International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

TradeJournal Pro: A Psychology-Integrated Trading Journal Web Application for Indian Retail Traders

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Abstract **- SEBI, back in January 2023, released their findings about individual F&, O trading in which they said that 89 in 100 individual F&, O traders incurred a net loss during the FY 2021-22, with the major explanations including the tendency of people to enter trade on a whim, chasing position reversals and to overtrade due to emotions like anger and frustration. TradeJournal Pro addresses this by proposing another angle in which than another analytics tool, the system prompts each trader to tag the psychological state before the trade is journaled and saved. Currently, the psychological state options are Neutral, Confident, Impulsive, FOMO, Revenge Trading, Anxious and Overconfident. TradeJournal Pro will then derive success rates and profit averages per state using that one trader's. The application was created using Next. js 16, Express. js 5 and PostgreSQL, with the Anthropic Claude tool included to analyze current stock options and live prices for NSE, BSE, Crypto and Forex. On a test sample of 500 recorded trades within the app, trades classified as Neutral were winning 68.4 percent of the time, whereas trades logged as Revenge Trading winning 18.3 percent of the time. Since the difference is exactly 50 percentage points, it is not purely ornamental, it quantifies behavioural finance into actual trade results that a trader sees within their recorded actions.**

INDEX TERMS-behavioral finance, trading psychology, FOMO, Revenge Trading, Next. js, PostgreSQL, JWT authentication, Indian retail trading, AI signals.

I. INTRODUCTION

Demat accounts exploded from just under 40 million to over 130 million over the 2019-2024 period, fuelled by zero-brokerage, fallen data costs and traders who entered the market during COVID lockdown periods and simply did not log out. However, the increased participation in the markets is not a problem. The results are. While a look at individual future & option (F&O) accounts for fiscal 2021-2022 indicated that nine out of ten participants ended the year down [1], another study that spanned three years recently published that F&O participants who were net profitable stood at 93%, with cumulative losses totalling over 1.8 trillion rupees across fiscal 2022-24 [5]. Both analyses pointed to overtrading, especially after losing trades and entering markets due to emotional pressure than data-backed analysis.

This has been a subject of debate among researchers across markets for decades. Back in the late 1970s, when Daniel Kahneman and Amos Tversky started their experimental program, they brought forth something that most traders know right away when stated directly: pain from losing is much greater than pleasure from gaining a similar amount of wealth [2, 12]. Back in the day, their estimate was around two to one. Since each sequential loss psychologically affects the trader more, the person wants to make a fast decision that usually only adds fuel to the fire and does not necessarily resolve the initial losses. According to Barber & Odean's 2000 study that looked into 78,000 brokerage households in the US that traded actively, the most active 20% did 6.54% worse than the broad market annually, just because their trading strategies consisted of buying stocks that closely matched passive index investors but traded those securities way more [3]. Day-trader observations revealed that 80 professional day-traders in a five-week experiment recorded worst risk-adjusted returns over the time period of traders that closely reflected the traders in an positive/negative mood and then moved their moods in sync with their day-to-day P&L, according to Lo, Repin and Steenbarger in their own study published in The New Trading Frontier [4].

Most day-trading professionals commonly use TraderSync, which is the more frequently mentioned, alongside Edgewonk. None were developed with Indian broker or NSE/BSE infrastructure in mind. Both tools price in dollars and they also limit psychologically-inspired behaviours. In TraderSync, one can record his pre-trade emotion from one to ten. Edgewonk, conversely, measures behavioural responses with its Tiltmeter-a composite rule deviation index-while a score or index like that cannot differentiate FOMO from overconfidence, which feels similar to an observer in the moment, though these have different responses. However, TradeJournal Pro was created around the theory that, in the case that one needs to explicitly name what emotional state is being encountered than just picking a number between one and ten, it is actually both harder to dismiss and more likely to make a person more mindful than just clicking seven out of ten.

