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A Data-Driven Intelligent Financial Management Framework for Educational Institutions Using Machine Learning and Agentic AI

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Abstract— *Student payments, receipts, bank activity, expenditures, scholarships and accounting records must be collected and verified throughout the academic year in an educational institution. A survey of school and college practices conducted for this project revealed that there were repetitive manual checks, verification and comparisons between payment confirmation, UTR or transaction-ID and bank reconciliation and report preparation. This paper proposes a single financial management workflow, comprising financial transaction processing, student fee management, automatic receipt generation, bank reconciliation, income and expenses records, information on scholarships and reporting in a tally compatible manner. Machine Learning (ML) is proposed for fee-collection forecasting, expense prediction, trend analysis and identification of unusual transactions, and a controlled Agentic AI component is proposed to interpret validated analytical results and assist administrators, with important financial actions kept under human approval. Phase-I of the project is reported in the paper which includes problem identification through institutional interaction, literature review, research gap, needs, objectives, architecture and methodology, evaluation plan. The ML and Agentic AI components have not yet been validated using institutional financial data, nor are there any reported experimental results; implementation and evaluation will be done in the coming phase.*

Index Terms—*educational financial management, machine learning, Agentic AI, bank reconciliation, UTR, fee management, scholarship management, financial forecasting, anomaly detection.*

I. INTRODUCTION

Financial administration is an integral part in running an educational institution. It is common for academic institutions to have to face student fees, payment confirmations, student receipts, bank transactions, costs, scholarships and accounting records every academic year. These activities are connected, yet they might be managed by means of various records and procedures, including payment gateways, pupil databases, bank statements, spreadsheets and bookkeeping software. The more students there are, and the more transactions are made, the more time it takes to verify them all by hand, and the more of them that will be entered incorrectly, thereby creating chaos in financial record-keeping.More students, more transactions means more time spent on manual verification and more data entry that will be wrong, making record-keeping a real mess..

This work commenced with investigating the problem areas where the use of Data Science, Machine Learning and Artificial Intelligence might be useful. They discussed financial management in education and were involved in schools and colleges for fee collection, QR or payment-link transactions, generation of receipts, verification of UTR, checking bank statements, fee status of students, expenses, scholarship and accounting entries. A problem kept coming back - information pertinent to one financial transaction is distributed across records. For instance, the payment record for a student has to be matched with the bank transaction; information from the same payment might have to be entered into another receipt or into the fee-status report or accounting entry.

An activity system which is data-driven and links the activities with each other rather than sees each as a separate action can reduce repetitive work. Machine Learning can take it one step further: if there is reliable historical data, ML can be used to analyze the data to predict the future and pinpoint transactions that require attention. This is then followed by an Agentic AI component which aids administrators in understanding these results. However, AI-generated output should not directly influence financial actions since the system processes institutional financial data.

The main contributions of the work reported here are:

1) a problem formulation and research gap for an education-focused financial workflow that spans fee payment, receipts, UTR-based reconciliation, income, expenses, scholarships, accounting and analytics;
2) a proposed framework and layered architecture connecting these activities with ML-based analysis and a controlled, human-approved Agentic AI layer;

3) an objective-wise methodology, staged implementation plan and evaluation plan to be carried out in the next phase; and
4) a clear statement of the work completed in Phase-I, so that planned work is not presented as experimental evidence.

The rest of the paper is organized as follows. Section II reviews related work. Section III formulates the problem and research gap. Section IV states the objectives. Section V presents the proposed framework, and Section VI the architecture. Section VII describes the Phase-I work, Section VIII the evaluation and implementation plan, Section IX the limitations and ethical considerations, and Section X concludes.

II. RELATED WORK

The literature review carried out in Phase-I covered financial forecasting, financial fraud detection, anomaly detection, data mining and intelligent financial analysis. Seven studies were considered (Table I). They show that Machine Learning can support prediction and pattern identification, and that AI-based methods can assist analysis and decision support.

