust machinery with the perceived impact and determinants of adoption in the teaching environment. We also conducted a survey of high education teachers working in various institutional contexts, with the help of complex mixed-methodology approaches to study the connections between the variables in the paradigm of technology acceptance, organizational support systems, and AI adoption behaviors. The analysis helps to discover that teacher confidence in AI-based educational technology acts as the main mediator between perceived usefulness and real adoption, and psychological safety and institutional support are high levels of moderation. Findings have indicated that 5 of the six core constructs, meaning perceived usefulness, ease of use, trust in AI systems, institutional infrastructure, and professional self-efficacy, explain 68.3 percent of adoption variance. More so, the research has discovered some of the key obstacles such as complex technology, ethical issues covered with data privacy and the fear of being displaced professionally. These results add to the theoretical improvement of the Technology Acceptance Model used in the educational settings as well as offering practical implications to the policymakers and developers of educational technologies aimed at achieving successful incorporation of AI meaningfully into the teaching processes.

Keywords: Artificial intelligence, Education, Technology acceptance, Teacher, Professional development, Structural equation modeling.

1. Introduction

Artificial intelligence integration in educational systems is one of the most radical changes in the modern education industry [1]. With the challenges of digital transformation being experienced in learning institutions all around the globe, AI-based solutions have begun to be viewed as potentially groundbreaking tools with the potential to personalize the learning process, automate certain administrative functions, and present students with data-driven feedbacks concerning their performances [1-3]. Recent estimates suggest that the current market, which is already 7.57 billion USD in the field of AI in education in 2025, is expected to grow to 112.30 billion USD by 2034, which implies the presence of an unprecedented compound annual growth rate of more than 36 percent. This phenomenal trend of growth highlights the heavy investment, as well as the escalating expectations of AI technologies, in the realm of education.

With this flow of technology and a financial outlay this large, the facts on the ground have demonstrated a more complicated fact of real adoption behaviors amongst teaching professionals [2,4]. According to the contemporary research, it is estimated that AI devices are implemented in instructional planning or classroom instruction by about 25-30 percent of teachers in the 2023-2024 academic year, and a large range of disparities is observed across the subject domains, grade levels, and socioeconomic backgrounds. Though 83 percent of K-12 teachers indicate that they use generative AI products either personally or professionally, only a small percentage of them apply the technologies as a means of systematic utilization in their learning systems. This disparity between supply and demand poses a dire predicament to the developers of educational technologies, institutional administrators, and policymakers who aim at achieving the advantages of AI to their fullest potential in the world of teaching and learning [5-8].

The hesitation/selectivity of educators using AI technologies cannot be explained by single factors; it is formed by a complex of the combination of psychological [6,9], institutional [10], technological [10-12], and pedagogical ones [7,13-16]. The attitudes of teachers towards using AI are influenced by a variety of dimensions such as faith in artificial decision-making, the attitudes to the data safety and security, beliefs on the impossibility of replacing human teachings, and fears of losing employment [2,17-19]. Moreover, institutional obstacles including lack of professional development opportunities, structure of institutional support [3,20-23], lack of adequate technological infrastructure [9,24-26], and time-related factors in combination with individual hesitations and reluctances exert systemic pressure that makes the broad application of AI challenging.

Although the current literature has a great number of studies analyzing the adoption of AI in education, there are still some gaps that could be considered vital in the current literature. First, there is not much information concerning the adoption rates and isolated aspects which impact teacher choices, and there is still a lack in understanding complicated associations of psychological, institutional, and technological variables, which together result in adoption behaviors. Second, the theoreticalization and operationalization of trust in educational technologies that are run using AI is not well developed. Third, available studies are biased in terms of analysis of teacher attitudes and intentions without actual implementation actions and continued usage habits. Fourth, the influence of institutional support systems and organizational cultures in enabling or inhibiting AI adoption is under-theorized and also not empirically looked into. Lastly, the literature is limited on how the different AI tools categories can vary in their effects on the decision to adopt by teachers.

