An Intelligent Web-Based Mental Health Management Platform with Rule-Based Music Therapy Recommendation

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ABSTRACT

This research developed a web-based application for mental health management with an emotional music therapy recommendation feature using Rule-Based Filtering. The system is designed to help individuals recognize and manage emotional conditions caused by life pressures, work stress, and often overlooked psychological issues. A 2023 survey showed that 43% of respondents were concerned about mental health problems, followed by stress at 40%, while 43.8% of parents of teenagers managed their children's mental health issues independently, 19.2% did not know where to seek help, and 15.4% believed the problems would improve on their own. The system analyzes daily emotional input and weekly PANAS questionnaires to classify moods (Positive, Negative, Mixed, Neutral) based on Positive Affect (PA) and Negative Affect (NA) scores, then recommends relevant music from the database. The technical implementation uses Laravel for the backend and Tailwind CSS for the frontend. Black Box Testing showed 100% functionality. User Acceptance Test (UAT) with 32 respondents resulted in UAT-J 90.25%, UAT-K 90.41%, UAT-R 89.18%, and UAT-A 91.24%. The System Usability Scale (SUS) reached an average score of 85 (very high), while the Net Promoter Score (NPS) was 59.37% (62.50% Promoters), indicating strong user satisfaction and loyalty. This research is expected to help individuals monitor emotional conditions and increase mental health awareness through an innovative music-based approach.

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I. INTRODUCTION

Mental health is a vital yet frequently overlooked aspect of human well-being. Many individuals face emotional challenges resulting from life pressures, occupational stress, and personal issues. According to the World Health Organization (WHO, 2024), an estimated 970 million people worldwide suffer from mental health problems, with 284 million experiencing anxiety disorders. Similarly, a 2023 global survey revealed that 43% of respondents identified mental health as their primary health concern, followed by stress at 40%. Another study involving 243 parents reported that 43.8% believed their adolescent children needed mental health support but chose to cope independently, 19.2% were unaware of where to seek help, and 15.4% assumed the issues would resolve on their own (Databoks, 2023). These findings highlight a significant gap in mental health awareness, access to care, and timely intervention.

Addressing mental health challenges therefore requires more than public awareness; it demands innovative, scalable, and accessible digital solutions that empower individuals to monitor and manage their emotional well-being. Information technology provides a promising pathway toward this goal. In particular, web-based applications integrated with therapeutic features such as personalized music recommendations have emerged as a potential digital intervention to support mental wellness. Leveraging modern web technologies—such as HTML, CSS, and PHP with the Laravel framework for backend development and Tailwind CSS for responsive design—enables developers to create interactive interfaces and manage emotional data efficiently through MySQL databases.

Such systems can help users track their emotions, identify mood patterns, and receive curated music recommendations aligned with their emotional states.

The development of health information systems has also been previously explored, such as the study by Delimayanti et al. which designed a prototype of a nursing management information system for primary health centers and hospitals in Depok, Indonesia. This research highlights the importance of applying information technology to support healthcare services, which serves as a foundation for extending such systems into the mental health domain as proposed in this study[1].

Several studies have demonstrated the potential of digital mental health tools in improving psychological outcomes. Firth et al. (2024) found that mobile mental health applications significantly reduce symptoms of anxiety and depression [2]. Similarly, Karyotaki et al. (2017) explored the combination of mood tracking and internet-based Cognitive Behavioral Therapy (CBT) to enhance users' mental resilience [3]. Ariyanto et al. (2024) further emphasized the effectiveness of mental health platforms like "Luminds,", particularly in supporting Generation Z through online consultation features [4]. These studies offer a strong foundation for exploring the role of digital applications in mental health, especially those that involve mood journaling and therapeutic guidance.

