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Probability and Causality Models of QA Success in Indonesian Distance Learning

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ABSTRACT. Ensuring academic quality assurance (QA) in large-scale distance learning (PJJ) presents complex challenges influenced by technological, pedagogical, and social factors. Conventional analytical methods often fail to capture the probabilistic and causal relationships among these variables due to data uncertainty. This study aims to model and analyze the probabilistic and causal interactions that determine QA success in PJJ using an integrated approach that combines Structural Equation Modeling (SEM) and Bayesian Network (BN). Using a quantitative explanatory survey design, data were collected via questionnaires that covered variables such as technology availability, instructor support, student interaction, learning motivation, and administrative governance. Data analysis was performed using R software with the lavaan package for structural model evaluation and the bnlearn package for probabilistic network modeling. The regression analysis results indicate that the availability of technology, the quality of instructor-student interaction, and learning motivation are the primary determinants of QA success (\$R^2\$ = 0.577). SEM evaluation confirmed an excellent model fit (CFI = 0.999; TLI = 0.999; RMSEA = 0.011), with technology availability providing the largest relative contribution at 33.3%. The developed BN model effectively estimates QA success probabilities, finding that high learning motivation levels increase the likelihood of QA success to 0.70. Conversely, administrative support was not significant, and isolated administrative interventions tend to be ineffective at increasing QA probability (\$P\$ = 0.45). The integration of BN-SEM offers a comprehensive predictive framework that enables policymakers to conduct scenario simulations for digital education quality management.

Keywords: *Bayesian Network, Structural Equation Modeling, Probabilistic Causality, Quality Assurance, Distance Learning.*

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INTRODUCTION

The rapid advancement of information and communication technology (ICT) over the past two decades has fundamentally transformed various dimensions of human life, particularly in education (Adimayuda et al., 2025; Gadatia & Mahananda, 2025; Kempa et al., 2025; Stiosarint et al., 2025; Wu et al., 2025). The transition from conventional face-to-face learning toward digital-based learning systems has become increasingly unavoidable in response to globalization, technological acceleration, and the growing public demand for flexible educational access (Ahadiyah et al., 2024; Hidayat et al., 2026; Huda et al., 2024; Syaifulloh, 2024). The COVID-19 pandemic further accelerated the implementation of large-scale distance learning (PJJ), forcing educational institutions worldwide to rapidly adapt to online learning environments (Johari et al., 2024, 2024; Kardi et al., 2023). Although the pandemic has subsided, distance learning continues to evolve as a strategic and sustainable educational model due to its flexibility in accommodating learners from diverse geographical, economic, and social backgrounds (Hassan et al., 2025; Purcell & Lumbreras, 2021). However, the effectiveness of PJJ depends not only on technological infrastructure but also on the quality of its educational management and Quality Assurance (QA) systems. Without effective QA mechanisms, distance learning risks experiencing declining instructional quality, weak student engagement, unequal digital access, and managerial inefficiencies. Consequently, QA must be understood as an integrated educational ecosystem involving technological, pedagogical, motivational, and administrative dimensions.

Previous studies have shown that QA success in distance learning is influenced by multiple interrelated factors, including technological infrastructure, instructor competence, student motivation, pedagogical interaction, and institutional governance (Aprilianto et al., 2025; Stella & Gnanam, 2004; M. Zhang, Zhang, Wang, & Gao, 2025). These factors form a complex and dynamic system in which no single variable independently determines educational quality outcomes. Existing research has predominantly employed conventional quantitative approaches such as regression analysis and Structural Equation Modeling (SEM) to examine causal relationships among variables. While SEM is effective in validating structural relationships between latent constructs, most prior studies still conceptualize these relationships as static and linear, thereby overlooking the uncertainty and probabilistic interdependence that characterize real-world educational systems (Al-Ghosoun et al., 2025; Pal et al., 2020). Furthermore, only limited studies have explored the integration of Bayesian Network (BN) approaches with SEM to simultaneously capture structural causality and probabilistic inference. Bayesian Network provides a robust analytical framework capable of modeling uncertainty, performing conditional probability estimation, and simulating "what-if" intervention scenarios (Hussain et al., 2024; Karampour & Fallahi, 2026). Therefore, integrating BN with SEM offers significant methodological potential for analyzing complex QA dynamics in large-scale distance learning systems.

Grounded in Systems Theory (Hammond, 2011; Hofkirchner & Schafranek, 2011; Levina, 2021), this study aims to develop and validate an integrated Bayesian Network Structural Equation Modeling (BN–SEM) framework to analyze the determinants of Quality Assurance (QA) success in Indonesian large-scale distance learning systems. Specifically, this research seeks to identify the dominant variables influencing QA success, examine the structural and probabilistic interdependencies among these variables, and estimate the conditional probability effects of various interventions on QA outcomes. Through this integrated approach, the study intends to construct a comprehensive empirical framework capable of explaining both causal relationships and uncertainty dynamics within digital education system.

