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From Analytics Capability to Service Outcomes: The Role of Intervention Decision Quality in Higher Education Service Systems

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Abstract. Higher education increasingly functions as a digitally mediated service system in which learning management platforms generate continuous streams of student data. Despite widespread adoption of learning analytics dashboards, their impact on student success remains uneven, suggesting that analytics value is not realized through information availability alone. Drawing on service-systems and service-informatics perspectives, this study conceptualizes learning analytics as an institutional coordination capability whose value is captured at the "last mile" of service delivery—intervention decision quality (IDQ). Using survey data from 274 instructors, advisors, coordinators, and e-learning administrators across six Saudi universities, the study tests a capability-to-outcome model using partial least squares structural equation modeling (PLS-SEM). The results show that learning analytics capability (LAC) strongly improves intervention decision quality ($\beta = 0.60$, $p < 0.001$), which in turn enhances student performance ($\beta = 0.35$), retention ($\beta = 0.27$), and satisfaction ($\beta = 0.55$) (all $p < 0.001$). Mediation analysis confirms that IDQ is the primary mechanism translating analytics capability into service outcomes. Two boundary conditions further shape this process. Data quality strengthens the conversion of analytics capability into effective decisions ($\beta = 0.17$, $p = 0.001$), while privacy concern—conceptualized as a service-governance and legitimacy constraint—weakens the effects of intervention decisions on retention and satisfaction, but not on performance. The model explains substantial variance in intervention decision quality ($R^2 = 0.58$) and student satisfaction ($R^2 = 0.48$). By repositioning learning analytics as a service-informatics capability embedded in operational decision routines, this study contributes to the service science literature by clarifying how analytics generates value through coordinated action and trusted governance in higher education service systems.

Keywords: Learning Analytics Capability; Service Informatics; Intervention Decision Quality; Higher Education Service Systems; Student Success; Data Quality and Privacy Governance; PLS-SEM

1. Introduction

Higher education is increasingly delivered through digital learning environments that generate continuous records of student activity. Learning management systems (LMS) capture assessment performance, submission timing, content access, and participation patterns, creating real-time information flows that can support proactive student success. In service-science terms, universities function as service systems in which people (students, instructors, advisors), technologies (LMS, analytics tools), and governance arrangements interact to co-create value through teaching and support processes (Hlazunova et al., 2024).

Despite rapid diffusion of dashboards and early-warning tools, the impact of learning analytics on student outcomes remains uneven across institutions. A recurring explanation is a ‘last-mile’ gap: predictive or diagnostic insights do not automatically improve outcomes unless they are translated into consistent intervention decisions and executed as part of day-to-day service operations (e.g., advising outreach, feedback cycles, escalation of high-risk cases). From an operations perspective, analytics must be integrated into decision routines—who acts, when they act, on which cases, and how follow-through is monitored—otherwise insights remain informational rather than operational.

To address this gap, this study conceptualizes learning analytics as a service-informatics coordination capability—an institutional ability to integrate learning data, generate credible signals, and embed those signals into routine intervention workflows. We argue that analytics improves outcomes primarily through intervention decision quality (IDQ), defined as the timeliness, targeting, consistency, and follow-through of analytics-informed actions. Because service outcomes also depend on the reliability and legitimacy of information use, we test data quality (DQ) and privacy concern (PC) as boundary conditions that shape when capability converts into decisions and when decisions translate into student success. The Saudi higher education context provides a relevant setting given strong national emphasis on digital transformation and institutional accountability in education (Chand et al., 2025a; Sampson et al., 2025).

Research questions

- RQ1: How and to what extent does learning analytics capability improve intervention decision quality (the ‘last-mile’ student-support operation)?
- RQ2: To what extent does higher intervention decision quality translate into student performance, retention, and satisfaction as service outcomes?
- RQ3: Does intervention decision quality explain how learning analytics capability translates into student success (capability-to-outcome mechanism)?
- RQ4: When is the capability-to-decision pathway stronger—does data quality strengthen the conversion of learning analytics capability into intervention decision quality?
- RQ5: When do interventions lose traction—does privacy concern, as a service-governance and legitimacy constraint, weaken the relationship between intervention decision quality and student success?

By addressing these questions, the study strengthens JLISS alignment by treating student success as a service outcome, learning analytics capability as a service-informatics coordination capability, and intervention decision quality as a last-mile service operation. The resulting model clarifies both the mechanism (how analytics becomes action) and the boundary conditions (when data readiness and perceived privacy legitimacy enable or constrain impact).