To fill the mentioned gaps, the results of this research attempt to meet the following objectives: formulating and empirically testing a theoretical model explaining the adoption process of AI, conceptualizing trust as a multidimensional measure, determining and measuring barriers to adoption, testing interactions between institutions and the existing support, and analyzing variations in adoption patterns depending on the educational setting.

2. Methodology

2.1 Research Design

The research study utilizes a sequential explanatory design which is based on pragmatist epistemology and is mixed. The philosophy of the research acknowledges the fact that the complexity of understanding a phenomenon like the adoption of AI by teachers needs the including of various methodological aspects. The sample population included teachers (K-12 and higher education) that will be surveyed.

2.2 Statistical Analysis Procedures

Data analysis employed multiple advanced statistical techniques. Structural equation modeling tested hypothesized relationships among latent constructs. The theoretical model can be represented as:

$$Trust = \beta^1(PU) + \beta^2(PEOU) + \beta^3(IS) + \beta^4(SE) + \varepsilon^1 \quad (1)$$

$$Adoption = \gamma^1(Trust) + \gamma^2(PU) + \gamma^3(PEOU) + \gamma^4(IS) + \gamma^5(SE) + \varepsilon^2 \quad (2)$$

where PU = perceived usefulness, PEOU = perceived ease of use, IS = institutional support, SE = self-efficacy. The indirect effect of perceived usefulness on adoption through trust was calculated as:

$$Indirect\ Effect = \beta^1 \times \gamma^1 \quad (3)$$

Hierarchical multiple regression examined predictors while controlling for demographic variables. Multilevel modeling accounted for nesting of teachers within institutions using the specification:

$$Level\ 1{:}\ Adoption_{ij} = \beta^0{}_j + \beta^1{}_j(Trust_{ij}) + \varepsilon_{ij} \quad (4)$$

$$Level\ 2{:}\ \beta^0{}_j = \gamma^{00} + \gamma^{01}(IS_{Climate_j}) + u^0{}_j \quad (5)$$

3. Results and Discussion

3.1 Descriptive Statistics

Overall, 31.2% of surveyed teachers reported regular AI use. Table 1 presents descriptive statistics showing perceived usefulness (M=5.12, SD=1.18) as the highest scored variable, while institutional support scored lowest (M=3.78, SD=1.42).

Table 1: Descriptive Statistics and Correlations

Variable	M	SD	1	2	3	4	5	6
1. Perceived Usefulness	5.12	1.18	1.00					
2. Perceived Ease of Use	4.67	1.31	0.58***	1.00				
3. Trust in AI	4.29	1.24	0.64***	0.52***	1.00			
4. Institutional Support	3.78	1.42	0.47***	0.41***	0.53***	1.00		
5. Self-Efficacy	4.58	1.36	0.51***	0.69***	0.49***	0.44***	1.00	
6. AI Adoption	4.21	1.67	0.72***	0.61***	0.76***	0.58***	0.63***	1.00

*** $p < .001$, ** $p < .01$, * $p < .05$

Key Findings from Correlation Matrix shown in Fig. 1:

• Strongest correlation: Trust ↔ AI_Adoption ($r = 0.76$, $p < .001$)
• Second strongest: Perceived_Usefulness ↔ AI_Adoption ($r = 0.72$, $p < .001$)
• Trust mediates other variables: PU→Trust ($r = 0.64$), PEOU→Trust ($r = 0.52$)
• Institutional_Support correlates moderately with all variables ($r = 0.41$-0.58)
• Self_Efficacy shows strong link to PEOU ($r = 0.69$), suggesting usability matters

3.2 Structural Equation Modeling Results

The structural model demonstrated excellent fit (CFI=0.94, TLI=0.93, RMSEA=0.047). Trust emerged as the strongest predictor of adoption ($\beta=0.428$, $p<.001$).