TABLE I. STUDIES REVIEWED IN PHASE-I AND THEIR RELEVANCE TO THE PROJECT

No.	Authors	Year	Source	Relevance to project
[1]	Wasserbacher and Spindler	2022	Digital Finance	Machine learning for financial forecasting
[2]	Hilal, Gadsden and Yawney	2022	Expert Systems with Applications	Anomaly detection
[3]	Ngai et al.	2011	Decision Support Systems	Data mining / classification
[4]	West and Bhattacharya	2016	Computers & Security	AI / fraud detection
[5]	Bolton and Hand	2002	Statistical Science	Statistical detection
[6]	Phua et al.	2010	arXiv / research survey	Data mining
[7]	Kou et al.	2004	Computers & Operations Research	Data mining

A. Financial Forecasting

Wasserbacher and Spindler [1] examined the use of Machine Learning in financial forecasting, planning and analysis. They are relevant because financial history may be helpful in forecasting fee collections and costs in the future. However, for an educational institution, the forecasting problem is not the same as in the commercial sector, as academic calendars, fee schedules, student enrolment and institutional activities affect records. Forecasting is therefore not viewed as a subsequent analytical phase, but not even taken for granted to be applicable in a different financial environment.

B. Financial Anomaly Detection

Hilal and Gadsden [2] studied the anomaly-detection techniques employed in financial fraud detection and Ngai et al. [3] discussed data-mining techniques for financial fraud detection and classification. The techniques that can be developed from these studies will be based on the ability to identify transactions that need to be further investigated. Not all transactions that are unusual are considered fraud. Anomaly detection can be used to find records that do not fit the pattern that the administrator expects to see, and then review them.

C. Intelligent Financial Analysis

West and Bhattacharya [4] reviewed intelligent approaches to financial fraud detection, while Bolton and Hand [5] discussed statistical approaches. Phua et al. [6] and Kou et al. [7] further examined data-mining approaches. These studies demonstrate the usefulness of analytical methods on financial data, but they do not provide the complete educational-institution workflow considered here. Fig. 1 summarizes the reviewed studies by relevance category and year.

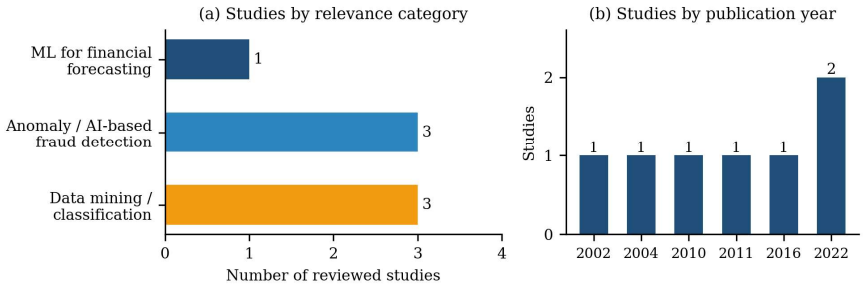

Fig. 1. Reviewed studies by (a) relevance category, as recorded in the Phase-I literature review, and (b) publication year.

III. PROBLEM FORMULATION AND RESEARCH GAP

An educational institution may need to maintain information on student registration and fee structure, fee payments, UTR or transaction IDs, receipts, bank transactions, income, expenses, scholarships, student-wise outstanding amounts, departmental financial information and accounting records. When these records are handled independently, staff may have to perform the same verification or matching task more than once. The project therefore addresses the following question: *how can the financial activities of an educational institution be connected through a data-driven system that reduces repetitive manual processing and provides reliable analytical support while keeping financial decisions under authorized human control?* The solution is not intended to remove administrative responsibility; the aim is to make the underlying information easier to collect, verify, analyse and report.

The reviewed literature covers several individual financial problems: forecasting, fraud detection, anomaly detection and data mining have each received considerable attention. The institution, however, must follow a financial transaction from its operational beginning to its reporting stage. A payment is not simply a number to be predicted: it may begin with a student, produce a receipt, appear in a bank statement, require UTR verification, change the student's pending-fee amount and eventually become part of an accounting or management report. The **research gap** identified in Phase-I is therefore the limited integration of these activities into an education-focused financial workflow that also incorporates Machine Learning and controlled Agentic AI assistance. The proposed work treats the financial process as a connected system rather than as a collection of unrelated analytical tasks.

