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Developing an Integrated Big Data Analytics Framework for Personalized E-Learning in Open and Distance Learning Institutions in Kenya

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Abstract: Big Data Analytics (BDA) offers open and distance learning (ODL) institutions a means of converting learner data into personalized support, yet many institutions in Kenya lack structured guidance for implementing it. Learner data remain fragmented across systems and are rarely translated into timely personalized interventions, a situation aggravated by infrastructure, skills and governance gaps. This study aimed to develop a framework for implementing BDA in personalized e-learning environments in ODL institutions in Kenya. A case study design was applied at the Open University of Kenya. Stratified, simple random and purposive sampling produced a sample of 293 students and staff, of whom 279 (95.2%) returned questionnaires. Interviews, collaborative framework meetings and document review supplemented the survey. Data were analysed using descriptive statistics, t-tests, ANOVA, multiple regression, thematic and content analysis, and partial least squares structural equation modelling. BDA ($\beta = 0.42$) and learning analytics ($\beta = 0.36$) significantly predicted personalized e-learning, and the model explained 62% of its variance. Faculty adoption and proficiency ($\beta = 0.18$) and quality of data infrastructure ($\beta = 0.21$) significantly moderated these effects. Document review and interviews exposed fragmented systems, weak governance and capacity gaps. The resulting Integrated Big Data Analytics–Enhanced Personalized Electronic Learning (IBDA-EPEL) framework showed acceptable reliability (composite reliability 0.88–0.93; AVE 0.62–0.73) and was validated by eight experts (mean 4.75/5). The study concludes that effective personalization requires integrated data, learning analytics, competent faculty, reliable infrastructure and governance. ODL institutions should adopt the framework through phased implementation supported by data integration, staff development and data governance.

Keywords: Big Data Analytics; Learning Analytics; Personalized E-Learning; Open and Distance Learning; Framework Development; Kenya

1. INTRODUCTION

The expansion of digital learning has changed how universities deliver higher education. E-learning allows students to access materials, assessments and lecturers across locations and time zones, which makes personalization increasingly important for institutions serving diverse and geographically dispersed learners [1]. Every interaction with a learning management system, student information system, online assessment or discussion forum generates data about participation, progress and performance. Big Data Analytics (BDA) allows institutions to examine these data to understand learner behaviour, identify students at risk and support more individualized learning [2].

However, data availability does not by itself produce personalized learning. Institutions must be able to collect, integrate, analyse and interpret learner data, and they need reliable infrastructure, skilled staff, effective data governance and safeguards for learner privacy [3]. The challenge has therefore shifted from generating educational data to making meaningful use of it so that learners receive appropriate support at the right time.

This challenge is pronounced in African and Kenyan Open and Distance Learning (ODL) contexts. Universities across the continent use electronic and distance learning to widen access, but they contend with uneven connectivity, digital skills, infrastructure and technical capacity. Kenya's higher education sector has adopted learning platforms, virtual classrooms and online assessment, and the establishment of the Open University of Kenya (OUK) in 2023 created a digitally delivered ODL institution whose learning activities generate substantial learner data [4], [5]. Yet differences in learner needs, engagement, retention and academic performance persist, alongside concerns about system integration, infrastructure, staff capacity, privacy and data governance.

The problem follows from this gap. Providing content online does not guarantee a learning experience that responds to individual learners' needs, abilities and circumstances [6]. Learner data in Kenyan ODL institutions may remain

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fragmented across systems, and limited analytical capacity, inadequate infrastructure, skills gaps and governance concerns restrict the translation of those data into timely feedback, early identification of struggling learners, adaptive learning activities and evidence-based decisions. The problem is therefore not a lack of learner data but the limited integration and effective use of that data for personalized electronic learning. Without a practical and context-sensitive approach, the potential of BDA remains largely unrealized.

Existing studies emphasize the potential of analytics, but they often examine isolated applications and give limited attention to how technological, analytical, pedagogical, human and institutional factors can be combined into an implementable framework for ODL institutions in developing countries [3]. This paper addresses that gap. It reports the third objective of a wider study, which was to develop a framework for the implementation of BDA in personalized e-learning environments in ODL institutions in Kenya. The paper is guided by one research question: How can a framework for the implementation of Big Data Analytics in personalized e-learning environments in Open and Distance Learning institutions in Kenya be developed? To answer it, the study draws on survey evidence from the OUK case, interviews, collaborative framework meetings and document review, and it contributes a validated framework that institutions can use to plan, implement and evaluate analytics-driven personalization.

2. LITERATURE REVIEW

2.1 Big Data Analytics and Learning Analytics in Higher Education

BDA transforms large volumes of educational data into information that supports teaching, learning and institutional decisions. Data originate from learning management systems, student information systems, online assessments, e-books and virtual classrooms, and they record log-ins, resource use, forum participation, submissions and results [7]. Cloud-based storage and integration allow institutions to combine these sources into a fuller picture of learners, while data mining, predictive modelling and machine learning reveal patterns and predict academic risk [7]. Learning analytics (LA) is the learner-focused application of these capabilities: it measures and analyses learner data to understand and improve learning. Evidence of benefit exists; Purdue University's Course Signals system identified students needing support early and linked prompt intervention to improved retention and performance [8].

Implementation, however, remains difficult. Privacy and ethical safeguards, integration of systems that use different formats, and shortages of qualified staff are recurring barriers [7]. Ashaari et al. argue that managerial, technological and human capabilities jointly determine whether analytics improves institutional performance [9]. Bellaj et al. add that adoption requires recognition of the complexity of educational systems and the involvement of multidisciplinary stakeholder teams, although their model remained theoretical [10]. By contrast, Pei et al. provide qualitative evidence that big data tools support personalization, predictive analytics and early intervention for at-risk students [11]. In the African context, Adeniyi et al. found that infrastructure, connectivity, policy support and digital literacy constrain e-learning adoption relative to the United States [12]. Together these studies agree that technical support and stakeholder collaboration are prerequisites for effective implementation.

