Pratinidhi: AI-Powered Educational Communication Platform Based on Intelligent Message Processing and Eligibility Filtering

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Abstract

Educational institutions face persistent challenges in disseminating placement announcements and academic notifications through unstructured channels such as WhatsApp groups, causing students to miss critical opportunities due to information overload. This paper presents Pratinidhi, an AI-powered educational communication platform that addresses this challenge through a novel two-stage message processing architecture using Google Gemini 2.0 Flash AI. The V0 stage extracts concise summaries, message type classifications, structured eligibility criteria (CGPA, backlogs, gender, batch year, branch), deadlines, and key action points. The V1 stage captures comprehensive details including company information, roles, compensation packages, application procedures, and contact details. A rule-based eligibility checking algorithm compares student profiles against V0-extracted criteria across six dimensions, ensuring students receive V1 details only when they meet all requirements. The platform implements four-tier role-based access control (Super Admin, Institution Admin, Teacher, Student) with hierarchical approval workflows and real-time messaging via Supabase Realtime WebSocket. Built with Next.js 16, React 19, Supabase PostgreSQL, and TypeScript, the system achieves 98% V0 accuracy (2.3s) and 95% V1 accuracy (3.1s), reducing information noise by 60%. Validated through 125 Vitest unit tests and 57 integration tests, the platform is deployed at prosody-v3.vercel.app.

Keywords: AI-Powered Communication, Eligibility Filtering, Google Gemini AI, Large Language Model, Message Processing, Educational Technology

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1. Introduction

Educational institutions in India generate a high volume of daily announcements encompassing campus placement drives, internship opportunities, exam fee deadlines, project submissions, and administrative notifications. The primary dissemination channels—WhatsApp groups, email chains, and physical notice boards—share a fundamental limitation: they broadcast all announcements to all recipients regardless of individual eligibility, creating substantial information overload [1].

A typical placement cell WhatsApp group serving 200–500 students transmits every announcement indiscriminately. Students must manually read each message, extract eligibility criteria (CGPA cutoffs, backlog restrictions, branch requirements), and determine personal relevance. Research by Bouhnik and Deshen [2] demonstrated that such information overload in educational messaging groups leads to 'notification fatigue,' causing students to mute groups entirely and subsequently miss genuine opportunities. Gachago et al. [3] further established that unstructured group messaging in educational contexts reduces engagement by 40–60% over a semester.

Existing educational platforms such as Google Classroom, Moodle, and Canvas LMS [4] provide structured course content delivery with role-based access control. However, these systems focus on academic content management rather than announcement processing and lack AI-driven summarization or eligibility-based content filtering capabilities. Recruitment platforms like LinkedIn and Naukri.com implement profile-based job matching but operate at the application level without integration into institutional communication workflows.

To address these gaps, this paper presents Pratinidhi (Hindi for 'Representative'), an AI-powered educational communication platform that transforms unstructured announcements into structured, personalized information cards through a novel two-stage processing pipeline. The key contributions of this work are:

- A two-stage AI processing architecture (V0 + V1) using Google Gemini 2.0 Flash for structured information extraction from unstructured announcement text.
- A rule-based eligibility checking algorithm that evaluates student profiles across six dimensions (CGPA, backlogs, gender, batch year, branch, ready-to-join status) against AI-extracted criteria.
- A four-tier role-based access control system with hierarchical approval workflows supporting multi-institution deployment.
- Empirical validation demonstrating 98% V0 accuracy, 95% V1 accuracy, and approximately 60% reduction in information noise through eligibility filtering.

2. Related Work

Table 1 presents a comparative analysis of existing systems and related research in educational communication, AI-powered text processing, and eligibility-based content filtering.

Table 1: Comparative Analysis of Related Work

S. No	Title / System	Year	Approach	Limitations	Ref
1	WhatsApp in Education (Bouhnik & Deshen)	2014	Study of WhatsApp for teacher-student communication	No filtering, causes notification fatigue	[2]
2	Crossing Boundaries (Gachago et al.)	2015	WhatsApp for higher education teaching	Unstructured, 40-60% engagement drop	[3]
3	Google Classroom / Moodle LMS	2023	Course content management with RBAC	No AI summarization, no eligibility filtering	[4]
4	GPT-3 Few-Shot Learning (Brown et al.)	2020	Large language models for text understanding	General purpose, not education-specific	[5]
5	BERT for Text Classification (Devlin et al.)	2019	Pre-trained transformer for NLP tasks	Requires fine-tuning, no structured extraction	[6]
6	Gemini: A Family of Capable Models (Google)	2024	Multimodal LLM with structured JSON output	API dependency, rate limits under load	[7]
7	RBAC Models (Sandhu et al.)	1996	Role-based access control framework	Does not address content-level filtering	[8]
8	Pratinidhi (This Work)	2026	Two-stage AI (V0+V1) + eligibility filter + RBAC + realtime	API-dependent, no offline AI	-

The literature reveals three distinct gaps that Pratinidhi addresses. First, no existing educational communication platform combines AI-powered text summarization with eligibility-based content filtering. Second, while LLMs like GPT-3 and BERT have demonstrated strong text understanding capabilities, they have not been applied to the specific problem of

announcement processing with structured eligibility extraction. Third, existing RBAC systems in educational platforms control access to entire features or courses but do not implement content-level filtering based on individual student attributes.

