Machine Learning Based GST Billing System for Payment Delay Prediction and Automated Payment Negotiation for MSMEs

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doi.org/10.64643/IJIRTV12I10-194476-459

***Abstract* — Late B2B payments have been a cash-flow problem for Indian MSMEs for a long time. At any given moment, over INR 10 lakh crore is locked in unpaid receivables. Industry reports show that a significant number of B2B invoices from small vendors are paid after their due dates. Popular billing tools like Tally, Zoho Books, and Vyapar manage invoicing and record-keeping well, but they only record delays after they happen. They do not provide any risk signal when an invoice is being created. The system in this paper addresses that issue. It integrates a Predictive Payment and Cashflow Negotiation module into a GST-compliant billing workflow. This system offers two key features that the reviewed tools lack. The first feature uses a multivariate linear regression model trained on 800 samples from the IBM Finance Factoring – Late Payment Histories dataset (Kaggle, 2022; 50,000 real B2B invoice records). It estimates how long a specific customer is likely to delay payment before the invoice is saved. This estimate informs a negotiation engine with 33 templates across 10 categories. It profiles each customer based on five factors: relationship depth, payment behavior, invoice size, delay severity, and escalation history. The second feature is a daily WhatsApp scheduler that updates the prediction for each invoice nearing its due date. It sends each customer a personalized message with discount offers based on their risk rating: Low, Medium, or High rather than a generic reminder. In testing with 200 records, the model achieved $R^2 = 0.9106$, RMSE = 0.5899 days, and MAE = 0.5171 days. The system is built on Node.js, Express.js, and MongoDB Atlas. Together, these two features transform a standard billing tool into a proactive cashflow intelligence platform for MSME vendors.**

***Index Terms — Customer Behavior Analysis, GST Billing,* Invoice Prediction, *Machine Learning, Multivariate Linear Regression, Negotiation Suggestion, Payment Delay Prediction,* Payment Risk Analysis.**

I. INTRODUCTION

Working capital issues have long affected Indian MSMEs, but the main problem persists: B2B customers often pay late. Industry reports suggest that many B2B invoices from small vendors are paid after the due date, tying up vital working capital in unpaid receivables. A large manufacturer can handle a two-week payment delay; however, a small vendor with tight margins often cannot. Even a 15 to 20 day delay can force them to delay procurement or take out loans at high short-term rates. These costs add up and eat into the expected profit of the initial transaction.

Billing software has genuinely improved financial record-keeping for Indian businesses. Tally, Zoho Books, and Vyapar all create GST-compliant invoices, handle tax calculations, and track payments effectively. Yet, they all miss one crucial point: they respond to delays instead of anticipating them. By the time a late payment appears in the ledger, the financial damage has often begun. More importantly, the vendor has lost the opportunity to negotiate right at the invoice creation, before extending credit. A vendor aware of a customer's high risk for payment delays at billing time could ask for a partial advance, offer a discount for early payment, shorten the credit term, or arrange payments in installments. No common billing software today provides this information when it can still make a difference.

1.1 Problem Statement

When an MSME vendor creates a credit invoice, their billing software does not provide a payment risk indicator for the future. The system tracks late payments once they occur, but it does not indicate at invoice creation if a customer is likely to pay on time. As a result, vendors often extend credit to customers who should have stricter terms based on their payment history, without any early warning. This absence of warning prevents vendors from taking preventive measures, such as requesting an advance, adjusting the credit period, or offering incentives for quick payment.

1.2 Proposed Solution

This paper describes a Machine Learning Based GST Billing System with an integrated Predictive Payment and Cashflow Negotiation module. It addresses the identified gap in two ways:

(1) Pre-billing ML Prediction with Negotiation Suggestions: Before the invoice is finalised, the system looks up the customer's payment history and uses a trained multivariate linear regression model to estimate the expected delay in days. Before the invoice is finalised, a negotiation suggestion engine that receives the predicted risk level provides ranked, context-aware recommendations.

