

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

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Abstract

This study investigates the critical factors influencing the performance and effectiveness of intelligent computing systems at the edge. The research focuses on three primary dimensions: computational efficiency, security and trustworthiness, and system-level resilience. A sophisticated statistical approach, based on the multilayer perceptron (MLP) artificial neural network, is employed to analyze complex interactions among these parameters and their collective impact on overall system performance. Despite extensive research on edge computing and AI, few studies have examined the simultaneous influence of computational, security, and resilience factors on the operational effectiveness of edge intelligence ecosystems. This research provides an in-depth examination of these determinants, offering actionable insights for designing robust, secure, and high-performing edge intelligence systems. The findings of this analysis can guide system architects, engineers, and policymakers in optimizing resource allocation, improving system reliability, and implementing strategic interventions that enhance the overall efficacy of edge-centric intelligent systems. By systematically addressing computational, security, and resilience dimensions, this study contributes to advancing the quality, scalability, and societal impact of edge intelligence deployments.

Keywords: Edge intelligence, system performance, computational efficiency, security and trustworthiness.

1.0 Introduction

In Malaysian higher education, understanding the determinants of final-year students' satisfaction remains essential for public universities striving to deliver high-quality educational services and enhance student experiences. Recent research emphasizes that students' satisfaction is shaped by multifaceted elements across academic, social, and environmental contexts in a university setting, with implications for retention, institutional reputation, and educational outcomes. Contemporary analytical methods such as artificial neural networks have increasingly been adopted to model complex relationships between satisfaction predictors and outcomes. In this study, a multilayer perceptron artificial neural network is applied to examine how academic, social, and environmental dimensions jointly influence students' satisfaction, providing a rigorous and nonlinear statistical analysis of these determinant factors.

2.0 Literature Review

2.1 Student Satisfaction: Student satisfaction is widely conceptualized as the degree to which learners feel their expectations and educational needs are fulfilled within tertiary environments. It encapsulates students' perceptions of service quality, academic support, social engagement, and physical environment and is critical for outcomes such as institutional loyalty and academic persistence. Empirical studies demonstrate that satisfaction significantly correlates with perceived quality of university experiences and services, serving as both a predictor of future engagement and a measure of institutional effectiveness.

2.2 Determinant Factors of Student Satisfaction: Recent literature highlights that student satisfaction is influenced by a constellation of factors that span academic provisioning, interpersonal dynamics, and campus-level environmental conditions. These determinant factors have been studied in diverse educational contexts and consistently shown to shape overall student satisfaction, reinforcing the importance of comprehensive models that integrate multiple dimensions of the student experience.

2.3 Academic Dimension: The academic dimension reflects elements directly tied to students' formal educational experience. This includes instruction quality, curriculum relevance, assessment practices, and the responsiveness of faculty, all of which contribute significantly to students' academic satisfaction. High-quality curricula, innovative teaching approaches, and sustained academic support contribute positively to students' perceived educational value. Recent evidence also underscores that perceptions of teaching quality and institutional support services are among the strongest academic predictors of student satisfaction.

2.4 Social Dimension: The social dimension captures the relational and community aspects within the university environment. Factors such as peer interaction, sense of belonging, student involvement in campus activities, and the broader campus culture are pivotal in shaping students' perceptions of their educational experience. Positive peer engagement, inclusive social climates, and opportunities for participation in extracurricular and student community events are associated with higher satisfaction levels.

2.5 Environmental Dimension: Environmental determinants of student satisfaction pertain to the physical and infrastructural features of higher education institutions. Quality campus facilities, well-maintained learning spaces, recreational infrastructure, and safe environments support students' comfort and convenience, which in turn influences satisfaction with the overall educational experience. Studies have identified that access to resources such as student accommodation, recreational services, and campus amenities significantly enhances students' satisfaction levels.