2.2 Personalized eLearning

Personalized e-learning adapts content, activities, assessment and feedback to learners' abilities, preferences and progress, rather than giving every learner identical material. Its core features include adaptive learning pathways, personalized recommendations and timely feedback, and the literature links them with improved engagement, motivation and performance [1], [6]. BDA strengthens personalization by combining data from multiple systems into learner profiles that support risk prediction and targeted intervention. Reviews of analytics-supported personalization confirm that analytics can underpin feedback, teaching adjustment and dynamic learning pathways, but they also report continuing concerns about privacy, ethics and the conditions required for effective implementation [13]. Murtaza et al. similarly identify technical, pedagogical and ethical challenges in AI-based personalized e-learning systems [6]. In Kenya, institutions hold substantial learner data, yet fragmented systems, limited analytical capability and the absence of comprehensive implementation frameworks leave much of it underused. For ODL institutions, whose learners are geographically dispersed and interact with the institution largely through digital systems, this underuse is costly because most evidence of learner progress is captured electronically.

2.3 Theoretical Foundations for Framework Development

The study is anchored in Connectivism, which explains learning through connections among people, information, technologies and networks and therefore treats learner-generated data in digital environments as a resource for understanding learners [14]. Constructivist learning theory supports the learner-centred logic of personalization because learners construct knowledge differently, and Learning Analytics Theory explains how learner data become educational insight. Two supporting theories are most directly relevant to framework development. The Technology Acceptance

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Model holds that perceived usefulness and perceived ease of use shape technology acceptance [15]. It grounds the framework's Faculty Adoption and Proficiency (FAP) construct, because analytics influence learning only when educators accept them and can apply them. Diffusion of Innovations explains how new practices are adopted and sustained within organizations through relative advantage, compatibility, complexity, trialability and observability [16]. It grounds the Quality of Data Infrastructure (QDI) construct and the emphasis on institutional readiness, pilot testing and sustained support. Taken together, the theories imply that personalized e-learning is not a purely technological process; it results from interaction among learners, educators, technology, data and institutional conditions.

The theories therefore map onto distinct framework components. Connectivism informs the digital learning environment and the BDA layer that processes the data generated through learner connections. Learning Analytics Theory informs the LA layer that converts those data into insight on engagement, assessment performance and risk. Constructivism informs the personalized e-learning layer in which insight is translated into customized content, adaptive pathways and feedback. TAM and Diffusion of Innovations supply the human and institutional conditions, namely FAP and QDI, that determine whether the preceding layers function in practice. This logic provides the theoretical rationale for treating the framework as an integrated system rather than a software architecture.

2.4 Moderating Conditions and Conceptual basis

The literature suggests that the effect of analytics on personalization depends on conditions beyond the technology. Faculty members with adequate digital skills and positive attitudes are more likely to use data-driven insights for adaptive instruction and feedback, whereas limited competence or resistance to change weakens the impact of analytics initiatives [3], [9]. Reliable connectivity, integrated systems, secure storage and sufficient computing capacity determine whether quality data can be collected, processed and acted upon [10], [12]. Learner engagement also matters, because analytics draw on student-generated data and richer participation permits more accurate personalization [2], [13]. These arguments informed a conceptual model in which BDA is the independent variable, personalized e-learning the dependent variable, and faculty adoption, ICT infrastructure and student engagement the moderating conditions.

2.5 Research Gap

Recent reviews show that the learning analytics literature often emphasizes analytics itself, while giving less attention to demonstrating how analytics improves learning [3]. Reviews also identify privacy, fairness and the practical demands of implementation as persisting concerns [13]. Four gaps follow. First, studies tend to examine particular analytical applications rather than an integrated approach linking data processing, learning analytics and personalized learning. Second, the connection between analytical findings and the design of personalized content, feedback and pathways is weak. Third, educator preparedness, infrastructure, governance, privacy and institutional support are inconsistently built into models of analytics-enabled personalization. Fourth, empirical evidence from Kenyan ODL institutions is limited. This study responds by developing an empirically grounded, theory-informed implementation framework for ODL institutions in Kenya.

3. METHODOLOGY

The study adopted a case study design with the Open University of Kenya (OUK) as the bounded case, which is appropriate for gaining in-depth understanding of a phenomenon within its real-life setting [17]. OUK was selected deliberately because, as Kenya's first public ODL university, it depends on digital platforms and therefore generates substantial learner data. A mixed-methods approach combined structured questionnaires with semi-structured interviews, collaborative meetings and document review so that quantitative relationships could be explained and enriched by qualitative evidence [18]. Because the objective required a practical framework rather than a single statistical test, it relied on synthesis of survey results, qualitative evidence, literature and expert insight.

The target population comprised 1,223 OUK members directly involved in the personalized e-learning environment: 1,208 students and 15 staff (academic and ICT personnel). Using Cochran's formula at a 95% confidence level and a 5% margin of error, an initial sample of 385 was calculated and then adjusted with the finite population correction, giving a sample of 293 [19]. Multistage sampling was used. Stratification separated students from staff; simple random sampling without replacement, drawn from the university's enrolment records with random numbers, selected student respondents; and purposive sampling selected staff and key informants according to their roles, knowledge and direct involvement in e-learning, ICT and administration. Of 293 questionnaires distributed, 279 were completed and returned (95.2%), comprising 264 students and 15 staff.

Four sources of evidence were used. First, an online questionnaire with closed-ended five-point Likert items was administered to accommodate geographically dispersed respondents and included a section of eight items on requirements

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for implementing BDA to address the framework objective. Second, semi-structured interviews with academic and ICT staff explored experiences, benefits, challenges, opportunities and the institutional support needed for adoption. Third, collaborative meetings held on Google Meet examined current data collection methods, tools and integration practices to identify requirements for the framework. Fourth, a document review of existing BDA frameworks, policy documents, institutional reports and published studies identified best practices and institutional gaps.

Face and content validity were established through review by three experts (two supervisors and one faculty member), who rated item relevance and clarity; the average validity score was 0.8, above the 0.6 threshold the study adopted for adequacy. Content validity followed established guidance on assessing content relevance [20]. A pilot study at the Technical University of Kenya, whose students learn in fully online classes comparable to OUK, tested clarity and reliability without contaminating the main sample. Internal consistency was acceptable on all scales: Cronbach's alpha was 0.791 for the eight framework-requirements items, 0.847 for BDA integration, 0.812 for personalized e-learning factors and 0.805 overall, all above the 0.70 benchmark [21].