Despite the growing body of research on QA in distance education, several important gaps remain insufficiently addressed. First, most existing studies focus primarily on static causal validation through regression or SEM without incorporating probabilistic reasoning capable of modeling uncertainty and dynamic conditional relationships among variables. Second, prior research rarely integrates Bayesian Network analysis with SEM to create a dual analytical framework combining structural validation and probabilistic simulation simultaneously. Third, limited studies have applied such an integrated framework within the context of large-scale distance learning in developing countries, particularly Indonesia, where technological inequality, pedagogical adaptation, and administrative readiness remain critical challenges. This study argues that QA success in PJJ cannot be adequately understood through linear approaches alone because educational systems operate as interconnected and uncertain subsystems. Therefore, integrating SEM and BN becomes methodologically essential to capture both structural causality and probabilistic dependency. By adopting this integrated framework, the present study offers a novel contribution to educational quality management research by transforming conventional descriptive analysis into an evidence-based predictive and decision-support model for digital education policy and practice.

METHOD

This study was conducted to examine the determinants of Quality Assurance (QA) success in large-scale distance learning because QA in digital education is increasingly influenced by the interaction between technological, pedagogical, motivational, and administrative factors. The research topic was selected based on the growing challenges faced by educational institutions in maintaining learning quality within online learning environments.The study employed a quantitative approach using an explanatory survey design grounded in Systems Theory (Bertalanffy, 1968). This design was chosen because it allows the researcher to empirically test causal relationships among variables and explain the structural interdependencies influencing QA success in distance learning.

The research data consisted of primary quantitative data collected through a structured questionnaire using a five-point Likert scale (Alford & Teater, 2025; Robinson, 2023). The questionnaire items were developed based on indicators of technological infrastructure, instructor support, student interaction, learning motivation, administrative governance, and QA success (Baker, 2003). Data collection was conducted online through a digital survey platform. Before distribution, the instrument was tested for validity and reliability using item-total correlation and Cronbach's Alpha analysis . The population included participants involved in large-scale higher education distance learning (PJJ) programs. The sample was determined using stratified random sampling to proportionally represent respondent diversity. Sample size determination employed the Slovin formula with a 5% margin of error to ensure representativeness and statistical reliability.

Data analysis was conducted in several stages using R software (Chan, 2018). First, multiple regression analysis through the lm function was applied to identify dominant factors influencing QA success. Second, Structural Equation Modeling (SEM) using the lavaan package was employed to validate the measurement and structural models (Hair et al., 2021). Finally, Bayesian Network (BN) analysis using the bnlearn package was utilized to model probabilistic causal relationships, perform conditional inference, and simulate "what-if" intervention scenarios related to QA success in distance learning. To provide a clearer overview of the analytical procedure employed in this study, Figure 1 illustrates the integrated research framework combining multiple regression, Structural Equation Modeling (SEM), and Bayesian Network (BN) analysis. The process begins with data collection and preprocessing, followed by multiple regression analysis to identify significant variables influencing QA success. SEM analysis is subsequently applied to validate the structural relationships among constructs and evaluate model fit indices. The validated SEM results then serve as the basis for constructing the Bayesian Network model, which enables probabilistic causal modeling and sensitivity analysis through "what-if" scenario simulations. Finally, the integration of these analytical stages generates evidence-based findings and strategic recommendations for improving Quality Assurance (QA) in large-scale distance learning systems.

