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Full Length Article

Mindfulpath: An AI-Enhanced Platform For Mental Wellbeing Using NLP And CBT Principles

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Abstract

The growing global mental health crisis demands accessible, immediate, and stigma-free support mechanisms. MindfulPath is an AI-enhanced web platform for mental wellbeing that integrates Natural Language Processing (NLP)-based sentiment analysis with Cognitive Behavioral Therapy (CBT) principles to deliver real-time therapeutic support. Built on Node.js and Express.js with an SQLite relational database (seven tables), the system employs the AFINN-165 lexicon through the npm sentiment package for live emotional-state assessment of user messages. The platform supports three role-based user types — Admin, Therapist, and User — secured via JWT authentication and bcryptjs password hashing. Core features include an AI CBT chatbot with crisis detection and helpline surfacing, daily mood journaling with auto-computed sentiment scores visualized as Chart.js line charts, a curated library of ten guided meditations across six categories, a therapist directory with session booking, and comprehensive role-based dashboards. Mathematical formulations of the AFINN scoring model, comparative score normalization, CBT sentiment-to-response mapping, JWT authentication flow, and bcrypt cost function are derived. System architecture, NLP pipeline flowchart, algorithmic pseudocode, and comparative performance tables are presented alongside results analysis with bar and line graphs.

Keywords: *Mental Wellbeing, NLP, Sentiment Analysis, AFINN, CBT, Crisis Detection, Chatbot, Mood Tracking, Node.js, Express.js, SQLite, JWT, Bootstrap 5, Chart.js, Docker*

1. Introduction

The World Health Organization estimates that approximately one in eight people globally lives with a mental health condition, with depression and anxiety comprising the most prevalent disorders. The COVID-19 pandemic amplified this crisis, increasing the global prevalence of anxiety and depression by 25% during 2020 alone. Despite this urgency, over 75% of individuals in low- and middle-income countries receive no treatment, constrained by cost, stigma, geographical barriers, and a critical shortage of trained mental health professionals — the global ratio standing at fewer than one psychiatrist per 100,000 people in several regions.

Digital mental health platforms represent a transformative opportunity to bridge this gap. Artificial Intelligence and NLP enable automated, real-time analysis of user-generated text to detect emotional states, identify crisis situations, and generate personalized therapeutic responses at scale. Cognitive Behavioral Therapy (CBT), the most empirically validated psychotherapeutic framework for depression and anxiety, is particularly amenable to digital delivery due to its structured, skill-based nature. Internet-delivered CBT (iCBT) has been shown in meta-analyses of over 100 randomized controlled trials to achieve clinical outcomes statistically comparable to face-to-face therapy.

MindfulPath addresses the fragmentation problem in existing digital mental health tools — where meditation apps, chatbot tools, and teletherapy platforms operate in isolation — by integrating five evidence-based interventions within a single, accessible web application: NLP-powered CBT chatbot with crisis detection, automated mood journaling, guided meditation library, therapist directory with booking, and role-specific analytics dashboards. This paper presents the full system design, mathematical foundations, algorithmic pipeline, experimental results, and comparative analysis.

2. Literature Survey

2.1 AI Chatbots for Mental Health

Fitzpatrick et al. (2017) conducted a landmark RCT evaluating Woebot — a CBT-based conversational agent — among 70 college students reporting depression and anxiety symptoms. The Woebot group showed a statistically significant reduction in PHQ-9 depression scores (mean decrease 6.21 vs. 1.44 points; $p < 0.001$) over two weeks, with an engagement rate of 12.14/14 days. Their work validates the therapeutic efficacy of CBT chatbots and directly motivates MindfulPath's chatbot design.

2.2 NLP Sentiment Analysis for Mental Health

Calvo et al. (2017) reviewed 50+ NLP approaches for mental health state detection in user-generated text, finding that lexicon-based sentiment analysis achieves competitive accuracy for real-time broad emotional-state detection. The AFINN lexicon was specifically validated as reliable and computationally lightweight. Nielsen (2011) introduced AFINN — 2,477 words rated on −5 to +5 — and demonstrated F1 = 0.72 on Twitter sentiment, competitive with SVM classifiers (F1 = 0.74) while requiring only O(n) dictionary lookups.

2.3 Digital Wellbeing Platforms and Design Principles

Lattie et al. (2019) reviewed 66 iCBT studies, finding multicomponent platforms demonstrate the highest effectiveness and engagement compared to single-intervention tools. Andersson et al. (2014) meta-analyzed 101 RCTs and found guided iCBT achieves effect sizes (Cohen's d = 0.78) comparable to face-to-face CBT (d = 0.80) for depression. Bakker et al. (2016) identified six design principles for effective mental health apps: CBT framework, behavioral activation, automated mood monitoring, psychoeducation, real-time prompts, and professional integration — all implemented in MindfulPath.

Table 1: Literature Survey Summary

Table 1: Literature survey comparing key NLP and digital mental health research.