However, prior research predominantly focuses on general mood tracking or cognitive-behavioral interventions, with limited attention to emotionally adaptive features such as personalized music therapy. The scientific gap lies in the absence of studies that specifically integrate rule-based filtering techniques to deliver tailored music recommendations based on in-depth mood and emotional analysis. While music has long been recognized as a powerful emotional regulator, its role in supporting mood regulation and coping strategies particularly among adolescents has been widely documented (Saarikallio & Erkkilä, 2020) [5]. The classification approach in this study aligns with Delimayanti's earlier works, which focused on classifying physiological signals such as EEG brainwaves for sleep stage detection and respiratory activities using depth images. Similarly, this system applies classification principles by mapping user input from PANAS questionnaires and emotion journals into distinct psychological states [6]. However, its application in real-time mental health systems remains underdeveloped in a structured and personalized format. Similarly, Yilma & Leiva (2025) [7] proposed cross-domain recommendation systems leveraging music preferences for art therapy, highlighting the potential of music as an emotional elicitation medium.

This study aims to address this gap by developing a web-based mental health management information system that not only facilitates emotion logging but also intelligently recommends therapeutic music using a rule-based filtering approach. By mapping users' emotional inputs to predefined music therapy rules, the system offers a practical and personalized tool for emotional regulation. It is anticipated that this solution can enhance emotional awareness and self-care while contributing to the broader discourse on the intersection of technology and mental health.

II. METHODS

This study adopts a system development approach utilizing the Waterfall model, a classical software engineering methodology characterized by a sequential and structured workflow. The Waterfall model was selected due to its clarity in delineating each development phase, from requirement analysis to system maintenance. This approach allows for meticulous planning, disciplined execution, and well-documented outcomes, which are essential for developing a functional and reliable mental health management system [8].

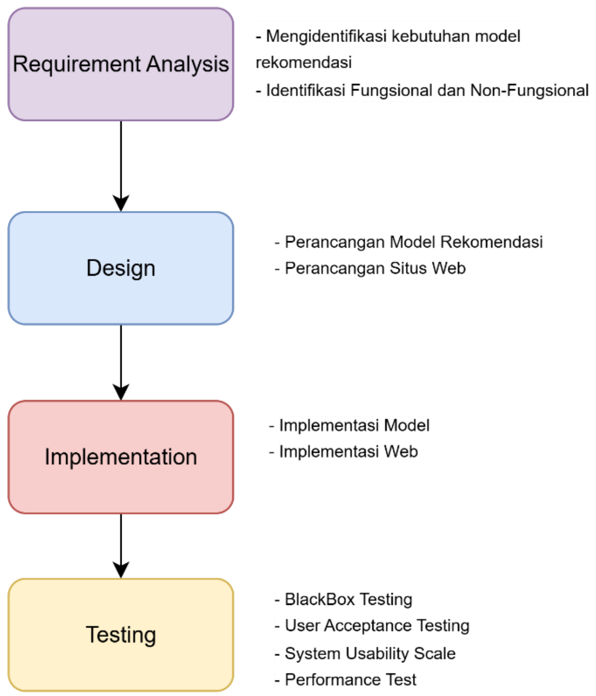

Figure 1. Research Flow

Figure 1 illustrates the research flow based on the Waterfall model, consisting of four main stages: Requirement Analysis, Design, Implementation, and Testing. Each stage represents a sequential process that ensures systematic system development and well-documented outcomes.

A. Requirements

The requirement phase began with a needs analysis conducted through an extensive literature review. The primary focus was to define the functional and data requirements for a music therapy recommendation system. This review covered key concepts such as the Valence-Arousal model of emotion for classifying mood states, the theory behind Rule-Based Filtering to serve as the foundation for the recommendation engine, and the principles of music therapy for mental well-being. Based on this analysis, the technology stack was selected, comprising the Laravel framework for the backend, Tailwind CSS for the user interface design, and MySQL as the database engine.

