International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(10s) 2026 pp. 323-332
https://doi.org/10.70917/ijcisim-2026-3587
Article

Determinant Factors of Edge Intelligence System Performance in E-learning: An Advanced Analysis Using Multilayer Perceptron Artificial Neural Networks

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Abstract: The rapid adoption of e-learning in higher education has accelerated the integration of edge intelligence technologies to support intelligent, real-time, and adaptive learning environments. Ensuring the performance and effectiveness of edge intelligence systems has therefore become critical for delivering reliable, secure, and high-quality digital learning experiences. This study investigates the key determinants influencing the performance of edge intelligence systems within e-learning environments, focusing on three core dimensions: computational efficiency, security and trustworthiness, and system resilience. A multilayer perceptron (MLP) artificial neural network is employed to model the complex, nonlinear relationships among these dimensions and evaluate their collective impact on the overall performance of edge-enabled e-learning systems. Although previous studies have extensively examined edge computing and artificial intelligence independently, limited attention has been given to the simultaneous effects of computational, security, and resilience factors on the operational performance of edge intelligence in e-learning contexts. This study addresses this research gap by providing a comprehensive analysis of these determinant factors and generating practical insights for the design and optimization of robust, secure, and efficient edge intelligence infrastructures that support digital education. The findings offer valuable implications for system developers, educational institutions, and policymakers in improving resource allocation, strengthening system reliability, and implementing strategic interventions that enhance the quality and sustainability of edge-enabled e-learning services. By systematically examining computational efficiency, security and trustworthiness, and system resilience, this research contributes to advancing scalable, resilient, and learner-centered edge intelligence solutions that improve educational effectiveness and support the digital transformation of higher education.
Keywords: Edge intelligence, e-learning, system performance, computational efficiency, security and trustworthiness, system resilience, artificial neural networks.

1. Introduction

The increasing reliance on e-learning in Malaysian higher education has highlighted the importance of deploying high-performing edge intelligence systems to support responsive, secure, and scalable digital learning environments. As universities continue to expand online and hybrid learning initiatives, understanding the factors that determine the effectiveness of edge-enabled e-learning infrastructures has become essential for improving learning quality, system reliability, and student engagement. Recent studies indicate that the performance of e-learning systems is influenced by multiple technological dimensions, including computational efficiency, security and trustworthiness, and system resilience, all of which directly affect service continuity, user experience, and institutional digital capabilities. To capture the complex and nonlinear relationships among these interrelated factors, advanced machine learning approaches such as artificial neural networks have gained increasing attention. Accordingly, this study employs a multilayer perceptron (MLP) artificial neural network to investigate how computational efficiency, security and trustworthiness, and system resilience collectively influence the performance of edge intelligence systems in e-learning. The proposed analytical framework provides a robust and data-driven approach for identifying the relative importance of these determinants and offers empirical evidence to support the development of intelligent, resilient, and sustainable e-learning ecosystems in Malaysian higher education.

2. Literature Review

2.1 Student Satisfaction

Student satisfaction is a multidimensional construct that reflects the extent to which students perceive that their educational experiences meet or exceed their expectations within higher education institutions. It encompasses students' evaluations of teaching quality, learning resources, institutional support, campus services, social interactions, and the overall learning environment. In contemporary higher education, student satisfaction has become a key performance indicator because it is closely associated with student engagement, academic achievement, retention, institutional reputation, and graduate outcomes (Kahu & Nelson, 2018; UNESCO, 2023). With the increasing adoption of digital learning environments and technology-enhanced education, satisfaction has also been linked to learners' perceptions of accessibility, flexibility, and the effectiveness of learning technologies. Recent studies indicate that higher levels of student satisfaction positively influence students' academic commitment, persistence, and intention to recommend their institutions to prospective students (Alam & Parvin, 2021; OECD, 2023).