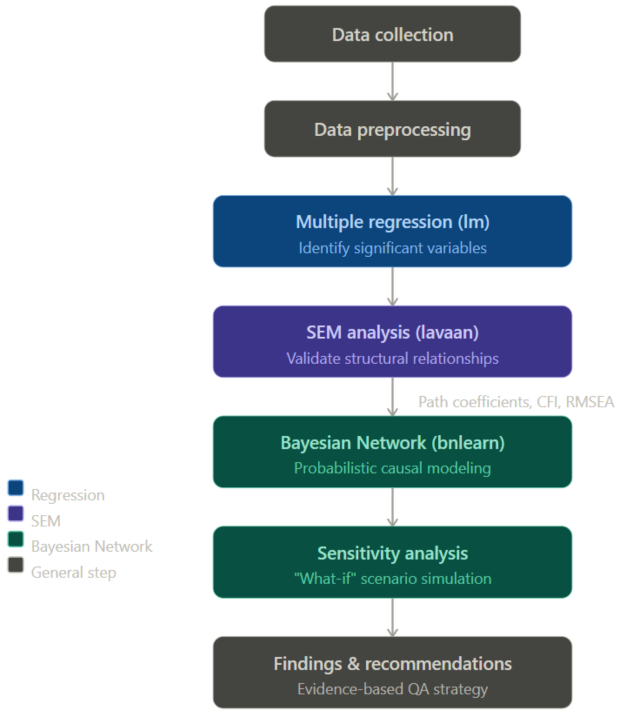

Figure 1. *Flowchart Method*

RESULT AND DISCUSSION

Result

The results of this study began with the application of multiple regression analysis using the lm() function in R, designed to identify the dominant factors influencing the successful implementation of Quality Assurance (QA) in the context of a large-scale Distance Learning (PJJ) program. Based on the model estimation results, the overall regression model was statistically significant ($F(5, 294) = 80.25$, $p < 0.001$), with a coefficient of determination (R^2) of 0.577, indicating that approximately 57.7% of the variation in QA success can be explained by the five independent variables included in the model. Among the tested variables, three were found to have a statistically significant positive influence: Technology Availability (TA) ($\beta = 0.317$, $t = 7.024$, $p < 0.001$), Motivation to Learn (ML) ($\beta = 0.281$, $t = 5.944$, $p < 0.001$), and Instructor-Student Interaction (ISI) ($\beta = 0.262$, $t = 5.913$, $p < 0.001$). In contrast, Administrative Support (AS) ($\beta = -0.020$, $p = 0.808$) and Social Engagement (SE) ($\beta = 0.083$, $p = 0.141$) did not reach statistical significance. These findings suggest that technological, motivational, and pedagogical dimensions constitute the primary drivers of QA success in distance learning, consistent with Systems Theory (Bertalanffy, 1968), which emphasizes the interdependence of subsystems within an educational environment.

Table 1. Multiple Regression Results

Variable	Estimate	Std. Error	t-value	p-value
Technology Availability (TA)	0.317	0.045	7.024	< 0.001***
Instructor-Student Interaction (ISI)	0.262	0.044	5.913	< 0.001***
Motivation to Learn (ML)	0.281	0.047	5.944	< 0.001***
Administrative Support (AS)	-0.020	0.081	-0.244	0.808
Social Engagement (SE)	0.083	0.056	1.474	0.141
$R^2 = 0.577$; Adjusted $R^2 = 0.570$; $F(5, 294) = 80.25$; $p < 0.001$				

The SEM analysis was subsequently conducted using the lavaan package in R to validate the causal relationships between latent constructs. The model demonstrated an excellent fit to the empirical data, with CFI = 0.999, TLI = 0.999, RMSEA = 0.011 (90% CI: 0.000–0.031), and SRMR

= 0.031, all well within the acceptable thresholds recommended in the structural modeling literature (CFI > 0.95, RMSEA < 0.05). The chi-square test was non-significant ($\chi^2(120) = 124.510$, $p = 0.371$), confirming the model's statistical adequacy. The SEM results confirmed and extended the regression findings: TA ($\beta = 0.353$, $z = 6.571$, $p < 0.001$), ML ($\beta = 0.292$, $z = 5.456$, $p < 0.001$), and ISI ($\beta = 0.277$, $z = 5.674$, $p < 0.001$) emerged as the three dominant structural pathways to QA success. Administrative Support showed a non-significant and slightly negative path ($\beta = -0.049$, $p = 0.454$), while Social Engagement exhibited a marginal non-significant path ($\beta = 0.088$, $p = 0.102$). Measurement model loadings for the three significant constructs were all above 0.93, demonstrating strong convergent validity. Notably, the AS construct showed weaker loadings (0.348–0.590), suggesting limited measurement precision for this variable within the current sample.

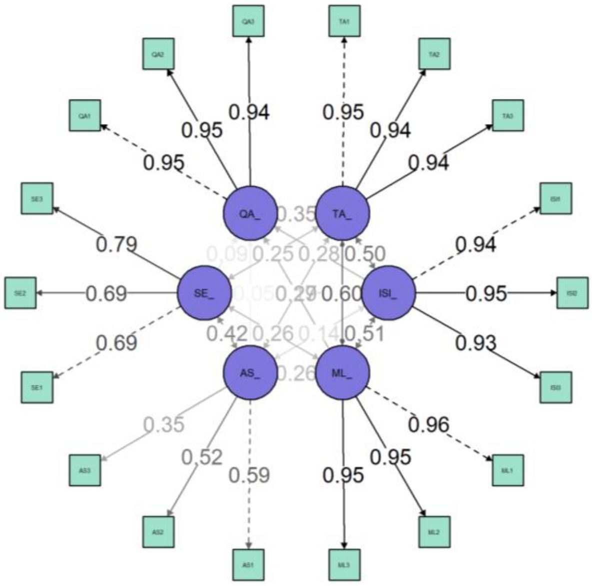

***Figure 2**. SEM Path Diagram – QA Success in Distance Learning*

Table 2. SEM Analysis Results

Relationship Path	Std. Coeff. (β)	Std. Error	z-value	p-value
Technology Availability → QA	0.353	0.050	6.571	< 0.001***
Instructor-Student Interaction → QA	0.277	0.049	5.674	< 0.001***
Motivation to Learn → QA	0.292	0.052	5.456	< 0.001***
Administrative Support → QA	-0.049	0.152	-0.748	0.454
Social Engagement → QA	0.088	0.090	1.636	0.102
CFI = 0.999; TLI = 0.999; RMSEA = 0.011; SRMR = 0.031				