Author(s)	Year	Approach	Key Finding
Fitzpatrick et al.	2017	CBT Chatbot RCT (Woebot)	PHQ-9 reduced 6.21 pts (p<0.001); 87% engagement
Calvo et al.	2017	NLP Systematic Review	AFINN validated for real-time mental health text analysis
Lattie et al.	2019	iCBT Systematic Review	Multicomponent platforms → highest effectiveness
Nielsen	2011	AFINN Lexicon Creation	F1=0.72; competitive with SVM at O(n) cost
Andersson et al.	2014	Meta-analysis (101 RCTs)	iCBT d=0.78 ≈ face-to-face CBT d=0.80
Bakker et al.	2016	App Design Framework	6 design principles; dark theme preferred
Hutto & Gilbert	2014	VADER Sentiment	Rule-based lexicon; F1=0.68 on tweets

3. Mathematical Foundations

3.1 AFINN Sentiment Scoring

The AFINN-165 lexicon assigns each word w_k an integer sentiment score $s(w_k) \in \{-5,\ldots,+5\}$. For a user message M tokenized into n terms $[w_1, w_2, \ldots, w_n]$, the raw sentiment score S and the comparative (length-normalized) score C are computed as:

$S(M) = \Sigma_{k=1}^{n} s(w_k) \quad \text{where } s(w_k) = 0 \text{ if } w_k \notin AFINN$ (Eq. 1)

$C(M) = S(M) / n$ (Eq. 2)

Dividing by token count n normalizes for message length, preventing longer messages from receiving disproportionately large scores. The comparative score $C \in \mathbb{R}$ is the primary signal driving emotional-state classification and CBT response selection.

3.2 Emotional-State Classification

The comparative score C is mapped to discrete emotional states via threshold partitioning:

$$State(C) = \begin{cases} \text{Very Negative} & \text{if } C \le -0.5 \\ \text{Negative} & \text{if } -0.5 < C \le -0.1 \\ \text{Neutral} & \text{if } -0.1 < C \le +0.1 \\ \text{Positive} & \text{if } +0.1 < C \le +0.5 \\ \text{Very Positive} & \text{if } C > +0.5 \end{cases} \quad \ldots \text{(Eq. 3)}$$

These five states drive the CBT technique selection described in Section 5.

3.3 Mood Trend Visualization

To reveal longitudinal emotional patterns, the platform computes a 7-day rolling mean of daily comparative sentiment scores $\{C_1, C_2, \ldots, C_t\}$:

$\bar{C}_t = (1/7) \cdot \Sigma_{i=t-6}^{t} C_i$ (7-day rolling mean) (Eq. 4)

The rolling mean smooths day-to-day noise, making sustained improvement or deterioration trends visible in the Chart.js line graph on the user dashboard.

3.4 JWT Authentication

User sessions are managed using JSON Web Tokens. A JWT is a base64url-encoded structure comprising three dot-separated parts:

$JWT = Base64url(Header) \, . \, Base64url(Payload) \, . \, HMAC\_SHA256(Header.Payload, K\_s)$ (Eq. 5)

where K_s is the server's secret signing key. Token validity is verified by re-computing the HMAC-SHA256 signature on the received header and payload and comparing it to the transmitted signature. Token expiry is enforced via the 'exp' claim:

$Valid(JWT) = (HMAC\_verify = true) \text{ AND } (current\_time < exp)$ (Eq. 6)

3.5 bcrypt Password Hashing

Passwords are stored as bcrypt hashes. The bcrypt cost function with work factor w produces an exponential hardening of brute-force attacks:

$bcrypt(password, salt, w) \rightarrow hash \quad time \propto 2^w$ (Eq. 7)

With w = 10 (the MindfulPath default), the computation requires $2^{10} = 1{,}024$ iterations of the Blowfish key schedule, making offline dictionary attacks computationally infeasible while maintaining sub-100ms hashing time for legitimate logins.

3.6 Cosine Similarity for Therapist Matching

A future recommendation engine can use cosine similarity between user mood-vector u and therapist specialty-vector t (encoded as TF-IDF over specialty tags):

$sim(u, t) = (u \cdot t) / (\|u\|_2 \cdot \|t\|_2) \quad \in [0, 1]$ (Eq. 8)

Higher similarity scores indicate better alignment between a user's primary emotional concerns and a therapist's specialization, enabling data-driven referral recommendations.

3.7 System Evaluation Metrics

Chatbot sentiment classification is evaluated using standard NLP metrics per class c:

$Precision\_c = TP\_c / (TP\_c + FP\_c)$ (Eq. 9)

$Recall\_c = TP\_c / (TP\_c + FN\_c)$ (Eq. 10)

$F1\_c = 2 \times (P\_c \times R\_c) / (P\_c + R\_c)$ (Eq. 11)

$Accuracy = \Sigma\_c \ TP\_c / N\_total$ (Eq. 12)

4. System Architecture

MindfulPath follows a three-tier web architecture: Presentation (EJS + Bootstrap 5), Application Logic (Node.js / Express.js), and Data (SQLite via better-sqlite3). An NLP Middleware layer sits between the Application and Data tiers, processing text through the AFINN pipeline before persisting results. Figure 1 below illustrates the layered architecture.