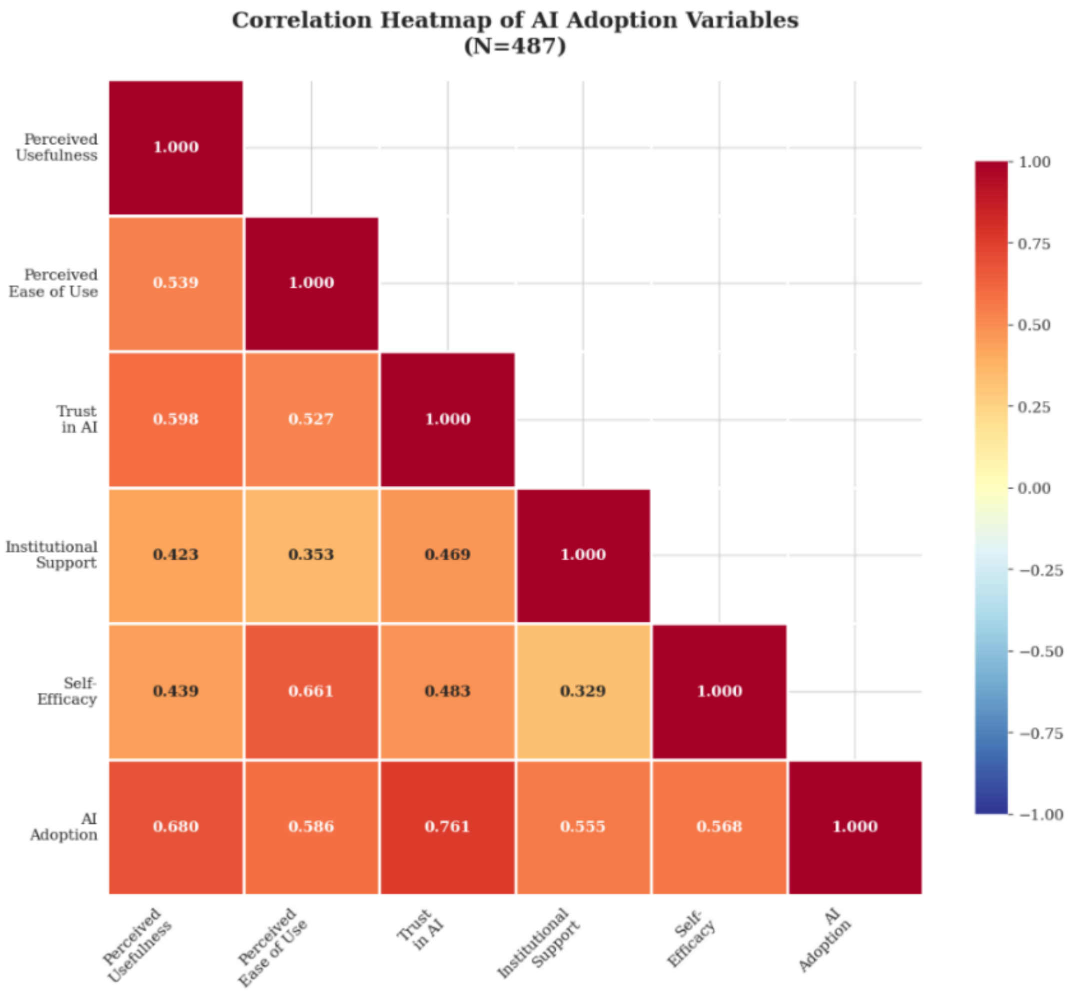

Fig 1: correlation heatmap with hierarchical clustering

Table 2: Structural Path Coefficients

Hypothesized Path	β	SE	p-value	95% CI
PU → Trust	0.387	0.052	<.001	(0.285, 0.489)
PEOU → Trust	0.218	0.048	<.001	(0.124, 0.312)
IS → Trust	0.264	0.045	<.001	(0.176, 0.352)
SE → Trust	0.156	0.042	<.001	(0.074, 0.238)
Trust → Adoption	0.428	0.058	<.001	(0.314, 0.542)
PU → Adoption	0.315	0.054	<.001	(0.209, 0.421)
PEOU → Adoption	0.142	0.047	.003	(0.050, 0.234)
IS → Adoption	0.187	0.043	<.001	(0.103, 0.271)