IV. OBJECTIVES

The project has six objectives, defined from the requirements and observations collected in Phase-I: (O1) a fee-payment workflow using QR codes, payment links or a payment gateway that generates digital receipts containing verified transaction information; (O2) student and administrator dashboards showing payment history, paid and pending fees, receipts, income and expenses; (O3) bank-statement processing and reconciliation using UTR or transaction ID, amount, date and other verified information; (O4) income, expense and scholarship management with reports at student, class and department levels and Tally-compatible accounting data; (O5) Machine Learning for fee-collection forecasting, expense prediction, trend analysis and identification of unusual transactions; and (O6) a controlled Agentic AI layer that interprets validated financial information, explains trends or anomalies and provides recommendations for administrator review.

V. PROPOSED FRAMEWORK

The framework is built around a sequence of financial activities rather than around a single AI model: student → fee/payment → transaction verification → receipt → bank reconciliation → financial records → reports and dashboards → ML analysis → Agentic AI assistance. The final decision remains with an authorized administrator.

A. Student Financial Records and Fee Calculation

The system maintains a financial profile for each student, containing the student name, class, branch, academic year, applicable fee structure and payment details. UTR or transaction information is associated with

this record, which becomes important when a bank statement is received later. The pending fee of a student is computed as

$$\text{Pending Fee} = \text{Total Fee} - \text{Paid Fee} \quad (1)$$

and is summarized at class, branch and department levels for administrators.

B. Fee Payment and Receipt Generation

The payment workflow (Fig. 2) begins when the student is presented with the applicable fee information. The student pays through a QR code or payment link, the payment is confirmed, the UTR or transaction ID is captured, and a digital receipt is generated automatically. Receipt information is stored for both the student and the institutional record and is available in the Student Portal. In Phase-I the workflow and the required fields were defined; live payment-gateway integration has not been completed and is part of the future implementation.

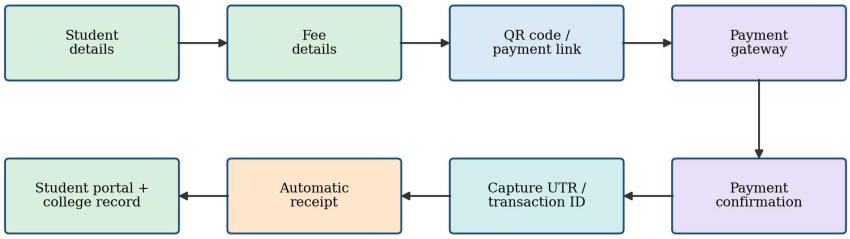

Fig. 2. Planned fee-payment and automatic receipt-generation workflow.

C. Bank Reconciliation

Bank reconciliation is one of the central parts of the framework. An uploaded or imported bank statement contains many transactions, from which the system extracts the transaction date, amount, UTR or transaction ID and other available information. These are compared with student payment records: the exact identifier (UTR or transaction ID) is the primary matching attribute, while amount, date and student information support verification. Each transaction is classified as matched, unmatched, or requiring further verification (Fig. 3), and a reconciliation report is produced. An unmatched record is not automatically treated as an error or as a fraudulent transaction; it is presented for administrator review. The reconciliation method was defined in Phase-I, while its implementation and validation remain future work.