(2) ML-Triggered Personalised WhatsApp Reminders: A daily automated scheduler finds invoices that are due soon, runs the full prediction pipeline for each customer, and sends a personalized WhatsApp message with the invoice details and a discount offer(if needed) that is tailored to that customer's risk profile. This replaces generic reminder texts with truly relevant, machine learning-driven outreach. No MSME billing platform in India currently integrates pre-billing prediction, context-aware negotiation suggestions, and ML-triggered WhatsApp reminders into a single system. A review of all pertinent literature substantiated this gap. Section II reviews related work. Section III describes the system architecture. Section IV explains the methodology. Section V presents the results and evaluation, and Section VI concludes the paper.

II. LITERATURE REVIEW

Before building anything new, we mapped what already exists. Seven recent publications on accounts receivable management, cashflow forecasting, and ML-based payment prediction were examined in detail. Each is compared with our system in terms of model type, prediction granularity, and practical fit for small businesses. That comparison exposes the gap this work addresses.

- Appel et al. (2020) created a system that could predict which invoices would be paid late. They used customer payment history as input and XGBoost as the model, and it was 81% accurate. It predicts the risk of future payments based on how people have paid in the past, just like our system. But it only tells you if a payment is going to be late, not how many days. It also doesn't have a suggestion engine or a WhatsApp reminder.
- Using a survival analysis model on supply chain data, Saini et al. (2024) predicted when each invoice would be paid. The study was published in Springer Nature. It has the same goal as our system: to guess when a certain invoice will be paid. But the result is a statistical curve, not a single number that a vendor can use. There is no integration with billing software, no suggestions, and no WhatsApp feature.
- Musyaffa et al. (2024) built a billing system that sends invoice and payment reminders to customers via WhatsApp, validated with 22 UAT test cases. This is the closest match to our WhatsApp reminder module. The difference is that their system sends the same message to every customer. Our system uses the ML prediction to send a different, personalised message based on each customer's payment history and risk level.
- Schoonbee et al. (2022) embedded a neural network inside a billing decision support tool that classifies invoices as on-time, 1–30 days late, or 31–60 days late, achieving 92.4% accuracy. This is the most similar architecture to our system — ML output shown to a user who then acts on it. The difference is that their system gives a delay category, not the actual number of days, and has no WhatsApp reminder or pre-billing prediction.
- Bahrami et al. (2020) predicted invoice payment using customer behavior data from 1.6 million customers, reaching up to 97% accuracy with

logistic regression. Like our system, it uses customer behavioral patterns as the main input. But it needs email logs, call records, and SMS history to work, which small vendors do not have. It also has no WhatsApp feature and no suggestion engine.

- Vora et al. (2024) tested multiple ML models — Decision Tree, Random Forest, Gradient Boosting, LGBM — to predict payment behavior using customer history, and found LGBM to work best . Their feature design is the closest to ours: payment frequency, delay history, and invoice amount are the same inputs we use. The difference is their system only classifies payments as late or on-time, is not connected to billing software, and has no WhatsApp or suggestion feature.
- Each of the six papers covers one part of what our system does — either payment prediction, behavioral analytics, or WhatsApp notification — but none combines all three. No existing MSME billing product in India predicts payment delay before saving an invoice, gives the vendor negotiation suggestions, and sends personalised WhatsApp reminders based on that prediction. Our system does all three together, which is the gap identified across all reviewed work. Table I shows this comparison clearly.

