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Modeling artificial intelligence readiness and semiotic override in Indonesian geometry education

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ABSTRACT

Hardware-centered modernization often equates classroom technology access with preparedness for artificial intelligence (AI)-supported learning, yet this assumption overlooks subject-specific cognitive barriers in geometry. This study introduces semiotic override (SMO) as a diagnostic construct describing students' tendency to rely on symbolic cues rather than genuine spatial visualization. A cross-sectional survey of 1,208 Indonesian secondary students from Java and the outer islands examined relationships among smartboard usage (SBU), SMO, spatial intuition (SPI), adaptive learning intention (ALI), and AI readiness (AIR). Data were analyzed using covariance-based structural equation modeling (SEM) with Bollen-Stine bootstrap and multi-group invariance testing. SBU did not significantly predict AIR. SMO negatively affected SPI, whereas ALI positively predicted AIR. The negative effect of SMO was stronger among students in the outer islands than in Java. The model explained 63% of AIR and 38% of SPI. These findings show that hardware exposure alone is insufficient for AI-oriented learning transformation. Geometry teachers should diagnose symbolic overreliance and strengthen visualization-based scaffolding, while school leaders and policymakers should balance infrastructure procurement with adaptive pedagogy, teacher support, and regional equity.

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1. INTRODUCTION

Artificial intelligence (AI) has become increasingly influential in education because it can support personalization, adaptive feedback, and data-informed teaching. However, many developing education systems still interpret technological modernization mainly as hardware procurement. In Indonesia, this pattern appears in the implementation of *Dana Alokasi Khusus Fisik* (DAK *Fisik*), which has supported the provision of smartboards and other classroom technologies [1], [2]. Although this investment reflects a commitment to digital transformation, evidence from global south contexts shows that greater hardware access does not automatically produce deeper pedagogical change or better learning outcomes [3], [4].

This problem is especially important in geometry classrooms. Geometry learning does not depend only on visual access to diagrams or displays. It also requires students to construct, transform, and interpret spatial representations. Prior studies show that students often struggle with spatial reasoning because they rely on symbolic conventions rather than genuine visualization [5], [6]. In practice, students may recognize dashed lines, familiar orientations, or routine signs without forming accurate three-dimensional mental images. Research on external visualization also indicates that screen-based representations can increase cognitive effort and may not activate the same processes involved in authentic imagery construction [7]–[10].

The present study addresses this classroom learning issue through the construct of semiotic override (SMO). SMO refers to students' tendency to substitute symbolic decoding for genuine spatial visualization. This construct explains why students may appear successful in routine geometry tasks but still struggle with transfer, mental rotation, and unfamiliar spatial forms [5], [6], [8]. At the same time, adaptive and AI-supported learning systems are increasingly promoted as tools for diagnosis, personalization, and scaffolding [11]–[16]. However, evidence remains limited on how geometry-specific cognitive barriers relate to students' readiness for AI-supported learning.

The Indonesian archipelagic context strengthens the relevance of this problem. Subnational educational inequality in Indonesia remains evident in learning outcomes, access to basic services, infrastructure, and institutional capacity, with greater disadvantages concentrated in remote and eastern regions [17]–[19]. Digital inclusion research also suggests that technology adoption in peripheral regions cannot simply follow urban assumptions, but must be understood in relation to local educational conditions and support structures [20], [21]. These disparities may shape not only access to technology but also the cognitive and pedagogical conditions under which students learn geometry.

This study therefore examines the relationships among smartboard usage (SBU), SMO, spatial intuition (SPI), adaptive learning intention (ALI), and AI readiness (AIR) within a single diagnostic model. The novelty of this study lies in its attempt to connect cognitive barriers in geometry learning, particularly SMO, with students' readiness for AI-supported adaptive learning in the Indonesian educational context. Previous studies have generally discussed geometry learning difficulties, visual representation, educational technology use, and AIR as separate issues, while limited attention has been given to how students' semiotic and spatial limitations may shape their readiness to participate in AI-based learning environments. By positioning SMO as a geometry-specific cognitive barrier, this study offers a diagnostic perspective for explaining why hardware exposure alone may not be sufficient to build students' AIR. Specifically, this study investigates whether SBU predicts AIR, whether SMO is associated with lower SPI, and whether the effect of SMO differs between Java and the outer islands. In doing so, the study contributes empirical evidence on the relationship between technology exposure, cognitive barriers, and readiness for adaptive learning in Indonesian geometry education.