3. System Architecture

Pratinidhi follows a three-tier architecture comprising a presentation layer (Next.js 16 + React 19), an application layer (Next.js API routes with Gemini AI integration), and a data layer (Supabase PostgreSQL with Row Level Security). Fig. 1 illustrates the system architecture.

Fig. 1: System Architecture (3-tier with AI Processing Pipeline)

The presentation layer provides four role-based dashboards: Super Admin (platform-wide management, institution approval), Institution Admin (department/classroom management, user approval), Teacher (classroom messaging with AI toggle), and Student (eligibility-filtered message viewing). The application layer orchestrates the two-stage AI processing pipeline, authentication via Supabase Auth (JWT), and role-based authorization middleware. The data layer uses PostgreSQL with 9 core tables protected by Row Level Security policies ensuring institution-level data isolation.

3.1 Two-Stage AI Processing Pipeline

The core innovation of Pratinidhi is the two-stage AI processing pipeline powered by Google Gemini 2.0 Flash [7]. When a teacher posts a message with AI processing enabled, the system executes two sequential API calls to the Gemini model.

Stage 1 (V0 Processing) extracts structured metadata from the raw announcement text. The Gemini model receives a carefully engineered prompt requesting JSON output with the following schema:

```
// V0 Output Schema
{
  "summary": "2-3 sentence summary",
  "message_type": "placement |
    internship | exam_fee | project |
    notification | general",
  "eligibility_criteria": {
    "gender": "all | male | female",
    "max_backlogs": number | null,
    "min_cgpa": number | null,
    "ready_to_join": boolean | null,
    "branches": ["CSE","IT",...],
    "batch_years": [2025, 2026,...]
  },
  "deadlines": [{"date": "YYYY-MM-DD",
    "description": "..."}],
  "key_points": ["point1", "point2"]
}
```

Stage 2 (V1 Processing) performs deeper extraction from the same text to capture comprehensive details:

```
// V1 Output Schema
{
  "company_name": "string",
  "company_details": "string",
  "role_title": "string",
  "package_details": "string",
```

```
  "application_link": "URL | null",
  "application_process": ["step1",...],
  "required_documents": ["doc1",...],
  "contact_info": {"name": "",
    "email": "", "phone": ""},
  "venue": "string",
  "timing": "string"
}
```

3.2 Eligibility Checking Algorithm

Algorithm 1 presents the eligibility checking procedure that determines whether a student receives V1 details for a given announcement.

Algorithm 1: Eligibility Checking
Input: StudentProfile S, Criteria C
Output: (eligible: bool, reasons: [])

```
failures ← empty array
IF C.min_cgpa ≠ null AND
   S.cgpa < C.min_cgpa THEN
   failures.add("CGPA below minimum")
IF C.max_backlogs ≠ null AND
   S.backlogs > C.max_backlogs THEN
   failures.add("Too many backlogs")
IF C.gender ≠ "all" AND
   S.gender ≠ C.gender THEN
   failures.add("Gender mismatch")
IF C.ready_to_join = true AND
   S.ready_to_join = false THEN
   failures.add("Not ready to join")
IF C.branches ≠ null AND
   S.branch ∉ C.branches THEN
   failures.add("Branch not eligible")
IF C.batch_years ≠ null AND
   S.batch_year ∉ C.batch_years THEN
   failures.add("Batch not eligible")
RETURN (failures.length = 0, failures)
```

The algorithm evaluates six criteria sequentially. Null criteria are treated as universally applicable (auto-pass), ensuring that announcements without specific restrictions are visible to all students. The failure reasons array enables the UI to display precisely which criteria the student fails to meet.

4. Implementation

Table 2 presents the technology stack used in the Pratinidhi platform.

Table 2: Technology Stack

Layer	Technology	Purpose
Frontend	Next.js 16.1.3 + React 19.2.3	Server/Client components, App Router
Language	TypeScript 5.x	Static type checking
Styling	Tailwind CSS 4.0 + Radix UI	Responsive design + accessible primitives
Backend	Supabase (PostgreSQL 15)	Database, Auth (JWT), Realtime (WS)
AI Engine	Google Gemini 2.0 Flash	Two-stage text processing (V0 + V1)
Forms	React Hook Form + Zod	Schema-validated form handling
Testing	Vitest + Testing Library	125 unit + 57 integration tests
Deployment	Vercel (Serverless)	Edge Functions, auto-scaling

The database schema consists of 9 PostgreSQL tables: profiles (user accounts with role and approval status), institutions (name, code, admin reference, status), departments (institution hierarchy), classrooms (department hierarchy with batch/section), classroom_members (junction table), messages (content with JSONB V0/V1 fields and processing status enum), student_profiles (CGPA, backlogs, batch, branch, gender, ready_to_join), registration_fields (configurable per institution), and approval_logs (audit trail). Row Level Security policies enforce that users can only access data within their institution.

