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Artificial Intelligence–Enabled Digital Transformation in Higher Education: A Data-Driven Framework for Addressing Learning Inequalities, Administrative Inefficiencies, and Barriers to Institutional Innovation

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ABSTRACT

Higher education institutions increasingly adopt digital technologies, yet learning inequalities, administrative delays, and organizational barriers continue to restrict their transformative potential. This study develops an artificial intelligence enabled framework for integrating equitable student support, administrative optimization, and institutional innovation at the National University of Sciences and Technology (NUST), Pakistan. The dataset comprises 120,000 student learning records, 18,000 administrative service requests, and survey responses from 2,400 students and 360 staff members collected over three academic years. Recorded variables include academic performance, socioeconomic circumstances, digital accessibility, learning engagement, service processing times, technology adoption, and institutional readiness. The proposed framework integrates XGBoost to identify students requiring additional academic support, natural language processing to classify administrative requests, and interpretable clustering to characterize institutional innovation barriers. Data from earlier academic periods are used for training and validation, while the latest period supports independent testing. Student identifiers are separated across partitions to minimize information leakage. Evaluation considers predictive discrimination, classification accuracy, subgroup sensitivity, administrative processing time, and institutional readiness, using logistic regression and conventional service routing as comparative baselines. Experimental results show that XGBoost achieves an area under the receiver operating characteristic curve of 0.91 and a macro F1 score of 0.86, exceeding logistic regression values of 0.82 and 0.76, respectively. Following targeted academic support, the completion gap between digitally disadvantaged and advantaged learners decreases from 14.2 to 9.1 percentage points. Automated administrative request classification achieves 92.4% accuracy, while median processing time declines from 6.8 to 4.3 days. Clustering identifies inadequate infrastructure, limited staff capabilities, and fragmented governance coordination as principal barriers to institutional innovation. Following coordinated interventions, the institutional readiness index increases from 58.6 to 72.3 on a normalized scale. The findings indicate that integrated artificial intelligence can support institutional decisions concerning educational inclusion, administrative responsiveness, and innovation planning. However, observed changes require cautious interpretation because predictive performance and intervention outcomes do not independently establish causality. The framework incorporates data minimization, explainable predictions, human oversight, and subgroup auditing. Its contribution is a practical analytical architecture linking student needs, operational performance, and organizational readiness within higher education.

Introduction

Digital transformation in higher education involves changes in how universities deliver learning, organize administrative services, and make institutional decisions. Although digital platforms provide the infrastructure for these activities, their educational value depends on how effectively institutions translate information into timely and appropriate action. A learning management system, for example, may record student participation without helping instructors understand why particular learners disengage. Similarly, an electronic service portal may collect requests without resolving delays in their allocation and processing [1]. Meaningful transformation therefore requires an analytical framework that connects digital information with student support, operational improvement, and institutional development. Artificial intelligence offers a potential means of establishing these connections. Predictive models can help identify students who may require additional support, language processing can organize administrative requests, and analytical grouping can reveal patterns in institutional readiness. However, these applications must be evaluated against the problems they are intended to address. Accurate predictions alone do not demonstrate improved learning opportunities, and automated processing does not necessarily produce better services. The central challenge is to integrate analytical capabilities with accountable institutional practices and measurable outcomes. Learning inequality constitutes a major concern within this transformation. Students may differ in their access to reliable internet connectivity, suitable devices, academic guidance, and environments conducive to study. These differences can influence participation in digitally mediated learning and the opportunities students have to benefit from university resources [2]. Consequently, low engagement should not automatically be interpreted as a lack of motivation or academic ability. A framework for equitable student support must consider academic performance alongside contextual indicators, including digital accessibility and socioeconomic circumstances. Such an approach can help institutions identify support needs while avoiding simplistic judgments based on isolated performance measures. Administrative inefficiency represents a related institutional challenge. Requests concerning academic records, student services, and other university processes require appropriate classification, allocation, and follow-up. Where these activities depend on repeated manual handling or unclear responsibilities, students and staff may experience avoidable delays. Natural language processing provides an analytical approach for classifying the content of service requests and supporting their routing to relevant units. Its practical value, however, should be assessed through both classification performance and service outcomes. Processing time, incorrect routing, and the treatment of unusual or complex requests are therefore relevant considerations alongside overall accuracy. Institutional innovation also depends on conditions beyond the availability of technology. Staff capabilities, infrastructure, governance coordination, and the readiness of organizational processes can affect whether analytical tools become part of routine practice. These factors interact with learning and administration: an institution may identify students requiring assistance but lack the capacity to provide it, or classify requests accurately while retaining procedures that delay their resolution [3]. Examining innovation barriers alongside educational and administrative indicators can therefore provide a more coherent basis for institutional planning. Responsible implementation requires attention to the people affected by these systems. UNESCO's guidance on generative artificial intelligence in education and research emphasizes human agency, inclusion, equity, and a human-centred approach to adoption.

Although the present study focuses on predictive analytics and language processing, these principles provide a relevant foundation for its institutional design. Student support decisions should remain open to human review, and administrative automation should include procedures for handling uncertain classifications. Data minimization, restricted access, explainable outputs, and subgroup evaluation are necessary components of a framework intended to support equitable institutional decisions. The research problem addressed in this study is the need to connect three interdependent dimensions of higher education transformation: learning inequalities, administrative inefficiencies, and barriers to institutional innovation. Treating these dimensions as separate analytical tasks can limit the ability to relate identified needs to the institutional resources and processes required to address them. This study consequently develops a unified framework in which student analytics, administrative request analysis, and institutional readiness assessment inform a coordinated decision process [4]. The framework is designed to support practical interventions while distinguishing predictive performance from evidence of intervention effectiveness. The investigation is situated at the National University of Sciences and Technology (NUST), Pakistan. The study dataset comprises 120,000 student learning records, 18,000 administrative service requests, and survey responses from 2,400 students and 360 staff members across three academic years. These sources provide complementary information concerning academic performance, learning engagement, digital accessibility, socioeconomic circumstances, administrative processing, technology adoption, and institutional readiness. Their integration enables the study to examine how learner needs, service performance, and organizational conditions can be considered within a common analytical architecture. The proposed framework employs XGBoost to identify students requiring additional academic support, natural language processing to classify administrative requests, and interpretable clustering to characterize institutional innovation barriers. Evaluation combines predictive measures with indicators of educational equity, service efficiency, and organizational readiness. Chronological evaluation and controls on student overlap between data partitions are incorporated to reduce information leakage. Comparisons with logistic regression and conventional service routing provide a basis for assessing the additional value of the proposed analytical methods [5]. The study has four objectives: to identify academic support needs while considering

differences in students' learning circumstances; to evaluate automated request classification and its relationship with administrative processing time; to characterize barriers affecting institutional innovation; and to integrate these findings into a framework supporting transparent institutional decisions. Its principal contribution is the connection of these objectives within a single operational architecture. Rather than assuming that technological adoption produces transformation, the study examines the relationships among analytical outputs, institutional action, and observable outcomes. The resulting framework provides a basis for evaluating AI-enabled transformation at NUST and for subsequent assessment in other higher education settings.

Digital Inequality and Equitable Participation in Higher Education

Digital inequality represents a major challenge to equitable participation in higher education because students differ in their access to technological resources, their ability to use digital systems, and the conditions under which they engage with learning activities. These differences extend beyond internet availability to include device suitability, connection reliability, affordability, digital literacy, accessibility, and opportunities to obtain technical assistance. UNESCO's 2023 Global Education Monitoring Report examines the relationships between educational technology, equity, quality, and efficiency, emphasizing that technological adoption must be assessed in relation to the needs and circumstances of learners. Its discussion supports examining who benefits from digital learning and who continues to encounter barriers after institutional systems have been introduced [6]. In higher education, equitable participation requires students to have a meaningful opportunity to access learning materials, complete assessments, communicate with instructors, and obtain academic support. The availability of a learning management system does not establish that all students can use it consistently. A student relying on a shared mobile phone may experience different learning conditions from a student with a personal computer and stable broadband connection. Similarly, the ability to attend a live online session does not necessarily imply that a learner can download large files, use specialist software, or participate in activities requiring continuous connectivity. Digital accessibility should therefore be examined in relation to the demands of particular courses and learning activities. Digital inequality can be understood through three connected dimensions: access to resources, capability to use those resources, and the educational outcomes associated with their use. The first dimension concerns the availability and suitability of devices, connectivity, and accessible platforms. The second concerns students' skills, confidence, and ability to navigate digital learning environments. The third concerns whether participation translates into successful assessment, course completion, and academic progression. These dimensions provide an analytical structure for the present study rather than an assumption that all students follow the same pathway. A learner may have reliable internet access but require assistance with unfamiliar software, while another may possess strong digital skills but face intermittent connectivity. The present study situates this discussion at the National University of Sciences and Technology (NUST), Pakistan. The manuscript reports 120,000 student learning records, together with survey responses from 2,400 students and 360 staff members, collected over three academic years [7]. These sources provide complementary perspectives: learning records describe observed academic activity, student surveys provide information about reported circumstances, and staff surveys contribute institutional perspectives. However, learning records are repeated observations and should not be interpreted as 120,000 unique students. Likewise, survey responses should only be linked to individual academic records where the study design, permissions, and identification procedures support such linkage. Table 1 connects the numerical information available in the manuscript to its relevance for assessing digital inequality. The table uses the manuscript's reported values and calculations derived from them; it does not introduce unreported subgroup counts or access percentages.