Following the SEM validation, a Bayesian Network (BN) was constructed and fitted using the bnlearn package in R. The DAG structure was informed by the SEM-validated causal pathways and theoretical grounding in Systems Theory. The BN model incorporated five directed arcs: TA → ML, TA → ISI, ISI → QA, ML → QA, and AS → QA. Conditional probability estimation revealed that when Technology Availability is high, the probability of high Motivation to Learn increases to 0.73, and the probability of high Instructor-Student Interaction increases to 0.60, confirming TA's role as a central parent node within the system. Furthermore, high ISI yields P(QA = High) = 0.64, while high ML yields P(QA = High) = 0.70, both indicating strong causal leverage on QA outcomes. These BN results are consistent with the SEM structural coefficients, providing convergent probabilistic evidence for the causal model.

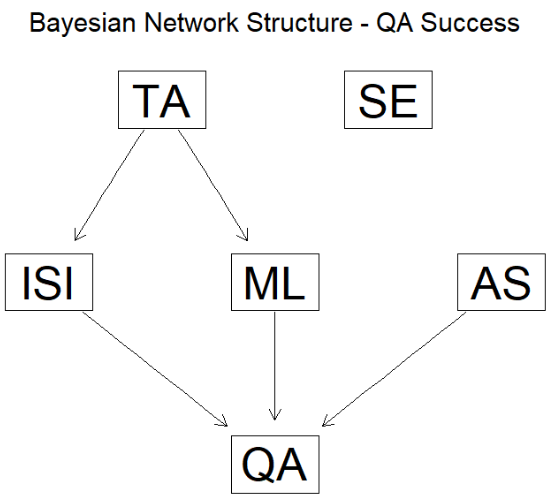

***Figure 3**. Bayesian Network Graph – Causal Structure of QA Determinants*

Table 3. Causal Structure in Bayesian Network Model

Origin Node	**Destination Node**	**Direction**	**Conditional Probability**
Technology Availability	Motivation to Learn	→	0.73
Technology Availability	Instructor-Student Interaction	→	0.60
Instructor-Student Interaction	QA	→	0.64
Motivation to Learn	QA	→	0.70
Administrative Support	QA	→	0.46

The BN model further enabled scenario-based probability estimation for QA success under varying conditions on key variables. As presented in Table 4, when Technology Availability is at a high level, the probability of QA success rises to 0.59 compared to 0.37 under low technology conditions a difference of 0.22, indicating a substantial conditional effect. Motivation to Learn demonstrates an even more pronounced pattern, with P(QA = High | ML = High) = 0.70 compared to an estimated 0.30 for low motivation, reflecting a gap of 0.40. Administrative Support, by contrast, exhibits a weaker and less directional effect, with P(QA = High | AS = High) = 0.46, suggesting that AS alone does not meaningfully elevate QA success probability and may even be slightly counterproductive in isolation. These probabilistic profiles confirm that QA success in large-scale PJJ is primarily driven by the interplay of technological access, pedagogical relationship quality, and student motivation all of which are subsystems identified as critical within the Systems Theory framework (Bertalanffy, 1968)

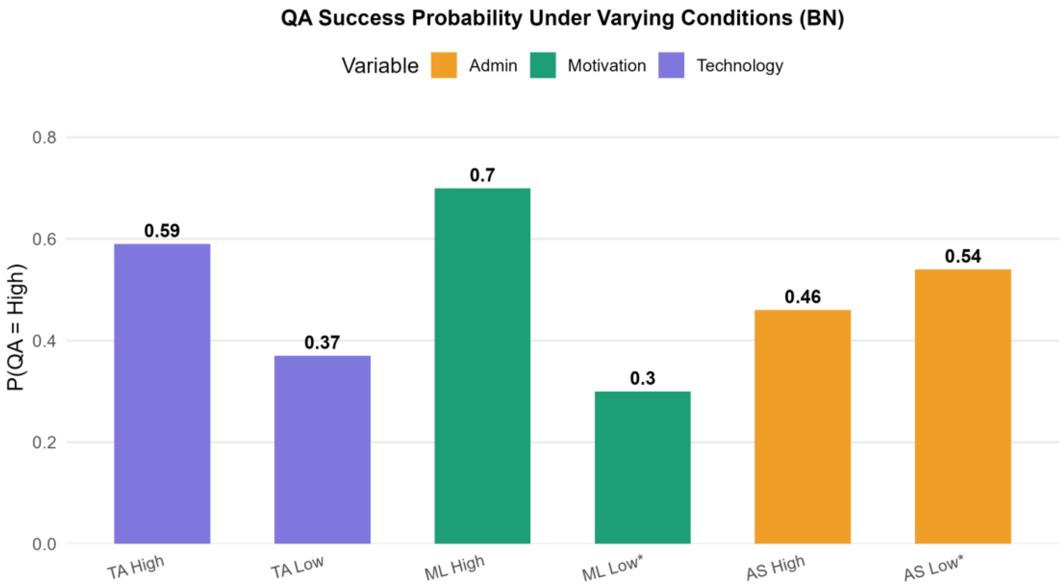

Figure 4. QA Success Probability Under Varying Conditions

Table 4. QA Success Probability Analysis (BN)