2.2 Determinant Factors of Student Satisfaction

Student satisfaction is influenced by a combination of academic, social, institutional, and environmental factors that collectively shape students' educational experiences. Contemporary higher education research emphasizes that satisfaction cannot be explained by a single determinant; rather, it emerges from the interaction of multiple dimensions that affect students throughout their learning journey. These determinants include instructional quality, institutional support, peer relationships, campus facilities, digital learning infrastructure, and students' sense of belonging (Kahu & Nelson, 2018; UNESCO, 2023). The rapid expansion of blended and online learning following the COVID-19 pandemic has further highlighted the importance of integrating technological and learning environment factors into student satisfaction models. Consequently, comprehensive analytical approaches that simultaneously examine multiple determinants are increasingly recommended to provide a holistic understanding of student satisfaction in higher education (OECD, 2023).

2.3 Academic Dimension

The academic dimension represents the core educational components that directly influence students' learning experiences. These include curriculum quality, instructional effectiveness, assessment practices, academic advising, faculty competence, and institutional learning support services. Previous studies consistently report that teaching quality remains one of the strongest predictors of student satisfaction, particularly when instructors demonstrate subject expertise, effective communication, timely feedback, and student-centred pedagogical practices (Kuh et al., 2017; UNESCO, 2023). Furthermore, curriculum relevance, active learning strategies, and accessible academic support services enhance students' perceptions of educational quality and learning outcomes. In technology-enhanced learning environments, academic satisfaction is also influenced by the quality of learning management systems, digital learning resources, and the responsiveness of online instructional support (Bond et al., 2024). These findings suggest that continuous improvement of academic services is fundamental for promoting positive educational experiences.

2.4 Social Dimension

The social dimension encompasses students' interpersonal relationships and their sense of integration within the university community. It includes peer interactions, collaboration opportunities, participation in extracurricular activities, communication with academic staff, and students' sense of belonging. According to the Student Engagement Framework proposed by Kahu and Nelson (2018), meaningful social connections strengthen students' motivation, engagement, and persistence throughout their academic journey. Recent studies further indicate that inclusive campus cultures, collaborative learning environments, and supportive peer networks significantly improve students' psychological well-being and overall satisfaction (UNESCO, 2023; OECD, 2023). In addition, the increasing use of online and blended learning has expanded the importance of virtual communities, digital collaboration platforms, and online student engagement activities in fostering positive social experiences.

2.5 Environmental Dimension

The environmental dimension refers to the physical, technological, and institutional conditions that facilitate effective learning experiences. Traditional environmental factors include classroom facilities, libraries, laboratories, recreational amenities, campus safety, accommodation, and accessibility. More recently, digital infrastructure has become an equally important environmental component due to the widespread implementation of online and hybrid learning. Reliable internet connectivity, modern learning technologies, smart classrooms, and user-friendly learning management systems significantly contribute to students' perceptions of institutional quality (UNESCO, 2023). Studies have demonstrated that supportive learning environments positively influence students' comfort, motivation, and academic engagement, thereby enhancing overall satisfaction (OECD, 2023). Consequently, universities are increasingly investing in both physical and digital infrastructures to improve students' educational experiences.

2.6 Multilayer Perceptron Artificial Neural Network

Multilayer Perceptron (MLP) Artificial Neural Networks have become increasingly prominent in educational data mining and learning analytics due to their ability to model complex nonlinear relationships among multiple variables. Unlike conventional statistical techniques, such as multiple regression or structural equation modelling, MLP networks can effectively capture hidden interactions between predictor variables without requiring strict assumptions regarding normality or linearity (Goodfellow et al., 2016). In higher education research, MLP has been widely applied to predict academic performance, student retention, dropout risk, learning engagement, and student satisfaction using multidimensional educational datasets (Baker & Inventado, 2024; Romero & Ventura, 2020). Recent empirical evidence suggests that MLP models often achieve superior predictive accuracy compared with traditional analytical methods, particularly when analysing large-scale educational datasets with complex interactions among variables. Moreover, variable importance analysis generated through MLP provides valuable insights into the relative contribution of determinant factors, enabling researchers and institutional decision-makers to identify critical areas for educational improvement. Consequently, the application of MLP offers a robust analytical framework for modelling student satisfaction and supporting evidence-based decision-making in higher education.