Table I: Comparison of Related Works and System Capabilities

Study	Metric	Pre-bill	Suggest	WhatsApp
Appel et al. [1]	Acc = 81%	No	No	No
Saini et al. [2]	Outperforms LR	No	No	No
Musyaffa et al. [3]	UAT: 22 cases	No	No	Yes
Schoonbee et al. [4]	Acc = 92.4%	No	No	No
Bahrami et al. [5]	Acc up to 97%	No	No	No
Vora et al. [6]	Best: LGBM	No	No	No
Proposed	$R^2 = 0.9106$	Yes	Yes	Yes

III. SYSTEM ARCHITECTURE

3.1 Technology Stack

The platform is a full-stack web application. Server-side logic runs on Node.js v20 with Express.js 4.x; data is persisted in MongoDB Atlas (cloud-hosted) via the Mongoose ODM. The frontend is intentionally lean—plain HTML5, CSS3, and Vanilla JavaScript—so the billing interface stays responsive on modest hardware. Table II shows the complete technology stack.

Table II: System Technology Stack

Layer	Technology
Frontend	HTML5, CSS3, Vanilla JavaScript
Backend	Node.js v20, Express.js 4.x
Database	MongoDB Atlas (Cloud) with Mongoose ODM
Authentication	JWT + bcrypt (.env secrets)
ML Model	Multivariate Linear Regression (trained offline)
Notifications	Twilio WhatsApp API
Scheduler	setInterval, 24-hour cycle
Server / Hosting	Netlify (frontend), Render (backend)
Browser Compatibility	Chrome, Firefox, Edge, Safari (modern versions)

3.2 System Modules and Data Flow

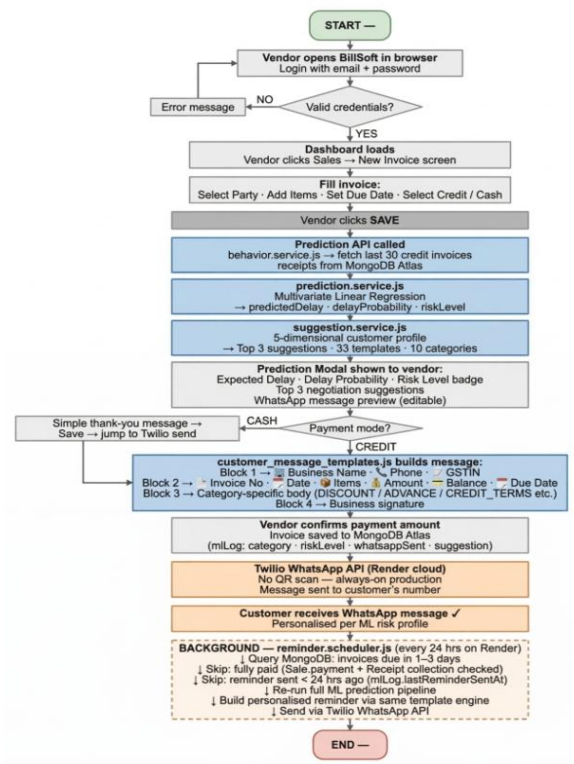


Fig. 1. Customer Journey — Invoice Creation to WhatsApp Message.

GST Invoice & Billing, Customer & Party Management, Transaction Management, Dashboard & Overview, User Authentication (JWT + bcrypt), and the Predictive Payment and Cashflow Negotiation Module are the six modules that make up the system. Before the invoice is finalised, the system retrieves the customer's previous 30 credit invoices from

MongoDB Atlas, executes the ML prediction pipeline, produces ranked negotiation recommendations, and shows a customised preview of a WhatsApp message when a vendor saves a credit invoice. For invoices that are due within one to three days, the daily scheduler reruns this pipeline and uses the Twilio WhatsApp API to send out reminders. The prediction service loads the trained regression coefficients from model_coefficients.json at server startup and performs real-time inference during invoice creation without retraining the model. The entire customer journey, from login to WhatsApp message delivery, is depicted in Fig. 1.