Questionnaire data were analysed using frequencies, percentages, means and standard deviations. Normality was confirmed using Shapiro–Wilk and Kolmogorov–Smirnov tests, skewness and kurtosis, histograms and Q–Q plots, after which independent-samples t-tests, one-way ANOVA and multiple regression with interaction terms were applied to test the effects of BDA and learning analytics on personalized e-learning and the moderating roles of faculty adoption and proficiency (FAP) and quality of data infrastructure (QDI). Interview transcripts and open-ended responses were analysed thematically [22], while document review and meeting records were subjected to content and thematic analysis to derive framework components. Framework constructs were then specified as reflective measurement models and assessed using partial least squares structural equation modelling (PLS-SEM), which suits exploratory, prediction-oriented research [23]. Indicator loadings of 0.70 or above were treated as ideal and 0.50–0.69 as acceptable in exploratory work [23]. Sub-construct contributions were expressed as normalized weights (indicator score divided by the construct total). Reliability was judged using composite reliability (threshold 0.70), convergent validity using average variance extracted (AVE ≥ 0.50) and discriminant validity using the Fornell–Larcker criterion [24].

The framework was validated by a panel of eight purposively selected experts in educational technology, big data analytics, learning analytics and ODL (two per field), who rated six criteria on a five-point scale. Their suggestions were incorporated into the final version. The proposal was approved by Kibabii University, a research permit was secured from the National Commission for Science, Technology and Innovation, and the participating institutions granted permission. Participation was voluntary, consent was informed, responses were anonymous and data were stored securely for academic use only [25].

4. FINDINGS AND DISCUSSION

This section reports the evidence used to answer the research question. Findings are presented in two groups. Preliminary findings describe the respondents and the baseline conditions at the Open University of Kenya (OUK) that a framework must address: the extent of analytics-supported personalization, user readiness, and challenges and opportunities. Core findings then present the qualitative, inferential and measurement evidence from which the framework was derived and validated. Each table is followed immediately by its interpretation and implication for framework development.

4.1 Response Rate and Respondent Profile

The credibility of a framework built from survey evidence depends on the participation achieved and on whether the respondents include both users and implementers of the e-learning system. Table 1 shows the response rate.

Table 1: Response rate

Category	Frequency	Percentage (%)
Questionnaires distributed	293	100.0
Questionnaires returned and usable	279	95.2
Not returned or incomplete	14	4.8

A response rate of 95.2% is high for an online survey and indicates that the topic was relevant to the university community and that the online mode suited respondents who study and work remotely. The implication is that the 279 usable questionnaires provide a sound basis for the inferential and measurement analyses that follow, with little risk of non-response bias distorting the framework's empirical foundation.

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Table 2 presents the characteristics of the respondents by gender and role.

Table 2: Respondent characteristics (n = 279)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	133	47.7
	Female	127	45.5
	Prefer not to say	19	6.8
Role	Students	264	94.6
	Staff (academic and technical)	15	5.4

The gender distribution was balanced, with only a small difference between male and female respondents. Students formed the large majority, which is expected because they are the principal users of the platform, while the 15 staff respondents contributed the institutional viewpoint on teaching practice, infrastructure and system management. Among student respondents, just over half (about 54%) were in their fourth year, so most had long exposure to the platform and could judge its personalization features from experience. The implication is that the framework reflects both user-level and organizational perspectives. However, the small number of staff means that staff-related inferences should be treated cautiously, which is one reason the study triangulated survey results with interviews, meetings and document review.

4.2 Current State of Analytics-Supported Personalization

A framework for implementation must start from what already exists. Table 3 summarizes the principal indicators of analytics-supported personalization at OUK.

Table 3: Selected indicators of analytics-supported personalization (n = 279)

Indicator	Favourable response	Frequency	Percentage (%)
Aware of BDA in learning	Yes	257	92.0
Familiar with how personal data are used	Moderately or very familiar	218	78.0
Received personalized feedback or recommendations	Yes	167	60.0
Engagement with the e-learning platform	High or very high	196	70.0
Personalized content improved learning	Greatly	182	65.3
Personalized suggestions were helpful	Very helpful	184	66.0
BDA accurately identifies strengths and weaknesses	Agree or strongly agree	245	87.8

Awareness and perceived value were high. More than nine in ten respondents knew that analytics can improve learning, and almost nine in ten agreed that analytics accurately identify their strengths and weaknesses. Roughly two-thirds judged personalized content and suggestions very helpful, and 70% reported high engagement. At the same time, only 60% had actually received personalized feedback or recommendations, 26% had not, and 14% were unsure, which shows that personalization is uneven across learners and courses. About one in five respondents (22%) had limited understanding of how their data are used, indicating a transparency gap.

The implication for the framework is twofold. First, the high perceived value supports investment in analytics-driven personalization, because the demand side is receptive. Second, the unevenness and transparency gaps show that existing practice is not institution-wide, so the framework must include mechanisms for standardizing personalization across courses, communicating clearly to learners how their data are used, and governing that use. Analytics capability alone had not yet produced consistent personalization.

4.3 Readiness for Implementation

Readiness conditions determine whether an analytics framework can be adopted and sustained. Table 4 presents the main readiness indicators drawn from the questionnaire.

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Table 4: Readiness indicators for BDA implementation (n = 279)

Readiness indicator	Favourable response	Frequency	Percentage (%)
Familiarity with BDA	In detail or somewhat	196	70.0
Willingness to adopt new technologies	Willing or very willing	268	96.0
Access to reliable digital infrastructure	Yes	222	79.6
Comfort with digital learning platforms	Very or somewhat comfortable	239	85.7
Confidence in institutional guidance	Confident or very confident	145	52.0
Perception of institutional support	Supportive or very supportive	182	65.1
Need for substantial support in using BDA	Extensive or a lot	119	42.8

Readiness was strong on the technology side. Nearly all respondents were willing to adopt new technologies and none was unwilling, most were comfortable with digital platforms, and about four in five had access to reliable infrastructure. Readiness was weaker on the human and institutional side. Only about half were confident in the institution's guidance, 30% had little or no familiarity with BDA, and every respondent needed at least some support, with 42.8% needing extensive or considerable help. Training views were mixed: just over half of those who answered the training item felt adequately trained, while roughly one-third did not.