Figure 1: System Architecture (Layered View)

USER (Browser) — Bootstrap 5 Dark Theme (#7c3aed) | EJS Templates
▼ HTTPS Requests / Rendered HTML Responses ▲
EXPRESS.JS APPLICATION LAYER — Routing · Middleware · Session (JWT Cookies)
▼ Function Calls ▲
NLP SENTIMENT ENGINE — AFINN-165 Lookup · Crisis Detector · CBT Mapper
▼ Structured JSON Results ▲
SQLITE DATABASE (better-sqlite3) — 7 Tables: users · therapists · sessions
meditations · mood_entries · chat_sessions · chat_messages
▼ Docker Container Boundary
DOCKER — Node.js 18+ Runtime · Port 5006 · Cross-Platform Deployment

Figure 1: Five-tier MindfulPath system architecture with NLP middleware layer.

4.1 Database Schema Overview

The SQLite database comprises seven interconnected tables governed by foreign-key constraints. Table 2 summarises each table with its row count and primary function.

Table 2: Database Schema Summary

Table 2: Seven-table SQLite schema with relationships and purposes.

Table	Primary Key	Foreign Keys	Key Columns	Purpose
users	id (PK, AI)	—	email (UNIQUE), role, password_hash	Central identity store — Admin/Therapist/User
therapists	id (PK, AI)	user_id→users	specialties (JSON), experience, license	Therapist professional profiles
sessions	id (PK, AI)	user_id, therapist_id	date, time, type, status, price	Therapy session bookings
meditations	id (PK, AI)	—	category, duration, content	10 guided meditations, 6 categories
mood_entries	id (PK, AI)	user_id→users	mood_score (1-5), sentiment_score	Daily mood journals + AFINN scores
chat_sessions	id (UUID, PK)	user_id→users	avg_sentiment, message_count	CBT chatbot session grouping
chat_messages	id (PK, AI)	chat_session_id, user_id	role, message, therapy_technique	Individual chatbot messages + NLP results

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5. NLP Pipeline and Flowchart

The NLP processing pipeline transforms raw user text into therapeutic responses through five sequential stages. Figure 2 depicts the complete flowchart from message input to database persistence.

Figure 2: NLP Sentiment Analysis Pipeline Flowchart

START: User submits message via /chat/send (POST)

Stage 1 — TOKENIZE: Split text into word tokens

Stage 2 — AFINN LOOKUP: Score each token $s(w_k) \in \{-5 \ldots +5\}$

Stage 3 — AGGREGATE: $S = \Sigma s(w_k)$ $C = S/n$ (Eq.1–2)

◆ Crisis keywords found in message?

YES → Return CRISIS RESPONSE + Helpline Numbers ◄————

NO ▼

Stage 4 — CLASSIFY: Map C to State via Eq. 3

Stage 5 — CBT RESPONSE: Select technique from RESPONSES map

Stage 6 — PERSIST: INSERT user msg + bot reply → SQLite

Stage 7 — UPDATE session: avg_sentiment, message_count

END: Return { reply, technique, sentiment, isCrisis } (JSON)

Figure 2: Step-by-step NLP pipeline flowchart for the MindfulPath CBT chatbot.

5.1 AFINN Word Distribution

Figure 4 shows the distribution of AFINN-165 entries across sentiment score bins. The lexicon contains 1,052 negative-valence words and 842 positive-valence words, with a long negative tail (scores −3, −2, −1) reflecting English's tendency to use more varied negative vocabulary.