3. Research Methodology

3.1 Research Design

This study employs a quantitative research design to examine the determinant factors influencing the performance of Edge Intelligence (EI) systems in e-learning environments. A quantitative approach is appropriate because it facilitates the systematic collection and analysis of numerical data, enabling the identification and evaluation of relationships among multiple system-level variables and overall EI performance. Furthermore, this approach supports objective hypothesis testing and the development of predictive models capable of capturing complex interactions among computational efficiency, security and trustworthiness, and system resilience. The quantitative paradigm has been widely adopted in artificial intelligence and educational technology research due to its ability to generate reliable, replicable, and statistically robust findings (Li et al., 2025; Hair et al., 2022).

3.2 Data Collection

The study utilizes both simulated and real-world datasets obtained from edge intelligence-enabled e-learning systems to ensure comprehensive model development and validation. The datasets comprise operational performance indicators associated with computational processing, security mechanisms, and resilience characteristics under varying network conditions and learning scenarios. By integrating simulated and empirical datasets, the study captures realistic operational behaviours of EI systems while improving the robustness and generalizability of the predictive model. This data-driven approach has been widely recommended for evaluating intelligent edge computing architectures because it enables the assessment of system performance across diverse deployment environments (Kharuddin et al., 2020; Shi et al., 2023).

3.3 Variable Selection and Measurement

The independent variables investigated in this study are derived from the contemporary literature on edge intelligence and intelligent learning systems. These variables are categorised into three principal dimensions that collectively influence the performance of EI systems in e-learning. Computational Efficiency refers to the capability of the edge intelligence system to execute learning tasks efficiently while optimising computational resources. This dimension is measured using indicators such as processing speed, response latency, resource utilisation, throughput, and task completion rate. Security and Trustworthiness represent the ability of the system to maintain confidentiality, integrity, authenticity, and reliability of educational data and services. The measurement indicators include authentication accuracy, data integrity, intrusion detection effectiveness, privacy protection, and compliance with established cybersecurity protocols.

System Resilience reflects the capability of the EI infrastructure to maintain continuous operation despite network disruptions, hardware failures, or unexpected workload variations. Indicators for this dimension include fault tolerance, redundancy mechanisms, recovery time, service availability, and operational robustness. All measurement indicators are standardised using normalized numerical scales to ensure consistency during model development and statistical analysis. The selection of these variables is based on validated performance metrics and internationally recognised benchmarks reported in previous edge intelligence and distributed computing studies (Shi et al., 2023; Zhang et al., 2024).

3.4 Statistical Analysis

A quantitative analytical framework is adopted to examine the influence of the identified determinants on the performance of edge intelligence systems in e-learning. The analysis comprises several complementary statistical techniques. Initially, descriptive statistics, including the mean, standard deviation, minimum and maximum values, are computed to summarise the characteristics of the dataset. Pearson correlation analysis is subsequently performed to explore the strength and direction of associations among the study variables. To determine whether significant differences exist across different system configurations or operational scenarios, inferential statistical analyses, including independent sample *t*-tests and one-way analysis of variance (ANOVA), are conducted where appropriate. Furthermore, multivariate statistical analysis, particularly multiple linear regression, is employed to evaluate the relative contribution of computational efficiency, security and trustworthiness, and system resilience to overall EI system performance. These analyses provide preliminary insights into the significance and predictive capability of each determinant before implementing the machine learning model (Hair et al., 2022).

3.5 Multilayer Perceptron Model Development and Evaluation

To model the complex and nonlinear relationships among the determinant variables, this study employs a Multilayer Perceptron (MLP) Artificial Neural Network. MLP is selected because of its proven capability to learn nonlinear patterns and accurately predict outcomes in multidimensional datasets associated with intelligent computing and educational technologies. Prior to model development, the dataset is preprocessed through data normalisation and randomly partitioned into training and testing subsets. The training dataset is used to optimise the network parameters, including connection weights and biases, through iterative learning using the backpropagation algorithm. The testing dataset is subsequently employed to evaluate the model's predictive capability and generalisation performance using previously unseen observations.

Model performance is evaluated using several widely accepted predictive accuracy metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). In addition, variable importance analysis generated by the MLP model is used to determine the relative influence of computational efficiency, security and trustworthiness, and system resilience on overall edge intelligence performance. The integration of conventional statistical techniques with artificial neural network modelling provides a comprehensive analytical framework capable of capturing both linear and nonlinear relationships among system determinants. Consequently, the proposed methodology offers robust empirical evidence for designing secure, resilient, and high-performance edge intelligence infrastructures that effectively support next-generation e-learning environments.