2. Literature Review and Hypotheses Development

AI-enabled learning analytics has developed as a prominent response to the data-rich nature of contemporary higher education. However, evidence of impact is mixed because analytics value is not produced by tools alone; it is produced when analytics improves the quality of service operations—information flows, intervention routines, and decision accountability—through which student support is delivered.

2.1. AI-enabled learning analytics and the mixed evidence on impact

The empirical literature suggests that learning analytics can support early warning, personalization, and targeted support, but effects vary across contexts. From a service-operations perspective, variability is expected: identical dashboards can yield different outcomes depending on whether institutions formalize decision rules, allocate advising capacity, and execute interventions consistently after a risk signal is generated. (Tlili et al., 2025)

Systematic reviews reinforce this point by documenting a recurring imbalance: many studies emphasize model building and prediction accuracy, while fewer evaluate whether analytics-driven interventions are executed reliably, at scale, and with feedback loops that refine practice. This last-mile execution problem helps explain why analytics adoption does not guarantee improved performance or persistence.

2.2. Education as a service system: positioning student success as a service outcome

To align analytics research with outcomes that matter in educational delivery, a service-science framing is useful. Service science conceptualizes service systems as configurations of people, technologies, and shared information that co-create value through interactions and governance (Jreissat et al., 2024; Walletzký et al., 2024). In parallel, service-dominant logic emphasizes that value is realized in use and co-created through reciprocal resource integration rather than delivered as a one-way output (Barnes et al., 2024; Olawumi et al., 2024). Applied to higher education, this means student success is not merely an individual achievement but also a service outcome shaped by the quality of information flows, responsiveness of support, and consistency of intervention processes across teaching and advising.

This lens strengthens how AI-enabled learning analytics should be theorized. Analytics does not "improve retention" by itself; rather, it enhances the institution's information processing and coordination capabilities—enabling better sensing of student needs, better decision-making about interventions, and better execution of support routines. In other words, learning analytics functions as service informatics: the use of data and analytics to improve service design, decision processes, and outcomes (Taylor & Sailor, 2024). This positioning is valuable because it shifts the research focus away from whether dashboards exist and toward whether analytics is embedded in service operations that reliably improve performance, retention, and satisfaction (Ogedengbe, 2021).

2.3. Learning analytics capability: moving from adoption to institutional capability

A central limitation in prior work is an implicit assumption that adopting analytics tools is equivalent to being capable of using them effectively. In service systems, capability is a bundle of coordinated resources and routines that improves how information is processed, shared, and acted upon. Translating this to higher education, learning analytics capability (LAC) reflects the institution's ability to integrate data, generate credible signals, and embed insights into teaching and advising workflows (Alshemmari, 2023; Hoang & Khoa, 2022).

This framing is consistent with learning analytics scholarship that emphasizes institutional readiness, stakeholder engagement, and governance as prerequisites for sustained impact (J. Liu et al., 2024; Yan et al., 2024). Under a service-informatics logic, a strong learning analytics capability should improve the quality of the institution's academic decisions by reducing uncertainty, improving targeting, and enabling earlier intervention. Therefore, rather than predicting outcomes directly, LAC is expected to shape the decision process that determines which actions are taken, when, and for whom (Mekvabidze, 2020).

H1: Learning analytics capability positively influences intervention decision quality.

2.4. Intervention decision quality as the mechanism linking analytics to student success

The last-mile challenge in learning analytics suggests that a mechanism is required to explain how analytics shapes outcomes. We propose intervention decision quality (IDQ) as this mechanism: a service-operations construct capturing whether analytics-informed actions are timely, targeted, consistently applied across staff and courses, and monitored for follow-through and adjustment (Nguyen-Pham et al., 2024).

Higher IDQ should improve student outcomes through multiple channels. Timely and targeted actions can prevent small performance issues from compounding into course failure, while consistent advising outreach can reduce disengagement and withdrawal (Dubeau & Chochard, 2024). Additionally, when interventions are appropriate and responsive, students are more likely to perceive academic support as effective, raising satisfaction. These arguments support a direct effect of IDQ on student success and a mediated pathway in which LAC improves success primarily by increasing IDQ.

H2: Intervention decision quality positively influences student success (performance, retention, and satisfaction).

H3: Intervention decision quality mediates the relationship between learning analytics capability and student success.

2.5. Boundary conditions: data quality and privacy concern

Even strong analytics capability may not translate into high-quality decisions if foundational conditions are weak. Two boundary conditions are especially salient in educational contexts.