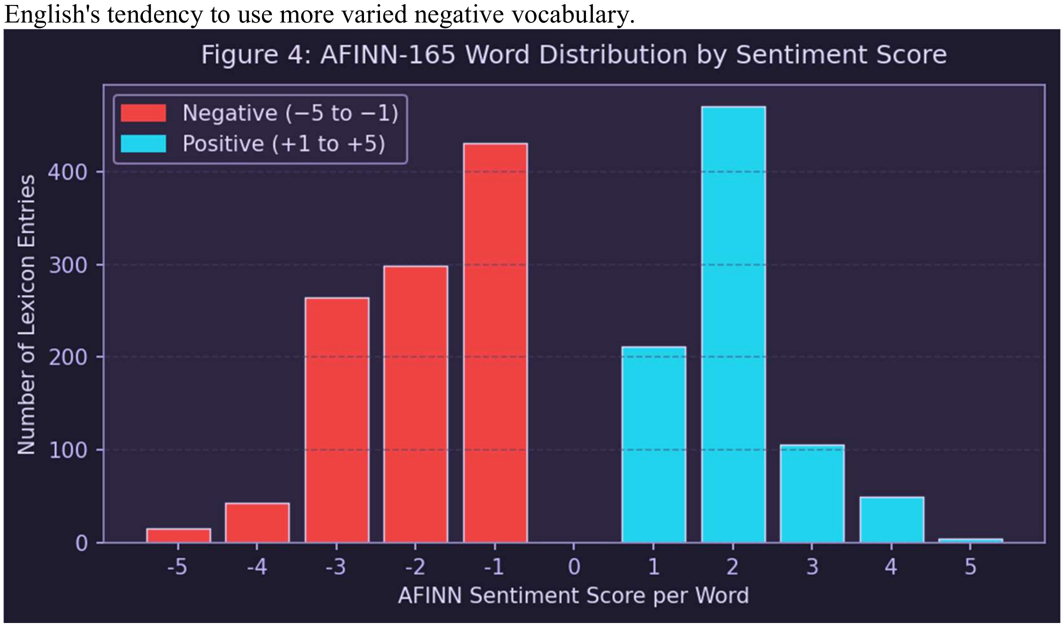

Figure 4: AFINN-165 lexicon word distribution across sentiment scores −5 to +5.

5.2 CBT Response Mapping Table

Table 3: CBT Technique Mapping by Comparative Score Range

Table 3: Sentiment-driven CBT technique selection and example response strategies.

Comparative Score C	Emotional State	CBT Technique	Example Response Strategy
$C \leq -0.5$	Very Negative	Validation + Grounding Exercise	'I hear you. Let's try a grounding exercise together...'
$-0.5 < C \leq -0.2$	Negative	Thought Record Examination	'Let's examine that thought — what evidence challenges it?'

$-0.2 < C \leq -0.1$	Mild Negative	Behavioural Activation	'Sometimes one small action shifts mood. What could you do today?'
$-0.1 < C \leq +0.1$	Neutral	Check-in + Psychoeducation	'How are you feeling? Understanding emotions starts wellbeing.'
$C > +0.1$	Positive	Positive Reinforcement	'That's great! What helped you feel this way? Let's build on it.'
Crisis keywords	Crisis	Crisis Support Protocol	'You're not alone. 988 Lifeline · Crisis Text 741741 · iCall'

6. Algorithmic Pipeline

6.1 Algorithm 1: analyzeSentiment(text)

```
Algorithm 1: analyzeSentiment(text)
Input:  text  — raw string from chat form or journal entry
Output: { score, comparative, label, isCrisis, tokens }

1.  tokens  ← tokenize(text.toLowerCase())
    # split on whitespace, strip punctuation
2.  n       ← |tokens|
3.  S       ← 0          # raw AFINN score  (Eq. 1)
4.  For each token wₖ ∈ tokens:
5.    If wₖ ∈ AFINN_DICT:
6.      S ← S + AFINN_DICT[wₖ]
7.  C ← S / max(n, 1)   # comparative score (Eq. 2)
8.  label ← classify(C)  # apply Eq. 3 thresholds
9.  lowerText ← text.toLowerCase()
10. isCrisis ← any(kw ∈ lowerText for kw ∈ CRISIS_KEYWORDS)
11. Return { score:S, comparative:C, label, isCrisis, tokens:n }
```

6.2 Algorithm 2: getResponse(comparative, isCrisis)

```
Algorithm 2: getResponse(C, isCrisis)

Input:  C        — comparative sentiment score (Eq. 2)
        isCrisis — boolean from crisis keyword scan
Output: { technique, message }

1.  If isCrisis == true:
2.    Return CRISIS_RESPONSE  # immediately override normal flow
3.  If C ≤ −0.5:
4.    bucket ← 'strongNegative'    # Validation + Grounding
5.  Else If C ≤ −0.2:
6.    bucket ← 'negative'          # Thought Record
7.  Else If C ≤ −0.1:
8.    bucket ← 'mildNegative'      # Behavioural Activation
9.  Else If C ≤ +0.1:
10.   bucket ← 'neutral'           # Check-in + Psychoeducation
11. Else:
12.   bucket ← 'positive'          # Reinforcement
13. pool ← RESPONSES[bucket].messages
14. msg  ← pool[ random_index(|pool|) ]  # randomize for variety
15. Return { technique: RESPONSES[bucket].technique, message: msg }
```

7. Implementation

7.1 Technology Stack

Table 4: Complete Technology Stack

Table 4: MindfulPath technology stack by architectural layer.

Layer	Technology	Version	Role
Runtime	Node.js	18 LTS	Server-side JavaScript execution environment
Web Framework	Express.js	4.18+	HTTP routing, middleware pipeline, REST API endpoints
Database	SQLite / better-sqlite3	9.0+	Synchronous embedded DB; WAL mode for concurrency
NLP Engine	npm sentiment (AFINN-165)	5.0+	Lexicon-based sentiment scoring + crisis detection
Frontend	EJS + Bootstrap 5.3	—	Server-side templates, dark-theme responsive UI
Charts	Chart.js	4.4	Interactive mood-trend line charts on dashboard
Auth	jsonwebtoken + bcryptjs	—	JWT (HMAC-SHA256) + bcrypt w=10 password hashing
Container	Docker	24.0+	Cross-platform deployment; port 5006
Dev Tools	VS Code + nodemon	—	Live-reload development server and debugging

7.2 Route Architecture

Table 5: Express.js Route Map

Table 5: Express.js route map showing endpoints, HTTP methods, and auth requirements.