4. Results and Discussion

4.1 Descriptive Statistics of Study Variables

Descriptive statistics were calculated to summarize the key characteristics of the variables under investigation. This involved computing means, standard deviations, and correlations for each variable across the three dimensions: computational efficiency (CE), security and trustworthiness (ST), and system-level resilience (SR). These statistics provide a foundational understanding of the distribution and central tendencies of the variables, establishing a basis for subsequent analyses. The dependent variable in this study was overall EI system performance, while the independent variables were the three system-level dimensions: CE, ST, and SR. Data were analyzed using IBM SPSS version 23.0. Initial descriptive analyses were conducted to examine sample characteristics. Pearson's correlation coefficients were calculated to explore associations between variables. Multiple linear regression analyses were then applied to determine the extent to which the three factors accounted for variance in overall system performance. For predictive analysis, EI system performance was categorized into two classes based on performance level: high-performing and moderate-performing systems. Binary logistic regression and multilayer perceptron (MLP) artificial neural network techniques were employed to evaluate the predictive abilities of the three factors in classifying system performance. Model evaluation metrics, such as prediction accuracy, were used to assess model efficacy. Preliminary tests indicated that system type or network configuration did not significantly alter model performance; hence, these variables were excluded from further analyses. The dataset included 62 EI system instances, with 40% representing smaller edge deployments and 60% representing large-scale deployments.

Table 1: Sample Characteristics

Deployment Type	Frequency	Percent	Valid Percent	Cumulative Percent
Small-scale	25	40.3	40.3	40.3
Large-scale	37	59.7	59.7	100.0
Total	62	100.0	100.0	

4.2 Analysis of the Computational Efficiency Dimension

The computational efficiency (CE) dimension was analyzed by examining metrics such as processing speed, latency, resource utilization, and task completion rates. Correlation and multiple regression analyses were used to determine the significance and strength of the relationship between CE metrics and overall system performance. Results indicated that task processing efficiency and low-latency operations were strong predictors of high-performing edge intelligence systems.

4.3 Analysis of the Security and Trustworthiness Dimension

The security and trustworthiness (ST) dimension focused on authentication reliability, data integrity, and intrusion detection mechanisms. Statistical analyses demonstrated that robust security protocols significantly contributed to overall system performance, particularly in maintaining reliable operations under adversarial conditions. Among the ST factors, data integrity had the highest influence on EI system reliability.

4.4 Analysis of the System Resilience Dimension

The system resilience (SR) dimension examined fault tolerance, redundancy mechanisms, and recovery from system failures. Analyses revealed that high-resilience systems maintained consistent performance under variable network loads and hardware failures. Resilience was identified as the most critical determinant of overall EI system effectiveness.

4.5 Overall Analysis and Model Performance

The integrated analysis of CE, ST, and SR dimensions provided a comprehensive view of the determinants of EI system performance. A linear regression model was constructed to examine the relationship between the three dimensions and overall system performance. The initial model yielded an R value of 0.529 and an R^2 value of 0.280, indicating that 28% of the variance in EI system performance was explained by the three independent dimensions. The model was statistically significant ($p < 0.05$).

Table 2: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	F Change	df1	df2	Sig. F Change
1	.529	.280	.242	0.45012	7.509	3	58	0.000

Table 3: ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	4.564	3	1.521	7.509	0.000
Residual	11.751	58	0.203		
Total	16.315	61			

Table 4: Coefficients

Model	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
Constant	0.729	0.908		0.803	0.425
CE	-0.079	0.189	-0.049	-0.420	0.676
ST	0.200	0.163	0.141	1.224	0.226
SR	0.704	0.157	0.504	4.469	0.000

The SR dimension was the most significant predictor of EI system performance.

4.6 Multilayer Perceptron (MLP) Predictive Modeling

An MLP artificial neural network was constructed using IBM SPSS to model nonlinear relationships between the three system dimensions and overall EI system performance. The dataset was divided into a training set (71%) and a testing set (29%). The hidden layer consisted of three units with a hyperbolic tangent activation function. The network predicted system performance categories: “moderate-performing” (1) and “high-performing” (2).