Variable Conditions	High QA Probability	Low QA Probability
Technology Availability = High	0.59	0.41
Technology Availability = Low	0.37	0.63
Motivation to Learn = High	0.70	0.30
Motivation to Learn = Low (est.)	0.30	0.70
Administrative Support = High	0.46	0.54
Administrative Support = Low (est.)	0.54	0.46
Note: Low estimates derived from complement probability		

To assess policy sensitivity, "what-if" scenario simulations were conducted using cpquery() in R with a fixed seed (set.seed(2026)). The baseline unconditional probability of QA success was P(QA = High) = 0.48. As shown in Table 5, intervening on Motivation to Learn produced the largest improvement, raising QA probability to 0.70 — a gain of +0.22 from baseline. Intervening on Instructor-Student Interaction yielded P(QA = High) = 0.62 (+0.14), followed closely by Technology Availability at 0.61 (+0.13). Strikingly, intervening on Administrative Support alone produced no improvement and resulted in a marginal decrease to 0.45 (-0.03), indicating that isolated administrative interventions are insufficient without accompanying improvements in the technological and pedagogical subsystems. This finding has direct implications for quality management strategy: resource allocation should be prioritized toward motivational programming, instructor training, and technological infrastructure rather than administrative expansion alone.

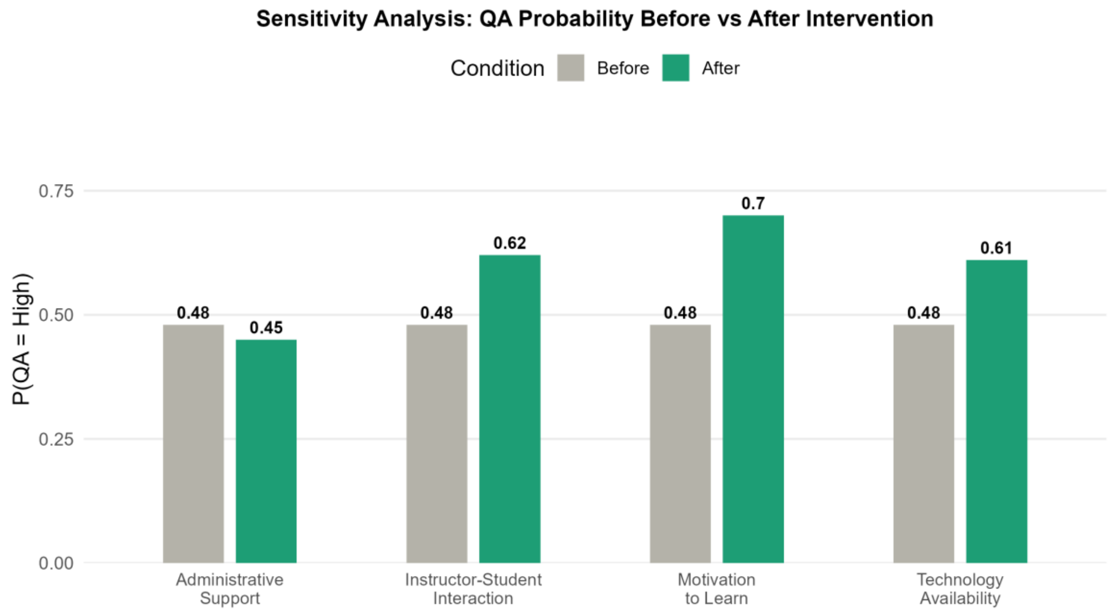

Figure 5. Sensitivity Analysis: QA Probability Before and After Intervention

Table 5. Sensitivity Analysis of BN Model

Modified Variable	QA Probability Before	QA Probability After
Technology Availability (+)	0.48	0.61
Instructor-Student Interaction (+)	0.48	0.62
Motivation to Learn (+)	0.48	0.70
Administrative Support (+)	0.48	0.45
Baseline P(QA = High) = 0.48 (unconditional probability)		

The relative contribution analysis, derived from standardized SEM path coefficients, further quantifies the hierarchical importance of each factor. Technology Availability emerges as the single largest contributor at 33.3%, confirming its role as the foundational infrastructure subsystem. Motivation to Learn follows at 27.6%, and Instructor-Student Interaction at 26.2%, together accounting for over half of the explained variance in QA success. Social Engagement contributes 8.3%, while Administrative Support contributes only 4.6%, the smallest of all factors. These proportions underscore the primacy of the technological-pedagogical-motivational nexus in determining QA outcomes