The assumption that classroom hardware automatically improves educational quality has been widely questioned. Studies from global south contexts show that increased digital access does not necessarily translate into meaningful instructional transformation, especially when pedagogical integration and training remain limited [3], [4], [22], [23]. In Indonesia, this issue is particularly relevant because classroom technologies are often distributed through centralized funding mechanisms that emphasize infrastructure provision over pedagogical need [1], [24], [25]. At the same time, teachers may express openness to technology while still facing barriers related to training, support, and practical implementation [26]–[28]. In this context, students' exposure to smartboards may reflect technological availability rather than meaningful AIR. Based on this reasoning, the first hypothesis (H1) proposes that SBU has no significant direct effect on AIR.

SPI is central to geometry learning because it enables students to construct, transform, and interpret two-dimensional and three-dimensional representations [29], [30]. However, prior studies suggest that students often experience difficulty because they depend on institutional symbols and visual conventions without building genuine personal meaning [5], [6]. Students who rely more heavily on symbolic conventions may therefore show weaker SPI, because errors in visualization often emerge when representation is processed as a cue system rather than as a basis for mental imagery [6], [8], [31], [32]. Accordingly, the second hypothesis (H2) proposes that SMO negatively affects SPI.

Adaptive and AI-supported systems have increasingly been discussed as tools for personalized instruction, diagnosis, and scaffolding [12], [13], [15]. Although their effectiveness in addressing geometry-specific misconceptions still requires further empirical testing, students' willingness to engage with adaptive systems remains an important precursor to use [11], [16]. In this study, ALI refers to students' willingness to engage with personalized, data-driven, and algorithmically supported learning environments. Prior work suggests that the acceptance of such systems is shaped by perceived usefulness, collaboration value, and readiness to interact with intelligent technologies [12]–[16], [33], [34]. Accordingly, the third hypothesis (H3) proposes that ALI positively affects AIR.

Regional inequality remains a major issue in Indonesian education, particularly in relation to infrastructure, access, and institutional capacity [17], [18]. Outside Java, schools often face weaker digital support, less stable infrastructure, and fewer opportunities for pedagogical innovation [19]. These differences may also shape how students depend on symbolic cues in geometry learning. For this reason, the present study further examines whether the negative effect of SMO on SPI differs between students in Java and those in the outer islands. Taken together, these hypotheses position AIR as an outcome shaped by technology exposure, geometry-specific cognitive barriers, adaptive learning orientation, and regional educational conditions.

2. METHOD

2.1. Research design

This study employed a quantitative, cross-sectional survey design to examine the relationships among SBU, SMO, SPI, ALI, and AIR. A cross-sectional approach was appropriate because the study aimed to test theoretically derived relationships among latent constructs at a single point in time and to compare those relationships across regional groups. The analytical framework was based on covariance-based structural equation modeling (SEM), which enables simultaneous assessment of measurement quality and structural relationships among constructs [35], [36].

2.2. Sampling and participants

The target population comprised secondary school students in grades 7 to 12 from public and private schools in Indonesia. A multi-stage stratified cluster sampling procedure was used. First, the sample was stratified into Java and the outer islands to capture broad geographical disparities documented in Indonesia's subnational education and human-capital outcomes [17], [18]. Second, schools were selected proportionate to accreditation level to ensure variation in school quality. Third, classrooms were selected within participating schools, and all students in those classrooms were invited to participate. Of the 1,350 questionnaires distributed, 1,282 were returned. After excluding questionnaires with more than 10% missing responses and completing case verification, 1,208 valid responses were retained, consisting of 604 students from Java and 604 from the outer islands. The final sample included 52.3% female and 47.7% male students. The target sample size was based on recommendations for SEM and multi-group analysis, with a minimum of 500 cases per regional group considered sufficient for stable estimation [35], [36].