IV. METHODOLOGY

4.1 Dataset and Feature Extraction

- Source: Kaggle 2022; IBM Finance Factoring – Late Payment Histories dataset.
- Size: 50,000 B2B invoice records from 1,425 distinct business clients
- Filter: Only invoices with valid due and payment dates that were cleared (isOpen = 0) were kept.
- Scaling: To fit the Indian MSME context, invoice amounts were rescaled from USD to INR 2,200–49,960.
- Results: 1,000 behavioural training samples, divided 80/20 into 200 held-out test records and 800 training records.
- The regression model was trained offline using 800 samples from the IBM Finance Factoring dataset. The resulting coefficients were exported to model_coefficients.json and used by the backend prediction service for real-time prediction during invoice creation.
- Activation: When a customer has at least three past-due or cleared credit invoices, Prediction becomes active. Since cash sales don't indicate a credit risk, they are not included.

Four features are extracted per customer:

- avgDelay — mean payment delay in days across all delayed invoices
- delayRatio — share of past invoices settled late
- invoiceAmount — current invoice value in INR
- paymentCount — total past payment transactions on record

4.2 Prediction Model and Risk Classification

- Algorithm: Multivariate Linear Regression. The regression model was trained offline using the IBM Finance Factoring dataset. The learned coefficients are stored in model_coefficients.json and loaded by the Node.js backend for real-time prediction.
- Choice rationale: Interpretability, real-time inference speed, and strong performance on this continuous delay target.
- Coefficients are saved to model_coefficients.json and loaded once at server startup — no per-request retraining.

Trained regression equation:

- $\text{predictedDelay} = 0.6955 \times \text{avgDelay} + 3.9962 \times \text{delayRatio} - 0.00000177 \times \text{invoiceAmount} - 0.03087 \times \text{paymentCount} + 0.16196$
- Key finding: delayRatio dominates with coefficient 3.9962 — payment consistency predicts delay more strongly than average delay magnitude.
- Customer with avgDelay = 5 days and delayRatio = 0.8 → predicted delay = $(0.6955\times5) + (3.9962\times0.8) = 3.48 + 3.20 = 6.68$ days ≈ 7 days

Predicted delay is normalised to a probability score (delay ÷ 30, capped at 1.0) and mapped to three risk bands:

- Low (<0.30) — activates REMINDER or RELATIONSHIP suggestions
- Medium (0.30–0.59) — activates DISCOUNT, CREDIT_TERMS, or SPLIT suggestions
- High (≥0.60) — activates CRITICAL, SUSPEND, or ADVANCE suggestions

4.3 Negotiation Suggestion Engine

The engine builds a five-dimensional customer profile before selecting suggestions:

- Relationship depth — new (≤ 4 invoices), loyal (≥ 10), or very loyal (≥ 20)
- Payment pattern — chronic late (delayRatio ≥ 0.80), occasional, reliable (<0.30), first-default, or improving
- Invoice size — small (<INR 15,000), medium, large, or very large (>INR 1,50,000)
- Delay severity — mild (1–5 days), moderate (5–12), severe (12–20), or critical (>20 days)

- Financial impact — dynamic advance percentage (10–40%, scaled to delayRatio) and early-payment discount amount

Suggestion selection process:

- 33 templates across 10 categories: CRITICAL, ADVANCE, DISCOUNT, CREDIT_TERMS, SPLIT, RELATIONSHIP, SUSPEND, REMINDER, ESCALATE, INSIGHT.
- Every template embeds ML-computed rupee amounts and day counts — no generic filler text.
- Templates carry priority scores 1–10; top three returned by weighted priority score.
- A SuggestionFeedback MongoDB collection records the outcome of negotiation suggestions. When an invoice passes its due date and the payment outcome becomes known, a feedback record is automatically created. These records are analysed to compute category success rates, which influence the ranking of future suggestions. Suggestions that historically lead to on-time payments are prioritised more prominently in subsequent recommendations.
- Each suggestion includes a confidence score (0–100%) and a trend label: worsening / improving / stable.

4.4 WhatsApp Reminder and Message Templates

Daily scheduler (setInterval, 24-hr cycle on Render) process:

- Queries MongoDB Atlas for unpaid invoices due within 1–3 days.
- Skips any invoice for which a reminder was already sent within the last 24 hours.
- Re-runs the full ML prediction pipeline for each qualifying invoice.
- Dispatches a personalised message via Twilio WhatsApp API — no QR scan Every Time, always-on production.