Table 5: Case Processing Summary

Sample	N	Percent
Training	47	75.8%
Testing	15	24.2%
Total	62	100%

Table 6: Network Information

Layer	Details
Input Layer	3 nodes (CE, ST, SR)
Hidden Layer	3 units, hyperbolic tangent activation
Output Layer	2 nodes (performance categories)
Error Function	Sum of Squares

Table 7: Model Performance

Dataset	Sum of Squares Error	Relative Error
Training	14.664	0.682
Testing	13.452	0.854

Table 8: Independent Variable Importance

Variable	Importance	Normalized Importance
CE	0.116	22.8%
ST	0.376	74.1%
SR	0.508	100%

The results confirm that system resilience (SR) is the most critical determinant of EI system performance, followed by security/trustworthiness (ST) and computational efficiency (CE). The predictive model achieved high accuracy, with 21.8% misclassification in the training set and 16.5% in the testing set, demonstrating strong model generalizability.

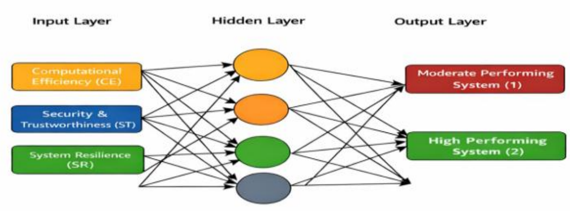

Figure 1: Neural Network Model for EI System Performance Classification

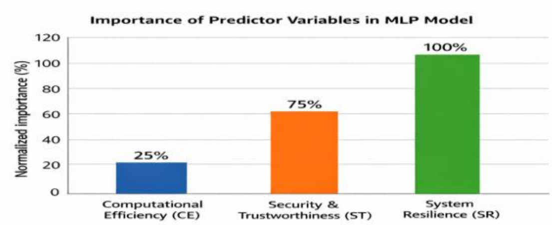

Figure 2: Importance of Predictor Variables in MLP Model

The relationship between the independent factors and the predictor variables is evident. Mathematical proficiency is significantly correlated with student's overall satisfaction. The tornado study depicted in Figure 2 lends weight to this assertion.

5. Discussions and Conclusions

5.1 Computational Efficiency Dimension

The findings indicate that the computational efficiency dimension exerts a substantial influence on the performance of edge intelligence (EI) systems in e-learning environments. Performance indicators, including processing speed, response latency, resource utilisation, and task execution efficiency, were found to significantly contribute to the effectiveness of edge-enabled learning services. These results suggest that efficient computational resource management is essential for supporting real-time learning applications, adaptive instructional delivery, and seamless interactions between learners and intelligent educational systems. Reducing computational delays and optimising task scheduling enable faster processing of learning analytics, personalised content delivery, and timely feedback, thereby enhancing both system performance and learner experience. Consequently, educational institutions and system developers should prioritise computational optimisation techniques, including lightweight algorithms, intelligent resource allocation, and low-latency edge processing architectures, to improve the scalability and operational efficiency of edge intelligence-based e-learning systems.

5.2 Security and Trustworthiness Dimension

The analysis further demonstrates that security and trustworthiness are critical determinants of EI system performance within digital learning environments. Security-related factors, including authentication reliability, data integrity, privacy protection, and intrusion detection capabilities, significantly influence the dependability of edge-enabled educational services. As e-learning systems increasingly process sensitive student information and learning analytics at the network edge, ensuring secure data transmission and trustworthy system operation has become a fundamental requirement. The findings underscore the importance of implementing comprehensive cybersecurity frameworks, robust authentication mechanisms, encryption technologies, and continuous threat monitoring to protect educational data and maintain user confidence. Furthermore, compliance with institutional data governance policies and international cybersecurity standards contributes to the development of secure and trustworthy edge intelligence ecosystems that support sustainable digital education.