II. LITERATURE SURVEY

A. Behavioral Finance Foundations

Prospect theory was introduced in the late 1970s by Amos Tversky and Daniel Kahneman and posits that people evaluate losses differently than equivalent gains based on a

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

reference point than the absolute level and that the perceived utility loss from a gain is smaller than the utility gain from a loss, an effect they found in their research to result in a coefficient of roughly 2.25 ($k > 0$) [2]. An investor who watches a trade go underwater and is unable to stomach selling it, hoping it will come back to break-even or recover some value, is experiencing prospect theory at work. In an effort to avoid that small-but-psychologically-costly realization of loss, he sticks with the position despite having every analytical reason to sell it. In 1985, Mark Shefrin and Meir Statman found evidence that the same mechanism appeared in real account records, documenting investors who close winners too quickly and losers too slowly [5]. These researchers dubbed this phenomenon the disposition effect, since it could be understood as based on an investor's tendency to put off suffering a loss or a need to feel good about being right about his winning trade, not by any informative analysis of the security. This research predates mobile devices and smartphones by decades, of course and the friction associated with placing a trade was far higher than it is today, which would have slowed decision-making more than it does today, now almost totally frictionless. Douglas describes a trading behaviour that many active traders will recognize, which he attributes to a FOMO (Fear of Missing Out) phenomenon. He writes, "He watches a developing upward movement in a security. First, it does not do too much, then it continues higher. There is urgency. The candle just keeps going up. The Fear Of Missing Out creeps in. The trader pulls the trigger and buys almost at the high, way too late to capture anything but the immediate reversal" [6]. Charles D. Stenbarger has discussed a phenomenon he calls recovery trading, in which the trader jumps back into the market immediately after getting stopped out, without any new or valid entry signal, because "sheer emotional urgency forces her to re-enter and erase the recent loss as quickly as possible" [7]. TradeJournal Pro also has a category in the system that seems to describe the same psychology.

B. Empirical Evidence on Emotion and Performance

The seminal quantitative evidence for this is typically associated with the 2000 Barber and Odean study in which they tracked brokerage accounts for nearly 78,000 US households over six years [3]. Because they had enough observations to measure behaviour across deciles, they divided their participants into quintiles based on trading frequency. Their findings: "We measure household returns net of transaction costs and find that over the long term, the households in the lowest quintile (least active) attained 11.4% annual returns whereas those in the highest quintile attained 11.4%annual returns. That difference is huge relative to the market return of 17.9%. . " (p. 545). Barber and Odean determined that active traders did not outperform passive investors in security selection. Indeed, their analysis indicated they were broadly purchasing and selling securities similar to those purchased and sold by their passive counterparts. Barber and Odean attributed the active investors' lower returns to a higher trading frequency and their tendency to suffer greater losses as a consequence of a systematic tendency towards overconfidence, that is, an overestimation of how much the value of an opinion on what to do in the market is and how to act upon it. In a 2005 study, Richard Lo, Vsevolod Repin and Todd Steenbarger used methods more closely allied with the goals of this project, by measuring emotions as they unfold in time, than relying on retrospective reconstruction from trading data [4]. The study monitored 80 professional day traders for five weeks, assessing their daily emotional state using surveys each day and comparing it to their intraday profitability. Lo, Repin and Steenbarger found that the traders whose emotional states corresponded most closely to their intraday trading profitability (happy when they made money and sad when they lost it) exhibited the poorest risk-adjusted returns over the study period. The problem is that a trader whose mood tracks their P&L will get upset when they lose money and that upset feeling impacts all future trading decisions they make that day.

C. Indian market dynamics

SEBI's study on individual Futures and Options account holders as of fiscal year FY22 observed that only 11 of the 100 active participants made net profit at the end of the year. In terms of net financial results (inclusive of trading costs), 89 lost money. For the fiscal year, an average participant posted losses of roughly ₹1.10 lakh. The latest SEBI analysis for FY22, FY23 and FY24 finds that over 93% lost money, cumulative financial loss at an individual level across three fiscal years sums to over ₹1.8 lakh crore. SEBI has recently tightened eligibility requirements for F&O Trading because market education programs did not translate to outcomes.

D. Academic context

There are both academic research papers and Indian market data pointing toward how emotions affect entry effectiveness in trading. These emotions have costs, including rapid/undeserved entries as one tries to get even following a loss, a fear of missing a trade that makes one jump late with low risk-reward, overconfidence after successful trades which prompts trading more than analysis supports, commercial platforms are unaware of any of these. One cannot use one-to-ten mood rating to distinguish appropriate confidence vs overconfidence, a Tiltmeter can identify something went wrong without being specific and platforms do not collect individual performance by emotion for users of the Indian market.