Each WhatsApp message contains three fixed blocks:

- Block 1 — Business header: name, phone number, GSTIN
- Block 2 — Invoice block: invoice number, date, items, amount, balance due, due date
- Block 3 — Category-specific body with ML-computed rupee amounts and deadlines
- No two customers receive the same message — all values are computed per customer from the live ML prediction output.

V. RESULTS AND EVALUATION

5.1 Model Performance

The model was evaluated on the 200 held-out test records derived from the IBM Finance Factoring dataset (50,000 real B2B invoice records). Table III presents the evaluation results.

These evaluation metrics were obtained during the offline model training phase using the IBM Finance Factoring dataset. The trained regression coefficients were exported to model_coefficients.json and are loaded by the backend prediction service for real-time inference.

Table III: ML Model Evaluation Metrics

Metric	Value	Interpretation
RMSE	0.5899 days	Error < 1 day average
MAE	0.5171 days	Deviation < 1 day average
R^2 Score	0.9106 (91.1%)	91.1% variance explained
Train Set	800 invoices	80% of IBM-derived samples
Test Set	200 invoices	20% held-out

These metrics were obtained during the offline model training phase and are reported here to demonstrate the predictive capability of the regression model.

An R^2 of 0.9106 on unseen data is a strong result for a four-feature linear model and confirms that customer behavioural signals carry most of the predictive information for this task. An RMSE of 0.5899 days means the model is accurate to within half a day on average—more than adequate for a risk classifier that groups customers into three broad bands.

5.2 Example Prediction Output

Table IV shows the complete prediction output for a Medium-risk customer with an INR 60,000 invoice, as returned to the vendor before the invoice is finalised.

Table IV: Example Prediction Output (INR 60,000 Invoice)

Parameter	Value
Avg. Historical Delay	12.0 days
Delay Ratio	75% (3 of 4 invoices)
Predicted Delay	11 days
Delay Probability	37%
Risk Level	MEDIUM

Top Suggestion	Offer early-payment discount of 2% if paid within 7 days
WhatsApp Message Type	Early payment incentive

5.3 Feature Comparison

Table V compares the proposed system against the three most widely used billing solutions in the Indian MSME market across all key features.

Table V: Feature Comparison with Existing Billing Systems

Feature	Tally	Zoho	Vyapar	Proposed
GST Invoice	Yes	Yes	Yes	Yes
Payment Tracking	Yes	Yes	Yes	Yes
Pre-billing Prediction	No	No	No	Yes
Risk Classification	No	No	No	Yes
Negotiation Suggestions	No	No	No	Yes
ML WhatsApp Reminder	No	No	No	Yes
Personalized Messages	No	No	No	Yes
Suggestion Feedback Learning	No	No	No	Yes

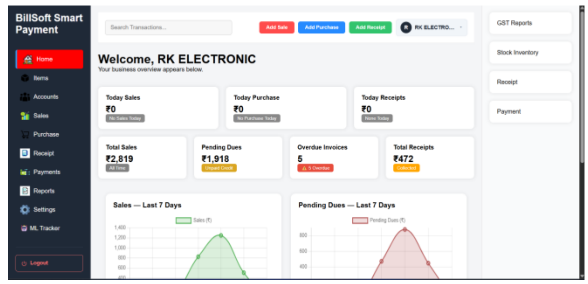
The comparison confirms that the proposed system introduces nine capabilities absent from all three existing mainstream billing solutions, each directly related to proactive payment risk management, customer intelligence, and adaptive suggestion learning.