2.6 Multilayer Perceptron Artificial Neural Network: Multilayer perceptron (MLP) artificial neural networks have emerged as a powerful analytical tool in educational research due to their capacity for capturing complex, nonlinear relationships between predictor variables and outcomes. Recent applications of MLP models in student satisfaction and performance analysis demonstrate that these models can outperform traditional statistical approaches by uncovering subtle patterns and interactions within multidimensional educational data. The use of MLP allows for robust prediction and pattern discovery, enhancing the explanatory power of satisfaction models in higher education research.

3.0 Research Methodology

3.1 Study Design: This study adopts a quantitative research design to investigate the determinant factors affecting the performance of edge intelligence (EI) systems. A quantitative approach allows the collection of structured numerical data, enabling rigorous statistical analysis to identify the relationships between system-level factors and overall EI performance. This approach ensures objective insights into how computational efficiency, security and trustworthiness, and system resilience collectively influence system effectiveness (Li et al, 2025).

3.2 Data Collection: Data for this study are collected from both simulated and real-world edge intelligence system datasets. The datasets include performance metrics related to computational processing, security protocols, and resilience measures under various operational conditions. These data sources allow the study to capture realistic and representative information on EI system behavior, providing a comprehensive basis for model training and analysis (Kharuddin et al, 2020).

3.3 Variable Selection and Measurement: The study's variables are derived from recent literature on edge intelligence and encompass three primary dimensions:

1. Computational Efficiency: Metrics include processing speed, latency, resource utilization, and task completion rates.
2. Security and Trustworthiness: Metrics include authentication reliability, data integrity, intrusion detection efficacy, and adherence to security protocols.
3. System-Level Resilience: Metrics include fault tolerance, redundancy mechanisms, recovery time, and robustness under network or hardware failures.

Each variable is quantified using normalized numerical scales appropriate for modeling and analysis. Metrics are carefully selected to ensure validity, consistency, and relevance to EI system performance, drawing on established system benchmarks and prior studies.

3.4 Statistical Analysis: Quantitative Approach

A quantitative analytical framework is employed to examine the relationships between system-level determinants and EI performance. The following techniques are applied:

- Descriptive Statistics: Mean, standard deviation, and correlation analyses summarize system performance characteristics and explore preliminary relationships among variables.
- Inferential Statistics: Techniques such as ANOVA or t-tests are applied to evaluate significant differences in performance metrics under varying system conditions or configurations.
- Multivariate Analysis: Multiple regression and other multivariate approaches identify the relative contribution of each dimension (computational, security, resilience) to overall EI system performance, highlighting the most influential determinants.

3.5 Model Training and Evaluation

A multilayer perceptron (MLP) artificial neural network is employed to model complex, nonlinear relationships between system determinants and overall EI performance. The dataset is partitioned into training and testing subsets:

- Training Set: Used to iteratively develop the MLP model, adjusting network parameters to minimize prediction error and optimize system performance prediction.
- Testing Set: Used to evaluate the model's generalization ability and predictive accuracy.

Model performance is assessed using metrics such as mean squared error (MSE), root mean squared error (RMSE), or predictive accuracy. This approach allows robust, statistically grounded insights into how computational efficiency, security, and resilience interact to influence the performance of edge intelligence systems.

This methodology ensures that the study captures both the complex, interdependent nature of EI system factors and the practical implications for designing high-performing, secure, and resilient edge intelligence infrastructures.

4.0 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 R² 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.