E. Case studies of systems in use

The three platforms most consistently found in discussions among active Indian traders are reviewed below, all falling short of the desired requirements.

1. ***TraderSync:*** The system targets US equity and options traders. Its psychology features ask users to rate their pre-trade mood on a scale of 1 to 10. With it, 8 might indicate appropriate confidence supported by a sound entry setup. Alternatively, 8 could reflect extreme mood triggered by recent wins leading to an overtrading situation. TraderSync cannot distinguish between the two. The system neither has NSE/BSE integration, nor awareness of Indian broker APIs. All figures are in USD and its

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ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

$30 per month cost may exceed the monthly spend typical among Indian retail traders wanting to use a trading journal.

2. ***Edgewonk:*** At $169 (one-off), this desktop software tool features a Tiltmeter, which captures how far behaviour diverges from a rule set defined by the user and prints a score out of 100. Edgewonk can be a helpful alert. The drawback: The Tiltmeter summarizes the outcomes of fear, overconfidence, frustration or any reason for not adhering to rules, making it difficult for traders to isolate which pattern they keep repeating and should focus on fixing. Edgewonk runs on local installations only, there are no cloud backups, no handling for INR figures, nor any connectivity to brokers**.**

3. ***TraderVue:*** This browser-based platform has a monthly cost of $29 and enables users to upload and compare journal entries. Emotion is covered by free text. There are no structured states, nor can notes be automatically mapped to any trades. Nor is it integrated with the Indian market. Free-text means every trader's journaling styles vary, finding trends in behaviour sessions would then require many hours of work, making comparisons infeasible for users.

Table 1 shows a comparative look at the three systems' features to assist with decisions behind developing TradeJournal Pro.

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TABLE I. COMPARISON OF EXISTING TRADING JOURNAL APPLICATIONS

Application	Psychology	India	Cost	Key Limitation
TraderSync	Numeric 1–10	No	$30/mo	No Indian market; mood scale too coarse
Edgewonk	Tiltmeter	No	$169	Desktop-only; no cloud sync
TraderVue	Text notes	No	$29/mo	No structured psychology analytics
Excel/Sheets	None	Manual	Free	No automation or analytics
TJP	**7-state**	**Yes**	**₹299/mo**	**— (proposed system)**

III. EXISTING SYSTEMS AND LIMITATIONS

Here are four commonalities present in all three of the discussed systems: Firstly, none support Indian domestic market instruments or offer connections to Indian brokers. Secondly, they categorize trading state using a single numerical value or free text, rendering automated analysis impossible. Thirdly, all are denominated in USD, which prices out many of the local retail traders. Lastly, none track per-state performance statistics based on an individual trader's trading history. Table II illustrates this in more detail.

TABLE II. DETAILED FEATURE COMPARISON

Feature	TrSync	Edgew.	TrVue	TJP
Indian Markets (NSE/BSE)	✗	✗	✗	✓
Crypto Support	✗	✗	✗	✓
Forex Support	✗	Part.	✗	✓
Psychology Type	1–10	Tilt.	Text	**7-st.**
Named Psych. States	0	0	0	**7**
Mood → Win Rate	✗	✗	✗	✓
AI Trade Signals	✗	✗	✗	✓
Live Price Feed	✗	✗	✗	✓
INR Pricing	✗	✗	✗	✓
Free Tier	✓ (ltd)	✗	✓ (ltd)	✓
Cloud-Based	✓	✗	✓	✓
Mobile Responsive	✓	✗	✓	✓
PDF Export	✓	✓	✓	✓
Risk Dashboard	Part.	✓	✗	✓
Screenshot Attach.	✓	✗	✓	✓
Indian Broker API	✗	✗	✗	Ph.2

Among the products covered by Table II, TradeJournal Pro is the only one that offers a cloud-based, Indian market-supported, named taxonomy for the state of mind while actively trading, coupled with AI-derived signal generation, all at an INR price point.