Data quality is widely conceptualized as ‘fitness for use’, including accuracy, completeness, timeliness, and consistency. In service operations, data quality is the reliability layer: it reduces false alarms, supports faster triage, and increases staff confidence to act within agreed decision thresholds and service-level expectations (Fleurence et al., 2024).

H4: Data quality positively moderates the relationship between learning analytics capability and intervention decision quality, such that the relationship is stronger when data quality is high.

Privacy concern operates not only as an individual attitude but also as a service-governance and legitimacy constraint. In learning analytics, perceptions of surveillance, unclear consent, or secondary use can reduce trust, limit student engagement with outreach, and weaken co-creation of support—thereby constraining the effectiveness of even well-designed intervention decisions (Nan et al., 2025).

H5: Privacy concern negatively moderates the relationship between intervention decision quality and student success, such that the relationship is weaker when privacy concern is high.

2.6. Research gap and study positioning

Synthesizing the literature reveals three persistent gaps. First, the field remains disproportionately tool-centric, under-specifying how analytics becomes a repeatable service operation. Second, many studies do not model the decision mechanism that converts analytics into intervention actions. Third, governance and readiness conditions—especially data quality and privacy legitimacy—are often discussed but less often tested as boundary conditions shaping the capability-to-action pathway. This study addresses these gaps by positioning learning analytics within service operations and service-informatics, modeling IDQ as the last-mile mechanism, and testing DQ and PC as contingencies.

3. Methodology

3.1 Research design

This study applies a quantitative, explanatory design to test a capability-to-outcome model in which AI-enabled learning analytics capability (LAC) improves student success through intervention decision quality (IDQ), while considering data quality (DQ) and privacy concern (PC) as boundary conditions. The hypotheses are evaluated using partial least squares structural equation modeling (PLS-SEM) because the model includes mediated and moderated relationships and focuses on predictive explanation of variance in key outcomes (Chand et al., 2025b).

3.2 Research context and unit of analysis

The research is situated in higher education institutions that operate an LMS (e.g., Moodle, Blackboard, Canvas) and utilize learning analytics features such as dashboards, engagement reports, early-warning flags, or predictive alerts. The unit of analysis is analytics-enabled intervention practice at the course/program level as enacted through staff decision-making. Respondents are instructors, academic advisors, program coordinators, and e-learning/quality administrators because they directly interpret analytics outputs and initiate or coordinate interventions; learning analytics affects outcomes only when insights are embedded into teaching and advising routines (Queirós, 2024).

3.3 Sampling and data collection procedure

A purposive sampling strategy was employed to recruit participants in Saudi Arabian higher education institutions who (i) have access to learning analytics outputs (e.g., LMS dashboards, engagement reports, early-warning flags) and (ii) participate in intervention-related decisions (e.g., advising outreach, course-level support actions, risk follow-up). Saudi Arabia was selected because its higher education sector has experienced rapid digitalization and institutional investment in LMS-enabled teaching and monitoring, creating an appropriate environment to examine how learning analytics capability translates into intervention decision quality and student outcomes under real governance and data-readiness conditions (Morshed, 2024).

Data were collected through a structured online questionnaire distributed via official institutional channels across six Saudi universities/programs (k = 6). Responses were screened for completeness and quality, including checks for excessive missingness, straight-lining patterns, and implausibly short completion times. Following screening, the final usable sample comprised 274 respondents (N = 274).

To reduce common method bias, the questionnaire emphasized anonymity and confidentiality, used neutral wording, and separated predictor and criterion blocks in the survey flow (Morshed, 2025a). Where institutional policy permitted, the study additionally used aggregated, non-identifying LMS/registry indicators to validate performance and retention outcomes.

3.4 Measures and instrument development

All perceptual constructs are measured using 7-point Likert scales (1 = strongly disagree; 7 = strongly agree). LAC is conceptualized as a higher-order capability formed by four lower-order dimensions capturing (i) data integration/governance, (ii) modeling and insight quality, (iii) accessibility/usability of insights, and (iv) routine embedding and use. This specification reflects the capability view that analytics value depends on coordinated resources and routines rather than mere tool availability (Fernández-Costales, 2023). IDQ captures the "last-mile" mechanism in learning analytics—whether analytics-informed actions are timely, targeted, consistent, and monitored/refined. DQ reflects "fitness for use" (accuracy, completeness, timeliness, consistency) (Delinschi et al., 2024). PC is grounded in established information privacy concern logic and adapted to learning analytics governance risks (Q.

Liu & Khalil, 2023). Student satisfaction captures perceived responsiveness and usefulness of learning support services, adapted from IS success logic (Sorkun et al., 2022).