These results are consistent with the Technology Acceptance Model, in which positive attitudes and perceived usefulness drive willingness [15], but they also show that willingness does not guarantee effective use. For the framework, the implication is that capacity building, user support and institutional guidance must be designed as core components rather than add-ons. The high willingness and digital comfort also indicate that a phased rollout can build on an engaged user base, which supports the use of pilot implementation within the framework.

4.4 Challenges and opportunities

A framework should address the barriers respondents experience and exploit the opportunities they value. Table 5 summarizes both.

Table 5: Challenges and opportunities in adopting BDA (n = 279)

Panel	Item	Frequency	Percentage (%)
A. Challenges	Insufficient resources	112	40.0
	Technical difficulties	70	25.0
	Lack of training	67	24.0
	Privacy concerns	30	11.0
B. Opportunities	Improved learning outcomes	169	60.5
	Data-driven decision-making	45	16.3
	Enhanced engagement	39	14.0
	Better resource allocation	26	9.3

Insufficient resources was the leading challenge (40%), followed by technical difficulties (25%) and lack of training (24%), so institutional and technical barriers outweighed ethical ones. Privacy concerns were cited by 11% of respondents, which is a minority but a significant one given that analytics depends on trust in how personal data are handled. On the opportunity side, 60.5% associated analytics with improved learning outcomes, and smaller groups pointed to evidence-based decisions, engagement and resource allocation.

The implication is that the framework must make resource planning, technical integration and training explicit requirements, and it must embed privacy and governance safeguards from the outset rather than treating them as afterthoughts. The strong association of analytics with learning outcomes indicates that the framework should keep learner benefit, rather than technology acquisition, as its organizing purpose. These findings agree with the wider literature, which identifies infrastructure, skills and privacy as recurring implementation barriers [7], [12]. Resource constraints deserve particular attention in the Kenyan ODL setting, where institutions must fund infrastructure, learner support and academic delivery at the same time. This suggests that the framework should be modular, allowing institutions to begin with high-value, low-cost components, such as integrating existing LMS and SIS data and enabling basic early-warning reports, before investing in more advanced predictive tools.

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4.5 Current Data Practices and Document Review

The framework required an understanding of how learner data are currently collected and managed and of what successful institutions do differently. Collaborative meetings held on Google Meet examined the first question, and a document review of existing BDA frameworks, policy documents, institutional reports and published studies examined the second. The meetings showed that OUK uses a mix of manual and digital data collection. The learning management system (LMS) and student information system (SIS) store core academic information such as attendance, grades and registration, but they operate independently with minimal integration and limited real-time data sharing. Some departments still rely on manual record-keeping for administrative reports, student feedback and hardcopy files, and use of digital systems varies because of gaps in digital literacy and inconsistent ICT support. Participants described the data environment as fragmented and underused, lacking a centralized platform capable of supporting comprehensive analytics. This matters for personalization because learner-level support requires a unified view of each learner's activity, assessment history and academic record. When LMS and SIS data cannot be combined, lecturers see only partial pictures of learners, and automated feedback or risk prediction cannot draw on the full range of available evidence. The meeting findings therefore help explain why only 60% of respondents had received personalized feedback (Table 3) and why data integration carried the highest weight within the BDA construct (Table 11). Table 6 presents the themes from the document review and the framework implication of each.

Table 6: Document review themes and implications for the framework

Emerging theme	Evidence from reviewed documents	Implication for the framework
Structured analytics ecosystems	Centralized data warehouses, dashboards, predictive models and integrated learning platforms	Technological components of the BDA layer
Fragmented institutional systems	Independent LMS and SIS, manual record-keeping, limited interoperability	Need for integrated data systems at OUK
Governance and compliance	Privacy policies, standard operating procedures, ethical guidelines, governance committees	Ethical and policy dimension; governance mechanisms
Weak governance structures	Limited privacy frameworks, inadequate security standards, few documented procedures	Governance structures and operational guidelines
Capacity building and enhancement	Dedicated analytics teams, continuous staff development, certification and digital literacy programmes	Faculty Adoption and Proficiency (FAP); training and technical support
Technical and human resource constraints	Limited analytics functions, insufficient tools, minimal staff training	Areas for institutional investment
Centralization and modernization of infrastructure	Centralized repositories, upgraded servers, deployment of analytics tools	Quality of Data Infrastructure (QDI)
Phased implementation	Pilot testing, phased deployment, stakeholder feedback, ongoing evaluation	Implementation roadmap

The review found that institutions with mature analytics ecosystems follow a layered architecture covering data acquisition, storage, processing, interpretation and visualization, draw on varied sources such as LMS logs, admission records and library usage, and support the technology with governance structures, capacity building and dedicated analytics units. Successful frameworks also prioritize scalability and interoperability. The gaps identified at OUK (fragmented systems, weak governance and limited expertise) mirror the barriers reported in the review and in the respondents' own accounts of resource, technical and training challenges (Table 5).

The implication is that the framework should be layered and integrative. It needs a centralized, interoperable data layer rather than separate system silos, explicit governance and privacy structures, sustained capacity building and a phased, pilot-first approach. These requirements are consistent with Ashaari et al., who argue that technological, managerial and human capabilities together determine analytics success [9], and with Bellaj et al., who emphasize multidisciplinary stakeholder involvement [10].

4.6 Interview Evidence

Semi-structured interviews with academic and ICT staff were analysed thematically to understand experiences, benefits, challenges, opportunities and institutional support needs. Six themes emerged, summarized in Table 7.

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Table 7: Interview themes and implications for the framework

Theme	Key finding	Implication for the framework
Experience with BDA-enabled personalized e-learning	OUK generates large volumes of data, but use for personalization is still limited	Integrated mechanisms to collect, analyse and use educational data
Influence on engagement and performance	Analytics could support engagement monitoring, progress tracking and early identification of struggling learners	Role of Learning Analytics in retention, engagement and success
Beneficial features	Dashboards, predictive analytics, automated feedback and learner profiling were valued	BDA features support adaptive pathways and student-centred education
Challenges	Inadequate ICT infrastructure, limited analytics skills, integration difficulties, privacy and security concerns	Infrastructure, faculty readiness and data governance in the framework
Opportunities	Better personalization, decision-making, reporting and learner support services	Potential to improve quality and effectiveness of e-learning
Institutional support required	Staff training, ICT investment, policies and collaboration among stakeholders	Institutional support as a framework component

Staff viewed analytics as transformative for learner support, teaching effectiveness and institutional decision-making, but conditional on addressing technological, human and policy challenges. They explained that early identification of struggling learners would let lecturers intervene before difficulties become severe, and that real-time performance information would allow teaching strategies to be adjusted. They also warned that without reliable infrastructure and trained personnel, the benefits of analytics may not be fully realized.