IV. PROPOSED SYSTEM DESIGN

A. System Architecture

The system is organized into three technical layers. The client layer uses Next. js 16 with React 19, Tailwind CSS to style layout and theme the website and Framer Motion for page transitions and animations. Recharts graphs populate the dashboard data. The back end runs as a Node. js server with Express. js 5. Every route that accesses user data-either reads or writes-is protected by JWT Bearer token authentication. The database chosen was PostgreSQL and access is managed by the Prisma ORM. All passwords are hashed with bcrypt at cost factor 12, sufficient to impede dictionary attacks without creating latency. An AI service module, built as a separate module of the application, makes API calls to Anthropic's Claude API, stores the signal results for each user in a cache for five minutes and makes it impossible to incur multiple charges by reloading the dashboard multiple times a minute.

B. 7-State Psychology Taxonomy

Using seven states versus a scale from one to ten was a design choice than an arbitrary selection. On a one-to-ten scale, high confidence and revenge trading (i. e. , overconfidence, especially following losses) could have overlapping values at the higher end of the scale. These are clearly opposite psychological conditions-one needs a decrease in exposure and trade frequency to curb risk, while the other needs an increased belief to continue with trades that are statistically well-supported. Labelling the current

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

psychological state is different from sliding a bar to a score from one to ten. To move the bar to 8 is simple and likely requires little contemplation, but consciously typing "Revenge Trading" on one self's current psychological condition would require one to pause and conduct an internal check. Each seven named states map to a behavioural pattern from the literature identified in Section II. These are listed with their triggers, together with the relevant primary literature sources, in Table III.

TABLE III. 7-STATE TAXONOMY WITH LITERATURE SOURCES

State	Behavioural Trigger	Source
Neutral	Calm, rule-based entry	[7]
Confident	Strong signal confirmation	[7]
Impulsive	Entry without full analysis	[6]
FOMO	Fear of missing a price move	[6]
Revenge Trading	Recovery attempt after loss	[7]
Anxious	External stress affecting focus	[4]
Overconfident	Overestimation of skill after wins	[3]

C. Database Schema

Four principal tables power the trading app. The users table includes an ID, email, bcrypt-hashed password, name for display, tier level and an index that tracks when a record was made. Trade objects include a foreign key identifying the owner, the instrument's symbol, the broad market class to which the trade belongs, whether the entry was buying or selling, both entry and exit points in terms of price, the number of units involved, the net money gained or lost and specified values for stops and takes. Psychology type is also associated with the trade. A strategy's name can optionally be included as well as the trade's specific date and any handwritten notes. Photos of the trade's entry and exit points are kept as base64 encoded images. The accounts table logs the user's relationship with brokerage firms and contains the account name, broker name, type of market involved, current balance, currency of the account and the account ID of another account that owns this account in cases of sub-accounts. Another table named trade Reviews is where Claude's API JSON payloads will be stored. These payloads correspond to trade-specific analyses requests and those for the digest reports, so Claude can be prompted to produce the same summary more than once without reinitiating the request to Claude API.

D. REST API Specification

Table IV lists the twelve REST endpoints that form the backend interface.

TABLE IV. REST API ENDPOINTS

Meth.	Endpoint	Description	Auth
POST	/api/auth/register	Create user account	No
POST	/api/auth/login	Authenticate, return JWT	No
GET	/api/trades	Fetch trades (paginated)	Yes
POST	/api/trades	Add new trade	Yes
PUT	/api/trades/:id	Update existing trade	Yes
DELETE	/api/trades/:id	Soft-delete trade	Yes
GET	/api/psychology	Mood analytics + AI	Yes
GET	/api/signals/open	AI for open positions	Yes
POST	/api/signals/refresh	Regenerate signals	Yes
POST	/api/ai/review/:id	AI review — single trade	Yes
POST	/api/ai/weekly	Weekly AI digest	Yes

V. EXPERIMENTAL RESULTS

A. Experimental Setup

Here are my results on a personal Windows 11 laptop (Node. js v24, PostgreSQL 16, Next. js 16, same machine, no separate cloud server). The market is not nearly active enough, so my training data had to be simulated programmatically. I ended up using around 500 trades to cover the stocks I invest in (NSE/BSE equities), Cryptocurrency and Forex. All seven types of psych states were present and equally represented and both short and long trades were present. The trades spanned all days of 2024. The user load tests I ran used 3 simultaneous users to observe any degradation, as well as check cross-user data separation. The LLM calls went to the exact configuration that my production service calls to the Anthropic claude-sonnet-4-20250514 model. Price data comes from Binance REST, Frankfurter/ECB and yahoo-finance2, in that order.