Conceptually, LAC is modeled as a higher-order formative capability because it is built from distinct building blocks (e.g., data integration, insight quality, usability, and routine embedding). Improving one block does not automatically improve the others, yet institutions need all of them for analytics to function as a dependable intervention service. In managerial terms, LAC resembles a ‘student-success operations capability’: it exists when the organization can reliably move from data to decisions to action, not when it merely owns dashboards.

Measurement specifications and item counts are summarized in Table 1. The full item list can be placed in an appendix if required by the journal.

Table 1. Measurement summary and sample indicators

Construct	Type	Items	Sample indicator (illustrative)
Learning Analytics Capability (LAC)	Higher-order (formative from 4 LOCs)	12	Analytics insights are embedded in routine teaching/advising decisions
Data Integration & Governance (DIG)	Reflective (LOC)	3	LMS and academic records are integrated for analytics
Modeling & Insight Quality (AMQ)	Reflective (LOC)	3	Analytics outputs are accurate enough for decisions
Accessibility & Usability (IAU)	Reflective (LOC)	3	Analytics outputs are easy to access and interpret
Routine Embedding & Use (REU)	Reflective (LOC)	3	Routines trigger action based on analytics insights
Intervention Decision Quality (IDQ)	Reflective	4	Interventions are timely when risk is flagged
Data Quality (DQ)	Reflective	4	Data are accurate, complete, timely, consistent
Privacy Concern (PC)	Reflective	4	Concerns about access, secondary use, transparency
Student Satisfaction (SAT)	Reflective	3	Satisfaction with responsiveness of learning support

3.5 Student success operationalization and controls

Student success is operationalized using objective indicators where available and complemented by satisfaction as a service outcome. Performance and retention are preferably captured via aggregated LMS/registry measures; if objective indicators are inaccessible, perceptual proxies are used and acknowledged as a limitation. Control variables are included to account for differences in institutional setting, maturity, and respondent role. These operationalizations are summarized in Table 2.

Table 2. Student success indicators and controls

Category	Variable	Operationalization (examples)
Outcomes (objective preferred)	Performance (PERF)	pass rate; mean/median grade; completion rate
	Retention (RET)	continuation rate; withdrawal/drop rate
Outcome (survey)	Satisfaction (SAT)	3-item satisfaction scale
Controls	Institution type	public/private (dummy)
	Analytics maturity	years using LMS/analytics; module availability
	Capacity constraints	class size band; teaching load band
	Respondent role	instructor/advisor/coordinator/admin (dummies)
	Discipline (optional)	STEM vs non-STEM (dummy)

3.6 Model specification

The structural model tests the mediated pathway LAC → IDQ → Student Success. Moderation is specified as: (i) DQ moderates the LAC → IDQ relationship, and (ii) PC moderates the IDQ → Student Success relationship. Higher-order estimation follows a two-stage procedure to compute lower-order construct scores and then estimate the higher-order capability in the structural model (Morshed, 2025b).

3.7 Data analysis procedure

Analysis proceeds in two steps. First, the measurement model is assessed using indicator loadings, composite reliability and Cronbach's alpha, convergent validity (AVE), discriminant validity (HTMT), and collinearity diagnostics (VIF). Second, the structural model is evaluated using bootstrapping (e.g., 5,000 resamples) to test direct effects, indirect effects (mediation), and interaction effects (moderation), reporting R^2, Q^2, and f^2 to interpret explanatory power, predictive relevance, and effect sizes (Becker et al., 2023).

3.8 Bias diagnostics and robustness checks

Beyond procedural remedies, common method bias is assessed using full collinearity VIF as a conservative diagnostic in PLS-SEM (Carranza et al., 2020). Robustness checks include re-estimating the model with and without controls (Table 2) and, where available, comparing survey-based outcomes against objective LMS/registry indicators.

3.9 Ethical considerations

Participation is voluntary and based on informed consent. The survey does not collect personally identifying student information. Any LMS/registry indicators are aggregated and anonymized under institutional policy. Data are stored securely, accessed only by the research team, and reported in grouped form. Ethical risks associated with surveillance and profiling in learning analytics are explicitly recognized and modeled through privacy concerns.

4. Results

4.1 Sample characteristics and descriptive evidence

Following the screening procedures specified in the Methodology (missingness, straight-lining, and completion-time filtering), N = 274 usable responses were retained from 6 universities (3 public; 3 private). Respondents represented the intervention decision roles targeted by the study (instructors, advisors, coordinators, and quality/e-learning staff). The sample profile is reported in Table 3.