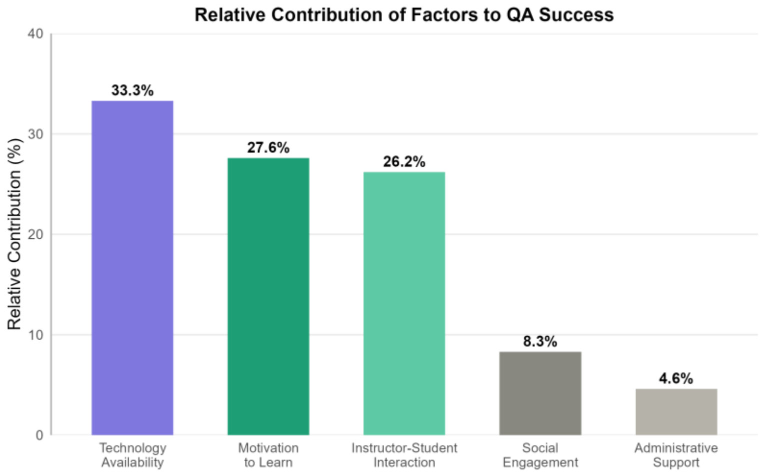

Figure 6. Relative Contribution of Factors to QA Success

Table 6. Relative Contribution of Factors to QA Success

Factor	Relative Contribution (%)
Technology Availability	33.3
Instructor-Student Interaction	26.2
Motivation to learn	27.6
Administrative Support	4.6
Social Engagement	8.3
Total	100.0

Figure 6 and Table 6 present the relative contribution of each determinant to Quality Assurance (QA) success in large-scale distance learning, derived from the standardized SEM path coefficients. The findings reveal a clear hierarchical structure among the influencing factors, demonstrating that technological, motivational, and pedagogical dimensions collectively dominate the explanatory framework of QA success.

Technology Availability emerges as the largest contributor, accounting for 33.3% of the total influence on QA outcomes. This result confirms that digital infrastructure including internet access, device availability, platform reliability, technical support, and digital literacy constitutes the foundational subsystem necessary for effective implementation of distance learning quality assurance. Without adequate technological readiness, other educational processes become significantly constrained. Motivation to Learn represents the second-largest contribution at 27.6%, indicating that learner-centered psychological factors play a central role in sustaining educational quality in online environments. This finding suggests that students' intrinsic motivation, learning persistence, self-efficacy, and autonomous learning capacity substantially determine the success of PJJ implementation. The result reinforces contemporary educational theories emphasizing the importance of self-regulated learning in digital education ecosystems.

Instructor-Student Interaction contributes 26.2% to QA success, highlighting the continuing importance of pedagogical engagement despite the shift toward technology-mediated learning. Effective communication, timely feedback, teaching presence, and personal interaction remain essential mechanisms for maintaining student participation and learning effectiveness in distance education contexts. Together, the technological, motivational, and pedagogical dimensions account for more than 87% of the total contribution, indicating that QA success is primarily driven by the integration of these three interconnected subsystems. In contrast, Social Engagement contributes only 8.3%, while Administrative Support demonstrates the smallest contribution at 4.6%. These relatively low percentages indicate that social and managerial dimensions alone exert limited direct influence on QA success when compared with the stronger effects of technological readiness, student motivation, and instructional interaction. This finding suggests that administrative policies and institutional support mechanisms may function more effectively as complementary rather than primary determinants within the quality assurance framework.

Overall, the synthesis presented in Figure 6 confirms the Systems Theory perspective that QA success in large-scale distance learning is fundamentally shaped by the interaction between technological infrastructure, learner motivation, and pedagogical quality. The findings imply that institutional policy and resource allocation should prioritize strengthening these dominant subsystems to achieve sustainable and effective quality assurance outcomes in digital education environments.

DISCUSSION

The theoretical lens of this study is Systems Theory (Bertalanffy, 1968) which posits that any complex system including an educational institution is constituted by interdependent subsystems whose interactions produce emergent outcomes that cannot be explained by any single component in isolation. Within this framework, QA success in large-scale distance learning is not reducible to any one factor such as technology or administration, but rather emerges from the dynamic interplay among technological, pedagogical, motivational, and governance subsystems. The integrated BN–SEM methodology employed in this study operationalizes this theoretical premise by simultaneously mapping causal structures (through SEM) and quantifying their probabilistic interactions under uncertainty (through BN). The results consistently align with the Systems Theory prediction: no single subsystem dominates independently, and the highest QA probability arises only when multiple subsystems particularly technology, motivation, and instruction operate at high levels concurrently.