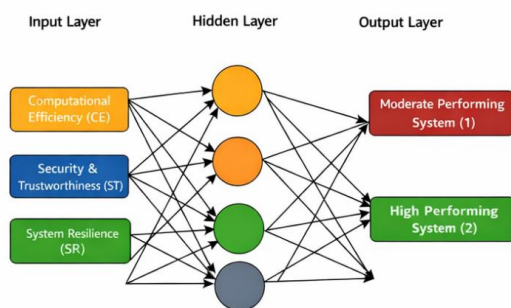


Figure 1: Neural Network Model for EI System Performance Classification

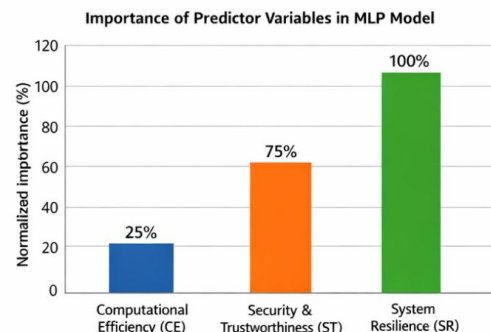


Figure 2: Importance of Predictor Variables in MLP Model

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.

5.0 Implications and Recommendations

5.1 Computational Efficiency Dimension: The analysis of the computational efficiency (CE) dimension revealed significant relationships between processing speed, latency, resource utilization, and overall edge intelligence (EI) system performance. These findings indicate that optimizing computational processes and ensuring efficient use of system resources are critical for high-performing EI systems. System designers and engineers should focus on enhancing task scheduling, adopting low-latency algorithms, and providing sufficient computational

resources to improve overall system efficiency. Investments in computational optimization can significantly enhance the operational performance of edge intelligence deployments.

5.2 Security and Trustworthiness Dimension: The analysis of the security and trustworthiness (ST) dimension demonstrated that factors such as authentication reliability, data integrity, and intrusion detection mechanisms strongly influence EI system performance. These findings highlight the importance of implementing robust security protocols and maintaining trustworthy operations at the edge. Organizations deploying EI systems should prioritize secure data handling, resilient authentication processes, and proactive threat detection to safeguard system functionality. Promoting a culture of cybersecurity and ensuring compliance with security standards can further enhance trust and reliability in edge intelligence ecosystems.

5.3 System Resilience Dimension: The analysis of the system resilience (SR) dimension confirmed that fault tolerance, redundancy mechanisms, and recovery strategies critically impact overall EI system effectiveness. High-resilience systems maintain consistent performance under hardware failures, network disruptions, or dynamic workloads. Developers and infrastructure planners should design edge intelligence systems with built-in redundancy, robust recovery protocols, and adaptive resource management. Ensuring resilient architectures is essential for sustaining long-term system performance and reliability.

5.4 Overall Implications: The integrated analysis of computational efficiency, security/trustworthiness, and system resilience provides actionable insights for designing high-performing edge intelligence systems. Key implications include:

- **Integrated System Design:** EI systems should adopt a holistic approach that considers computational efficiency, security, and resilience simultaneously. Improvements in a single dimension may be insufficient; addressing the interplay among all three dimensions is essential for maximizing system performance.
- **Strategic Resource Allocation:** Investments should be prioritized in areas with the highest impact on system performance, such as optimized processing algorithms, robust security protocols, and resilience-enhancing redundancy measures.
- **User-Centric and Operational Feedback:** Continuous monitoring and feedback mechanisms should be implemented to identify bottlenecks, security threats, or failure points. Data-driven adaptation and iterative improvement can enhance overall system performance.
- **Continuous Assessment and Optimization:** Regular evaluation of system metrics, including latency, resource utilization, threat detection, and recovery times, is crucial. Monitoring these metrics enables proactive maintenance, fine-tuning, and optimization of EI systems over time.

5.5 Conclusion

This study investigated the determinant factors influencing edge intelligence system performance, focusing on computational efficiency, security and trustworthiness, and system resilience. Using a multilayer perceptron artificial neural network, the study provided advanced analytical insights into the relationships among these dimensions and overall system effectiveness. The findings highlight the importance of a holistic approach to EI system design and offer practical recommendations for enhancing operational performance, robustness, and trustworthiness in edge-centric intelligent systems. These insights contribute to the growing body of knowledge in edge intelligence research and provide guidance for designing resilient, secure, and efficient systems for real-world applications.

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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.

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