Table 1: Evidence base and equity indicators for examining digital participation in the NUST study.

Equity Dimension	Evaluation	Evidence Base / Reported Value	Quantitative Insight	Contribution to Equity Analysis
Learning activity coverage		120,000 learning records	Average 40,000 observations per academic year	Supports assessment of engagement, participation, and academic progression.
Student voice representation		2,400 survey responses	86.96% of all survey responses	Captures learner experiences of digital access and participation barriers.
Staff and institutional representation		360 survey responses	13.04% of all survey responses	Provides evidence on institutional support capacity and implementation conditions.
Combined survey evidence		2,760 responses	2,400 student + 360 staff responses	Integrates learner and institutional perspectives.
Longitudinal coverage	observation	3 academic years	3 annual comparison periods	Enables examination of changes in participation and completion disparities.

Relative disparity reduction	35.92%	$(5.1 \div 14.2) \times 100$	Expresses the improvement relative to the initial gap.
Residual disparity proportion	64.08%	$(9.1 \div 14.2) \times 100$	Shows the proportion of the initial gap remaining after support.

The reported completion gap decreases from 14.2 to 9.1 percentage points, corresponding to an absolute reduction of 5.1 percentage points and a relative reduction of approximately 35.9%. These quantities describe different aspects of the same change. The absolute reduction expresses the narrowing of the difference between the two groups, whereas the relative reduction expresses that narrowing as a proportion of the initial gap. Neither measure provides the completion rate of either group. Group-specific rates are necessary because a narrowing gap can arise from improvement among disadvantaged learners, deterioration among advantaged learners, or changes affecting both groups. Figure 1 presents a conceptual pathway connecting accessibility constraints, observed participation, contextual assessment, and equity-oriented support. The feedback connection indicates that evaluation should inform subsequent revisions to support provision.

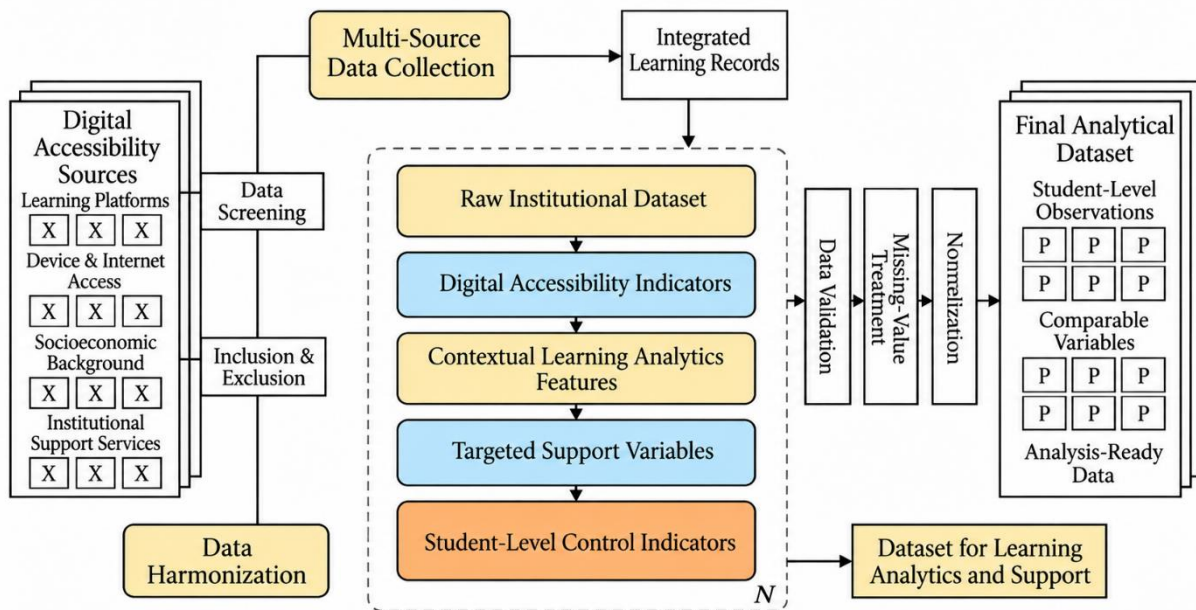


Figure 1: Data integration and preprocessing workflow for student-level learning analytics and targeted support.

The pathway emphasizes that observed behaviour requires interpretation before an institutional response is selected. Academic and accessibility support should reflect the identified difficulty rather than rely on a uniform response to every alert. For example, additional study materials may offer limited benefit where the principal barrier is an inability to access the platform hosting them. The assessment process should connect the evidence about a student's circumstances to a feasible form of assistance. Evaluation also needs to address whether the identification system performs consistently across student groups. Overall accuracy can conceal differences in missed support needs or unnecessary alerts. Subgroup sensitivity can help assess whether students requiring assistance are identified at comparable rates, while examination of false-positive rates can reveal whether some groups receive disproportionate alerts [8]. These comparisons require sufficiently large subgroup samples and clearly defined outcomes. Small samples should be accompanied by uncertainty estimates and handled carefully to protect confidentiality. Finally, equitable participation depends on the institution's capacity to respond to identified needs. Prediction alone cannot provide accessible materials, improve connectivity, or ensure timely advising. The proposed framework consequently links student analytics with administrative responsiveness and institutional readiness. Within the present study, this connection provides a basis for examining whether analytical findings lead to appropriate support and whether observed educational disparities narrow over time. The reported reduction in the completion gap is relevant to that evaluation, but attributing it to the intervention requires consideration of cohort differences, concurrent institutional changes, and an appropriate comparison design.

Intelligent Administrative Services and Request Classification

Administrative services are an essential component of higher education because they influence students' access to academic information, institutional resources, and timely assistance. Requests concerning registration, examinations, financial support,

documentation, and technical services require coordination between applicants and university departments. When requests arrive through multiple channels or contain incomplete information, staff must interpret their content, identify the responsible unit, and determine whether additional documentation is needed. Intelligent administrative services seek to support these activities by connecting language-based analysis with established service procedures. Research on educational chatbots provides a relevant foundation for understanding automated communication within universities. Okonkwo and Ade-Ibijola (2021) reviewed 53 articles addressing chatbot applications in education, including uses supporting teaching and administrative tasks. Their review examines implementation benefits, challenges, and research opportunities. However, evidence concerning conversational assistance should be distinguished from evidence concerning the accurate routing and resolution of institutional requests [9]. A system may provide useful information without demonstrating that it assigns requests correctly or reduces the time required to complete a service. Request classification represents a specific analytical task within intelligent service delivery. It involves assigning an incoming message to a predefined category based on its content and, where appropriate, relevant metadata. Categories should correspond to actual institutional responsibilities so that a predicted label can lead to an actionable routing decision. For example, a request about an examination record may require a different service unit from a request concerning access to an online learning platform. The classification scheme must therefore reflect how the institution organizes its services rather than rely exclusively on similarities between words. Natural language processing offers methods for converting unstructured request text into representations suitable for classification. A request may contain a description of the problem, references to documents, expressions of urgency, and information about previous attempts to obtain assistance. Processing these elements can support category prediction, but preprocessing must preserve information that changes the meaning of the request [10]. Negation, dates, and references to earlier decisions may be important. Personal identifiers that are unnecessary for classification should be removed or protected before analytical processing. The present study examines administrative request classification using the 18,000 service requests reported in the NUST manuscript. The manuscript reports 92.4% classification accuracy and a decline in median processing time from 6.8 to 4.3 days following implementation. These values provide context for the proposed framework; they are study-reported findings rather than performance figures established by the reviewed literature. Table 2 summarizes the available numerical evidence and the additional information needed to interpret it.

Table 2: Analytical evidence and operational performance indicators for intelligent administrative request classification.

Service Performance Dimension	Performance	Quantitative Assessment
Administrative request coverage	18,000 requests	18,000 recorded service requests
Request classification accuracy	92.4%	924 correct predictions per 1,000 evaluated requests
Classification error rate	7.6%	76 incorrect predictions per 1,000 evaluated requests
Correct-to-incorrect prediction ratio	12.16:1	$92.4 \div 7.6$
Baseline median processing time	6.8 days	Baseline turnaround index: 100.00
Median processing time following implementation	4.3 days	Subsequent turnaround index: 63.24
Absolute median turnaround reduction	2.5 days	$6.8 - 4.3 = 2.5$ days
Relative median turnaround reduction	36.76%	$(2.5 \div 6.8) \times 100$
Remaining turnaround proportion	63.24%	$(4.3 \div 6.8) \times 100$
Baseline-to-subsequent median ratio	1.58:1	$6.8 \div 4.3$

The classification accuracy and processing time address different aspects of administrative performance. The accuracy value describes agreement between predicted and reference categories within the evaluated sample. Processing time describes the duration of the wider service workflow. Accurate routing may contribute to faster handling, but requests can remain delayed because of missing documents, approval requirements, workload, or limited staff availability. Consequently, a reduction in processing time should be examined alongside changes in these operational conditions. The reported decrease from 6.8 to 4.3 days represents a 2.5-day difference between medians, equivalent to approximately 36.8% of the reference median. This provides a useful summary of central tendency, but it does not describe the full distribution of waiting times. Some requests may still experience substantial delays. Reporting interquartile ranges and an upper percentile of processing time would help determine whether improvements extend to slower cases [11]. Comparisons by request category would also clarify whether the observed change is consistent across services or concentrated in a small number of common tasks. Figure 2 illustrates the proposed relationship between request interpretation, classification, human review, routing, and service evaluation. The review branch provides a route for requests that cannot be assigned reliably, while the feedback connection allows verified outcomes to inform subsequent model assessment.