These accounts corroborate the survey and document evidence and explain the mechanisms behind them: data exist but are not converted into action, and the conversion depends on people and infrastructure. The implication is that the framework should treat Learning Analytics as the bridge between raw data and personalized intervention, and should make faculty capability, infrastructure and institutional support explicit enabling conditions. The finding is consistent with qualitative evidence that big data tools support personalization and early intervention [11]. Interviewees also stressed institutional commitment: staff training, investment in ICT infrastructure, supportive policies and collaboration among university management, ICT teams and academic staff were seen as preconditions for adoption. This theme directly shaped the inclusion of institutional support and governance as enabling conditions in the framework.

4.7 Differences between Respondent Groups

Before specifying the framework, the study tested whether engagement and perceptions differed across groups, because material differences would imply the need for targeted components. Table 8 summarizes the results.

Table 8: Tests of group differences

Test	Comparison	Statistic	Result
Independent-samples t-test	Engagement score, male versus female	$t = 1.23$, $p > .05$	No significant difference
Independent-samples t-test	Perception of BDA adoption, students versus lecturers	$t = 3.45$, $p < .01$	Significant difference
One-way ANOVA	Engagement by year of study	$F = 5.52$, $p < .01$, $\eta^2 = .12$	Significant; Year 4 higher

Engagement did not differ by gender, which suggests that analytics-driven personalization is similarly received by male and female learners and need not be gender-targeted. By contrast, students and lecturers perceived BDA adoption differently, which indicates that faculty need targeted capacity-building programmes. This role difference should be read carefully because staff respondents were few, yet it is consistent with the training and support needs reported in Table 4 and with the interview emphasis on staff capacity. Fourth-year students reported higher engagement than other years, with a medium-to-large effect size, suggesting that longer experience with personalized platforms increases familiarity and responsiveness. The implication is that the framework should include differentiated onboarding and support, with particular attention to first-year learners and to faculty, rather than assuming uniform readiness across user groups.

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4.8 Regression Evidence for the Framework Relationships

The central relationships of the framework were tested using multiple regression after normality assumptions were confirmed (Shapiro–Wilk $p > .05$; skewness between −0.42 and −0.27; kurtosis between −0.33 and −0.19). The model tested whether BDA and Learning Analytics (LA) predict personalized e-learning (PEL), and whether Faculty Adoption and Proficiency (FAP) and Quality of Data Infrastructure (QDI) strengthen those relationships. Table 9 presents the results.

Table 9: Regression results for personalized e-learning

Panel A: Model summary	**R**	**R^2**	**Adjusted R^2**	**Std. error**	**F**	**Sig.**
Model 1	0.787	0.620	0.611	0.482	68.34	.000

Panel B: Predictor	**β**	**Std. error**	**t**	**p**
Big Data Analytics (BDA)	0.42	0.063	6.12	< .001
Learning Analytics (LA)	0.36	0.071	5.01	< .001
BDA × FAP	0.18	0.064	2.85	.004
LA × QDI	0.21	0.067	3.12	.002

The model was statistically significant and explained 62% of the variance in personalized e-learning, which is a substantial share. BDA was the strongest predictor ($\beta = 0.42$), followed by LA ($\beta = 0.36$), showing that both institution-wide data capability and learner-focused analytics contribute independently to personalization. Both interaction terms were significant. FAP strengthened the BDA–PEL relationship ($\beta = 0.18$), meaning that analytics produce greater personalization where faculty have the knowledge, skills and willingness to use them. QDI strengthened the LA–PEL relationship ($\beta = 0.21$), meaning that learner-focused analytics deliver more where infrastructure is reliable, integrated and well managed.

The implication is central to the framework: analytics capability is necessary but not sufficient. BDA and LA form the analytical core, while FAP and QDI act as conditions that amplify or limit their effect. This is the empirical justification for placing FAP and QDI as moderating components, in line with Diffusion of Innovations, which stresses organizational readiness and infrastructure [16], and the Technology Acceptance Model, which stresses users' acceptance and ability [15]. The findings also reflect arguments that the practical value of learning analytics depends on educators and institutional conditions [3]. The coefficients also carry practical meaning. Because both interaction terms were positive, the model suggests that investment in faculty development raises the return on BDA capability, and that investment in data infrastructure raises the return on learning analytics. Institutions with limited budgets should therefore avoid acquiring analytics tools without parallel investment in people and systems, since the benefit of analytics appears conditional rather than automatic.

4.9 Framework Development: Constructs and Indicators

The evidence above was synthesized into the Integrated Big Data Analytics–Enhanced Personalized Electronic Learning (IBDA-EPEL) framework. Six latent constructs were specified as reflective measurement models, each with indicators derived from the literature, questionnaire findings, interviews and document review. Table 10 presents them.

Table 10: Framework constructs, indicators and sources

Construct	**Role in framework**	**Indicators**	**Evidence source**
Big Data Analytics (BDA)	Foundational data layer	Data processing, data availability, analytics tools, analytics adoption, institutional support	Literature, questionnaire, interviews
Learning Analytics (LA)	Learner-focused analytical layer	Engagement monitoring, assessment tracking, identification of at-risk learners, analytics dashboards	Literature, questionnaire
Personalized E-Learning (PEL)	Pedagogical layer	Content customization, adaptive learning, learner profiling, personalized feedback	Literature, empirical findings
Enhanced Personalized E-Learning (EPEL)	Outcome layer	Learner engagement, academic performance, satisfaction, retention	Study findings
Faculty Adoption and Proficiency (FAP)	Moderator	Data literacy, analytics competence, positive attitude toward analytics	Questionnaire, interviews
Quality of Data Infrastructure (QDI)	Moderator	Reliability, interoperability, security, scalability	Document review, questionnaire

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The structure follows the logic that emerged from the findings. BDA provides the capacity to collect, integrate and process educational data; LA converts learner data into insight on engagement, performance and risk; PEL translates insight into customized content, pathways and feedback; and the outcomes of this chain are improved engagement, performance, satisfaction and retention. FAP and QDI moderate the chain, as the regression results showed. The constructs also build on the conceptual model that guided the study, in which BDA influences personalized e-learning while faculty adoption, ICT infrastructure and student engagement condition that influence. In the final measurement model, faculty adoption and ICT infrastructure were operationalized as FAP and QDI, and learner engagement appears as an outcome indicator of enhanced personalized e-learning. The implication is that the framework treats personalization as a connected process in which every layer depends on the one beneath it and on the human and infrastructural conditions around it, rather than as an isolated technology.