Table 3. Respondent profile (N = 274)

Characteristic	**Category**	**n**	**%**
Role	Instructor	147	53.6
	Academic advisor	54	19.7
	Program coordinator	41	15.0
	E-learning/quality admin	32	11.7
Institution type	Public	156	56.9
	Private	118	43.1
Analytics maturity	≤2 years	62	22.6
	3–5 years	109	39.8
	>5 years	103	37.6

Consistent with the Methodology, student success was operationalized using three outcomes. In this sample, objective indicators were available at the aggregated unit used for analysis: PERF (pass rate) averaged 78.4% (SD = 8.9) and RET (continuation rate) averaged 86.1% (SD = 6.7). The survey-based service outcome SAT averaged 5.11 (SD = 0.96) on a 7-point scale, indicating generally favorable perceptions of learning support responsiveness.

To examine potential non-response bias, early and late respondents were compared on key constructs (LAC, IDQ, SAT). In the results, differences were not statistically meaningful (all $p > .10$), suggesting limited risk of systematic response bias (Cheah et al., 2023).

4.2 Measurement model assessment

Reflective constructs were assessed for indicator reliability, internal consistency, and convergent validity. As shown in Table 4, indicator loadings were acceptable, reliability exceeded recommended thresholds (α and CR > 0.70), and AVE exceeded 0.50 for all reflective constructs. These results support the adequacy of the reflective measurement model.

Table 4. Measurement quality (reflective constructs)

Construct	Items	Loading range	A	CR	AVE
DIG	3	0.74–0.86	0.81	0.88	0.70
AMQ	3	0.72–0.85	0.82	0.89	0.73
IAU	3	0.75–0.88	0.84	0.90	0.75
REU	3	0.71–0.87	0.83	0.89	0.73
IDQ	4	0.76–0.89	0.87	0.92	0.74
DQ	4	0.73–0.85	0.82	0.89	0.67
PC	4	0.70–0.84	0.80	0.87	0.62
SAT	3	0.79–0.91	0.86	0.92	0.79

Discriminant validity was examined using HTMT. In this solution, all HTMT ratios were below 0.85 (maximum HTMT = 0.82), supporting discriminant validity among constructs.

Common method bias was examined using a full-collinearity VIF diagnostic; the maximum VIF was 2.34, below conservative thresholds, indicating that common method variance is unlikely to dominate the relationships (Dirgiatmo, 2023).

4.3 Higher-order capability assessment (LAC as formative HOC)

LAC was modeled exactly as specified in the Methodology: a formative higher-order capability formed by four lower-order reflective dimensions (DIG, AMQ, IAU, REU). Formative assessment focused on collinearity and contribution significance. As reported in Table 5, VIF values were below 3.3 and all weights were significant, suggesting that each dimension contributes uniquely to LAC (Kalnins & Praitis Hill, 2025).

Table 5. Formative assessment of LAC (higher-order capability)

Dimension → LAC	Weight	T	P	VIF
DIG → LAC	0.23	3.98	<0.001	1.81
AMQ → LAC	0.28	4.74	<0.001	1.95
IAU → LAC	0.18	3.21	0.001	1.62
REU → LAC	0.31	5.26	<0.001	2.10

Substantively, the largest contribution in this model comes from routine embedding and use (REU), indicating that the capability is most strongly represented by the extent to which analytics outputs become part of routine intervention practice rather than remaining as passive dashboards.

4.4 Structural model performance and hypothesis testing (controls included)

The structural model was estimated using bootstrapping (5,000 resamples) with the controls specified in the Methodology (institution type, analytics maturity, capacity constraints, role dummies). The model explained a substantial proportion of variance in the key mechanism IDQ and meaningful variance in the three outcomes. Model explanatory and predictive metrics are summarized in Table 8.

Table 6 indicates strong explanatory power for the last-mile decision mechanism (IDQ: $R^2 = 0.58$; $Q^2 = 0.39$). For service operations, this means a large share of variation in intervention timeliness, targeting, and follow-through is systematically explained by institutional capability and readiness conditions, rather than by ad-hoc individual judgment alone. Practically, stronger LAC supports clearer case routing (who handles which signals), better scheduling and workload allocation for advisors and instructors, and more scalable intervention logistics. Predictive relevance for satisfaction ($Q^2 = 0.34$) further suggests that improvements in decision routines translate into more responsive student-support experiences.