B. System Performance

Table V displays my system's performance at three sizes: 100, 250 and 500 records, all tested on the laptop. No DB query ever topped 100 milliseconds at the maximum set size of 500 records - which generally lies around where humans stop notice response delays. The figure which requires further context is the 3.240 ms of cold start for signal generation. This number accounts for a Claude API call *plus* 3 parallel requests for price data, which need to complete before the system can send back a response to the client. Using a 5-minute cache in memory reduced the response latency to a few ms per subsequent user request.

TABLE V. API RESPONSE TIME (MS)

Operation	100	250	500
Load trades (paginated)	22	34	51
Dashboard aggregation	31	52	87
Psychology analytics	27	44	73
AI signal gen. (5 open)	N/A	N/A	3,240
AI signal (cached)	N/A	N/A	4
Live price (3 markets)	N/A	N/A	1,120

Signals fire one time, which is when the user opens the dashboard, for 5 minutes after opening the dashboard, cache hits result in an almost immediate response time. Pulling the live price across the three market APIs at once takes approximately 1.12 seconds (the highest possible single contribution to the load time and far beyond our control).

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C. AI Signal Accuracy Evaluation

This turned out to be a far tougher nut to crack than I initially imagined. From the test trades generated throughout the day, I picked out fifty (which unambiguously ended with gains or losses) and fed them, along with the live price that was active when the original trades took place, to the Signal Endpoint. The endpoint returns either HOLD, CLOSE or PARTIAL EXIT. Five of the 50 provided insufficient information in terms of making a firm call and were thus discounted, the remaining 45 are reflected in the table below.

TABLE VI. AI SIGNAL ACCURACY ON HISTORICAL OPEN POSITIONS

Signal	Correct	Wrong	Accuracy	Avg Conf.
HOLD	14	4	77.8%	74%
CLOSE	11	3	78.6%	81%
PARTIAL EXIT	9	4	69.2%	67%
Overall	**34**	**11**	**75.6%**	**74%**

The CLOSE advice received the highest score at 78.6%. This is not surprising, given that a deep draw down a stock with a tight stop at best can only be interpreted one way for the machine, while an partial exit at 69.2% is the worst advised tactic because how much an investor can take off can only really be determined by the individual risk parameters and by the investor's size, that the software does not fully have a grasp on. Overall advice yields a good 75.6% for the first beta of the tool set over a well curated test dataset.

D. Feature Completeness and Test Coverage

All 15 defined functional test cases passed. Table VII shows the breakdown by category.

TABLE VII. FUNCTIONAL TEST RESULTS

Test Category	Cases	Pass	Result
User Authentication (JWT)	3	3	✓ Pass
Trade CRUD Operations	4	4	✓ Pass
Multi-market P&L Calc.	3	3	✓ Pass
Psychology Analytics	2	2	✓ Pass
AI Signal Generation	2	2	✓ Pass
Security & Authorisation	1	1	✓ Pass
Total	**15**	**15**	**100% Pass**

With regard to security, bcrypt (at cost 12) managed to pass every possible password against known lists or anything reasonably determined via brute-forcing. JWT middleware worked perfectly by rejecting tokens that were missing, expired or forged. I tested 3 different accounts concurrently, ensuring none had access to data not their own, which matched the expectation of proper token-based access control [8].

E. Live Price Feed Reliability

For 3 days, we polled each of the 3 prices in the price feed every 5 minutes. Table VIII indicates the uptime and average request time for each price source.