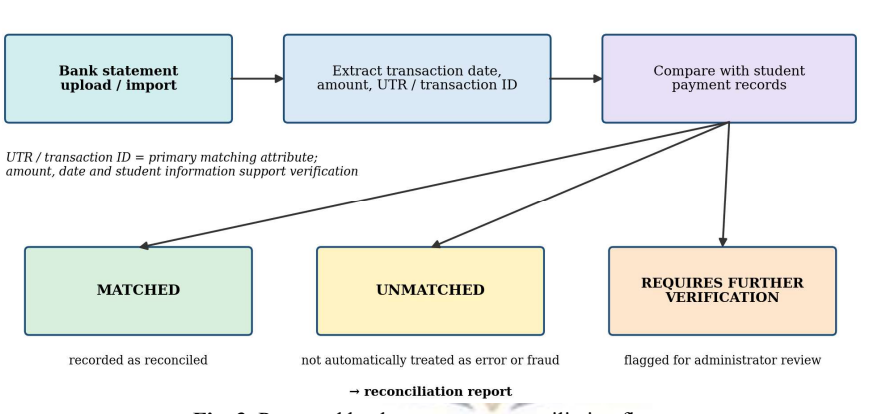

Fig. 3. Proposed bank-statement reconciliation flow.

D. Income, Expense, Scholarship and Accounting Management

Institutional income is maintained in a structured form so that administrators can view collection patterns and generate reports. Expenses are recorded under predefined categories with payment details (manual cheque or online), which also provides the historical data needed for later expense analysis. Scholarship information, including records associated with MahaDBT, is uploaded and mapped to student records so that paid, pending and remaining scholarship amounts can be maintained where the required information is available. Verified

records are prepared in Tally-compatible files, subject to the institution's Tally configuration and supported import mechanism; such files must be validated before import into accounting software.

E. Machine Learning Methodology

The ML component is planned for a later stage because it depends on suitable historical financial data. The intended workflow (Fig. 4a) is: historical financial records → data cleaning → feature preparation → train/test split and model training → prediction or anomaly analysis → evaluation. Two applications are identified. The first is forecasting of fee collection and expenses, whose periodic patterns can be studied once enough validated data are available; the Phase-I methodology identifies the mean absolute error, root mean square error and coefficient of determination as evaluation measures:

$$\mathrm{MAE} = (1/n)\,\Sigma_{i=1}^{n}\,|y_i - \hat{y}_i| \tag{2}$$

$$\mathrm{RMSE} = \sqrt{[(1/n)\,\Sigma_{i=1}^{n}\,(y_i - \hat{y}_i)^2]} \tag{3}$$

$$R^2 = 1 - \Sigma_i(y_i - \hat{y}_i)^2 \,/\, \Sigma_i(y_i - \bar{y})^2 \tag{4}$$

where y_i is the observed value, $\hat{y}_i$ the predicted value and $\bar{y}$ the mean of the observations. The second application is anomaly detection: records that differ from the normal pattern, such as an unusually large expense or an unexpected transaction, are highlighted for examination, not accused. This keeps ML output in a decision-support role. At present no forecasting accuracy is reported, because no model has been validated on institutional financial data.

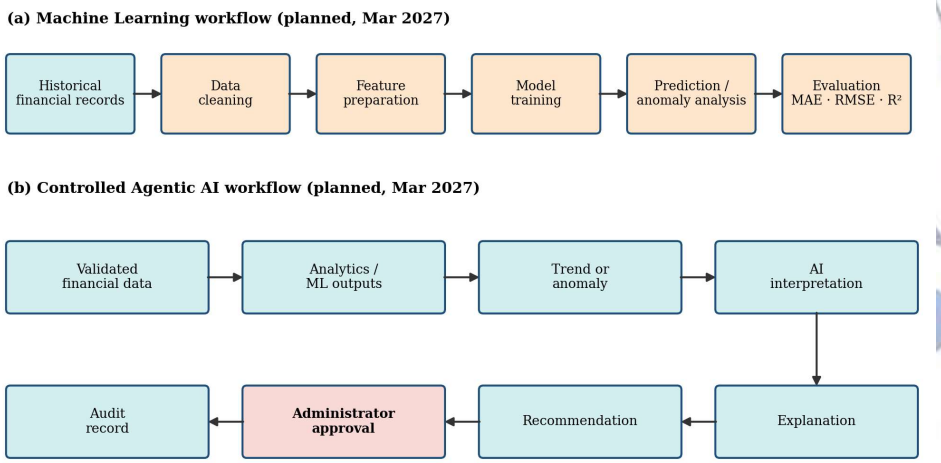

Fig. 4. Planned (a) Machine Learning workflow and (b) controlled Agentic AI workflow with human approval and audit record.