In this study, the functional requirements included features such as user registration and login, daily emotion journaling, weekly mood assessment using the PANAS questionnaire, music recommendations based on mood classification, and administrative functions to manage music and articles. Non-functional requirements included ease of use, responsive design for multi-device access, data security, and reliable system performance. These requirements provided the foundation for subsequent design and implementation.

B. Design

During the design phase, the system architecture and user interface (UI) were developed. A central focus was placed on designing the system's logic, where the rules for the Rule-Based Filtering method were formulated to connect specific user moods with appropriate music recommendations. In parallel, application wireframes were created to visualize the layout and user flow. These wireframes covered key features, including the emotion journal, the weekly mood tracker, mental health articles, and the music recommendation interface. The entire UI was designed to be intuitive, simple, and responsive to ensure an optimal user experience across various devices.

In addition, the system design incorporated a mood classification logic based on the Positive Affect (PA) and Negative Affect (NA) scores from the PANAS questionnaire. PA values above 30 combined with NA values below 15 were classified as a Positive mood, while PA below 20 and NA above 25 indicated a Negative mood. Balanced scores (PA 20–30 and NA 20–25) were categorized as Neutral, and all other mixed values were considered as Mixed mood. This classification scheme was embedded into the design to ensure that user inputs could be consistently mapped to appropriate therapeutic music recommendations [9].

The design also included the development of a music database structured according to emotional categories. Each mood category (Happy, Sad, Anxious, Angry) was mapped to specific music genres using a rule-based filtering approach. For example, Happy moods were mapped to Pop or Dance tracks with high valence and medium-to-high energy, while Anxious moods were associated with ambient or instrumental music characterized by low valence and low energy. The initial database consisted of 16 curated tracks covering these four categories.

Rule-based filtering, as applied in this system, directly links user mood categories to corresponding music tracks through predefined mappings. This approach is considered one of the most transparent and interpretable methods in recommendation systems, allowing researchers and end users to understand how recommendations are generated (Isinkaye, Folajimi, & Ojokoh, 2020) [10].

The effectiveness of a rule-based system largely depends on the selection and processing of relevant features from the input data, an approach that has also proven crucial in other classification domains such as text analysis for event identification. In this context, the features of valence and energy from music are selected as the foundation for building transparent and effective recommendation rules[11].

C. Implementation

The implementation phase commenced with the development of the web application using the Laravel framework for backend logic and Tailwind CSS to build the frontend interface according to the previously designed wireframes. Key features were implemented, including the emotion journaling feature, the weekly mood tracker integrated with the PANAS(Positifve and Negative Affect Schedule questionnaire, and the rule-based music recommendation system. A MySQL database was integrated to store all user-generated data, such as emotional logs and interaction history. This process aimed to deliver a fully functional and integrated system [12].

1) Mood Assessment using PANAS

The weekly mood tracker was implemented using the Positive Affect and Negative Affect Schedule (PANAS). The questionnaire consists of 20 items, with 10 representing Positive Affect (PA) and 10 representing Negative Affect (NA). Each item was rated on a 1–5 Likert scale.

The PA and NA scores were then classified into four mood categories using predefined thresholds:

- Positive Mood: PA > 35 and NA < 25
- Negative Mood: PA < 25 and NA > 35
- Neutral Mood: PA < 25 and NA < 25
- Mixed Mood: any other combination

This classification enables the system to monitor users' emotional patterns on a weekly basis and provide feedback regarding their general mental state.

2) Daily Emotion Journaling and Rule-Based Filtering

In addition to the weekly tracker, users can log their daily emotions through the journal feature. The journal allows users to select one of four primary emotions (Happy, Sad, Anxious, Angry) and optionally write a short note describing their feelings.

The emotion input from the journal acts as the trigger for the music recommendation system. A rule-based filtering mechanism was designed to map each emotion category to a specific set of musical characteristics, defined by valence (positivity of the music) and energy (intensity of the music).