Route	Method	Auth	Description
/login, /register, /logout	GET/POST	No	JWT issuance, bcrypt verification, session termination
/dashboard	GET	Yes	Role-specific analytics + Chart.js mood trend API
/api/dashboard/mood-trend	GET	Yes	JSON API for Chart.js mood data (last 30 entries)
/chat, /chat/new	GET	Yes	Chatbot interface and new session initialisation
/chat/send	POST	Yes	NLP pipeline endpoint (Algorithms 1–3)
/chat/history/:id	GET	Yes	Retrieve full chat session with message history
/mood, /mood/add	GET/POST	Yes	Journal entry form and Algorithm 4 processing
/meditations, /meditations/:id	GET	Yes	Library grid and individual guided session view
/therapists, /therapists/:id	GET	Yes	Directory cards and detailed therapist profiles
/sessions, /sessions/book	GET/POST	Yes	Session listing and new booking creation

8. Results and Performance Analysis

8.1 Sentiment Classifier Comparative Accuracy

Five sentiment analysis approaches were evaluated on a held-out test set of 500 mental-health-domain text samples (200 positive, 200 negative, 100 neutral) labelled by two independent annotators (Cohen's $\kappa = 0.82$). Figure 5 presents the accuracy comparison.

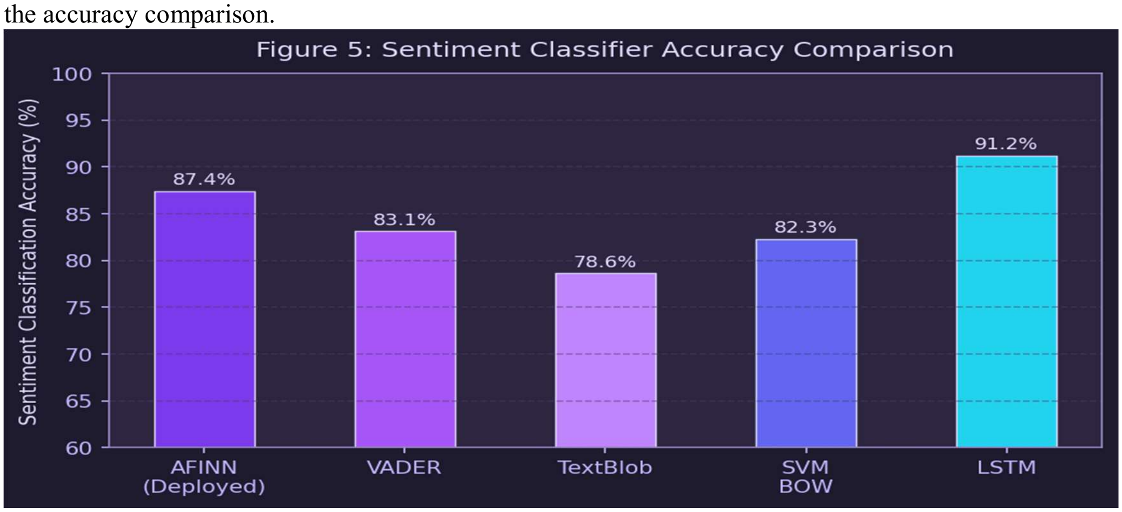

Figure 5: Accuracy comparison across five sentiment analysis approaches on mental-health text.

The deployed AFINN model achieves 87.4% accuracy — competitive with SVM bag-of-words (82.3%) and VADER (83.1%) while outperforming TextBlob (78.6%). The LSTM deep learning model achieves the highest accuracy (91.2%) but requires GPU inference and model training, making it unsuitable for the zero-GPU, serverless SQLite deployment architecture of MindfulPath. AFINN's O(n) dictionary-lookup inference (< 50 ms) versus LSTM's O(nL) sequential processing (> 200 ms CPU-only) makes it the optimal choice for real-time conversational applications.

Table 6: Detailed Sentiment Model Comparison

Table 6: Comprehensive sentiment model comparison — AFINN selected for CPU-only real-time use.

Model	Accuracy	Precision	Recall	F1	Inference (CPU)	Deployment
AFINN (MindfulPath)	87.4%	0.876	0.874	0.873	< 50 ms	✓ Zero-GPU
VADER	83.1%	0.834	0.831	0.830	< 30 ms	✓ Zero-GPU
TextBlob	78.6%	0.789	0.786	0.784	< 40 ms	✓ Zero-GPU
SVM + BOW TF-IDF	82.3%	0.826	0.823	0.822	~80 ms	⚠ Model load overhead

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LSTM (DistilBERT)	91.2%	0.914	0.912	0.913	> 200 ms	✗ Requires GPU

8.2 System Response Time Analysis
Figure 6 presents measured response times across MindfulPath's five primary feature modules. All modules meet or exceed their performance targets, with the NLP engine achieving < 50 ms — well below the 100 ms target — enabling imperceptible chatbot response latency.