4.10 Relative Contribution of Sub-Constructs

To determine which elements deserve priority, normalized weights were computed from indicator scores within each construct, so that the weights in each construct sum to 1.000. Table 11 presents the results.

Table 11: Normalized weights of framework sub-constructs

Construct	Sub-construct	Indicator score	Normalized weight
BDA	Data processing	0.78	0.328
	Data integration	0.81	0.340
	Data utilization	0.79	0.332
LA	Learner engagement monitoring	0.83	0.255
	Assessment performance tracking	0.80	0.245
	Early identification of at-risk learners	0.85	0.261
	Analytics dashboard support	0.78	0.239
PEL	Content customization	0.86	0.253
	Adaptive learning pathways	0.88	0.259
	Learner profiling	0.82	0.241
	Personalized feedback	0.84	0.247
EPEL	Learner engagement	0.89	0.260
	Academic performance	0.85	0.249
	Learner satisfaction	0.87	0.254
	Learner retention	0.81	0.237

Within each construct, the weights were close, which indicates that the sub-constructs are interdependent and that none should be developed in isolation. Nonetheless, the highest weights point to priorities. Data integration carried the largest weight within BDA (0.340), reinforcing the document-review finding that fragmented systems are the principal technical obstacle. Early identification of at-risk learners was the most influential LA component (0.261), consistent with staff views that timely intervention is the most valuable application. Adaptive learning pathways led within PEL (0.259), and learner engagement was the strongest outcome (0.260). Learner retention had the lowest weight (0.237), but it remains important for an ODL institution because attrition is a persistent concern.

The implication is that implementation should sequence investment sensibly: integrate data first, develop early-warning capability within learning analytics, and then use adaptive pathways to personalize learning, while keeping all components in balance. The narrow spread of weights cautions against over-investing in one element, such as dashboards, at the expense of the others.

4.11 Indicator loadings

The quality of the measurement model was first examined through standardized indicator loadings. Table 12 summarizes them.

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Table 12: Standardized indicator loadings by construct

Construct	Indicators and standardized loadings (λ)	Total loading
BDA	BDA1 data processing and integration 0.78; BDA2 timeliness of data availability 0.74; BDA3 adoption of big data tools 0.81; BDA4 willingness to use analytics in teaching 0.76; BDA5 institutional support 0.79	3.88
LA	LA1 monitoring engagement 0.83; LA2 tracking assessment performance 0.80; LA3 early identification of at-risk learners 0.85; LA4 use of dashboards for decisions 0.78	3.26
PEL	PEL1 content customization 0.86; PEL2 adaptive pathways 0.88; PEL3 learner profiling accuracy 0.82; PEL4 personalized feedback 0.84	3.40
EPEL	EPEL1 increased engagement 0.89; EPEL2 improved performance 0.85; EPEL3 improved satisfaction 0.87; EPEL4 reduced dropout 0.81	3.42
FAP	FAP1 faculty data literacy 0.83; FAP2 competence in analytics tools 0.86; FAP3 positive attitude 0.79	2.48
QDI	QDI1 reliability of data systems 0.88; QDI2 integration and interoperability 0.84; QDI3 security and privacy controls 0.82; QDI4 scalability of infrastructure 0.86	3.40

All 24 indicators loaded at 0.74 or above, exceeding the 0.70 level regarded as ideal [23]. The highest loadings were for increased learner engagement (0.89), adaptive learning pathways (0.88) and reliability of data systems (0.88), while the lowest was timeliness of data availability (0.74), still acceptable. The implication is that the indicators are strong and valid measures of their constructs, and that the framework can be operationalized in practice using these indicators as an institutional readiness and monitoring checklist. The comparatively lower loadings for timeliness of data and willingness to use analytics point to real-time data access and faculty motivation as areas needing deliberate attention.

4.12 Construct Reliability and Validity

Reliability and convergent validity were assessed using composite reliability (CR) and average variance extracted (AVE). Table 13 presents the results.

Table 13: Composite reliability and convergent validity

Construct	Composite reliability (CR)	Average variance extracted (AVE)
Big Data Analytics	0.89	0.62
Learning Analytics	0.91	0.67
Personalized E-Learning	0.92	0.71
Enhanced Personalized E-Learning	0.93	0.73
Faculty Adoption and Proficiency	0.88	0.65
Quality of Data Infrastructure	0.91	0.69

All constructs exceeded the 0.70 threshold for composite reliability and the 0.50 threshold for AVE [24], indicating internal consistency and that each construct explains more than half of the variance of its indicators. Discriminant validity was supported by the Fornell–Larcker criterion, since the square root of each construct's AVE exceeded its correlations with other constructs. The implication is that the constructs are reliable and empirically distinct, so the framework's components are not redundant and its structure is statistically defensible. Together with the acceptable reliability of the questionnaire scales in the pilot study, this gives confidence that the framework rests on sound measurement and that its components can be assessed consistently across institutions.

4.13 Expert validation of the framework

Statistical adequacy does not show that a framework is useful, so the proposed framework was also appraised by eight experts, two each from educational technology, big data analytics, learning analytics and ODL. They rated six criteria on a five-point scale. Table 14 presents their ratings.

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Table 14: Expert validation of the IBDA-EPEL framework (n = 8)

Validation criterion	Mean	Standard deviation	Decision
Clarity of constructs	4.75	0.46	Accepted
Logical relationships among constructs	4.63	0.52	Accepted
Relevance to Open and Distance Learning	4.88	0.35	Accepted
Appropriateness of moderating variables	4.63	0.52	Accepted
Practical applicability	4.75	0.46	Accepted
Overall completeness	4.88	0.35	Accepted
Overall	4.75	0.44	Framework validated

All criteria were accepted, with an overall mean of 4.75 out of 5. Relevance to ODL and overall completeness received the highest ratings (4.88), and the experts specifically endorsed the inclusion of FAP and QDI as moderators, observing that analytics success is rarely determined by technology alone. Their suggestions concerned clarity of construct descriptions and alignment with theory, and these were incorporated. The implication is that the framework has strong content validity and practical credibility. The small panel size is a limitation, and field testing in operational settings remains necessary.