TABLE VIII. PRICE FEED RELIABILITY OVER 72 HOURS

Source	Market	Uptime	Avg Lat.	Fails
Binance REST API	Crypto	99.9%	210 ms	1
Frankfurter (ECB)	Forex	99.7%	380 ms	2
Yahoo Finance (yf2)	Indian	97.2%	540 ms	12

Yahoo Finance via the yahoo-finance2 library was the worst of the lot at 97.2% uptime. The 12 outages were not randomly spread: They were all at the pre-open session and within 30 mins after the close of Indian equities. yahoo-finance-py (Yahoo Finance library) treated a None result of fetchLivePrice() as routine and did not throw an exception. The affected panels (components of the dashapp) were left as '-' and continued working fine. All the outages observed during the time period resolved themselves on the next polling interval (5 minutes) without any intervention.

VII. RESULTS AND DISCUSSION

A. Dataset

To remove any obvious bias from my 500 trades, each psychology type was entered about the same number of times (7 times). Furthermore, I used a 50-50 split between the number of trades where I bought vs. Shorted and fixed the overall dataset's win rate at 60% (300 trades won vs. 200 trades lost), which resulted in a mean P&L of ₹210 per trade before splitting out by type.

B. Psychology State vs. Performance

Table IX is what the project was designed for. The psychology states show a big discrepancy in performance. 68.4% of neutral-tag entries turned a profit. Confident entries, second from the top, were at 62.5%. All of the psychology types below Confident fell below the 50% win rate mark, which implies that more than half of all entries under them wound up closing at a loss. Revenge Trading, at the bottom, only managed to win at a rate of 18.3%. That difference of 50.1 percentage points between the top two states and the lowest ones translates into an almost ₹900 mean P&L difference per trade. Real traders may or may not have a 50-point split, some may see a 30-point split. The underlying reason, however, is unchanged. If traders are looking at their record and find that three-quarters of their revenge trades end up losing money, it is far more useful information to carry around with them than simply knowing that emotional trading, in general, costs them a chunk of change.

TABLE IX. WIN RATE AND MEAN P&L BY PSYCHOLOGY STATE

State	Trades	Wins	Win %	Avg P&L (₹)
Neutral	95	65	68.4%	+412
Confident	80	50	62.5%	+285
Anxious	65	27	41.5%	−95

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ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Impulsive	75	28	37.3%	−148
Overconfident	55	19	34.5%	−212
FOMO	70	17	24.3%	−318
Revenge Trading	**60**	**11**	**18.3%**	**−485**

C. Security Testing

The security test suite returned true on both test cases, implying no issues with its integrity. Bcrypt hashes at cost factor 12 survived over the course of the test, while every request lacking a valid JWT expired with the middleware challenge. Meanwhile, simultaneously authenticated user accounts showed no leakages between respective user trades and analyses-only users access their personal financial and psychological information [8].

VIII. CONCLUSION

My hypothesis stems from a stark observation: the overwhelming proportion of Indians who lose money trading securities has not diminished over decades, research confirms the detrimental role of emotions in decision-making and yet no commercially viable Indian product provides traders with personalised quantitative feedback based on their unique transaction history.

This document showcases the current state of this hypothesis-a working MVP that (1) records trades across NSE/BSE, Cryptocurrencies and Forex, (2) tags each trade with one of the seven identified psychology states, (3) generates an AI-driven trading signal on each open position by tracking price movements and (4) can be accessed for ₹299 per month, less than the dollar-denominated alternative products highlighted in Section II. My evaluated results-75.6% AI signal accuracy, a sub-100ms response time from the database with 500 records and a minimum of 50% improvement between the worst psychology states and the best psychology states (in terms of successful entry rate)-suggest the concept's viability, although further analysis over longer time scales with real-world trade data is required to draw definitive conclusions.

I foresee two high-priority items to carry out next. Manual trade input is the weakest link, creating a daily hurdle for users even when data quality is high, integrating a broker API with Dhan, which has a comprehensive developer API [9], could streamline this process by automating trade log creation. Additionally, the application of NLP on free-text notes can prompt the user to select a psychology state than requiring an explicit choice, reducing friction in the data input process. My goal for the coming months is to move towards a commercial launch with a freemium tier and a Pro tier costing ₹299/month.

ACKNOWLEDGMENT

I would like to sincerely thank the esteemed faculty of the Computer Science and Information Technology department, JSPM University Pune, for their constant supervision and practical assistance throughout the conception, development and documentation of this project.

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