5.4 System Validation

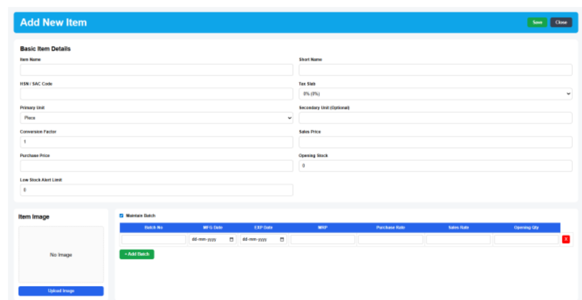
All six modules were put through functional testing. API endpoints were exercised using Postman for CRUD operations, prediction requests, and scheduler triggers. JWT authentication, MongoDB Atlas connectivity, and bcrypt password flows were tested with both valid inputs and deliberately malformed ones. The WhatsApp scheduler was validated by setting near-future due dates on test invoices and confirming message dispatch. Under standard conditions the prediction API returns a complete response fast enough for real-time display during invoice creation without interrupting the vendor's workflow.

- GST Billing Software Module (Snapshot 5.1-5.8)

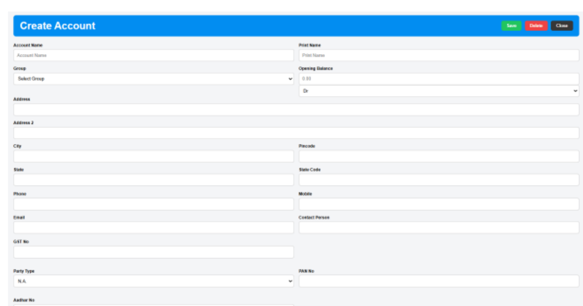
Snapshot 5.1. Login Page – User login



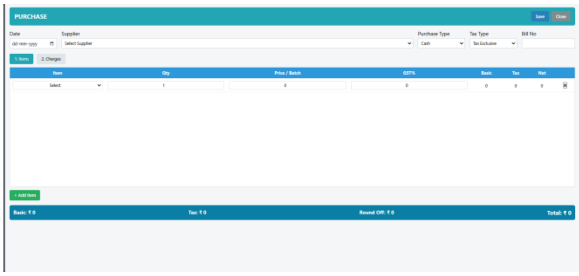
Snapshot 5.2: Dashboard – Business Overview



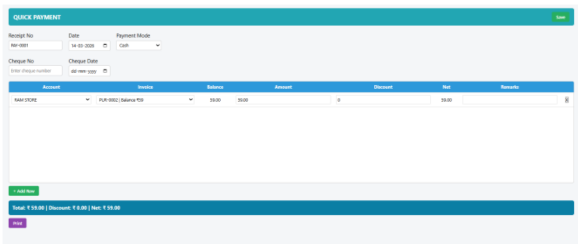
Snapshot 5.3: Add New Item – Product Creation Form



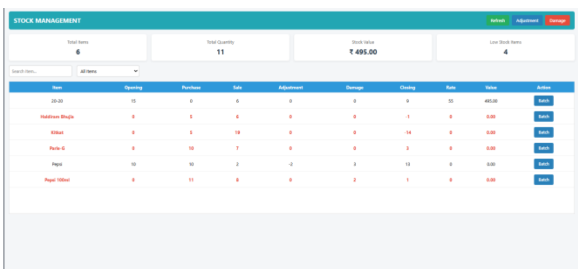
Snapshot 5.4: Create Account – Business Account Registration



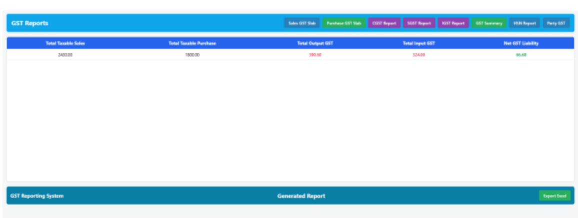
Snapshot 5.5: Purchase Entry – Purchase Transaction Management