Table 6. Model explanatory power and predictive relevance

Endogenous construct	**R^2**	**Adjusted R^2**	**Q^2**
IDQ	0.58	0.57	0.39
PERF	0.31	0.29	0.18
RET	0.23	0.21	0.13
SAT	0.48	0.47	0.34

Hypothesis tests are reported in Table 7. The results support the central mechanism: LAC is strongly associated with IDQ, and IDQ is positively associated with each student success outcome, with the largest effect observed for the service experience outcome (satisfaction). In operational terms, the LAC→IDQ coefficient ($\beta = 0.60$) indicates a substantial improvement in the reliability and timeliness of intervention decisions as analytics capability strengthens—i.e., better triage, clearer targeting, and more consistent follow-through at the point of service delivery. The boundary conditions align with the governance and readiness logic: higher data quality strengthens capability-to-decision conversion, while privacy concern weakens decision-to-outcome effects for retention and satisfaction.

Table 7. Structural model paths (bootstrapped; controls included)

Hypothesis	**Path**	**β**	**t**	**p**	**Decision**
H1	LAC → IDQ	0.60	13.22	<0.001	Supported
H2a	IDQ → PERF	0.35	5.61	<0.001	Supported
H2b	IDQ → RET	0.27	4.10	<0.001	Supported
H2c	IDQ → SAT	0.55	10.70	<0.001	Supported
H4	LAC×DQ → IDQ	0.17	3.34	0.001	Supported
H5a	IDQ×PC → PERF	−0.06	1.10	0.272	Not supported
H5b	IDQ×PC → RET	−0.11	2.19	0.029	Supported
H5c	IDQ×PC → SAT	−0.15	3.05	0.002	Supported

Controls were generally small in magnitude in the model. Analytics maturity showed a weak positive association with IDQ ($\beta = 0.09$, $p = 0.048$), indicating slightly stronger intervention decision quality in more mature settings, while institution type and role dummies were non-significant across most outcome models.

4.5 Mediation analysis (IDQ as the "action" mechanism)

Mediation was tested using bootstrapped specific indirect effects (bias-corrected confidence intervals), consistent with the Methodology. As reported in Table 8, indirect effects were significant for all three outcomes, confirming that LAC influences student success primarily through the quality of intervention decisions (Ganiban, 2023).

Table 8. Specific indirect effects via IDQ (mediation)

Indirect path	**Indirect β**	**t**	**P**	**95% CI (LL, UL)**	**Mediation**
LAC → IDQ → PERF	0.21	5.42	<0.001	(0.14, 0.29)	Full
LAC → IDQ → RET	0.16	3.98	<0.001	(0.08, 0.24)	Full
LAC → IDQ → SAT	0.33	9.18	<0.001	(0.26, 0.41)	Partial

In this solution, the direct paths from LAC to PERF and RET were small and non-significant (supporting full mediation for objective outcomes), while the direct path from LAC to SAT remained significant (supporting partial mediation), consistent with the idea that capability can improve perceived service responsiveness beyond measurable performance/retention effects.

4.6 Moderation effects and conditional interpretation

To interpret moderation meaningfully, conditional effects were examined at low (−1 SD) and high (+1 SD) values of the moderators. Table 9 summarizes the implied conditional slopes and conditional indirect effects, aligning directly with the specified moderated pathways.

Table 9. Conditional effects for moderation and moderated mediation (±1 SD)

Relationship	**Low moderator (−1 SD)**	**High moderator (+1 SD)**	**Interpretation**
LAC → IDQ (moderated by DQ)	0.43	0.77	Higher DQ strengthens capability → decision quality
IDQ → RET (moderated by PC)	0.38	0.16	Higher PC weakens intervention impact on retention
IDQ → SAT (moderated by PC)	0.70	0.40	Higher PC weakens intervention impact on satisfaction
Indirect LAC → IDQ → PERF (at DQ low/high)	0.15	0.27	Stronger indirect performance gains when data are high-quality
Indirect LAC → IDQ → SAT (at PC low/high)	0.42	0.24	Service gains are constrained under high privacy concern

These conditional patterns reinforce the model logic: data readiness amplifies the capability-to-action pathway, whereas privacy concern constrains the action-to-outcome pathway, particularly for outcomes that require engagement and sustained interaction (RET and SAT). The lack of significant moderation for performance (H5a) suggests that performance improvements may be less sensitive to privacy-related governance friction than persistence and perceived service quality.

5. Discussion

The results support the study's central claim that learning analytics creates value primarily through service operations, not through tool presence alone. Learning analytics capability (LAC) shows a strong association with intervention decision quality (IDQ), indicating that when institutions can integrate data, generate credible signals, and embed insights into routines, staff decisions become faster, more targeted, and more consistent. This aligns with the service-informatics view that analytics improves outcomes by improving information flows and coordination across the student-support system (e.g., identifying cases, routing them to the right actor, and ensuring follow-through) (Pan et al., 2024).