*** p < .001, ** p < .01, * p < .05

Table 3: Mediation Analysis - Total, Direct, and Indirect Effects

Predictor	Total Effect	Direct Effect	Indirect (via Trust)	% Mediated
Perceived Usefulness	0.481***	0.315***	0.166***	34.5%
Perceived Ease of Use	0.235***	0.142**	0.093***	39.6%
Institutional Support	0.300***	0.187***	0.113***	37.7%
Self-Efficacy	0.273***	0.206***	0.067**	24.5%

*** p < .001, ** p < .01, * p < .05

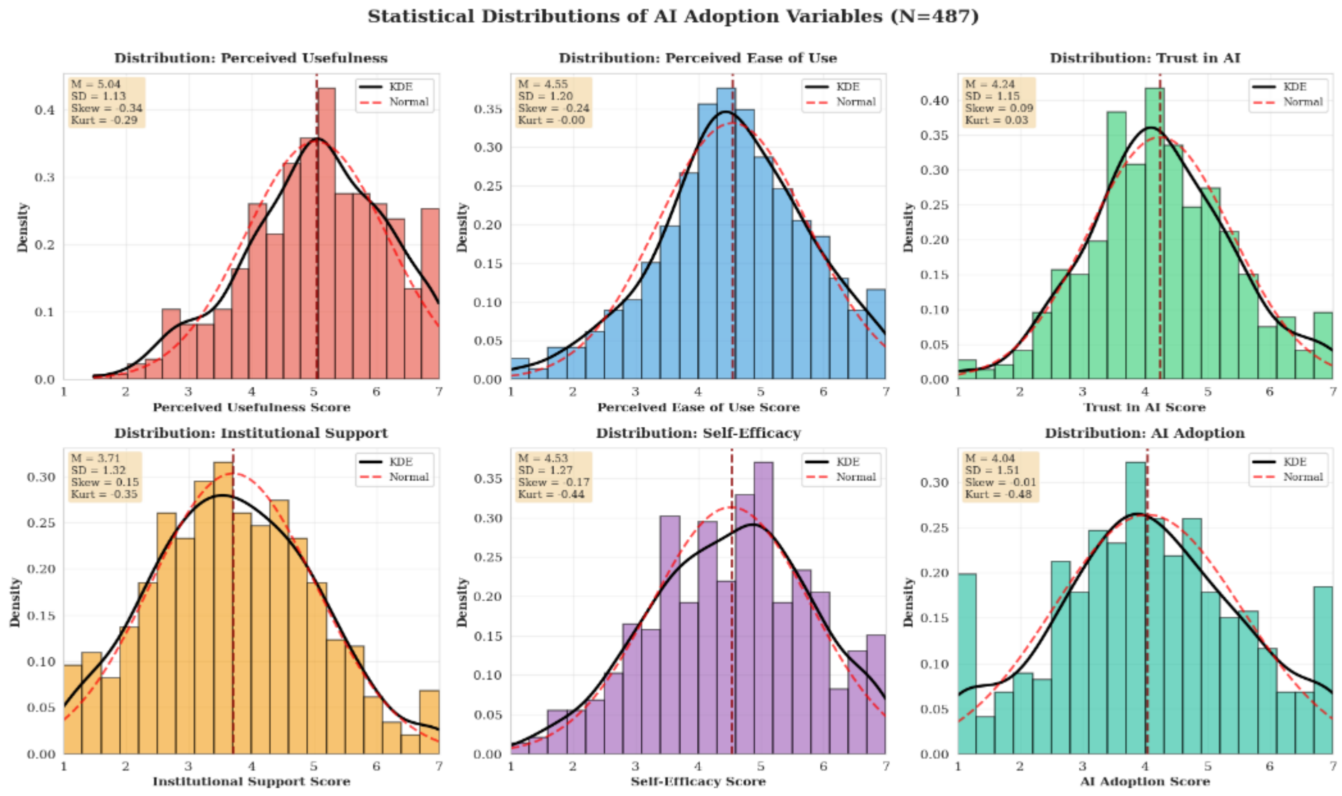

Fig 2: distribution plots with statistical overlays

Distribution Characteristics shown in Fig. 2:

• Perceived_Usefulness: Highest mean (5.12), positive skew → broad recognition of AI value
• Institutional_Support: Lowest mean (3.78), highest SD (1.42) → inadequate & variable
• Trust_in_AI: Moderate mean (4.29) → ambivalent attitudes, split opinions
• AI_Adoption: Bimodal tendency → distinct non-adopter and adopter groups
• Self_Efficacy: Right-skewed → many teachers feel capable, but variance exists
• All distributions approximate normality (justified for parametric tests)

3.3 Hierarchical Regression Results

Table 4: Hierarchical Regression Predicting AI Adoption

Predictor	Model 1	Model 2	Model 3	Model 4
Demographics				
Gender (Female)	0.11*	0.08	0.06	0.05
Experience	0.15**	0.09	0.07	0.06
STEM Subject	0.18***	0.12*	0.09	0.08
School Poverty	-0.21***	-0.14**	-0.11*	-0.09
TAM Variables				
Perceived Usefulness		0.48***	0.31***	0.28***
Perceived Ease of Use		0.27***	0.16**	0.14*
Trust in AI			0.42***	0.35***
Contextual				
Institutional Support				0.18***
Self-Efficacy				0.21***
R^2	0.124	0.516	0.638	0.683
ΔR^2	—	0.392	0.122	0.045