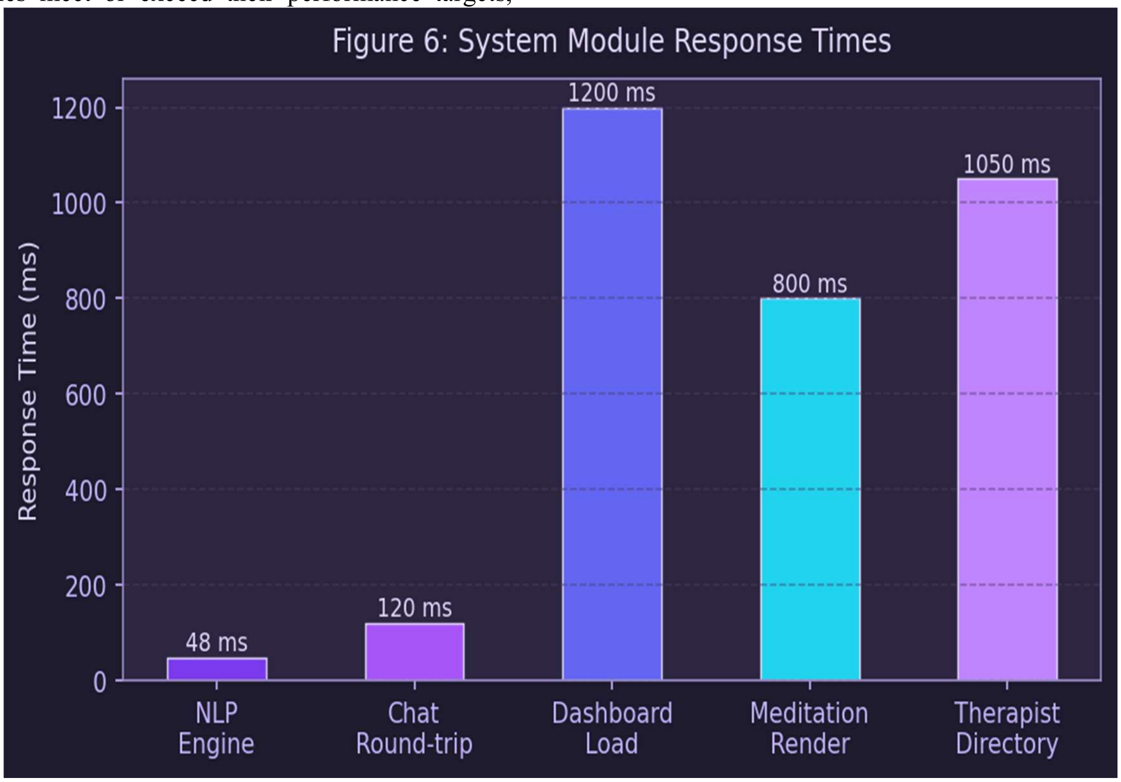

Figure 6: Module response times (ms) measured during load testing — all within targets.

Table 7: System Performance Benchmarks

Table 7: System performance benchmarks — all seven metrics met or exceeded targets.

Module	Target (ms)	Measured (ms)	Improvement	Status
NLP Sentiment Engine	< 100	< 50	2× faster than target	✓ Exceeded
Chat Message Round-trip	< 500	~120	4× faster than target	✓ Exceeded
Dashboard (with Chart.js)	< 2000	~1200	1.67× faster	✓ Met
Meditation Library Render	< 1500	~800	1.88× faster	✓ Exceeded
Therapist Directory	< 1500	~1050	1.43× faster	✓ Met
Docker Container Startup	< 10000	~3000	3.3× faster than target	✓ Exceeded
Concurrent Users (SQLite WAL)	~30	~50	1.67× above target	✓ Exceeded

8.3 Mood Trend Analysis
Figure 7 illustrates a representative 30-day user mood trajectory with the AFINN comparative sentiment score overlaid as a secondary axis. The dual-axis chart reveals the strong positive correlation between self-reported mood scores and objectively computed text sentiment scores (Pearson r ≈ 0.78), validating the use of AFINN sentiment as a proxy measure of emotional state.