The rules were formulated as follows:

- Happy → Pop/Dance; valence 0.61–0.92; energy 0.45–0.96
- Sad → Ballad/Acoustic; valence 0.03–0.30; energy 0.12–0.49
- Anxious → Ambient/Instrumental; valence 0.07–0.18; energy 0.05–0.31

- Angry → Rock/Metal; valence 0.30–0.65; energy > 0.90

Whenever a user submits a journal entry, the system queries the music database (consisting of 16 curated tracks) and retrieves songs matching the emotion's valence–energy range. The recommendation is then presented as a playlist that users can listen to directly from the application.

3) System Workflow. The overall workflow of the implementation can be summarized as follows:

- Input:
  (a) PANAS Questionnaire (weekly) → mood classification;
  (b) Emotion Journal (daily) → emotion selection.
- Processing: Rule-Based Filtering engine maps input mood/emotion to music database.
- Output: Personalized music recommendations aligned with users' emotional state.

Since the system handles sensitive emotional and personal data, several security mechanisms were implemented during development. User authentication was designed with encrypted login credentials, and password storage applied hashing techniques. Role-based access control was also enforced to differentiate administrator access from regular users, ensuring confidentiality of emotional journals and personal information. Future improvements will extend these measures with stronger encryption and anonymization methods.

D. System Testing and Evaluation

Following the implementation, the system was verified using several testing methods. Functional testing was conducted to ensure that each feature including the emotion journal, the PANAS questionnaire, and the recommendation engine operated according to its specifications. A total of 20 Black Box Testing scenarios were designed and executed, all of which were successfully passed, indicating 100% functionality. User interface testing was also performed to validate that the responsive design functioned correctly across different devices, such as desktops and smartphones.

Subsequently, a user-based evaluation was carried out to gather feedback on the application's usability and effectiveness. Instruments included the System Usability Scale (SUS), which provided a quantitative measure of ease of use, and the Net Promoter Score (NPS), which evaluated user satisfaction and loyalty. A User Acceptance Test (UAT) was also conducted to assess how well the system met user needs. Performance testing such as response time and load testing was not conducted in this study and is identified as an area for future work.

In addition to functional and usability testing, this study also conducted performance testing, which focused on measuring response time and load testing under concurrent requests. Response time was measured by recording the average processing duration (in milliseconds) for each major page of the system, while load testing simulated multiple concurrent users to evaluate stability and failure rates. The methodology followed principles outlined by IJSR (2024), which emphasizes scalability and bottleneck identification in web applications [13]. These evaluations provide a clearer picture of the system's readiness for real-world deployment.

III. RESULT AND DISCUSSION

This section presents the findings of the research, focusing on the evaluation and analysis of the intelligent web-based mental health management platform, Vibely. The discussion emphasizes the performance of the rule-based music recommendation model, its validation through quantitative testing, and the system's usability and user acceptance. The explanation of the website interface is briefly included to demonstrate the implementation of the designed model.

A. Rule-Based Model Design

The Rule-Based Filtering model constitutes the core mechanism of the system's music recommendation feature. Its primary purpose is to deliver personalized and contextually relevant music therapy recommendations based on the user's recorded emotional states and weekly mood assessments.

The model design considers four key aspects:

1) Input Data Sources.

- Daily Emotion Journaling: user-selected emotions and optional notes describing emotional context.
- Weekly PANAS Questionnaire: Positive Affect (PA) and Negative Affect (NA) scores derived from the standardized PANAS scale.

2) *Rule Logic Structure.* The logic engine consists of predefined if–then rules that connect users' emotional states with corresponding music types. The rules were formulated based on literature concerning emotional response to music and therapeutic applications. Example structures include:

- IF (emotion = "Sad") THEN recommend_music ("Sad Emotion Playlist")
- IF (NA = High AND PA = Low) THEN recommend_music ("Mood Booster Playlist")

These conditional mappings ensure interpretability and traceability between input emotions and musical output in recommendation systems.