2.3. Instrument development

Data were collected using a 30-item self-report questionnaire measuring five latent constructs: SBU, SMO, SPI, ALI, and AIR. All items were rated on a 7-point Likert scale ranging from 1=strongly disagree to 7=strongly agree. Item development followed a deductive approach grounded in the theoretical framework, prior visualization and adaptive learning studies, and established procedures for scale development and validation [5], [6], [12], [15], [37]. SBU refers to students' reported exposure to and use of smartboard-supported learning activities in mathematics classrooms. SMO refers to students' tendency to rely on symbolic cues, visual conventions, or familiar notations instead of constructing genuine spatial visualization in geometry tasks. SPI refers to students' perceived ability to construct, manipulate, and interpret two-dimensional and three-dimensional geometric representations. ALI refers to students' willingness to engage with personalized, responsive, and algorithmically supported learning environments. AIR refers to students' perceived preparedness, confidence, and openness to participate in AI-supported learning. SBU items were adapted from studies on interactive display use and educational technology integration [3], [38]. SMO items were developed for this study to capture symbolic dependency, visualization displacement, and transfer difficulty in geometry learning, drawing conceptually from ontosemiotic and visualization research [5], [6]. SPI items were adapted from spatial ability and visualization literature [29], [39], while ALI items were adapted from work on adaptive learning systems and intelligent tutoring environments [12], [15]. AIR items were developed to capture students' confidence, openness, and perceived preparedness to engage with adaptive learning environments [16], [34]. The initial item pool consisted of 45 items, which was reduced to 36 after expert review. A pilot study with 150 secondary students who were not included in the main sample was then conducted to assess item quality. Items with low corrected item-total correlations, weak factor loadings, or problematic cross-loadings were removed, resulting in a final 30-item instrument. The questionnaire was originally developed in English and translated into Bahasa Indonesia using back-translation and expert review to ensure semantic equivalence.

Table 1 presents the operational definitions of the five constructs used in this study. The table clarifies how SBU, SMO, SPI, ALI, and AIR were conceptually defined before being translated into questionnaire indicators. This explanation is important because the study examines not only students' exposure to technology, but also the cognitive and motivational conditions that may shape their readiness for AI-supported learning.

Table 1. Operational definition of constructs

Construct	Operational definition	Measurement focus
SBU	Students' reported exposure to and use of smartboard-supported learning activities in mathematics classrooms.	Frequency of use, classroom interaction, teacher-guided use, perceived integration.
SMO	Students' tendency to rely on symbolic cues, visual conventions, or familiar notations instead of constructing genuine spatial visualization in geometry tasks.	Symbolic dependency, visualization displacement, transfer difficulty.
SPI	Students' perceived ability to construct, manipulate, and interpret two-dimensional and three-dimensional geometric representations.	Mental rotation, spatial transformation, hidden structure interpretation, geometric form recognition.
ALI	Students' willingness to engage with personalized, responsive, and algorithmically supported learning environments.	Openness to personalization, willingness to receive adaptive feedback, perceived value of intelligent support.
AIR	Students' perceived preparedness, confidence, and openness to participate in AI-supported learning.	Confidence, perceived preparedness, openness to AI-supported feedback, perceived relevance of AI for learning.

2.4. Data collection procedures

Data collection was conducted from September to November 2025. Ethical approval was obtained from the relevant institutional review boards, and permissions were secured from education authorities and school principals prior to administration. Students were informed about the purpose of the study, confidentiality procedures, and the voluntary nature of participation. Written consent was obtained from participants aged 18 years and above, while parental consent and student assent were obtained for minors. The questionnaire was administered in paper-based format during regular class sessions by trained research assistants. Completion time ranged from approximately 20 to 25 minutes. To reduce order effects, two versions of the questionnaire with different item sequences were distributed. Completed questionnaires were collected immediately, and data entry was conducted using double-entry verification procedures to minimize coding errors.