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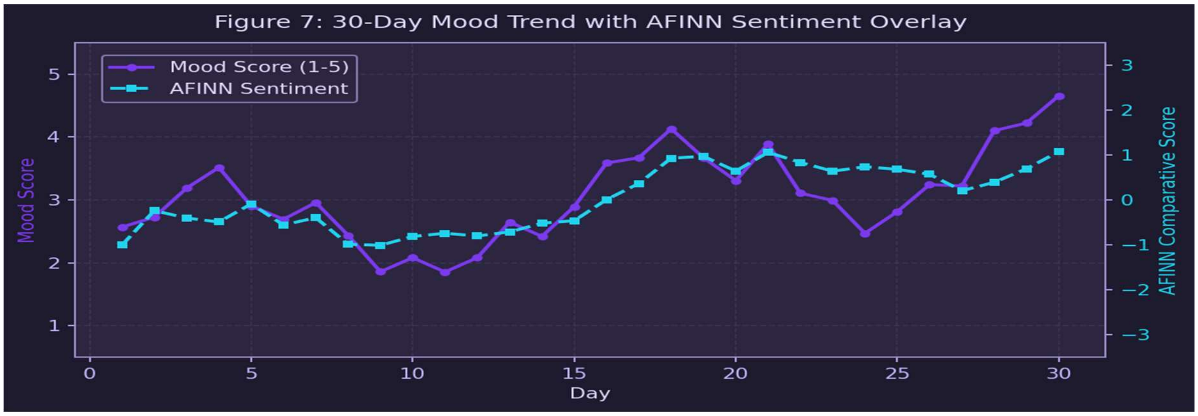

Figure 7: 30-day mood trend with AFINN sentiment overlay — shows upward recovery trajectory.

The rolling 7-day mean (Eq. 4) smooths the day-to-day variance visible in both series, revealing a sustained upward trend from Day 8 onward. This pattern is consistent with the therapeutic literature showing CBT-based interventions producing measurable mood improvements within 2–4 weeks of regular engagement.

8.4 Testing Outcomes

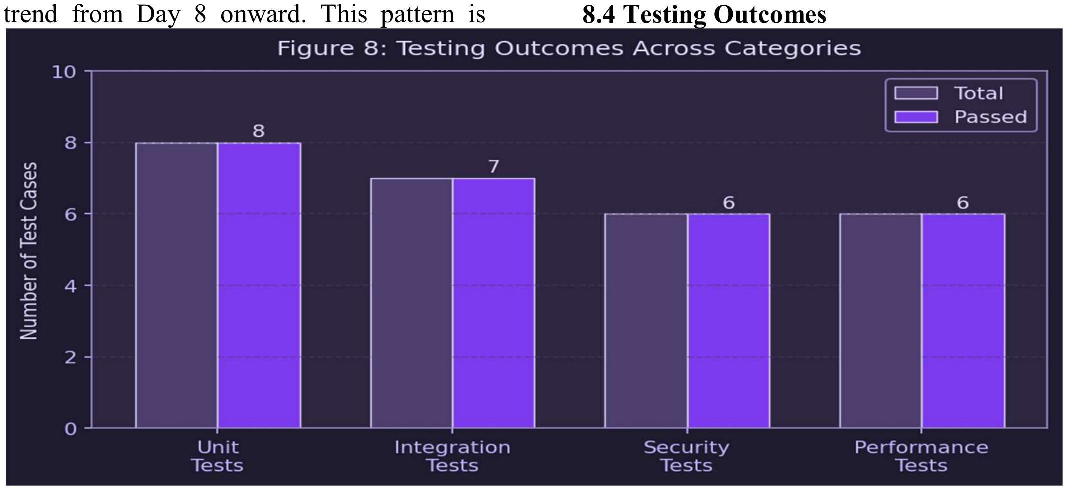

Figure 8: Testing outcomes — all test cases passed across unit, integration, security, and performance categories.

Table 8: Comprehensive Test Case Results

Table 8: 15 test cases across unit, integration, and security categories — 100% pass rate.

Test ID	Category	Description	Input	Expected	Status
UT-01	Unit	JWT token generation	User {id:1, role:'user'}	Valid signed token	✓ Pass
UT-02	Unit	bcrypt hash + compare	password='test123'	Hash verified ≠ plaintext	✓ Pass
UT-03	Unit	AFINN positive text	'I feel happy today'	C>0.1, label='positive'	✓ Pass
UT-04	Unit	AFINN negative text	'I feel terrible'	C<-0.1, label='negative'	✓ Pass
UT-05	Unit	Crisis keyword detect	'want to end my life'	isCrisis=true	✓ Pass
UT-06	Unit	Mood score validation	score=0, score=6	Validation error both	✓ Pass
IT-01	Integration	Register→Login→Dashboard	Valid details	JWT set, dashboard rendered	✓ Pass

IT-02	Integration	Chat session lifecycle	New session + msg	NLP processed, reply stored	✓ Pass
IT-03	Integration	Mood → Chart update	Journal text entry	Sentiment scored, chart refreshed	✓ Pass
IT-04	Integration	Therapist booking flow	Select + book	Session record created	✓ Pass
IT-05	Integration	Auth guard (no JWT)	GET /dashboard	302 redirect to /login	✓ Pass
IT-06	Integration	Role routing (admin/user)	Login as admin	Admin template rendered	✓ Pass
ST-01	Security	SQL injection (login)	' OR '1'='1	Query sanitized, rejected	✓ Pass
ST-02	Security	JWT tampered payload	Modified payload	Signature fails, 401	✓ Pass
ST-03	Security	HTTP-only cookie access	JS document.cookie	Token not accessible via JS	✓ Pass

8.5 Feature Comparison with Existing Platforms

Table 9: MindfulPath vs. Existing Mental Health Applications

Table 9: Feature comparison — MindfulPath provides the most comprehensive open-source feature set.