3) *Music Database Design.* The music dataset is categorized according to valence–energy attributes, drawn from the Circumplex Model of Affect, where valence represents the positivity of a song and energy represents its arousal intensity. The dataset includes 16 curated tracks classified into four emotion categories (Happy, Sad, Anxious, Angry).

4) Model Output. The model produces a ranked list of therapeutic music recommendations, presented to users via the web interface. Each recommendation is personalized according to the latest emotional inputs, ensuring that the response is data-driven rather than random.

B. Scoping Music

The implementation of the music recommendation system began with the scoping of music for emotional therapy recommendations based on the Circumplex Model approach, which uses two primary dimensions in emotion classification: valence and arousal (energy). These two parameters were tested on the Emotionify platform, which provides quantitative values for each song, allowing for the development of a music-mapping strategy tailored to the user's emotional state [14].

1) Valence measures how positive or pleasant a song sounds, with a value range from 0 (very negative) to 1 (very positive

2) Energy measures the intensity and activity level of a song, also on a scale from 0 to 1. Songs with high energy are typically fast, loud, or intense, while those with low energy tend to be slow and calm.

Based on the combination of these two dimensions, songs were classified to address four primary emotions used in this system [15].

The valence and energy ranges above are used to recommend music that aligns with specific emotional conditions. Each emotion, as illustrated in Table 1, is linked to distinct genres and therapeutic goals, ranging from uplifting mood, providing space for reflection, easing anxiety, to channeling anger in a healthy manner. By mapping music into defined valence and energy ranges, the system can associate song characteristics with the desired emotional response.

TABLE I
EMOTION RANGE VALENCE AND ENERGY

Emotion	Genre & Reason	Valence	Energy
Angry	Extreme Metal/Rock; matches arousal and channels emotion healthily	0.30–0.65	> 0.90
Anxious	Ambient/relaxing instrumental; reduces stress & heart rate	0.07–0.18	0.05–0.31
Sad	Ballad, Acoustic, Instrumental; provides space for reflection & emotional expression	0.03–0.30	0.12–0.49
Happy	Pop, Funk, Dance; maintains & enhances positive mood	0.61–0.92	0.45–0.96

Music representing happy emotions is characterized by cheerful, energetic, and motivating qualities. Such songs are effective in enhancing mood and sustaining a positive emotional state throughout activities. Table 2 presents selected songs for happy emotions, along with their valence and energy values.

TABLE II
SCOPING HAPPY MUSIC

No	Title	Artist	Valence	Energy
1	Uptown Funk	Mark Ronson	0,928	0,609
2	Binks Sake	Miura Jam BR	0,804	0,479
3	Happy	Day 6	0,614	0,963
4	Butter	BTS	0,695	0,459

Sad music typically features qualities that encourage emotional reflection and facilitate the expression of feelings. Some songs also offer a sense of hope that may support gradual emotional recovery. Table 3 lists selected songs representing sad emotions, with their corresponding valence and energy values.

TABLE III
SCOPING SAD MUSIC

No	Title	Artist	Valence	Energy
1	Aerith's Theme	Nobuo Uematsu	0.039	0.129
2	Sadness and Sorrow	MUSASHI PROJECT	0.040	0.183
3	Ending Scene	IU	0.232	0.323
4	Through the Night	IU	0.284	0.313

Music for reducing anxiety often has a slow tempo, soft texture, and is frequently instrumental or ambient. Scientifically, such music has been shown to lower heart rate, blood pressure, and cortisol levels, helping listeners feel calmer and more relaxed. The most notable example is Weightless by Marconi Union, which, according to Mindlab International, can reduce anxiety by up to 65% [16]. Other anxiety-reducing music recommendations fall within the valence range of 0.07–0.22 and energy range of 0.05–0.31, as exemplified by Weightless. Table 4 lists selected songs for anxious emotions, with their valence and energy values.