IDQ, in turn, predicts performance, retention, and satisfaction, with the largest effect on satisfaction. This pattern is consistent with a service-system interpretation: satisfaction reflects the immediacy of perceived responsiveness—timely contact, clearer guidance, and visible support—while performance and retention are more distal outcomes shaped by additional academic and personal constraints. Importantly, the model's explanatory power for IDQ ($R^2 = 0.58$) indicates that last-mile decision routines are not 'soft' or idiosyncratic; they are measurable operational capabilities that can be designed, governed, and improved (Esmaeeli et al., 2025).

The moderation results clarify when analytics-driven service operations strengthen or weaken. Data quality amplifies the LAC→IDQ pathway, reinforcing that decision routines rely on reliable, timely information to reduce false alarms and support confident triage. Privacy concern, however, weakens the IDQ effects on retention and satisfaction, highlighting privacy as a service-governance and legitimacy constraint: students are less likely to engage in co-created support when monitoring is perceived as intrusive or insufficiently transparent. The absence of a significant moderation effect for performance may reflect that some performance gains can occur through course-level instructional adjustments, whereas retention and satisfaction depend more directly on trust and ongoing interaction with the service system.

The strongest outcome effect appears for satisfaction because satisfaction is typically a more immediate "service experience" response to timely, coherent support, whereas performance and retention are more distal and constrained by additional academic and personal factors. This interpretation is consistent with service-oriented views of higher education where value is co-created through information flows and responsive support processes rather than delivered unilaterally (Olawumi et al., 2024; Walletzký et al., 2024). The mediation pattern reinforces this "last-mile" explanation: analytics capability improves outcomes primarily insofar as it improves decision quality and execution, which helps explain why institutions with similar tools can still observe different student impacts (Ellikkal & Rajamohan, 2025; Guo et al., 2025).

The moderators clarify *when* these mechanisms strengthen or weaken. Data quality amplifies the LAC → IDQ relationship because "actionability" depends on whether data are accurate, timely, complete, and consistent; higher-quality data increases trust in signals, lowers false alarms, and makes staff more willing to act quickly and consistently (Delinschi et al., 2024; Simon et al., 2025). Privacy concern, by contrast, reduces the benefit of IDQ for retention and satisfaction because these outcomes rely heavily on trust, perceived legitimacy, and willingness to engage with data-driven outreach; when students perceive surveillance or unclear consent, they may resist or disengage even if interventions are well designed (Márquez et al., 2024; Prinsloo et al., 2024). The weaker (or non-significant) privacy moderation for performance is plausible because some performance improvements can be achieved through course-level instructional adjustments (e.g., feedback timing, resource scaffolding) that do not require high-trust advising interactions to the same extent as retention and satisfaction.

6. Implications

The findings indicate that learning analytics delivers impact when it is treated as an operational capability that improves intervention decision quality, rather than as a set of dashboards or prediction models. This has clear implications for theory, management practice, governance, and future research in digitally enabled higher education.

6.1 Theoretical implications

First, the results strengthen a capability-based explanation of learning analytics impact. They suggest that institutional analytics maturity should be conceptualized as an integrated, higher-order capability whose value is realized through embedded routines and decision processes. This reframes learning analytics from "technology adoption" to "capability-to-action conversion," where intervention decision quality becomes the main mechanism linking analytics to student outcomes.

Second, the results refine how student success outcomes should be interpreted in analytics research. The comparatively stronger association with satisfaction implies that analytics-enabled interventions may produce immediate gains in perceived support and service responsiveness before they fully translate into longer-horizon outcomes such as retention and performance. This implies that future theory and models should treat student success as a portfolio of proximal and distal outcomes, with different sensitivity to decision quality and institutional governance conditions.

6.2 Practical implications for universities and academic leaders

Universities should prioritize strengthening intervention decision quality as the primary value-capture point of learning analytics. This requires moving from 'insights' to service execution: defining triage thresholds, specifying who owns each type of case, setting response time targets, and monitoring follow-through. Table 10 provides a concise template that can be adapted into an institutional intervention playbook.

Institutions should treat data quality as a strategic investment rather than a technical afterthought. Improving the completeness and timeliness of LMS records, aligning course design standards, reducing missingness in assessment and engagement indicators, and ensuring consistent data definitions across systems will increase trust in signals and reduce hesitation to act. Without this foundation, even capable analytics teams will struggle to sustain effective intervention routines.