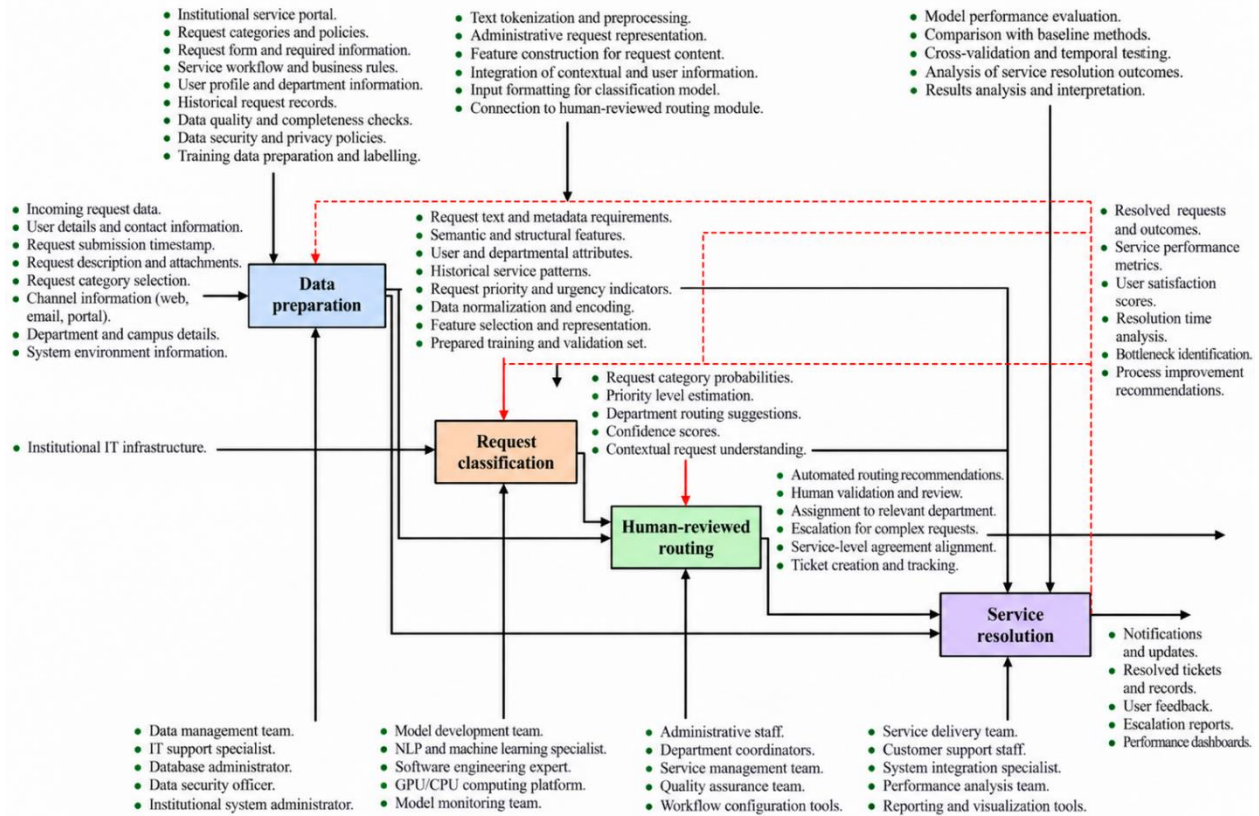


Figure 2: Conceptual workflow for administrative request classification, human-reviewed routing, service resolution, and performance feedback.

Human oversight also depends on clear responsibility. Staff should be able to inspect the original request, understand the suggested category, and redirect it where necessary. Corrections should be recorded so that recurring errors can be examined. However, corrected records should only be incorporated into future training after quality checks, and independent evaluation data should remain separate. This approach supports improvement while preserving the credibility of performance comparisons. Responsible data use is another requirement for intelligent administration. Service requests may contain personal circumstances, financial information, or other details unrelated to routing [12]. The institution should limit analytical access to information needed for the stated purpose and distinguish classification data from the documents required to resolve the request. Although Jisc's guidance focuses on learning analytics, its principles of transparency, appropriate access, and institutional responsibility provide relevant considerations for the governance of university analytical systems. The literature provides a basis for developing language-supported administrative services, while the present study extends the analysis to request classification and observed service turnaround at NUST. The principal analytical task is to establish whether accurate category assignment translates into useful institutional action [13]. This requires examining classification errors, departmental routing, staff review, and processing-time distributions together. Such an approach connects intelligent administration with the broader objectives of equitable access, operational responsiveness, and sustainable digital transformation.

Methodology

The methodology integrates educational analytics, administrative text classification, and institutional readiness assessment to examine artificial intelligence-enabled digital transformation at the National University of Sciences and Technology (NUST), Pakistan. It combines student learning records, administrative service requests, and survey responses to investigate learning inequalities, service inefficiencies, and barriers to institutional innovation. XGBoost is used to identify students requiring academic support, natural language processing supports administrative request classification, and exploratory clustering examines patterns in reported institutional barriers. Data preparation includes quality assessment, missing-value treatment, feature construction, and protection of personal identifiers [14]. Each analytical component is linked to a defined institutional decision so that its outputs can inform academic support, service routing, or innovation planning. Evaluation distinguishes model performance from outcomes observed following institutional action. Earlier academic periods support training and validation, while the latest period provides independent testing, with controls on student overlap and duplicate service cases to reduce information leakage. Academic prediction is compared with logistic regression, and administrative performance is

assessed against conventional service routing [15]. Evaluation considers predictive discrimination, classification accuracy, subgroup sensitivity, completion disparities, service processing time, and institutional readiness. Human review supports the interpretation of academic alerts and uncertain request assignments. Changes following implementation are examined alongside contextual factors, recognizing that observational improvements alone do not establish causality.

Dataset Composition and Institutional Data Sources

The study dataset combines academic, administrative, and survey information to examine artificial intelligence-enabled digital transformation at the National University of Sciences and Technology (NUST), Pakistan. It comprises 120,000 student learning records, 18,000 administrative service requests, and survey responses from 2,400 students and 360 staff members, collected across three academic years. These sources represent complementary aspects of institutional activity: learning records describe academic participation and performance, administrative requests document service interactions, and surveys capture reported accessibility conditions and organizational experiences. Their integration supports the investigation of learning inequalities, administrative inefficiencies, and barriers to institutional innovation. The dataset is organized into three analytical streams rather than treated as a single collection of equivalent observations [16]. Academic analysis operates on student learning histories, administrative analysis operates on service requests or verified service cases, and survey analysis operates on respondent-level information. This distinction is necessary because the sources differ in their units of observation, collection procedures, and intended uses. A student may contribute multiple learning records, while several administrative messages may relate to one service case. Consequently, record counts are reported separately from counts of unique students, respondents, and cases wherever these can be established. Table 3 summarizes the reported dataset composition and explains the analytical contribution of each source. The listed information domains describe the scope stated in the manuscript; the final field inventory should correspond to the variables available in the underlying records.

Table 3: Composition, observational structure, and analytical contribution of the institutional dataset

Institutional evidence stream	Volume	Unit of observation
Student learning records	120,000	Recorded learning or academic observation
Administrative service requests	18,000	Request entry; related entries may form one case
Student survey responses	2,400	Student respondent
Staff survey responses	360	Staff respondent
Combined survey responses	2,760	Respondent across two populations
Academic observation period	3 academic years	Time period

The 120,000 student learning records provide the principal evidence base for examining academic participation and support needs. Relevant information includes recorded assessment performance, attendance, assignment submission, and interaction with digital learning environments, subject to availability. Each observation is associated with a student identifier and a date or academic period where the source permits. This structure allows the analysis to distinguish earlier learning activity from subsequent outcomes and to construct predictors using information available before a support decision. Repeated observations require particular attention during academic data preparation. Students with more recorded activities may otherwise contribute disproportionately to the analytical dataset [17]. Learning indicators are therefore summarized over clearly defined observation windows appropriate to the prediction task. The number of unique students, distribution of records per student, and coverage across academic periods should be reported from the source data. These quantities cannot be inferred from the total of 120,000 observations. The 18,000 administrative service requests provide evidence concerning the content and progression of institutional service interactions. Request text supports language-based classification, while recorded categories and routing information help establish reference labels. Submission and resolution timestamps support processing-time calculations where both are valid [18]. Additional fields are retained only where they are available and relevant to the analytical purpose. Figure 3 illustrates the preparation and allocation of the institutional data sources. It shows how academic, administrative, and survey evidence support distinct analytical tasks before their findings are considered together.