TABLE IV
SCOPING ANXIETY MUSIC

No	Title	Artist	Valence	Energy
1	Tender Strength	Yu-Peng Chen, HOYO-MiX	0.135	0.060
2	As Ballad	Lambert	0.174	0.050
3	Moonlike Smile	Yu-Peng Chen, Zach Huang	0.071	0.190
4	Weightless	Marconi Union	0.079	0.220

To address anger, the system recommends songs with high intensity. Extreme genres such as metal or rock help listeners channel anger constructively without worsening emotional states. According to Sharman and Dingle (2015), metal music does not increase anger but instead makes listeners feel more active and emotionally regulated. Such music has been shown to reduce stress and irritation while helping align physiological arousal levels. Table 5 lists selected songs representing angry emotions, with their valence and energy values.

TABLE V
SCOPING ANGRY MUSIC

No	Title	Artist	Valence	Energy
1	Psychosocial	Slipknot	0.307	0.981
2	Nxde	(G)I-DLE	0.651	0.912
3	Kick Back	Kenshi Yonezu	0.302	0.938
4	Inferno	Mrs. GREEN APPLE	0.694	0.930

The analysis of music scoping calculations revealed that the four emotional categories possess distinct valence and energy ranges for music recommendations, each highlighting unique musical characteristics. Happy music is identified by high valence and medium-to-high energy, as shown in Table 2, and is effective for sustaining positive moods. In contrast, sad music is characterized by low valence and low-to-medium energy, as presented in Table 3, and is designed to facilitate emotional reflection and expression. Music associated with anxiety demonstrates very low valence and very low energy, as illustrated in Table 4, with the primary aim of calming the listener and alleviating anxiety. Meanwhile, angry music exhibits moderate valence and very high energy, as shown in Table 5, functioning as a constructive outlet for the release of strong emotions.

C. Model Validation and Analysis

To assess the therapeutic effectiveness of this music scoping, an alignment test was conducted by comparing the predetermined music characteristics with the intended emotional goals. The results indicated that the valence and energy ranges for sad and happy emotions were the most effective, showing high alignment with therapeutic objectives. The definition of anxious emotions also performed strongly. In contrast, scoping for angry emotions proved effective for emotional release but may require further validation regarding individual responses. These differences highlight the importance of ongoing validation to determine which scoping methods are most relevant to users' emotional responses.

Subsequently, an analysis was conducted to measure how distinct the valence and energy ranges of each emotional category were compared to the others. Higher scores indicate greater differences in musical characteristics. The analysis revealed that the range for angry emotions was the most distinct compared to other categories, making it an outlier in terms of intensity. Conversely, the ranges for sad and anxious emotions had the lowest difference scores, indicating that the musical characteristics of these two emotions are the most consistent and closely aligned within the negative emotion spectrum.

D. Implementation of the Rule Logic

The rule logic was implemented in the Laravel framework (PHP) to automate the process of determining a user's mood category and retrieving suitable therapeutic music. This logic governs two primary recommendation scenarios: (1) weekly PANAS-based recommendations and (2) daily emotion-based recommendations.

1) Weekly PANAS-Based Recommendation. After a user completes the PANAS questionnaire, the system calculates the Positive Affect (PA) and Negative Affect (NA) scores. Based on these scores, a classification function called determineMood($pa, $na) is executed to identify the overall mood type.

```php
private function determineMood($pa, $na) {
        // Menghitung level PA dan NA
        $paMood = $pa > 35 ? 'tinggi' : ($pa >= 25 ? 'sedang' : 'rendah');
        $naMood = $na > 35 ? 'tinggi' : ($na >= 25 ? 'sedang' : 'rendah');

        // Menentukan tipe Mood
        if ($paMood === 'tinggi' && $naMood === 'rendah') return 'Positif';
        if ($paMood === 'rendah' && $naMood === 'tinggi') return 'Negatif';
        if ($paMood === 'tinggi' && $naMood === 'tinggi') return 'Campuran';
        if ($paMood === 'rendah' && $naMood === 'rendah') return 'Netral';

        if ($paMood === 'sedang' && $naMood === 'sedang') return 'Netral';
        if ($paMood === 'tinggi' && $naMood === 'sedang') return 'Positif';
        if ($paMood === 'sedang' && $naMood === 'rendah') return 'Positif';
        if ($paMood === 'rendah' && $naMood === 'sedang') return 'Negatif';
        if ($paMood === 'sedang' && $naMood === 'tinggi') return 'Negatif';

        // Default
        return 'Netral';
    }
```