4.14 The IBDA-EPEL framework and its implementation

Taken together, the findings answer the research question. The framework was developed through a structured, evidence-based process: baseline analysis of current practice, triangulation of survey, interview, meeting and document evidence, specification and testing of construct relationships, measurement validation and expert appraisal. Table 15 consolidates the resulting layers and what each requires in an ODL institution.

Table 15: Layers of the IBDA-EPEL framework and implementation requirements

Framework layer	Function	Key requirements from the evidence
Data infrastructure and governance (QDI)	Moderates the effect of learning analytics; supports all layers	Reliable, interoperable, secure and scalable systems; privacy policies, standard procedures and governance committees
Big Data Analytics (BDA)	Collects, integrates, processes and uses educational data	Centralized repository linking LMS, SIS and assessment data; timely data; analytics tools
Learning Analytics (LA)	Turns learner data into insight	Engagement monitoring, assessment tracking, early identification of at-risk learners, understandable dashboards
Personalized E-Learning (PEL)	Applies insight pedagogically	Content customization, adaptive pathways, learner profiling, personalized feedback
Enhanced outcomes (EPEL)	Indicates framework success	Engagement, performance, satisfaction and retention indicators
Faculty Adoption and Proficiency (FAP)	Moderates the effect of BDA; enables use of insight	Data literacy training, continuous professional development, technical support, learner orientation

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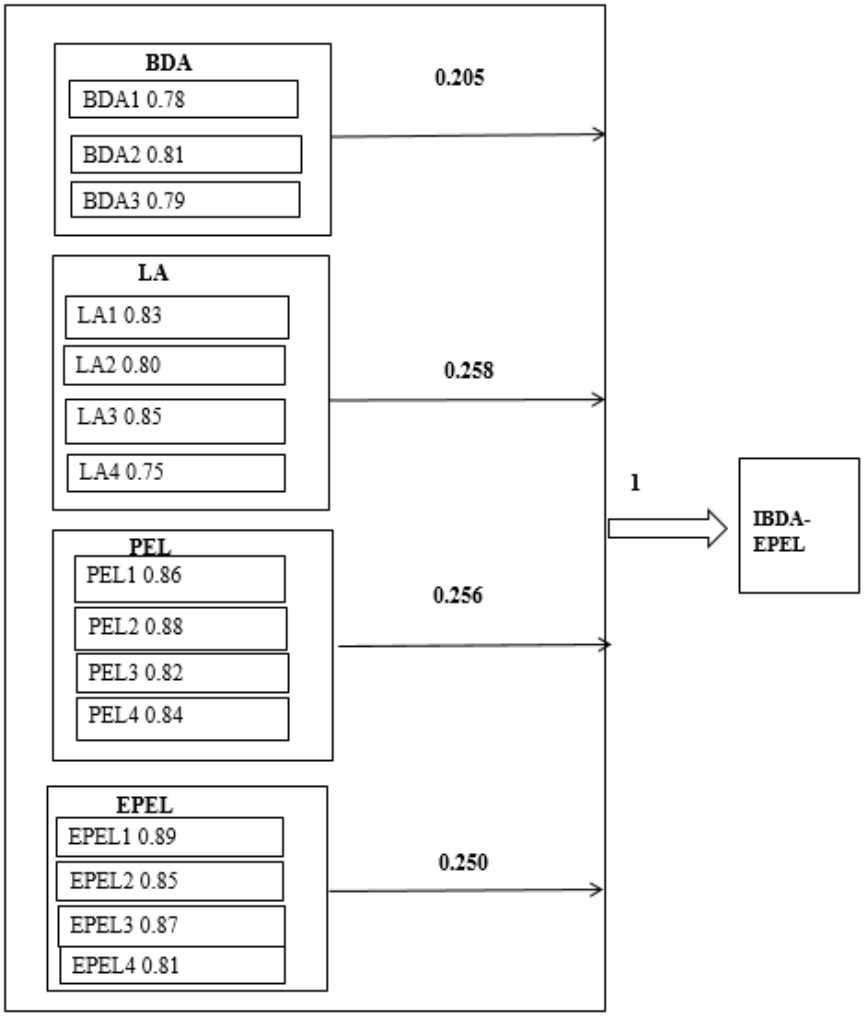


Figure 1 Integrated Big Data Analytics Framework for Enhanced Personalized

The development process can be summarized in five steps. First, baseline evidence from the survey, meetings and document review identified what OUK already has (awareness, willingness and digital comfort) and what it lacks (integration, governance and capacity). Second, theory and literature defined the constructs and their expected relationships. Third, regression analysis tested those relationships and confirmed the moderating roles of FAP and QDI. Fourth, the measurement model established that the indicators were reliable and valid. Fifth, expert appraisal confirmed clarity, logic, relevance to ODL and practical applicability. This sequence shows that the framework is not an assumed model but one grounded empirically and conceptually, which answers the question of how such a framework can be developed.

The findings also indicate how the framework should be implemented. Evidence from the document review, interviews and regression results points to a phased approach in which readiness is assessed before technology is introduced, and in which capacity building and evaluation accompany every stage. Table 16 sets out the resulting roadmap.

Table 16: Phased implementation roadmap derived from the findings

Phase	Key activities	Empirical basis
1. Readiness assessment	Audit data sources, infrastructure, staff capability, governance and e-learning processes	Fragmented systems and capacity gaps (Tables 5, 6)
2. Data integration and governance	Build an interoperable repository; adopt privacy, security and data-use policies	Data integration weight; governance themes (Tables 6, 11)

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3. Learning analytics development	Deploy engagement monitoring, assessment tracking, early-warning and dashboards	Learning analytics effect (Table 9); at-risk identification (Table 11)
4. Pilot implementation	Test personalization with selected courses and stakeholder feedback	Phased implementation theme (Table 6)
5. Capacity building	Train faculty and orient learners in data use	FAP moderation; support needs (Tables 4, 8, 9)
6. Evaluation and scaling	Track engagement, performance, satisfaction and retention; scale progressively	Outcome indicators (Tables 10, 11)

The implication is that the framework gives ODL institutions both a conceptual structure and a practical sequence. Institutions can use it to assess readiness, prioritize investments and monitor results, and they can adapt it to their infrastructure, learner characteristics and resources.