F. Controlled Agentic AI Decision Support

The Agentic AI layer comes at the end of the data and analytical layers (Fig. 4b) deliberately. Validated financial data process through analytics and ML; the AI has determined a trend or anomaly, creates an explanation and a recommendation, the recommendation is sent to an administrator who approves it and the audit record is added. The decision to go with this one is due to the fact that the AI part shouldn't be the first point of financial facts. If an analytical model detects an abnormal expense trend, such as a spike in expenses, the Agentic AI will attempt to identify the trend using approved data and other tools, after which the administration will determine if the trend must be investigated further. AI-generated recommendations are kept between humans and critical financial decisions.

VI. SYSTEM ARCHITECTURE

The architecture (Fig. 5) has the following parts. The *user interface* serves students, administrators and authorized staff; the Student Portal shows fee details, payment and receipts, and the Admin Portal provides the Income Dashboard, Expense Dashboard and Scholarship Module. The *core application* manages authentication, student information, fee records, payments, receipts, expenses, scholarships and reports. The *financial data layer* holds structured student records and bank transactions (transaction ID/UTR, amount, date

and description) in a transaction database fed by the payment gateway. The *reconciliation engine* marks exact matches as reconciled and passes other records to ML analysis, consisting of classification and anomaly detection. The *Agentic AI layer* uses validated outputs for planning, tool calling, analysis and reporting. Reporting services produce student reports, financial reports and Tally-compatible exports. A *control layer* applies authentication, role-based access, validation and audit logging across the system to restrict access and maintain traceability.

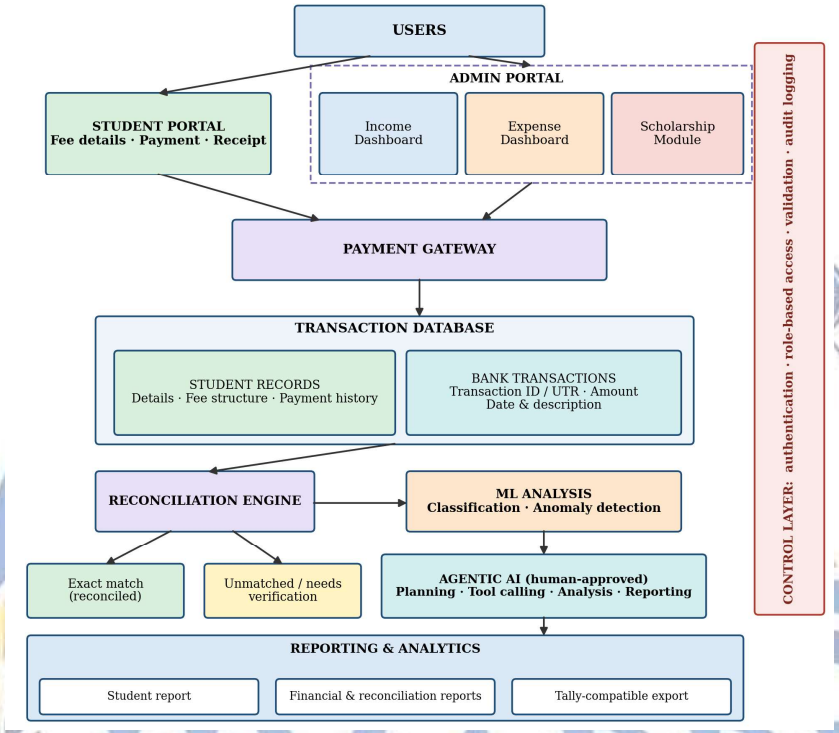

Fig. 5. Proposed layered architecture of the financial management framework.