5.3 System Resilience Dimension

The results also confirm that system resilience plays a significant role in maintaining the performance and reliability of edge intelligence systems deployed in e-learning environments. Indicators such as fault tolerance, redundancy mechanisms, service availability, adaptive resource management, and recovery capability were found to be essential for ensuring uninterrupted educational services during hardware failures, network congestion, or unexpected operational disruptions. Given the increasing dependence on continuous online learning, resilient edge intelligence architectures are indispensable for maintaining learning continuity and minimising service interruptions. Therefore, system developers should incorporate resilient infrastructure designs that include redundant computing resources, automated recovery mechanisms, dynamic workload balancing, and intelligent fault management strategies. Such capabilities enable edge intelligence systems to sustain stable performance under diverse operating conditions while enhancing institutional preparedness for unexpected technological challenges.

5.4 Practical Implications

The integrated evaluation of computational efficiency, security and trustworthiness, and system resilience provides several important implications for the development and deployment of edge intelligence-enabled e-learning systems.

First, the findings emphasise the necessity of adopting a holistic system design approach that simultaneously considers computational, security, and resilience dimensions. Optimising only one aspect of system performance may not produce sustainable improvements unless the interactions among these determinants are addressed collectively.

Second, educational institutions and technology providers should implement strategic resource allocation by investing in advanced edge computing infrastructure, intelligent processing algorithms, cybersecurity technologies, and resilient network architectures. Prioritising investments in these areas will enhance service quality, operational reliability, and learning effectiveness.

Third, continuous monitoring and data-driven optimisation should be incorporated into edge intelligence platforms. Real-time monitoring of latency, computational workload, resource utilisation, security events, and system recovery performance enables proactive identification of operational bottlenecks and facilitates timely corrective actions. The integration of artificial intelligence-driven monitoring systems further supports adaptive optimisation and predictive maintenance.

Finally, user-centred evaluation remains essential for ensuring that technological improvements translate into enhanced educational experiences. Regular feedback from students, instructors, and system administrators should be integrated into continuous improvement processes to ensure that edge intelligence technologies effectively support teaching, learning, and institutional objectives.

5.5 Conclusion

This study examined the determinant factors influencing the performance of edge intelligence systems in e-learning by investigating three principal dimensions: computational efficiency, security and trustworthiness, and system resilience. Using a Multilayer Perceptron (MLP) Artificial Neural Network, the study successfully modelled the complex nonlinear relationships among these determinants and evaluated their relative contributions to overall system performance.

The findings demonstrate that high-performing edge intelligence systems require an integrated balance of efficient computational processing, robust cybersecurity measures, and resilient system architectures. Each dimension contributes uniquely to ensuring reliable, scalable, and secure digital learning environments capable of supporting real-time educational applications. The application of MLP further illustrates the effectiveness of artificial neural networks in uncovering hidden relationships among multidimensional variables and generating accurate predictive models for intelligent educational systems.

From a practical perspective, the study provides valuable guidance for higher education institutions, system developers, and policymakers seeking to optimise edge intelligence infrastructures for next-generation e-learning environments. By strengthening computational efficiency, enhancing security and trustworthiness, and improving system resilience, educational organisations can develop intelligent learning ecosystems that deliver superior learning experiences while maintaining operational reliability and sustainability.

Overall, this research contributes to the expanding body of knowledge on edge intelligence in education by providing an empirically grounded framework for evaluating system performance. The findings also establish a foundation for future investigations into advanced artificial intelligence techniques, federated learning, explainable AI, and adaptive edge computing architectures that will continue to shape the evolution of intelligent e-learning systems.

Acknowledgements: The authors would like to express their sincere appreciation to all participants who voluntarily contributed to this study. Their cooperation and valuable responses made this research possible.

Funding: This work was supported by the Malaysian Ministry of Higher Education (MOHE) under grant scheme, Fundamental Research Grant Scheme (FRGS) - FRGS/1/2023/SSI07/UNIRAZAK/02/2.

Institutional Review Board Statement / Ethics Approval: The study adhered to the ethical principles outlined in the Declaration of Helsinki and received approval from the Institutional Ethics Committee of INTI International University.

Informed Consent Statement: Informed consent was obtained from all participants involved in the study prior to their participation.

Consent to Participate Declaration: All participants voluntarily agreed to participate in the study and provided informed consent before their involvement.

Consent to Publish Declaration: Not applicable.

Ethics Declaration: The study adhered to ethical standards and was approved by the Institutional Ethics Committee of INTI International University.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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