2.5. Data screening and analysis

Data were analyzed using IBM SPSS Statistics 29 and IBM SPSS AMOS 29. Screening was conducted before model estimation. Item-level missing data among retained cases were minimal, at less than 2% per item, and were handled using full information maximum likelihood, which is appropriate under missing-at-random assumptions. Potential multivariate outliers were identified using Mahalanobis distance; however, no case was removed solely on statistical grounds, and sensitivity checks were used to ensure robustness. Because multivariate normality was not assumed, model evaluation relied on Bollen-Stine bootstrap with 5,000 resamples. Confirmatory factor analysis was first conducted to assess the measurement model, followed by structural model estimation to test the hypothesized paths [35]. Model fit was evaluated using Chi-square/degrees of freedom (χ^2/df), comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), following commonly used criteria in SEM [35]. Convergent validity was assessed through standardized factor loadings, composite reliability (CR), and average variance extracted (AVE), while discriminant validity was examined using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) [40]. Common method bias was assessed through the unmeasured latent method factor procedure [41]. To test regional differences, multi-group invariance analysis was conducted across Java and outer-island groups, using changes in fit indices, particularly ΔCFI$\leq$0.01, as the primary criterion [42].

3. RESULTS AND DISCUSSION

3.1. Preliminary analyses

Prior to model estimation, the dataset was screened for missing values, outliers, and multivariate normality. Item-level missing data were minimal and were handled using full information maximum likelihood. Mardia's coefficient of multivariate kurtosis indicated a significant deviation from normality (Mardia=28.43, critical ratio=15.67, $p<0.001$); therefore, all subsequent inferences were based on

Bollen-Stine bootstrap estimates with 5,000 resamples. Table 2 presents the descriptive statistics and inter-construct correlations. SBU showed a weak and non-significant association with AIR ($r=0.05$, $p=0.12$). In contrast, SMO was negatively correlated with SPI ($r=-0.58$, $p<0.001$), while ALI had the strongest positive correlation with AIR ($r=0.71$, $p<0.001$). These preliminary patterns were consistent with the hypothesized model.

Table 2. Descriptive statistics and correlations

Construct	Mean	SD	SBU	SMO	SPI	ALI
SBU	4.82	1.23	(0.82)			
SMO	4.15	1.45	0.38**	(0.85)		
SPI	4.58	1.31	-0.29**	-0.58**	(0.81)	
ALI	5.21	1.18	0.42**	0.47**	0.44**	(0.88)
AIR	4.96	1.27	0.05	-0.49**	0.52**	0.71**

Note: diagonal in parentheses represents the square root of AVE. ** $p<0.01$.

3.2. Measurement model

A confirmatory factor analysis was conducted to evaluate the five-factor measurement model comprising SBU, SMO, SPI, ALI, and AIR. The initial model demonstrated acceptable fit. Modification indices suggested localized shared variance between two SMO indicators related to hidden-edge interpretation in cube representation; because both items reflected a highly similar task-specific cognitive demand, correlating their residuals was considered theoretically justified. The revised measurement model demonstrated good fit, as shown in Table 3. All retained indicators loaded significantly on their intended constructs, and standardized loadings exceeded the recommended minimum threshold. CR and AVE supported convergent validity. Discriminant validity was further supported by HTMT of correlations values below 0.85. Table 4 presents the HTMT ratios among the five constructs and shows that all values remained below the recommended threshold. This indicates that the constructs measured in the study were empirically distinguishable from one another. Common method bias was assessed using the unmeasured latent method factor approach, and the small change in loadings suggested that common method bias did not materially threaten the interpretation of the results.

Table 3. Summary of measurement model fit and construct validity

Indicator	Value
Initial model χ^2/df	2.89
Initial model CFI	0.95
Initial model TLI	0.94
Initial model RMSEA	0.052
Initial model SRMR	0.048
Revised model χ^2/df	2.38
Revised model CFI	0.97
Revised model TLI	0.96
Revised model RMSEA	0.041
Revised model SRMR	0.035
Standardized loading range	0.78–0.89
CR range	0.84–0.91
AVE range	0.62–0.77
Common method variance	8.3%

Table 4. HTMT ratios for discriminant validity

Construct	SBU	SMO	SPI	ALI	AIR
SBU	—				
SMO	0.42	—			
SPI	0.38	0.67	—		
ALI	0.45	0.51	0.48	—	
AIR	0.29	0.53	0.56	0.72	—

Note: HTMT<0.85 indicates discriminant validity.