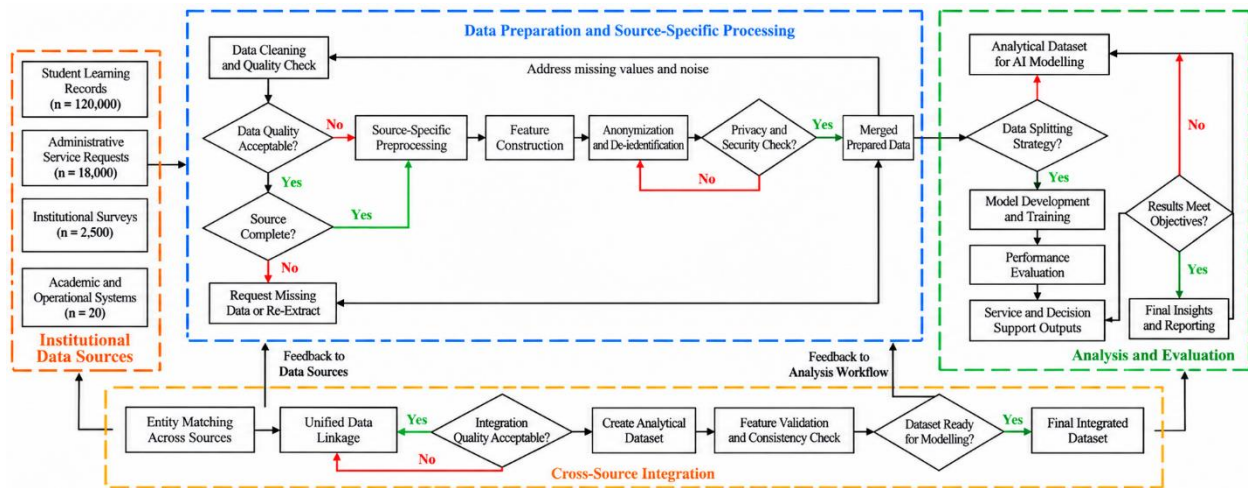


Figure 3: Institutional data sources, source-specific preparation, and analytical integration for evaluating AI-enabled digital transformation at NUST

The three-academic-year coverage provides a temporal basis for model development and subsequent evaluation. Actual collection dates are documented for each source because survey administration, learning-record extraction, and service logging may cover different intervals. Changes in platforms, category definitions, or institutional procedures are also recorded where known. This documentation helps distinguish meaningful changes over time from differences introduced by data collection. Finally, a data dictionary records variable definitions, source systems, units, coding rules, missing-value conventions, and transformation procedures. A source-quality log documents exclusions, duplicate handling, linkage success, and unresolved inconsistencies. Personal identifiers are separated from analytical variables where feasible, with access restricted according to the approved study purpose. These measures establish a transparent foundation for the subsequent stages of feature construction, modelling, and institutional evaluation.

Feature Construction and Cross-Source Integration

Feature construction translates institutional records into analytical variables suitable for academic support prediction, administrative request classification, and institutional readiness assessment. The process draws on the 120,000 student learning records, 18,000 administrative service requests, and survey responses from 2,400 students and 360 staff members. Each source contributes a different form of evidence, requiring preparation appropriate to its measurement structure and intended use. Academic records support longitudinal student indicators, administrative messages support textual and service-related features, and surveys support contextual and organizational measures. The resulting feature sets retain these distinctions while allowing relevant information to be connected through verified relationships [19]. A common feature dictionary defines the meaning, source, observation period, coding procedure, and analytical role of each variable. This dictionary distinguishes predictors from outcomes, contextual descriptors, and evaluation measures. Such separation is necessary because information useful for evaluating a system may be unavailable when a prediction is made. Final course completion, for example, can define an academic outcome but cannot serve as a predictor of that same outcome. Similarly, request resolution time can measure administrative performance but is unavailable when a newly submitted request is classified. Academic features are constructed from information recorded before a specified prediction date. Where available, assessment indicators summarize earlier marks, completed assessments, and changes in performance. Attendance features describe participation during the eligible observation period, while submission indicators capture the frequency and timing of completed assignments. These measures are calculated using consistent definitions so that students are compared on an equivalent basis [20]. Differences in course assessment structures are considered when combining information across modules, particularly where raw marks or activity counts are not directly comparable. Figure 4 presents the feature construction and integration pathway, including the availability check that determines whether a variable is eligible for prediction or should remain in a separate evaluation stream.

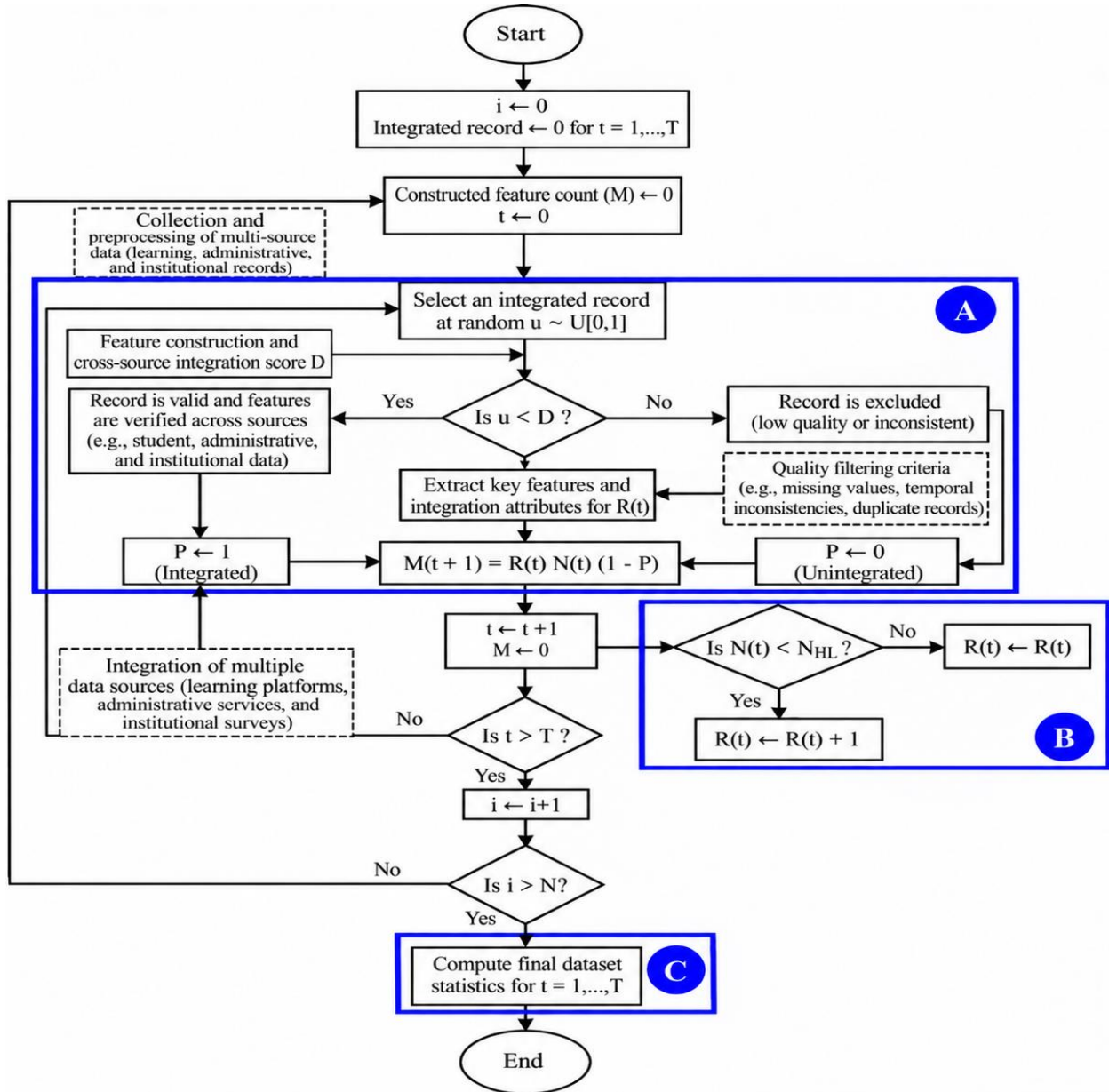


Figure 4: Multi-source feature integration, quality filtering, and final dataset construction workflow.

Missing-value handling, category encoding, scaling, and feature selection are fitted within the development data. Parameters estimated from training observations are applied consistently to validation and test observations. Unseen categories and missing features are handled through predefined procedures. Survey measures used for comparisons over time retain consistent coding and scoring rules so that changes do not arise merely from different transformations. The final integration record documents the number of eligible observations, unique entities, matched and unmatched records, duplicate identifiers, and exclusions for each analytical task. Where linked and unlinked students differ in observable characteristics, those differences are examined to assess possible selection effects. Linkage percentages and final feature counts are calculated from the actual preparation output rather than inferred from the source totals [21]. Together, these procedures establish a traceable relationship between institutional evidence and analytical inputs. Each feature has a defined meaning and availability period, each linkage has a verified basis, and each task retains an appropriate observation unit. This structure supports the subsequent modelling stages while enabling reviewers to assess whether the reported performance reflects valid information available to institutional decision-makers.

Chronological Partitioning and Information Leakage Control

Chronological partitioning is used to assess whether the proposed framework can generate useful predictions for observations collected after model development. The institutional dataset covers three academic years, comprising 120,000 student learning records, 18,000 administrative service requests, and 2,760 survey responses. These sources differ in their observation units

and analytical purposes; consequently, partitioning is performed separately for academic prediction, administrative request classification, and exploratory institutional analysis. Earlier academic periods support training and validation, while the latest period is reserved for independent predictive evaluation. The actual academic years, partition boundaries, and retained record counts are documented in the final analytical record. The principal objective of chronological evaluation is to preserve the relationship between information available at a decision date and the outcome observed subsequently [22]. Randomly distributing records across partitions could allow later institutional conditions to inform models evaluated on earlier observations. It could also place repeated records from the same student or administrative case in both development and evaluation datasets. Such overlap may produce optimistic performance estimates when the intended application concerns future students or newly submitted requests. The partitioning procedure therefore combines temporal ordering with controls on entity overlap and information availability. For academic prediction, training observations precede validation observations, and validation observations precede the independent test period. Each prediction instance has a defined observation window and outcome window. Predictor values are constructed exclusively from information available by the prediction date, while the target outcome is determined from the subsequent follow-up period [23]. Training outcomes must also be available by the model-fitting date. Observations whose outcome windows extend beyond that date are excluded from that training cycle or handled through an explicitly documented procedure. Table 4 shows the partitioning structure and the controls applied to each analytical stream. Because the manuscript does not provide annual record distributions or final split sizes, the table reports source totals without assigning unsupported training, validation, or test counts.