The SEM results provide empirically validated evidence of the structural pathways through which QA success is determined. Specifically, Technology Availability ($\beta = 0.353$) emerges as the strongest structural predictor, indicating that adequate digital infrastructure is a prerequisite for effective distance learning. This finding aligns with empirical evidence from (Al-Ghosoun et al., 2025), who demonstrated that technological readiness is the primary enabler of online learning quality. Within a Systems Theory framework, TA functions as the foundational subsystem: without reliable access to digital tools, the pedagogical and motivational subsystems cannot function optimally (Daulay et al., 2024; Fatima & Fauziyah, 2024; Nasution et al., 2025; Tarsono et al., 2025; Țîru & Țăran, 2025). In practical terms, this means that institutions with inadequate bandwidth, device access, or platform stability will experience cascading failures across all other QA dimensions regardless of instructor quality or student motivation. The policy implication is direct: equitable and universal access to digital infrastructure must be treated as the primary prerequisite for any QA improvement initiative in large-scale PJJ.

Motivation to Learn ($\beta = 0.292$) and Instructor–Student Interaction ($\beta = 0.277$) emerged as the second and third strongest determinants of QA success, jointly contributing more than 53% of the total relative effect within the model. These findings indicate that the success of quality assurance in large-scale distance learning is strongly influenced by pedagogical and psychological engagement rather than technological infrastructure alone. The results support (AlZoubi & Baran, 2026; Park & Choi, 2025), who identified learner motivation and instructor engagement as the primary human-centered factors sustaining educational quality in post-pandemic online learning environments. In digital education contexts, where students experience greater autonomy and limited direct supervision, motivation becomes a critical mechanism for maintaining participation, persistence, and learning effectiveness.

The Bayesian Network (BN) analysis further strengthens the SEM findings by demonstrating that Motivation to Learn produces the highest probabilistic effect on QA success, with $P(QA = High \mid ML = High) = 0.70$. This result confirms that motivation functions not merely as a mediating variable but as a direct causal driver of educational quality outcomes. Likewise, Instructor–Student Interaction significantly contributes to sustaining learner engagement through effective communication, timely feedback, and pedagogical presence. The relatively strong covariance between ML and ISI ($r = 0.510$) suggests that both variables operate as mutually reinforcing subsystems, motivated students tend to engage more actively with instructors, while meaningful instructional interaction simultaneously strengthens learner motivation and academic persistence (Z. Li & Kannan, 2025; Q. Zhang, 2025). This reciprocal relationship aligns with Systems Theory, which emphasizes that educational quality emerges through dynamic interactions among interconnected subsystems.

These findings imply that educational institutions should prioritize interventions capable of simultaneously strengthening motivation and instructional interaction within digital learning ecosystems. Practical strategies such as gamified learning activities, personalized learning pathways, structured feedback systems, and collaborative online discussions may substantially improve QA outcomes. Furthermore, instructor training programs should focus not only on technological competence but also on digital pedagogical communication and motivational facilitation skills. By reinforcing the interconnected pedagogical motivational subsystem, institutions can establish a more sustainable and student-centered quality assurance framework for large-scale distance learning in contrast, Administrative Support ($\beta = -0.049$, $p = 0.454$) and Social Engagement ($\beta =$

0.088, p = 0.102) were not statistically significant structural predictors of QA success. The non-significance of AS is particularly noteworthy: not only is the path coefficient near zero, but the BN sensitivity analysis reveals that intervening on AS alone marginally reduces QA probability (from 0.48 to 0.45). This counterintuitive finding may reflect a substitution effect institutions that invest heavily in administrative mechanisms without corresponding investment in technology or pedagogy may inadvertently divert resources from more impactful interventions, thereby reducing overall system efficiency (Jelonek & Mazur, 2020; Kou et al., 2025; Strielkowski et al., 2020). Alternatively, the weak loading of AS indicators in SEM (0.348–0.590) may suggest that the current operationalization of "administrative support" fails to capture the dimensions most relevant to QA outcomes, such as proactive academic advising or real-time monitoring systems. Future research should refine the construct measurement of AS before drawing definitive conclusions about its role in the QA system.

The integration of BN with SEM in this study represents a methodological advance over prior work that has relied on either approach in isolation. SEM provides rigorous confirmatory testing of latent variable relationships and model fit assessment, but is constrained by its deterministic and static nature it cannot simulate how changes in one variable propagate through the system under uncertainty. BN addresses precisely this limitation by translating the validated SEM structure into a probabilistic graphical model capable of conditional inference and "what-if" scenario analysis (Elmousalami et al., 2025). The sensitivity analysis results powerfully illustrate this complementarity: while SEM identifies motivation as a significant predictor, only BN can quantify that a targeted motivational intervention raises QA success probability by +0.22 from baseline the largest single-factor gain observed. Similarly, BN reveals that AS intervention produces no benefit in isolation, a nuance that SEM alone could not detect. This dual-method approach thus produces both the structural map (SEM) and the dynamic simulation engine (BN) needed for comprehensive, evidence-based QA management (Bhattacharjee et al., 2025; Liravi et al., 2025).