3.3. Structural model

Following confirmation of acceptable measurement properties, the hypothesized structural relationships were tested using covariance-based SEM. The structural model demonstrated satisfactory fit (χ^2/df=2.45, CFI=0.96, TLI=0.95, RMSEA=0.044, SRMR=0.041), and the Bollen-Stine bootstrap p-value of

0.21 indicated that the model adequately reproduced the observed covariance matrix. As shown in Figure 1 and Table 5, the path from SBU to AIR was non-significant (β=0.04, 95% CI [-0.02, 0.10], p=0.38), supporting H1. The path from SMO to SPI was negative and significant (β=-0.62, 95% CI [-0.71, -0.53], p<0.001), supporting H2. The path from ALI to AIR was positive and significant (β=0.78, 95% CI [0.70, 0.85], p<0.001), supporting H3. The model explained 63% of the variance in AIR and 38% of the variance in SPI.

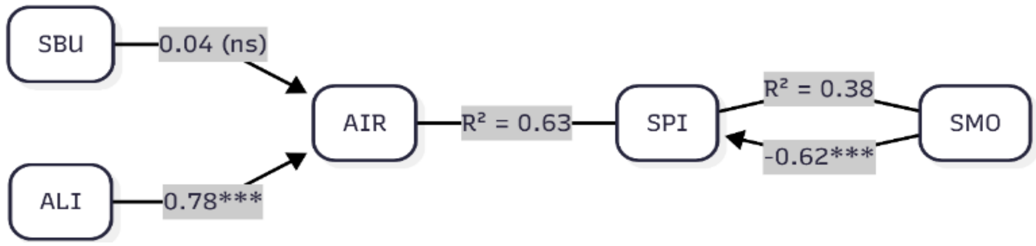

Figure 1. SEM path diagram with standardized coefficients

Table 5. Hypothesis testing results

Hypothesis	Path	β	SE	95% CI	p	Decision
H1	SBU→AIR	0.04	0.03	[-0.02, 0.10]	0.38	Supported
H2	SMO→SPI	-0.62	0.05	[-0.71, -0.53]	<0.001	Supported
H3	ALI→AIR	0.78	0.04	[0.70, 0.85]	<0.001	Supported

Note: β=standardized coefficient; SE=standard error; CI=bias-corrected bootstrap confidence interval.

3.4. Multi-group analysis

Multi-group invariance testing was conducted to assess whether the measurement and structural models operated similarly across Java and outer-island subsamples. Configural, metric, and scalar invariance were established, as the changes in CFI remained below the recommended threshold of 0.01. This provided a basis for meaningful structural comparison across groups. As shown in Table 6, the negative effect of SMO on SPI was significantly stronger in the outer islands (β=-0.71, 95% CI [-0.80, -0.62]) than in Java (β=-0.53, 95% CI [-0.63, -0.43]), with a statistically significant difference between the two coefficients (z=2.67, p<0.01). No significant regional differences were observed for the paths from SBU to AIR or from ALI to AIR.

Table 6. Multi-group analysis: path coefficients by region

Path	Java (n=604)	95% CI	Outer islands (n=604)	95% CI	Δβ	z
SMO→SPI	-0.53	[-0.63, -0.43]	-0.71	[-0.80, -0.62]	0.18	2.67

3.5. Discussion

The findings provide a coherent explanation of why hardware-centered modernization may have limited impact on students' AIR. First, SBU did not significantly predict AIR. This suggests that the mere presence of classroom technology does not necessarily translate into greater preparedness for AI-supported learning. The result is consistent with studies showing that digital tools often remain at the level of access or surface use when pedagogical integration is weak or training is insufficient [3], [22], [23], [26]–[28].