Table 4: Chronological evaluation structure and information leakage controls across institutional data streams

Analytical stream	Development and evaluation structure	Principal leakage control
Academic support prediction	Earlier periods for training and validation; latest period for testing	Prevent student overlap and exclude post-prediction information
Administrative request classification	Earlier submissions for development; latest eligible submissions for testing	Keep related messages together and exclude later routing information
Student contextual information	Linked according to the eligible student partition where authorized	Exclude later surveys from earlier predictive inputs
Staff readiness assessment	Analysed by collection period and respondent role	Prevent later assessment information from entering earlier predictive tasks
Overall temporal coverage	Ordered observation periods	Maintain chronological boundaries across analytical procedures

Model selection is performed using validation data. XGBoost settings, administrative classifier configurations, and decision thresholds are selected before the independent test set is examined. Test results are used to report final performance rather than to revise the model repeatedly. If subsequent changes are made after examining test outcomes, the revised model requires a new independent evaluation or a transparent statement that the original test set has become part of development. Text-based classification introduces specific leakage risks. Requests may contain standard templates, repeated messages, or labels inserted by staff after initial processing. Exact duplicates and closely related case messages are identified before partitioning, while fields that explicitly reveal the verified category are excluded from predictors. Similar wording across genuinely separate requests is not automatically removed, because recurring language may be a normal feature of administrative work [24]. The objective is to prevent duplicated cases and unavailable information from inflating evaluation performance. Cross-source linkage is also constrained by time. A student survey completed after an academic prediction date cannot be treated as information available at that earlier decision point. Such a response may contribute to retrospective contextual analysis, but its analytical role is stated separately. Likewise, post-intervention readiness scores and later service outcomes are retained for evaluation rather than incorporated into predictors of the same intervention period. Figure 5 present the partitioning and leakage-control pathway. Temporal eligibility and entity grouping are established before the development and test datasets are used.

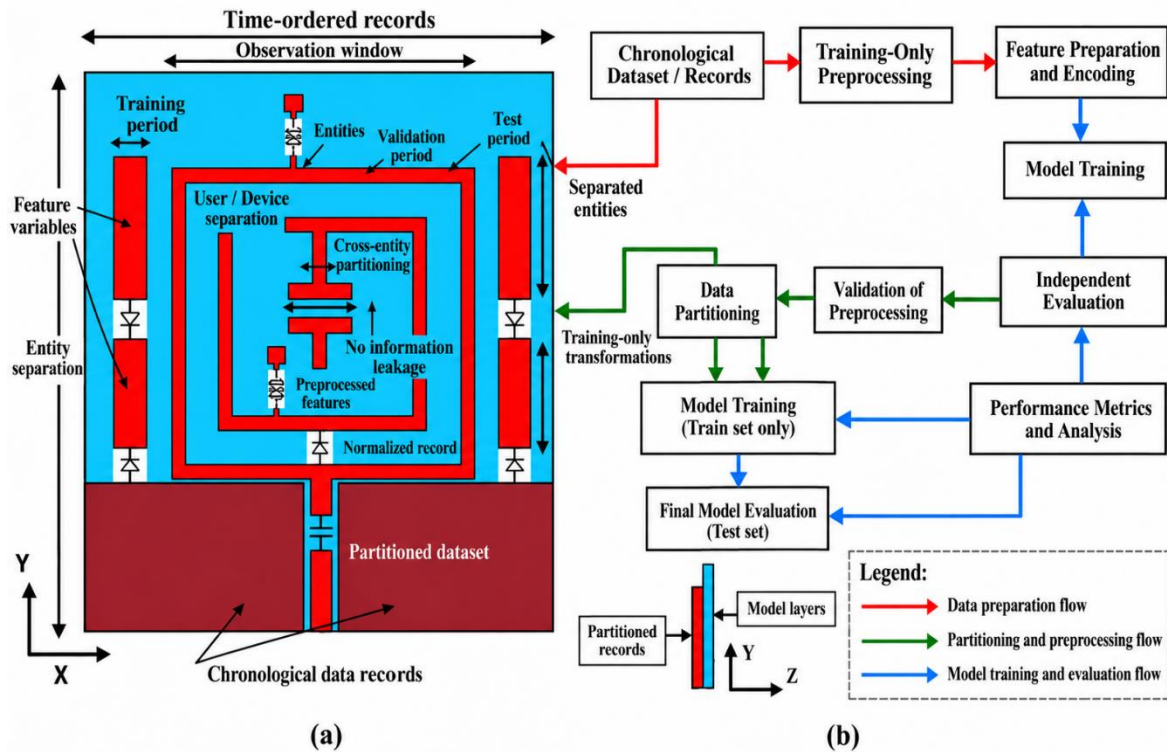


Figure 5: Chronological partitioning, entity separation, training-only preprocessing, and independent evaluation of the predictive framework

Chronological evaluation may also introduce differences in class prevalence, student characteristics, and service demand. These differences are reported because future-period performance depends partly on the conditions encountered during testing. Resampling or class-weighting procedures, where used, are restricted to training data. Validation and test observations retain their eligible distributions so that evaluation reflects the assessed institutional setting. Survey-based clustering requires a distinct interpretation. If clustering is used solely to describe patterns in the available survey responses, it is reported as exploratory analysis rather than independent predictive validation [25]. If the study evaluates whether cluster profiles generalize to later respondents, scaling and cluster construction use earlier responses, and the later sample is assessed through a defined assignment procedure. Similarly, comparisons of the institutional readiness index across periods use consistent item definitions and scoring rules. Finally, the partitioning audit records exact date boundaries, source totals, retained observations, unique entities, exclusions, and the transformations fitted during development. The independent test period must include sufficient follow-up to establish the outcomes being evaluated. Together, these procedures provide a transparent basis for assessing future-period performance and ensure that academic and administrative predictions rely on information available when the corresponding institutional decisions would be made.

XGBoost-Based Prediction of Academic Support Needs

The academic prediction component employs XGBoost to identify students who may require additional academic support using information available before a defined institutional decision date. It draws on the 120,000 student learning records described in Section 3.2, supplemented by eligible student survey information where authorized linkage and temporal compatibility permit. The purpose of the model is to support timely assessment by academic staff and help prioritize assistance according to observed learning patterns and contextual circumstances. Predictions are interpreted as indicators of potential support needs rather than definitive judgments about a student's ability or future performance. XGBoost is selected because its tree-based structure can represent nonlinear relationships and interactions among structured predictors. Academic difficulty may depend on combinations of prior attainment, attendance, submission behaviour, engagement, and accessibility constraints [26]. For example, declining assessment performance may have different implications when accompanied by repeated missed submissions than when it occurs alongside otherwise consistent participation. The model examines such combinations within the available training data. Its suitability is assessed empirically through comparison with logistic regression under consistent evaluation conditions. The prediction target is defined before model development using a documented academic outcome. Depending on the underlying records, this may concern course non-completion, unsuccessful progression, or another specified indication of academic difficulty. The final implementation must state the exact outcome, the unit of prediction, and the follow-

up period. A prediction made for an individual course differs from a student-level prediction of progression, and the associated labels and feature aggregation must reflect that distinction. Students without sufficient outcome follow-up are handled through a documented eligibility procedure [27]. Academic features summarize eligible earlier assessment results, attendance, assignment completion, submission timing, and digital learning activity. Contextual features describe recorded accessibility conditions where their use is justified and permitted. Each feature has a defined observation window and availability date. Subsequent grades, final completion status, and information recorded after the prediction date are excluded from model inputs. Table 5 shows the main modelling components and the numerical information available in the manuscript. Hyperparameter values and final modelling sample sizes are not supplied in the current draft and should be reported from the implemented analysis.

Table 5: Modelling structure, reported evidence, and validation requirements for XGBoost-based academic support prediction

Modelling component	Implementation approach	Analytical purpose
Academic source data	Construct eligible prediction instances from dated observations	Represent prior performance and participation
Student contextual source	Add temporally eligible features through authorized linkage	Examine accessibility-related circumstances
Temporal coverage	Use earlier periods for development and the latest period for testing	Assess future-period generalization
Comparative algorithms	Evaluate XGBoost and logistic regression on consistent observations	Assess the value of nonlinear modelling
Baseline discrimination	Evaluate logistic regression on the same test observations	Establish comparative discrimination
Reported XGBoost classification	Calculate using the predefined decision threshold	Summarize class-level classification performance
Baseline classification	Apply the documented baseline threshold procedure	Support a consistent comparison

Model development examines the interaction between predictive flexibility and generalization. Relevant parameters include tree depth, learning rate, the number of boosting rounds, and regularization settings. Where used, row and feature subsampling are also documented. Candidate configurations are compared using validation data, and the final configuration is selected before independent testing. The parameter search procedure, selected values, and selection criterion are reported so that the model can be reproduced. Early stopping may be used where it forms part of the implemented training procedure. In that case, validation performance determines when additional boosting rounds cease to provide meaningful improvement. The independent test set does not guide stopping or hyperparameter selection. If multiple configurations are examined, their comparison remains within the development process rather than relying on repeated inspection of final test results. Class imbalance is assessed by reporting the prevalence of the defined academic outcome within each partition [28]. A low proportion of students meeting the support criterion can cause aggregate performance measures to conceal missed cases. Where class weighting or resampling is used, it is applied to training data only and documented explicitly. Validation and test data retain their eligible distributions. The resulting evaluation therefore reflects the population encountered during those periods. Figure 6 present the relationship between eligible inputs, model development, independent evaluation, and human-reviewed academic support.