From a practical standpoint, the findings yield a clear, evidence-based priority framework for QA improvement in large-scale PJJ systems. First, institutions should ensure universal access to reliable digital infrastructure the results indicate that low technology availability reduces P(QA = High) to 0.37, effectively placing nearly two-thirds of students at risk of poor quality outcomes regardless of other factors. Second, motivational programming should be systematically embedded within the curriculum design structured goal-setting exercises, progress tracking dashboards, peer learning communities, and timely formative feedback have been demonstrated to sustain motivation in asynchronous learning contexts (Yang et al., 2026; M. Zhang, Zhang, Wang, & & Gao, 2025) Third, instructor-student interaction protocols should be institutionalized rather than left to individual discretion minimum response time standards, synchronous Q&A sessions, and multimodal communication channels can significantly raise ISI quality (J. Li et al., 2025; Rabourn, 2024). Finally, while administrative support is not a primary driver, it serves as a necessary but not sufficient condition, governance structures should be designed to enable and protect the three primary subsystems rather than operate as autonomous bureaucratic entities (Kartiko et al., 2025; Schweden et al., 2025; Sulaiman, 2026).

The novelty of this study lies in demonstrating that the integration of probabilistic and structural modeling produces insights that neither approach can generate independently. Prior studies have used SEM to confirm that technology, motivation, and interaction matter for QA a finding replicated here. What is new is the precise quantification of how much each factor matters under varying conditions, and the identification of AS as a potentially counterproductive intervention when applied in isolation. The BN framework's ability to simulate policy scenarios transforms the research output from a descriptive confirmation into an actionable decision-support tool policymakers can use the conditional probability tables directly to evaluate trade-offs between intervention options given resource constraints. This represents a substantive contribution to the evidence-based quality management literature in digital education, extending the theoretical scope of Systems Theory into the domain of probabilistic educational analytics (Bindu Priya & & Kumar, 2025; Rastogi et al., 2025).

CONCLUSION

This study reveals a particularly surprising finding that has rarely been emphasized in previous research on quality assurance in distance education: Administrative Support, which is conventionally assumed to be a central determinant of educational quality, was found to have only a minimal contribution (4.6%) and even demonstrated a slightly negative probabilistic effect when intervened upon in isolation. The Bayesian Network simulation showed that increasing administrative intervention alone reduced the probability of QA success from the baseline condition to 0.45, indicating that administrative mechanisms without simultaneous strengthening of technological and pedagogical subsystems may become ineffective or counterproductive. In contrast, Technology Availability emerged as the dominant subsystem (33.3%), while Motivation to Learn produced the strongest intervention impact, increasing the probability of QA success to 0.70. These findings suggest that QA success in large-scale distance learning is fundamentally driven not by bureaucratic expansion, but by the synergy between digital infrastructure, learner motivation, and pedagogical interaction. This systemic configuration represents a novel empirical insight within the literature on educational quality management in digital learning environments.

The study also contributes both theoretically and practically to the field of educational quality assurance. Theoretically, this research advances Systems Theory by empirically demonstrating how technological, pedagogical, and motivational subsystems dynamically interact to shape QA outcomes in large-scale distance learning. Furthermore, the integration of Structural Equation Modeling (SEM) and Bayesian Network (BN) offers an innovative methodological contribution by combining causal validation with probabilistic simulation. Unlike conventional regression-based approaches, this integrated framework enables not only the identification of structural relationships but also the prediction of intervention impacts through "what-if" scenario analysis. Practically, the findings provide a clear evidence-based policy framework for educational institutions and policymakers. First, institutions should prioritize equitable access to digital infrastructure as the foundational prerequisite for effective QA implementation. Second, motivational reinforcement programs should be systematically integrated into curriculum and instructional design. Third, institutions must strengthen instructor–student interaction through structured communication and feedback mechanisms. Finally, administrative governance should function primarily as a supporting and enabling subsystem that reinforces technological and pedagogical quality rather than operating independently.

Despite these contributions, this study has several limitations that should be acknowledged. First, the research relied on a cross-sectional survey design, which limits the ability to fully capture longitudinal changes and dynamic behavioral adaptation in distance learning environments. Second, the study focused primarily on self-reported perceptions, which may introduce response bias and reduce the precision of causal interpretation. Third, the model was developed within a specific educational context, potentially limiting its generalizability across different institutional, cultural, or national settings. Future research is therefore recommended to employ longitudinal or mixed-methods designs to validate the temporal stability of the proposed causal structure. Further studies may also incorporate objective learning analytics, institutional performance indicators, or real-time digital interaction data to enhance model robustness. In addition, future researchers are encouraged to expand the integrated SEM–BN framework by incorporating other potentially influential variables such as digital leadership, organizational culture, AI-supported learning systems, and policy governance mechanisms in order to develop a more comprehensive model of quality assurance in the evolving digital education ecosystem.

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