VII. PHASE-I METHODOLOGY AND WORK COMPLETED

The project did not begin with model development; the first phase was used to establish whether the problem was worth solving and what the system would need. The work was carried out in four 15-day intervals (Fig. 6). In the first interval the team investigated problem areas in Data Science, Machine Learning and AI, shortlisted financial-management problems in educational institutions, and identified stakeholders and initial requirements. In the second, schools and colleges were visited and discussions were held with relevant staff on fee collection and payment processes. In the third, the collected information was analysed, the difficulties of the existing process were studied, and the requirements and objectives were finalized. In the fourth, the project topic was finalized and the required technologies, tools, scope, basic workflow and architecture were studied.

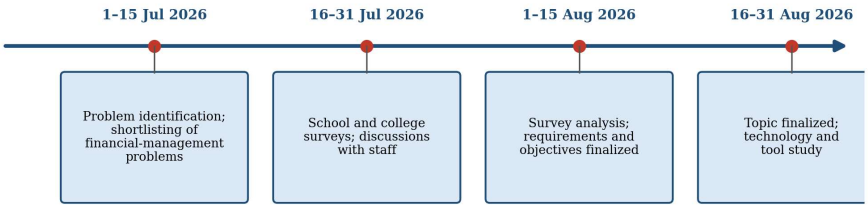

Fig. 6. Phase-I work carried out in four 15-day intervals (July–August 2026).

The output of Phase-I is therefore a problem definition, a requirements specification, a research foundation and a system design, not a completed software system. Table II shows the methodology and Phase-I status of each objective: O1–O4 are partially satisfied, with workflows, required fields and matching methodology defined but implementation and validation planned, while the ML (O5) and Agentic AI (O6) objectives are at

the planning stage, with model selection, data requirements, evaluation methodology and the human-in-the-loop methodology defined.

TABLE II. OBJECTIVE-WISE METHODOLOGY AND PHASE-I STATUS

Objective	Methodology	Phase-I status
O1 – Fee payment and receipt	Student registration → fee details → payment link/QR → gateway → confirmation → UTR/transaction ID capture → automatic receipt → student portal and college record	Partially satisfied: workflow, fields and receipt/reconciliation design completed; live gateway integration planned
O2 – Dashboards	Authentication → role-based access → payment history, receipt, paid/pending status → admin income/expense views → reports and filters	Partially satisfied: requirements and information architecture defined; implementation planned
O3 – Bank reconciliation	Statement import → extract date, amount, UTR → match with student records → matched/unmatched → reconciliation report	Partially satisfied: matching methodology and data fields defined; implementation and validation planned
O4 – Income, expense, scholarship, accounting	Income records → expense categories and entries → cheque/online payment details → scholarship upload and mapping → paid/pending calculation → reports → Tally-compatible export	Partially satisfied: module and report workflow designed; institutional integration planned
O5 – ML forecasting and anomaly detection	Historical data → preprocessing → feature engineering → train/test split → forecasting models → MAE/RMSE/R^2 → anomaly detection → validate alerts	Planned: model selection, data requirements and evaluation methodology defined
O6 – Agentic AI decision support	Validated data → analytics/tools → trend/anomaly interpretation → explanation → controlled recommendation → human approval → audit log	Planned: architecture and human-in-the-loop methodology defined

VIII. EVALUATION AND IMPLEMENTATION PLAN

Evaluation will be performed after the relevant components have been implemented. The planned measures are summarized in Table III; no performance values are reported here, because those experiments belong to the implementation phase. The initial implementation will be tested with sample or controlled financial data before any use with real institutional records.

TABLE III. PLANNED EVALUATION OF EACH COMPONENT

Component	Evaluation measure
Fee processing	Calculation correctness
Receipt generation	Data correctness
Bank reconciliation	Transaction matching and reconciliation accuracy
Scholarship mapping	Mapping correctness
Reports	Report accuracy
Forecasting	MAE, RMSE and R^2
Anomaly detection	Appropriate detection measures (to be finalized)
Application	Response time and usability
Security	Access-control and security testing

Implementation follows a staged, dependency-based plan (Fig. 7), because later modules depend on the data produced by earlier ones. September–October 2026: authentication, database, Student Portal, payment/receipt workflow and backend APIs. November–December 2026: bank-statement processing, UTR reconciliation, Income Dashboard, student-, class- and department-wise reports and Tally-compatible export. January 2027: Expense Dashboard, manual cheque and online expense workflow, and expense reconciliation. February 2027: scholarship/MahaDBT upload, student mapping and paid/pending/remaining calculations. March 2027: ML forecasting, collection prediction, anomaly detection, Agentic AI decision support, integration and testing. April 2027: security hardening, performance and user testing, deployment, documentation, the final research paper and presentation. The order is deliberate: training an analytical model before reliable financial records exist would make its evaluation difficult to interpret.