Snapshot 5.6: Quick Payment – Supplier Payment Processing

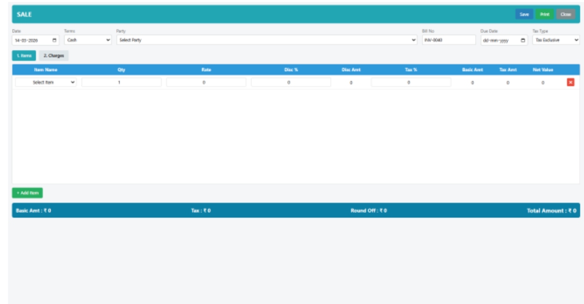


Snapshot 5.7: Stock Management – Inventory Tracking

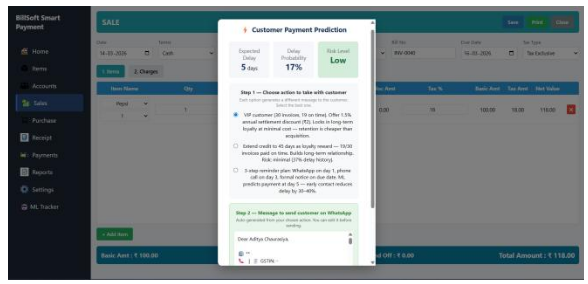


Snapshot 5.8: GST Reporting Dashboard – Tax Calculation System

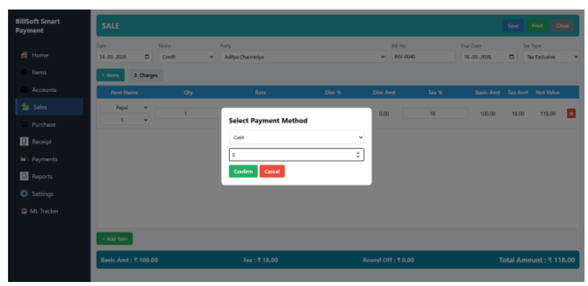
- ML Prediction & Negotiation Module (Snapshot 5.9-5.16)



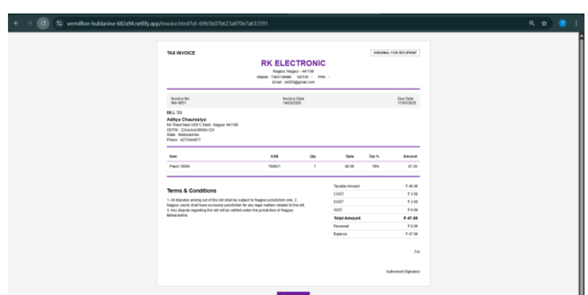
Snapshot 5.9: Sales Billing Interface – Invoice Generation



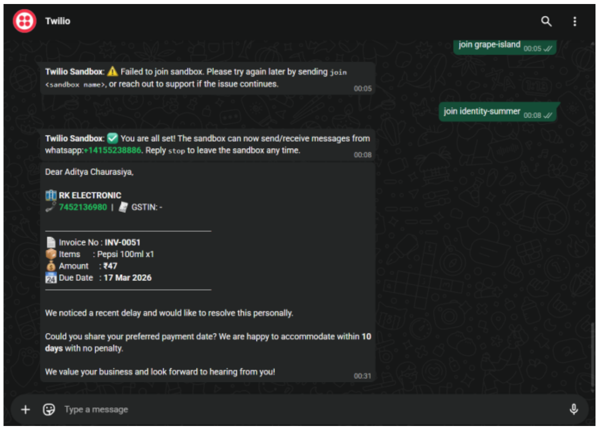
Snapshot 5.10: ML-Based Customer Payment Prediction



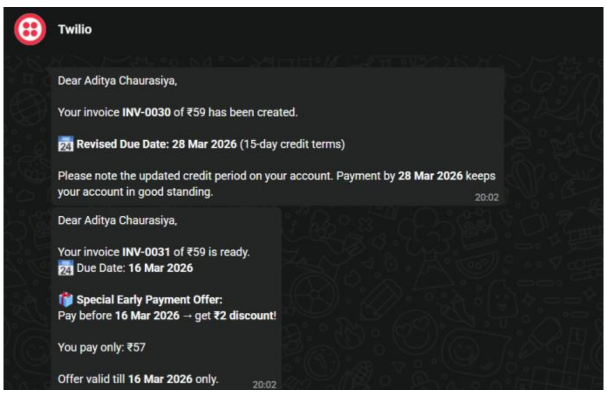
Snapshot 5.11: Sales Invoice Finalization and Payment Confirmation