4.15 Discussion

The findings show that a framework for BDA in personalized e-learning can be developed by combining empirical evidence on current practice with tested relationships among constructs and validation of the resulting structure. Four points stand out in relation to theory and prior research.

First, the results confirm that personalized e-learning is socio-technical. The strong BDA and LA effects align with Connectivism and Learning Analytics Theory, which hold that data generated through digital connections can be converted into insight for learners [14]. The significant moderation by FAP and QDI, however, confirms that technology cannot be separated from its human and institutional setting. This agrees with Ashaari et al., who emphasize combined managerial, technological and human capabilities [9], and with Bellaj et al., who stress organizational conditions and stakeholder collaboration [10], while adding quantified evidence of moderation that these largely conceptual studies did not provide.

Second, the high willingness to adopt technology, alongside substantial support needs and mixed confidence in institutional guidance, illustrates the Technology Acceptance Model's point that acceptance is necessary but insufficient [15]. The infrastructure, governance and phased implementation requirements reflect Diffusion of Innovations, in which compatibility, complexity and trialability determine whether an innovation is sustained [16]. The challenges reported at OUK also resemble those documented across African institutions, including infrastructure, connectivity and digital literacy constraints [12].

Third, the framework addresses gaps in the literature. Reviews note that analytics research often stresses analytics over demonstrable learning benefit and that privacy and implementation demands are persistent concerns [3], [13]. By linking data integration, learning analytics, personalization, outcomes and enabling conditions in one validated structure, and by supplying a phased roadmap with governance built in, the IBDA-EPEL framework responds to the call for integrated, context-sensitive approaches.

Fourth, the findings carry practical implications for ODL institutions in Kenya, where learners are geographically dispersed and connectivity and device access vary. Because about one in five respondents lacked full access to reliable infrastructure and a substantial minority needed extensive support, personalization should be designed around these realities rather than assuming the conditions of highly resourced institutions. Institutions should treat educational data as a strategic resource, communicate transparently with learners about how data are used, and invest in faculty capacity so that lecturers can interpret analytics without becoming data scientists. Leadership commitment, reflected in the finding that most respondents saw the institution as supportive, offers a favourable base, but the mixed confidence in institutional guidance indicates that policy direction and communication still need strengthening.

The study has limitations that should be recognized. The framework was developed and tested in a single case, relied substantially on perceptions rather than direct analysis of system data, and was validated by a small expert panel. It therefore requires testing in other institutions and over time before wider generalization.

5. CONCLUSION

This study achieved Objective Three by developing and validating the Integrated Big Data Analytics–Enhanced Personalized Electronic Learning (IBDA-EPEL) framework for Open and Distance Learning (ODL) institutions in Kenya. Grounded in empirical findings, literature, institutional evidence and expert evaluation, the framework integrates big data analytics, learning analytics, personalized e-learning, faculty adoption and proficiency, and data infrastructure

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quality. The findings showed that big data analytics (β = 0.42) and learning analytics (β = 0.36) significantly predicted personalized e-learning, while faculty proficiency and infrastructure quality moderated these relationships. The framework demonstrated acceptable measurement reliability and validity, with composite reliability values of 0.88–0.93 and average variance extracted of 0.62–0.73. Expert evaluation yielded an overall mean score of 4.75 out of 5, supporting its relevance and practical applicability. Implementation should proceed through phased data integration, capacity building, governance, pilot testing and continuous evaluation. Further field testing is recommended to establish its effectiveness across diverse ODL institutions.

6. RECOMMENDATIONS AND SUGGESTIONS FOR FURTHER STUDIE

6.1 Recommendations

Based on Objective Three, which focused on developing a framework for implementing Big Data Analytics (BDA) in personalized e-learning environments, Open and Distance Learning (ODL) institutions in Kenya should adopt the Integrated Big Data Analytics–Enhanced Personalized Electronic Learning (IBDA-EPEL) framework as a guide for strengthening data-driven education. First, institutions should integrate data from learning management systems, student information systems, online assessments and other digital platforms to establish a centralized and interoperable data environment. Second, universities should invest in reliable technological infrastructure, secure data storage and appropriate analytical tools to support timely learner monitoring, predictive analysis and personalized interventions. Third, continuous professional development should be provided to lecturers, ICT personnel and administrators to strengthen their analytical competencies and capacity to interpret learning data. Fourth, institutions should establish clear data governance policies addressing privacy, informed consent, access control, security and responsible data use. Fifth, implementation should follow a phased approach involving institutional readiness assessment, pilot testing, stakeholder consultation, monitoring and progressive scaling. Regular evaluation should assess learner engagement, academic performance, satisfaction and retention to determine whether the framework achieves its intended outcomes.

6.2 Suggestions for Further Studies

Further studies should test the IBDA-EPEL framework in multiple public and private ODL institutions across Kenya to establish its generalizability. Longitudinal research should examine its effects on learner engagement, academic performance and retention over time. Future researchers should also investigate implementation costs, institutional readiness, data privacy and the effectiveness of predictive analytics in identifying at-risk learners.

7. DISCLOSURE OF THE USE OF ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) tools were used in preparing this paper to support language refinement, improve grammatical accuracy, enhance clarity, and assist in organizing academic arguments. AI-assisted support was also used to improve the presentation of the literature review, methodology, findings, discussion, and framework development. The use of these tools was guided by principles of academic integrity, transparency, accountability, and responsible research practice. AI was treated as an assistive resource rather than a substitute for the researchers' scholarly judgment, original contributions, or responsibility for the research outcomes. The researchers retained responsibility for the study design, data collection, analysis, interpretation of findings, framework development, and conclusions. All AI-assisted suggestions were subject to human review and verification to ensure consistency with the study evidence and academic requirements. Confidential participant information and identifiable research data were not intentionally disclosed to AI tools. The authors accept full responsibility for the accuracy, originality, ethical compliance, and integrity of the final manuscript.

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