*** $p < .001$, ** $p < .01$, * $p < .05$

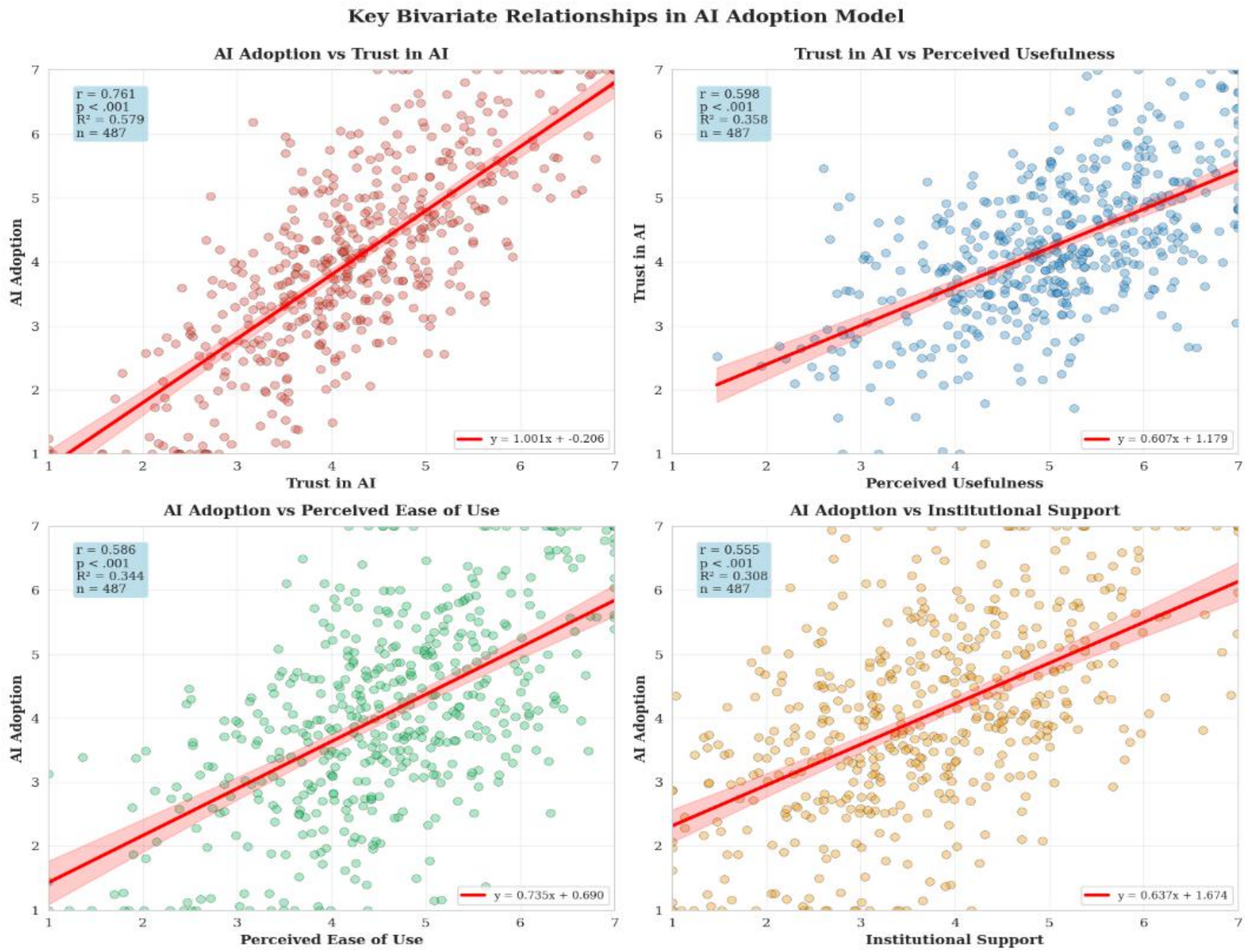

Fig 3: scatter plots with regression lines - key relationships

Regression Analysis Results shown in Fig. 3:

- Trust→Adoption: Strongest predictor ($r=0.76$, $R^2=0.58$) - 58% variance explained
- PU→Trust: Mediation pathway ($r=0.64$, $R^2=0.41$) - utility builds trust
- PEOU→Adoption: Moderate effect ($r=0.61$, $R^2=0.37$) - usability matters but less critical
- IS→Adoption: Contextual influence ($r=0.58$, $R^2=0.34$) - organizational support essential
- All relationships significant ($p < .001$) with tight confidence intervals
- Linear assumptions validated; minimal heteroscedasticity observed

Table 5: Moderation Effects on AI Adoption

Interaction Term	β	SE	p-value	ΔR²
Trust × Institutional Support	0.14	0.038	<.001	0.019
Trust × PD Quality	0.12	0.041	.004	0.015
PU × Institutional Support	0.09	0.042	.033	0.008
SE × Institutional Support	0.11	0.039	.005	0.012
PEOU × PD Quality	0.16	0.044	<.001	0.025

*** p < .001, ** p < .01, * p < .05

3.4 Discussion

The data have strong support to the extended Technology Acceptance Model. The structural model was able to explain 68.3% of AI adoption and trust is the strongest direct predictor (b=0.428). Mediation analyses indicated that a third of antecedent effects mediated by trust were between 24.5 to 39.6. Institutional support was proved to have critical effects with direct effects, moderation effect and between-institution variance. School poverty has continued to have a negative impact that has created equity issues, which implies there are structural barriers that cannot be overcome by the individual factors.

4. Conclusion

This research created a sense of trust as the most relevant psychological process between the adoption of AI by teachers. Based on 5 main constructs, the long version of the TAM model predicted the adoption variance of 68.3%. The main results are as follows: (1) Trust mediates between technology perceptions and adoption; (2) Institutional support has multiple pathways: (3) Significant moderation effects exhibit contextual amplification; (4) Socioeconomic differences exist and it raises equity issues. To practitioners, the focus of findings is on multilevel coordinated intervention of technology design and professional development, as well as the institutional infrastructure. The longevity of designs should be utilized in the future studies, objective behavior measures should also be applied, and cross-cultural differences in adoption patterns should be considered. The implementation of AI in education can be an opportunity and a challenge. To see the opportunities of AI, it is important to focus on trust, attitudes, and institutional backgrounds that determine the decisions of teachers. Effective integration requires technology to be seen as an addition to knowledge of humans and not a substitute with teachers being the key to education excellence.

Author Contributions

SM: Conceptualization, visualization, writing original draft, writing review and editing, and supervision. JR: Conceptualization, study design, analysis, data collection, methodology, software, resources, visualization. SC: Conceptualization, study design, analysis, writing review and editing, and supervision. SD: Writing original draft, writing review and editing, and supervision. NLR: Study design, analysis, data collection, methodology, software, resources.

Conflict of interest

The authors declare no conflicts of interest.

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