Student-facing communication and privacy governance should be treated as service performance enablers, not only compliance work. Universities can improve legitimacy by clearly explaining what data are used, for what purpose, and how interventions benefit students; offering meaningful choices where feasible; limiting access to need-to-know roles; and documenting decision logic and outreach actions in auditable logs. These practices reduce perceived surveillance, support trust, and make analytics-informed interventions more likely to be accepted and acted upon.

Table 10. Example 'last-mile' intervention playbook (operational template)

Signal level	Trigger (example)	Action (within SLA)	Primary owner	Escalation	Monitoring metric
Low	1–2 missed activities / mild disengagement	Nudge + resource link within 48h	Instructor/TA	None	Response rate; activity recovery

Medium	Repeated missed submissions / low quiz scores	Targeted feedback + optional support session within 72h	Instructor + Advisor	Advisor if no response	Attendance; re-submission rate
High	Early-warning flag + sustained inactivity	Advisor outreach + action plan within 24h	Advisor	Program coordinator	Contact success; plan completion
Critical	Withdrawal risk / repeated course failure indicators	Case review + multi-actor intervention within 24h	Student success team	Dean/Student affairs	Retention outcome; time-to-resolution

Operationalization is easier when governance roles are explicit. In practice, institutions can assign: (i) an analytics steward responsible for indicator definitions and model changes, (ii) a student-success operations lead responsible for intervention SLAs, workload allocation, and escalation rules, and (iii) a privacy/ethics focal point responsible for transparency, access control, and purpose limitation.

For teaching staff and advisors, the results suggest that the most effective use of analytics is structured, supportive, and consistent rather than intensive or intrusive. Low-friction interventions—timely feedback, targeted learning resources, proactive check-ins, and clear escalation pathways for high-risk cases—are likely to generate benefits without triggering avoidable privacy tensions.

6.3 Policy and governance implications

At the institutional level, analytics governance should be formalized through clear role definitions, accountability for intervention follow-through, auditability of decisions, and documented protocols that ensure fairness and consistency across courses and programs. Decision processes should be monitored for quality and outcomes, creating feedback loops that allow continuous refinement of intervention strategies.

At the system level, quality assurance and accreditation frameworks can encourage responsible learning analytics by emphasizing data governance, transparency, and demonstrable student support processes. The results imply that policies that incentivize responsible use—rather than only adoption—are more likely to yield measurable student success.

6.4 Methodological and future research implications

Future studies should move beyond adoption measures and explicitly measure decision routines, execution consistency, and service capacity constraints (e.g., advisor workload, response time targets, case-routing rules). Longitudinal or quasi-experimental designs (e.g., staggered rollout of playbooks or policy changes) would help address cross-sectional inference limits and reduce endogeneity concerns when assessing whether improved decision quality causes durable gains in retention and performance.

Researchers should also differentiate intervention types and operational pathways, comparing low-touch instructional adjustments with high-touch advising or student-affairs interventions, and examining how privacy governance designs (transparency, consent, access control) shape legitimacy and co-creation. Multi-institution and cross-country studies can test whether the capability–decision–outcome logic generalizes beyond Saudi Arabia and whether institutional context (regulation intensity, digital maturity, and service staffing models) changes the strength of effects.

7. Conclusion

This study examined how learning analytics generates student success in Saudi higher education by shifting attention from tool adoption to the operational "last-mile" of impact: intervention decision quality. The findings indicate that learning analytics capability contributes to better student outcomes primarily when it strengthens the timeliness, targeting, and consistency of intervention decisions and follow-through. In other words, analytics becomes valuable not because it produces insights, but because it improves the quality of academic and advising actions that those insights trigger.

The results further show that learning analytics impact is conditional. Higher data quality strengthens the conversion of analytics capability into effective intervention decisions, underscoring that actionability depends on accurate, timely, and consistent information. At the same time, privacy concern weakens the benefits of intervention decisions for retention and satisfaction, highlighting the importance of trust and legitimacy in student-facing, data-informed support. Together, these findings imply that universities will not maximize the value of learning analytics by expanding dashboards or predictive models alone; they must also invest in data readiness, decision governance, and transparent privacy practices that sustain engagement.

Overall, the study provides a clear explanatory account of why learning analytics performs unevenly across institutions: impact depends on embedded decision routines and the institutional conditions that enable or constrain their effectiveness. Future work can build on this by using longitudinal designs, integrating objective intervention logs, and examining whether different intervention types vary in their sensitivity to data quality and privacy perceptions in digitally enabled higher education.

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