Second, SMO had a strong negative effect on SPI. This finding indicates that students who rely more heavily on symbolic conventions as substitutes for genuine visualization tend to demonstrate weaker SPI. From a cognitive perspective, SMO functions as a learning barrier because students process geometric signs as surface cues rather than as representational tools for constructing spatial meaning. In this condition, students may identify dashed lines, angles, or familiar orientations correctly, but still fail to mentally transform, rotate, or reconstruct geometric objects in unfamiliar situations. The result supports the ontosemiotic perspective, which emphasizes the tension between formal representation and learners' internal meaning-making [5], [6]. It also aligns with prior work showing that representation-based shortcuts may interfere with transfer, conceptual flexibility, and deeper visuospatial understanding [8], [31], [32].

This interpretation has important implications for AI-based geometry learning. Adaptive systems may provide personalized feedback, but such feedback will be less effective if the system only detects whether students choose correct symbolic answers without diagnosing how they construct spatial meaning. Instructional design should therefore include tasks that require students to explain visual reasoning, compare two-dimensional and three-dimensional representations, and justify how a geometric object changes under rotation, projection, or transformation. Visual scaffolding is also needed so that students do not merely follow symbolic conventions displayed on a smartboard, but gradually develop the ability to build mental images and transfer them across new problem situations. In this sense, students' readiness for adaptive learning is not only a matter of access to AI-supported systems, but also a matter of cognitive readiness to benefit from diagnostic feedback and visual learning support.

Third, ALI emerged as the strongest positive predictor of AIR. Students who were more willing to engage with personalized and responsive learning environments also reported higher AIR. This result suggests that readiness is shaped less by passive exposure to hardware and more by students' orientation toward adaptive forms of instruction [12], [13], [15], [16], [34].

The regional analysis adds an important contextual dimension. The negative effect of SMO on SPI was significantly stronger in the outer islands than in Java. This suggests that symbolic dependence may be more detrimental in contexts where educational support, infrastructure continuity, and conceptual scaffolding are less consistent [17]–[19], [21]. Taken together, these findings indicate that improving educational technology policy requires a shift in emphasis. Hardware provision remains important, but it is insufficient when cognitive barriers in subject-specific learning are left unaddressed. The present study does not claim that adaptive systems have already solved such problems. Rather, it shows that students' openness to adaptive learning is strongly related to AIR, while symbolic overreliance remains a substantial constraint in geometry learning.

The findings have direct implications for geometry teaching. Teachers should not assume that students understand spatial relations simply because they can identify symbols or follow visual conventions on a smartboard. The strong negative relationship between SMO and SPI indicates that geometry instruction should include explicit visualization training, mental rotation exercises, comparison of two-dimensional and three-dimensional representations, and tasks that require students to explain how they construct spatial meaning. For school leaders, the findings suggest that smartboard procurement should be accompanied by teacher training, structured lesson design, and diagnostic assessment of students' spatial reasoning. For policymakers, the regional difference between Java and the outer islands shows that technology modernization should not rely on uniform hardware distribution alone. Schools in peripheral regions need sustained pedagogical support, stable infrastructure, and adaptive learning resources that respond to local learning constraints.

4. CONCLUSION

This study examined how SBU, SMO, SPI, ALI, and AIR are related in Indonesian geometry education. The findings show that SBU did not significantly predict AIR, which indicates that hardware exposure alone is not enough to prepare students for AI-supported learning. SMO had a strong negative effect on SPI, showing that dependence on symbolic conventions can limit genuine visualization in geometry. ALI was the strongest positive predictor of AIR, which suggests that students' openness to personalized and responsive learning is central to future digital learning transformation. The stronger negative effect of SMO in the outer islands shows that regional inequality may intensify cognitive barriers in geometry learning.

The theoretical contribution of this study lies in offering a diagnostic model that explains AIR not only as a technological issue, but also as a cognitive and semiotic issue in subject-specific learning. This model also shows that digital learning reform should not focus only on hardware procurement, but also on students' spatial reasoning, symbolic dependence, and readiness to benefit from adaptive feedback. Since this study used a cross-sectional design, self-report measures, and ALI rather than actual system engagement, future research should use performance-based spatial tasks, longitudinal designs, and classroom interventions to test how visualization scaffolding and adaptive learning systems can reduce SMO.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This study complied with relevant ethical regulations and the Helsinki Declaration. Ethical approval, research permission, voluntary participation, anonymity, and research-only data use were ensured.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [AK], upon reasonable request.

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