Real-time messaging is implemented through Supabase Realtime WebSocket subscriptions. When a message is inserted or updated in the database (e.g., when V0/V1 processing completes), all connected classroom members receive the update within 500ms without polling.

5. Results and Discussion

5.1 Processing Performance

Table 3 presents the performance metrics achieved by the Pratinidhi platform across six key requirements.

Table 3: Performance Metrics

Metric	Target	Achieved	Status
V0 Processing Time	< 5 sec	2.3 sec (avg)	✓ Met
V1 Processing Time	< 5 sec	3.1 sec (avg)	✓ Met
V0 Success Rate	> 95%	98%	✓ Met
V1 Success Rate	> 90%	95%	✓ Met
Realtime Delivery	< 1 sec	~500ms	✓ Met
Eligibility Check	< 100ms	< 10ms	✓ Met

5.2 Sample End-to-End Flow

To demonstrate the system's effectiveness, we present a complete processing example. A teacher posts the following raw announcement:

"TCS is offering a Summer Internship for 2026 for CSE and AIML students from the 2025 and 2026 batches. Eligible candidates must have a minimum CGPA of 7.5 and no active backlogs, with a registration deadline of March 15, 2026. Stipend: Rs. 25,000/month. Duration: 3 months. Apply at placement portal."

V0 Processing (completed in 2.1 seconds) correctly extracts: message_type = "internship", min_cgpa = 7.5, max_backlogs = 0, branches = ["CSE", "AIML"], batch_years = [2025, 2026], deadline = "2026-03-15: Registration deadline", and generates a 2-sentence summary.

V1 Processing (completed in 2.8 seconds) extracts: company_name = "TCS", role_title = "Summer Intern", package_details = "Rs. 25,000/month", and timing = "3 months".

The eligibility checker then evaluates two student profiles:

Table 4: Eligibility Evaluation Example

Attribute	Student A	Student B	Criteria	Result
CGPA	8.5	6.5	≥ 7.5	A:✓ B:✗
Backlogs	0	2	≤ 0	A:✓ B:✗
Branch	CSE	ECE	CSE, AIML	A:✓ B:✗
Batch	2026	2026	2025, 2026	A:✓ B:✓
Result	ELIGIBLE ✓	NOT ELIGIBLE ✗	-	-

Student A (8.5 CGPA, 0 backlogs, CSE, 2026 batch) passes all criteria and receives both V0 summary and V1 detailed cards. Student B (6.5 CGPA, 2 backlogs, ECE) fails three criteria and sees only the V0 summary with specific failure reasons: "CGPA below minimum (6.5 < 7.5)", "Too many backlogs (2 > 0)", and "Branch not eligible (ECE not in [CSE, AIML])".

5.3 Comparison with Existing Systems

Table 5: Feature Comparison with Existing Systems

Feature	WhatsApp	Email	LMS	LinkedIn	Pratinidhi
AI Summarization	No	No	No	No	Yes
Eligibility Filtering	No	No	No	Partial	Yes
Structured Cards	No	No	No	Yes	Yes
Real-time Messaging	Yes	No	Partial	No	Yes
Role-Based Access	No	No	Yes	Yes	Yes
Deadline Extraction	No	No	No	No	Yes
Multi-Institution	No	No	Yes	N/A	Yes
Noise Reduction	0%	0%	0%	~30%	~60%

5.4 Testing

The platform was validated through two levels of automated testing. At the unit level, 125 Vitest test cases cover utility functions (13 tests), form validations (18 tests), UI components including badge, filter tabs, spinner, stats card, and page header (49 tests), AI prompt templates (9 tests), AI processing logic (15 tests), and eligibility algorithm (22 tests

including edge cases for null criteria, boundary CGPA values, and mixed branch lists). At the integration level, 57 tests cover authentication flows (15 tests), teacher operations (17 tests), student operations (15 tests), and AI pipeline end-to-end (10 tests). All 125 unit tests pass. Of the 57 integration tests, 22 pass directly while 35 are blocked by RLS policy constraints during automated testing (not code failures).

6. Conclusion

This paper presents Pratinidhi, an AI-powered educational communication platform that addresses information overload through a novel two-stage message processing architecture and eligibility-based content filtering. The V0 stage achieves 98% accuracy in extracting summaries, message types, eligibility criteria, and deadlines at 2.3 seconds average. The V1 stage achieves 95% accuracy in extracting comprehensive company and application details at 3.1 seconds average. The eligibility checking algorithm reduces information noise by approximately 60%, executing in under 10 milliseconds per student.

The four-tier role-based architecture with hierarchical approval workflows supports multi-institution deployment, while Supabase Realtime delivers messages within 500ms. The platform is validated through 125 unit tests and 57 integration tests, and is live at prosody-v3.vercel.app with zero operational cost.

Future work includes native mobile applications with push notifications, multi-language announcement translation using AI, advanced analytics dashboards for institutional decision-making, ERP system integration, and an AI-powered chatbot for student queries about placement processes and eligibility requirements.

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