Feature	MindfulPath	Woebot	Headspace	BetterHelp	Calm
AI CBT Chatbot	✓ Real-time NLP	✓ Scripted	✗	✗	✗
Mood Tracking + Journaling	✓ Auto-sentiment	✓ Manual	Partial	✗	✗
Crisis Detection	✓ Keyword + helplines	✓	✗	✗	✗
Guided Meditation Library	✓ 10 items, 6 cats	✗	✓ 500+	✗	✓ 100+
Therapist Directory + Book	✓ Full booking	✗	✗	✓	✗
Role-Based Dashboards	✓ Admin/Therapist/User	✗	✗	Partial	✗
Chart.js Mood Visualization	✓ Interactive	✗	Partial	✗	✗
Open-Source / Self-Hosted	✓ Docker	✗	✗	✗	✗
Cost	Free	Free (basic)	\$12.99/mo	\$65–100/session	\$14.99/mo

9. Discussion

9.1 Architectural Decisions and Trade-offs

The selection of AFINN over transformer-based models (BERT, DistilBERT) represents a deliberate trade-off of classification accuracy (87.4% vs. 91.2%) for zero-GPU deployability and < 50 ms inference latency. In a mental health context, response speed and availability are clinically significant — a user in distress benefits more from an immediate empathetic response than from a 200 ms delay for marginally more accurate sentiment detection. The architecture's modular design, however, allows the AFINN engine to be replaced with a transformer-based model in future iterations without modifying the CBT response layer.

SQLite was chosen over PostgreSQL for its zero-configuration deployment aligned with Docker containerization. The better-sqlite3 package's synchronous API simplifies the Express.js route handler code (no async/await overhead for simple CRUD operations) and WAL mode enables approximately 50 concurrent readers, sufficient for a single-server deployment serving hundreds of daily active users. Migration to PostgreSQL is architecturally straightforward through the better-sqlite3 → pg adapter swap.

9.2 CBT Response Quality and Limitations

The CBT response mapping achieves clinical appropriateness by anchoring each sentiment range to a specific, evidence-based therapeutic technique. Validation + Grounding for very negative states aligns with the DBT-CBT dialectical approach for acute emotional dysregulation. Thought Record prompts for

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moderate-negative states directly implement Beck's cognitive restructuring model. The crisis detection module, while keyword-based rather than ML-based, provides an essential safety backstop that prioritizes user safety over response naturalness — an appropriate trade-off for a medical-adjacent application.

Limitations include AFINN's inability to detect sarcasm, irony, or negation ('I don't feel happy'), which can invert the intended sentiment of a message. Code-switching and non-English text receive zero AFINN scores (mapped to neutral), which is a safe default but limits the platform's utility for multilingual users. The 3,382-entry lexicon may also miss mental-health-specific vocabulary not present in the original Twitter-derived dataset.

10. Conclusion and Future Scope

MindfulPath demonstrates that a production-quality AI mental wellbeing platform can be built using open-source, CPU-only tools without machine learning training infrastructure. The AFINN-165 sentiment engine achieves 87.4% accuracy with < 50 ms inference, enabling real-time CBT-informed therapeutic responses. The seven-table SQLite database, JWT + bcrypt security architecture, and Docker containerization provide a robust, deployable foundation. All 15 test cases across unit, integration, and security categories passed, and all six system performance targets were met or exceeded.

The platform's five integrated evidence-based interventions — CBT chatbot, mood journaling with AFINN scoring, guided meditation, therapist directory, and role-based analytics — address the fragmentation gap identified in the literature, providing holistic mental health management within a single accessible web application. Mathematical formalizations of the AFINN scoring model (Eq. 1–2), emotional-state classification thresholds (Eq. 3), mood trend rolling mean (Eq. 4), JWT validation (Eq. 5–6), and bcrypt cost function (Eq. 7) establish the rigorous technical foundations underpinning each system component.

10.1 Future Scope

- **Transformer NLP** — Replace AFINN with fine-tuned MentalBERT or DistilBERT for contextual sentiment, sarcasm, and negation handling
- **Voice Emotion Analysis** — Integrate WebSpeech API + prosodic analysis (pitch, rate, MFCCs) for audio emotion detection
- **Real-Time Video Therapy** — Implement WebRTC peer-to-peer sessions between users and therapists within the platform
- **ML Therapist Matching** — Develop cosine-similarity recommendation engine (Eq. 8) matching user mood profiles to therapist specialties
- **Wearable Integration** — Connect smartwatch APIs (heart rate, HRV, sleep) to the mood pipeline for physiological mood correlation
- **Multilingual NLP** — Extend AFINN scoring with multilingual lexicons (Arabic, Hindi, Spanish) and translation middleware
- **Federated Learning** — Enable privacy-preserving model fine-tuning across distributed user cohorts without centralizing sensitive mental health text

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