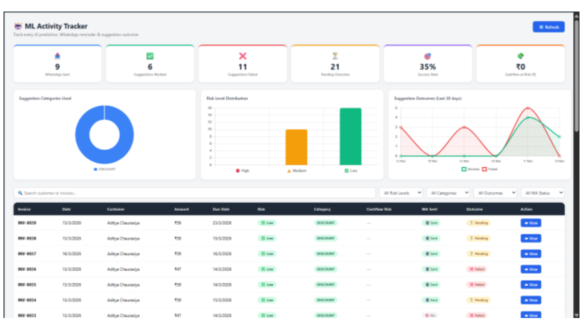
Snapshot 5.12: GST Tax Invoice Generation



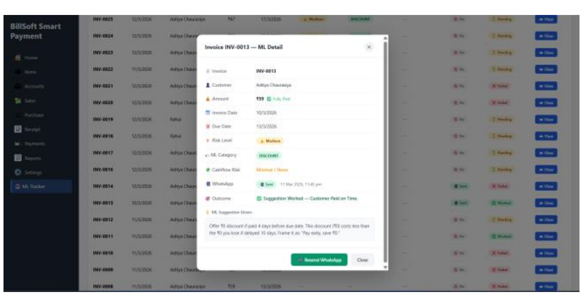
Snapshot 5.13: Automated WhatsApp Invoice Notification



Snapshot 5.14: ML-Generated Payment Reminder



Snapshot 5.15: ML Activity Tracker –Performance Dashboard



Snapshot 5.16: Invoice ML Detail – ML Prediction and Negotiation Insight

VI. CONCLUSION

This paper introduced a GST-integrated billing system for Indian MSMEs built around a Predictive Payment and Cashflow Negotiation module. The core idea is straightforward: give vendors actionable risk information at invoice creation time, when they can still do something about it, rather than after the delay has already begun. The trained multivariate linear regression model achieved $R^2 = 0.9106$, RMSE = 0.5899 days, and MAE = 0.5171 days on held-out real-world B2B invoice data, demonstrating that four simple behavioural features are sufficient for accurate real-time prediction.

The proposed system offers two features missing from all seven reviewed works and from Tally, Zoho Books, and Vyapar: (1) Pre-billing risk assessment with context-aware negotiation suggestions from a v4.0 feedback-weighted engine featuring 33 templates and 10 categories, five-dimensional customer profiling, confidence scores, trend detection, and an adaptive feedback loop backed by a SuggestionFeedback MongoDB collection that adjusts category priorities over time; and (2) Machine learning-triggered personalised WhatsApp reminders, replacing generic notifications with tailored outreach tied to real risk data. The feature comparison shows that none of these capabilities exist in any of the three mainstream billing products. Future work will: (1) compare Random Forest, XGBoost, and LSTM models against the linear regression baseline on Indian MSME payment data; (2) collect real transaction records from Indian MSME vendors for domain-specific retraining; (3) measure the actual reduction in average payment delay from personalised WhatsApp outreach in live deployment; and (4) build a mobile application to extend access to field-based MSME vendors.

ACKNOWLEDGMENT

The authors thank the Department of Computer Science and Engineering at G H Raisoni University, Amravati, for providing the institutional resources that supported this work. Special thanks are due to Dr. Trupti Meshram, Assistant Professor, for expert guidance and consistent encouragement throughout this research. The authors also acknowledge IBM and the Kaggle community for making the IBM Finance Factoring – Late Payment Histories dataset openly available; it forms the empirical backbone of model training and validation.

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