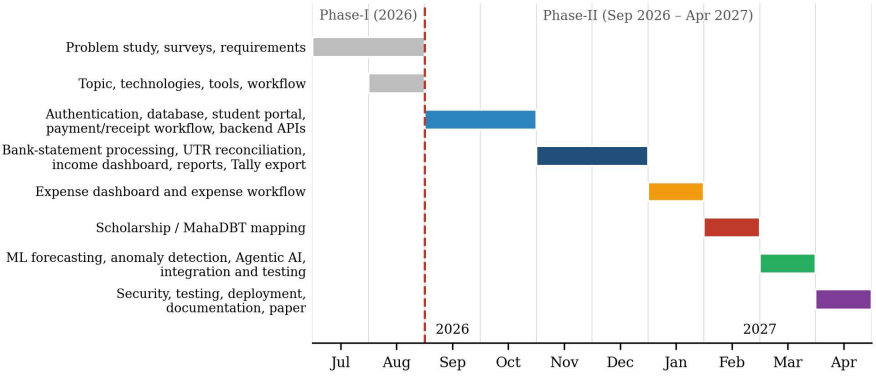

Fig. 7. Phase-I (completed) and planned Phase-II implementation roadmap, July 2026 – April 2027.

IX. LIMITATIONS AND ETHICAL CONSIDERATIONS

Several issues must be addressed before the framework is used with real institutional records.

- **Data quality.** Reconciliation and reporting depend on the quality of the underlying records; missing or incorrect UTRs, amounts or dates can affect automatic matching.
- **ML reliability.** Financial behaviour changes over time, so a model trained on historical patterns may predict less well when the pattern changes. ML outputs are decision-support information, not guaranteed results.
- **AI-generated explanations.** The Agentic AI may produce incorrect or incomplete explanations or recommendations. Its output is restricted to validated data and approved tools and is reviewed by authorized personnel.
- **Privacy and access.** Student and institutional financial information must be protected from unauthorized access, misuse and unnecessary disclosure, using authentication, role-based access, data validation, authorized data handling and audit logging.
- **Human control.** The system does not make important financial decisions automatically; corrections, accounting updates and other consequential actions remain under authorized human supervision.
- **External records.** Scholarship and financial records from external sources such as MahaDBT, and generated Tally-compatible files, must be verified before use in reconciliation or import into accounting software.
- **Controlled testing.** The initial system will be tested with sample or controlled data before deployment with real records.

X. CONCLUSION AND FUTURE WORK

The Phase-I study produced the design of a data-driven financial management framework for educational institutions. The project started from an examination of existing financial procedures and discussions with institutions, not directly from an AI model, and these activities revealed recurring requirements around payment management, receipt generation, bank reconciliation, expenses, scholarships and reporting. The framework connects these activities and adds two analytical layers: Machine Learning for forecasting and anomaly detection once sufficient validated data are available, and a controlled Agentic AI component that supports interpretation while leaving important financial decisions to authorized administrators.

At the end of Phase-I, the problem definition, research gap, objectives, requirements, architecture and evaluation approach have been established. The expected contribution is an integrated approach, not a single ML algorithm: a unified platform for student fees, receipts, bank reconciliation, income, expenses, scholarships, reports, ML-based analysis and Agentic AI assistance, intended to reduce repetitive manual reconciliation, improve record accuracy and give clearer financial visibility. Implementation and experimental validation remain for the subsequent phase, and future versions of this paper will report measured results for reconciliation accuracy, forecasting error, anomaly detection, usability, response time and security.

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