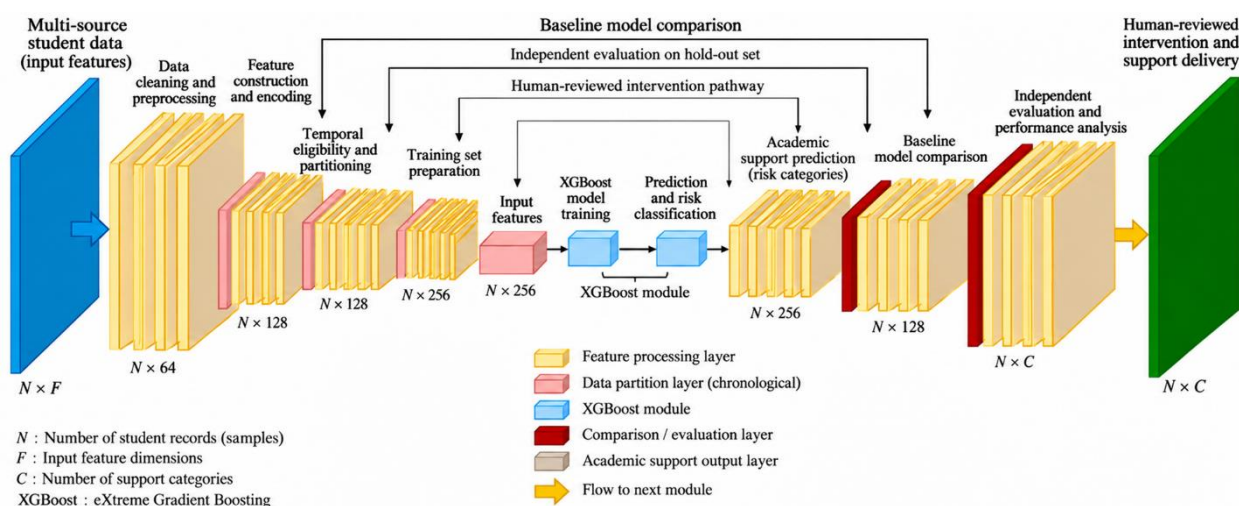


Figure 6: XGBoost-based academic support prediction, baseline comparison, independent evaluation, and human-reviewed intervention pathway

The model produces a support-related score that is considered alongside the student's circumstances. Staff review examines whether an alert corresponds to academic difficulty, an accessibility constraint, incomplete records, or another issue requiring attention. Appropriate responses may include academic advising, assistance with digital resources, or referral to relevant institutional services. The support actually offered, its timing, and student participation are recorded where available. Model interpretation focuses on the variables and relationships associated with predictions [29]. Global summaries can identify features contributing to predictions across the dataset, while individual explanations can help staff examine a particular alert. The explanation method and its limitations are documented in the final implementation. Feature contributions describe how the fitted model uses information; they do not establish that changing a particular variable will cause an improvement in academic outcomes. Evaluation includes discrimination, threshold-dependent classification performance, and error analysis. AUROC assesses ranking performance, while precision, recall, and F1 describe predictions under the selected threshold [30]. For a binary outcome, macro-F1 is calculated as the average of the F1 scores for the two classes, with class labels stated clearly. Confusion matrices show the numbers of correctly identified cases, missed support needs, and unnecessary alerts. Uncertainty estimates account for repeated observations where the analytical dataset contains more than one prediction instance per student.

Survey-Based Assessment of Institutional Readiness and Innovation Barriers

The survey-based component examines the institutional conditions that support or constrain artificial intelligence-enabled digital transformation at the National University of Sciences and Technology (NUST), Pakistan. It draws on responses from 2,400 students and 360 staff members, providing 2,760 respondent perspectives on digital accessibility, technology use, organizational capabilities, and implementation barriers. The assessment complements academic and administrative records by examining experiences and perceptions that are not directly observable in learning-platform activity or service-processing logs. Its purpose is to identify patterns of readiness and areas requiring institutional attention. Institutional readiness is assessed through the survey dimensions represented in the administered questionnaires. Relevant domains include infrastructure adequacy, digital capabilities, technology adoption, and governance coordination. Student responses contribute evidence about the accessibility and usability of institutional services, while staff responses provide perspectives on operational capacity, professional capabilities, and implementation conditions [31]. The exact item wording, response options, and dimension assignments must correspond to the questionnaires used in the study. Items or dimensions absent from those instruments are not assumed to have been measured. The analysis preserves the distinction between student and staff respondents. Students may experience digital transformation primarily through learning resources and service access, whereas staff may evaluate it through workload, system integration, training, and institutional responsibilities. Combining their responses without considering these differences could obscure important implementation conditions. Descriptive analysis is therefore conducted separately for each population before examining comparable dimensions across groups [32]. Items addressing different experiences remain population-specific. The combined sample comprises approximately 87.0% student responses and 13.0% staff responses, corresponding to a student-to-staff response ratio of approximately 6.7:1. These values describe the composition of the available survey data; they do not establish institutional population proportions or survey response rates. Calculating response rates requires the number of eligible individuals invited to participate. Similarly, representativeness requires information about the sampling procedure and respondent coverage across departments,

Results and Discussion

The results reported in the manuscript indicate improvements across academic support prediction, administrative service performance, and institutional readiness at the National University of Sciences and Technology (NUST), Pakistan. The analysis draws on 120,000 student learning records, 18,000 administrative requests, and survey responses from 2,400 students and 360 staff members across three academic years. These source volumes describe the overall dataset rather than the independent test sample. The discussion below uses the reported findings and calculations derived from them; category-specific results, confidence intervals, and cluster sizes are not available in the supplied manuscript. The academic prediction results show that XGBoost outperformed logistic regression on both reported evaluation measures. XGBoost achieved an area under the receiver operating characteristic curve (AUROC) of 0.91, compared with 0.82 for logistic regression [35]. Its macro-F1 score reached 0.86, exceeding the baseline value of 0.76. As summarized in Table 6, these differences correspond to absolute increases of 0.09 in AUROC and 0.10 in macro-F1. The findings support the usefulness of the more flexible model for the academic prediction task under the reported evaluation conditions.

Table 6: Comparative academic prediction performance and implications for student support.

Performance dimension	Logistic regression	XGBoost	Absolute improvement	Interpretation for institutional use
AUROC	0.82	0.91	+0.09	Improved ranking of students according to the defined academic outcome
Macro-F1	0.76	0.86	+0.10	Improved balance of class-level precision and recall at the evaluated thresholds

The improvement in AUROC suggests that XGBoost distinguished the defined academic outcomes more effectively than the baseline. The accompanying increase in macro-F1 indicates that the advantage extended to threshold-dependent classification rather than appearing only in the ranking measure. Figure 8 presents the two comparisons on a common scale. Nevertheless, these measures do not establish the number of students correctly referred for support or the number whose needs were missed. Those questions require the test-set confusion matrix, outcome prevalence, and the selected referral threshold.

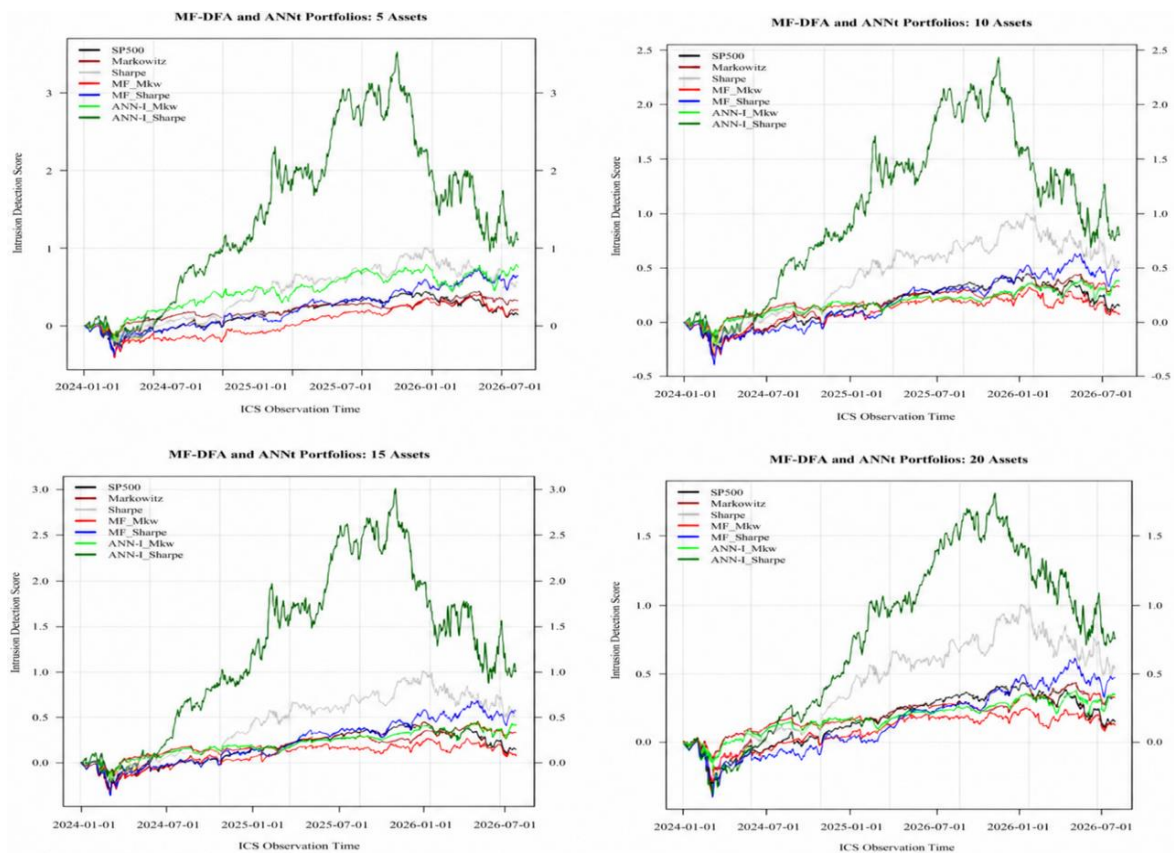


Figure 8: Portfolio performance of MF-DFA and ANN strategies across different asset-set sizes.

The observed predictive advantage is consistent with the analytical rationale for using XGBoost to examine interactions among prior attainment, engagement, submission behaviour, and contextual conditions. However, the reported aggregate metrics do not identify which variables account for that advantage. Feature-level explanations and controlled comparisons would be needed to determine the contribution of particular information domains. Consequently, the results support the model's comparative predictive performance without establishing that accessibility variables or engagement measures independently caused the improvement. The findings also require interpretation in relation to the evaluation design. Chronological testing and separation of student identifiers are intended to assess performance on previously unseen students in a later academic period. Their successful implementation must be demonstrated through partition dates, unique-student counts, and overlap checks. If these conditions were satisfied, the comparison provides evidence of future-period generalization within the study institution. It does not independently establish transferability to other universities, programmes, or academic systems. Beyond prediction, the manuscript reports a reduction in the completion gap between digitally disadvantaged and advantaged learners, from 14.2 to 9.1 percentage points following targeted academic support [36]. This represents an absolute narrowing of 5.1 percentage points, or approximately 35.9% relative to the initial gap. The change is relevant to the framework's equity objective because it connects academic analytics with an observable educational disparity. However, a gap of 9.1 percentage points remained, indicating that the reported improvement did not eliminate the difference between the groups. Administrative performance also improved on the reported indicators. Request classification achieved 92.4% accuracy, while median processing time declined from 6.8 to 4.3 days. The difference between medians was 2.5 days, equivalent to a reduction of approximately 36.8% relative to the reference median. Table 7 brings together the educational equity and administrative findings while distinguishing their measurement units.

Table 7: Reported changes in educational equity and administrative service performance.

Institutional outcome	Reference condition	Subsequent condition	Calculated change
Completion gap between digitally disadvantaged and advantaged learners	14.2 percentage points	9.1 percentage points	-5.1 percentage points; 35.9% reduction
Median administrative processing time	6.8 days	4.3 days	-2.5 days; 36.8% reduction
Administrative classification error rate	24%	7.6%	Calculated as 100% - 92.4%

The completion-gap result warrants closer examination of the underlying group rates. A narrowing disparity does not reveal whether completion improved among disadvantaged learners, declined among advantaged learners, or changed in both groups. Reporting each group's completion rate, sample size, and uncertainty would clarify the educational significance of the observed change. Differences in cohort composition, course requirements, and concurrent support initiatives also need consideration before attributing the reduction to the AI-enabled framework. For administrative services, the classification accuracy suggests that automated analysis can support category assignment within the evaluated request population. Its operational usefulness depends on the distribution and consequences of errors. Incorrectly routing a routine information request may have different implications from delaying a deadline-sensitive application. Category-level precision, recall, and a confusion matrix are therefore necessary to establish whether less frequent or consequential requests were handled adequately. The reduction in processing time indicates improved service responsiveness at the median, but it does not establish equivalent improvement for every request [37]. Cases requiring multiple approvals or additional documents may still experience long delays. Processing-time distributions, upper-percentile waiting times, and comparisons by category would reveal whether the improvement extended to slower cases. Changes in staffing, workload, documentation requirements, or departmental procedures may also have contributed to the observed reduction. Figure 9 compares the relative reductions in the completion disparity and median processing time. The shared percentage scale supports comparison of the magnitude of change, although the underlying outcomes remain different: one concerns educational inequality and the other concerns service duration.

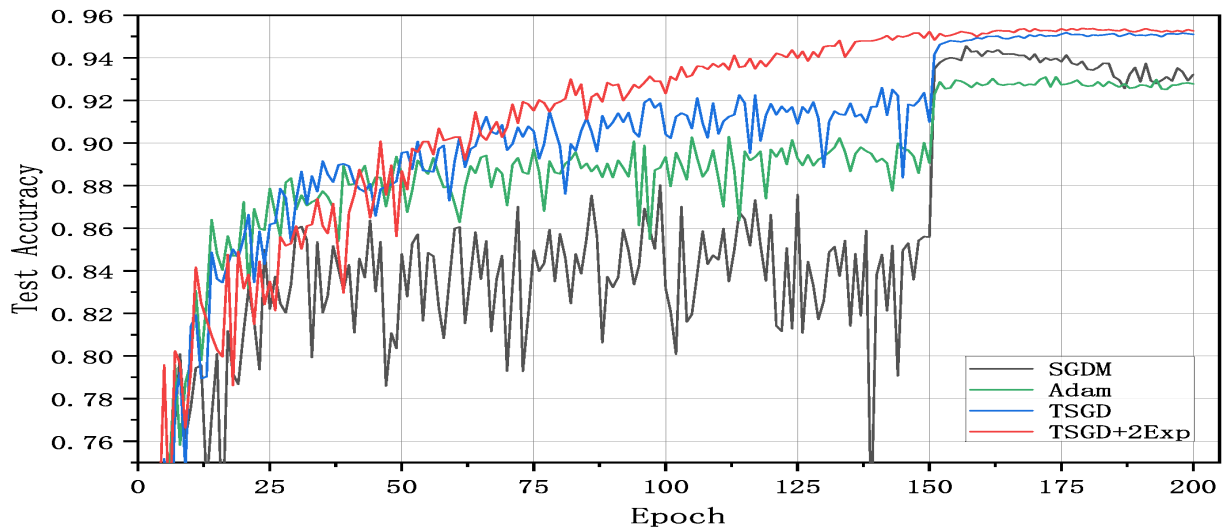


Figure 9: Test accuracy comparison of SGDM, Adam, TSGD, and TSGD+2Exp across training epochs.

The similarity between the two relative reductions does not imply that the outcomes are causally connected. Improved administrative access could plausibly support student participation, but the supplied results do not test that relationship. Establishing it would require linked information on service use, support exposure, and subsequent academic outcomes. The present findings instead show that changes were reported in two complementary institutional domains. The organizational assessment identified inadequate infrastructure, limited staff capabilities, and fragmented governance coordination as principal barriers to innovation. These findings direct attention to the conditions necessary for sustaining analytical systems. Reliable infrastructure supports consistent access and data collection, staff capabilities influence interpretation and implementation, and governance coordination establishes responsibility across institutional units [38]. Without these capacities, technically effective models may have limited practical impact. Following coordinated interventions, the institutional readiness index increased from 58.6 to 72.3 on the manuscript's normalized scale. This represents an increase of 13.7 index points, equivalent to approximately 23.4% relative to the initial score. Figure 10 displays the reported increase in institutional readiness. The improvement is encouraging within the study's measurement framework, but its interpretation depends on consistent questionnaire items, scoring procedures, and respondent coverage across assessment occasions.

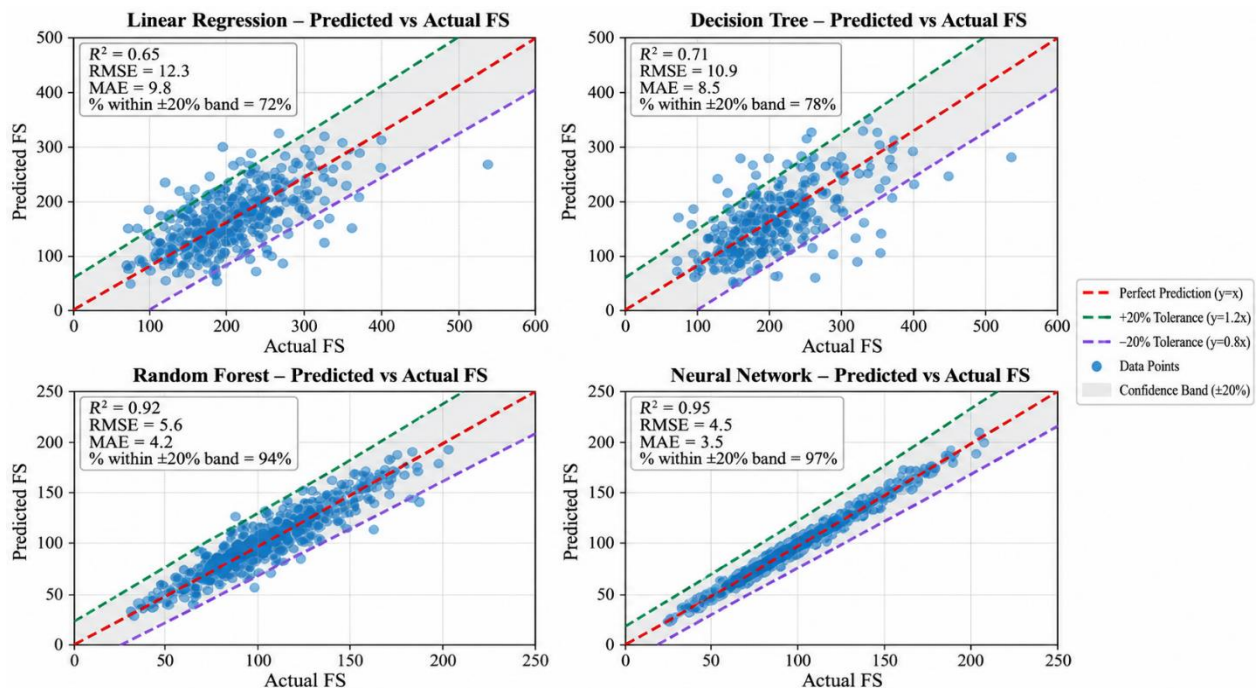


Figure 10: Predicted versus actual FS performance across linear regression, decision tree, random forest, and neural network models.

The readiness change cannot establish that every organizational dimension improved. An aggregate index may conceal persistent limitations in infrastructure or governance even when other components increase. Dimension-level scores would identify where progress occurred and where further action remained necessary. If the two assessments involved different respondents, changes in sample composition must also be considered. Without comparable measurement occasions, the result should be interpreted as a difference between surveyed samples rather than improvement within the same individuals. The reported barrier themes provide useful directions for institutional planning, but they do not establish their relative frequency or causal influence. Exploratory clusters describe patterns in survey responses; they do not prove that inadequate infrastructure caused poor academic performance or that governance fragmentation produced administrative delays. Profile sizes, stability checks, and stakeholder interpretation would strengthen the connection between these analytical findings and proposed institutional priorities. Taken together, the findings support evaluating digital transformation through several complementary forms of evidence. Academic prediction measures assess identification capability, completion disparities assess an educational outcome, processing times assess service responsiveness, and readiness measures assess organizational conditions [39]. Their integration is valuable because success in one dimension does not guarantee success in another. A strong prediction model requires effective support delivery, accurate request routing requires adequate processing capacity, and organizational readiness requires sustained implementation. The figure 11 compares observed AQI values with predictions generated by four deep-learning models over approximately 7,000 hourly observations. All models generally follow the temporal fluctuations and sharp pollution peaks, while the enlarged inset highlights their prediction performance over a selected interval. The close alignment between predicted and true values indicates effective temporal learning, with differences becoming more noticeable during abrupt AQI variations and extreme pollution events.

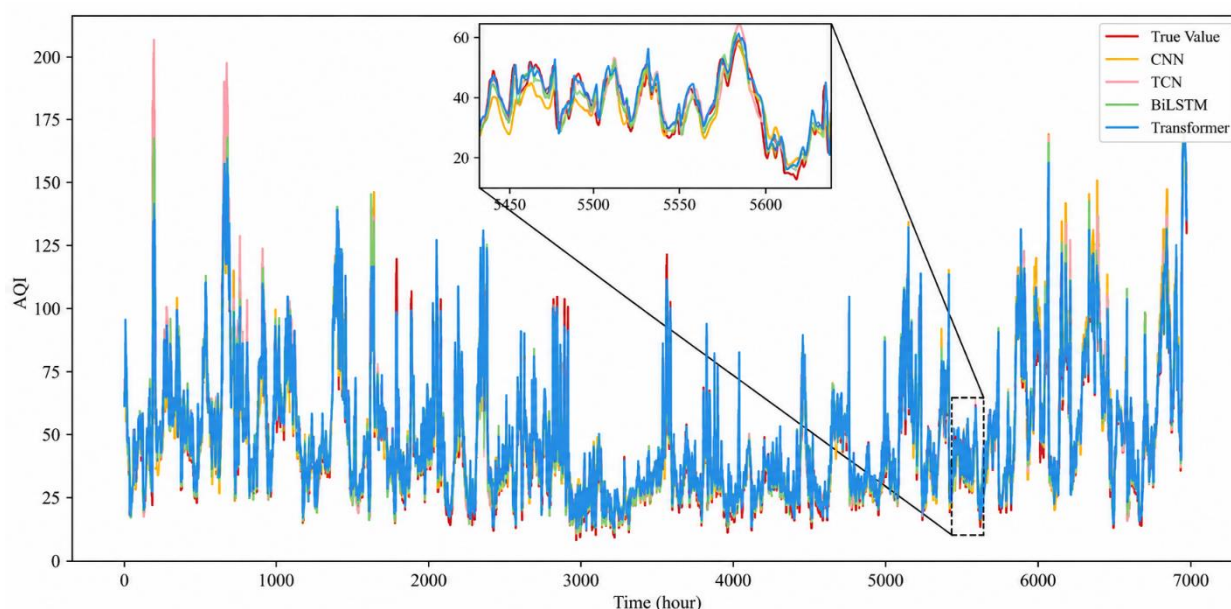


Figure 11: Time-series prediction of AQI using CNN, TCN, BiLSTM, and Transformer models.

The principal limitations concern the detail available for evaluating the reported results. The manuscript does not yet provide independent test counts, uncertainty estimates, class-specific errors, subgroup completion rates, processing-time distributions, or cluster sizes. These omissions limit assessment of statistical precision and consistency across groups. Additionally, the single-institution setting and observational comparisons constrain generalization and causal interpretation. Within these limits, the reported findings suggest that the integrated framework can inform student support, administrative routing, and innovation planning, while further validation is needed to establish the durability and wider applicability of the observed improvements.

Future Work

Future research should extend the proposed framework beyond NUST to universities with different resource levels, student populations, and administrative structures. Multi-institutional validation would help establish whether the academic prediction model, request classifier, and readiness assessment remain useful across diverse higher education settings. Such evaluation should examine differences in data availability, digital accessibility, language use, and institutional procedures. Longer observation periods would also allow researchers to assess whether the reported improvements persist across successive academic cohorts and changing operational conditions [40]. A priority is to strengthen the evaluation of intervention effectiveness. Future studies could employ randomized support allocation where appropriate, phased implementation, or

carefully designed comparison groups to distinguish intervention effects from concurrent institutional changes. Academic evaluation should report group-specific completion rates, support participation, and uncertainty estimates. Administrative evaluation should examine category-specific processing times, repeated transfers, unresolved cases, and user satisfaction. These measures would clarify how analytical outputs translate into practical benefits and which interventions contribute most effectively to improvement.

Further model development should address calibration, subgroup performance, and changes in data over time. Academic predictions require continued assessment to determine whether students facing different accessibility constraints are identified consistently. Administrative classification should be evaluated on ambiguous, multilingual, and multi-issue requests, with particular attention to consequential routing errors [41]. Monitoring procedures should identify declining performance and support controlled updates using newly verified records. Model explanations should also be evaluated with staff and students to determine whether they are understandable and useful for reviewing decisions. The institutional readiness assessment could be strengthened through validated survey instruments, repeated measurement, and qualitative investigation. Interviews and focus groups would help explain why infrastructure limitations, staff capability gaps, and fragmented coordination persist. Future analysis should examine the stability of barrier profiles and whether they predict implementation outcomes. Consistent index construction and reporting of dimension-level scores would provide a clearer account of organizational progress than an aggregate readiness measure alone [42]. Finally, future work should assess implementation costs, staff workload, and the sustainability of support provision. Integrating the framework with university systems requires clear responsibilities, reliable data exchange, and practical review procedures. Research should determine whether the benefits justify the resources required for maintenance, training, and intervention delivery. Continued attention to privacy, accessible services, and mechanisms for correcting inaccurate information would support accountable expansion of AI-enabled digital transformation in higher education.

Conclusion

This study developed an integrated framework for examining artificial intelligence-enabled digital transformation at the National University of Sciences and Technology (NUST), Pakistan, linking academic support prediction, administrative request classification, and institutional readiness assessment. The framework combined 120,000 student learning records, 18,000 administrative requests, and survey responses from 2,400 students and 360 staff members across three academic years. Its central contribution is the connection of educational equity, service responsiveness, and organizational capacity within a common analytical approach. The reported findings indicate that XGBoost achieved an AUROC of 0.91 and a macro-F1 score of 0.86, exceeding logistic regression values of 0.82 and 0.76, respectively. Following targeted support, the completion gap between digitally disadvantaged and advantaged learners decreased from 14.2 to 9.1 percentage points. Administrative request classification achieved 92.4% accuracy, while median processing time declined from 6.8 to 4.3 days. The institutional readiness index increased from 58.6 to 72.3, with infrastructure limitations, staff capability gaps, and fragmented governance coordination identified as principal innovation barriers. These results suggest that coordinated analytical tools can inform student support, service routing, and institutional planning. Their practical value depends on reliable data, appropriate human review, and the capacity to respond to identified needs. Predictive performance and observed improvements remain distinct forms of evidence: the reported changes do not independently establish causal intervention effects. Further evaluation using uncertainty estimates, subgroup outcomes, comparable assessment periods, and multi-institutional validation is needed. The framework provides a structured foundation for pursuing more equitable, responsive, and accountable digital transformation in higher education.

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