Figure 2. Mood Determination Logic

Figure 2 shows the rule-based mood determination logic that classifies PA and NA levels into high, medium, or low thresholds.

The function combines these two dimensions to generate one of four possible mood types: Positive, Negative, Mixed, or Neutral. This approach ensures the model remains interpretable, allowing a direct understanding of how emotional data influence the system's recommendations. Once the mood type is determined, it is used as a query condition to retrieve corresponding music recommendations from the mood_song table, as shown in Figure 3.

```php
// Ambil rekomendasi musik berdasarkan mood
    $recommendedSongs = MoodSong::where('mood_type', $moodType)->get();
```

Figure 3. Retrieving Music Recommendations by Mood

As shown in Figure 3, the system queries the mood_song table to fetch songs whose mood_type value matches the detected emotional classification. This enables a dynamic mapping between psychological affective states and curated therapeutic playlists.

2) Daily Emotion-Based Recommendation. The second logic scenario handles real-time emotion journaling. When users record their daily emotions, the selected emotion serves as a direct input parameter for filtering songs from the songs table.

```
$emotion = session('selected_emotion');

        $songs = null;
        if ($emotion) {
            $songs = Song::where('emotion', $emotion)->get();
        }
```

Figure 4. Retrieving Music Recommendations by Emotion

As seen in Figure 4, once the user's daily emotion is retrieved from the session variable, the system executes a query to filter songs whose emotion field corresponds to the selected label (e.g., "Happy," "Sad," "Anxious"). This mechanism enables a fast, rule-based recommendation flow that adapts instantly to the user's current mood state.

E. Black Box Testing

Black Box Testing was performed to verify the functional requirements of the system without inspecting the internal code structure. A total of 20 test scenarios were designed to cover all primary features, including user registration, login, emotion journaling, PANAS questionnaire submission, music and content management by the admin, and logout procedures. The testing results, detailed in Table 6 of the research report, showed that all 20 scenarios passed successfully, achieving a 100% success rate. This outcome confirms that the system is functionally stable and all features operate according to the predefined specifications [17].

TABLE VI
BLACK BOX TESTING RESULT

Total Scenario	Success	Percentage of Success
20	20	100%

F. Profile of Respondents

The demographic profile of the respondents in this study is presented to provide better context for interpreting the usability testing results. A total of 32 participants were involved in the evaluation process. The respondents were selected based on the segmentation of the primary target users of the application late adolescents and young adults (18–24 years) who tend to be more active in using web- and mobile-based applications to support daily activities, including mental health management. This age range is also considered more open to adopting technology and alternative therapeutic methods, such as music recommendation systems.

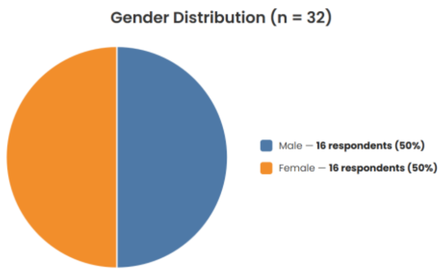

Figure 5. Respondent Gender Distribution

Figure 5 illustrates the gender distribution of respondents. The participants were evenly divided, consisting of 50% male and 50% female users. This balanced distribution ensures that the usability evaluation represents feedback from both genders equally.

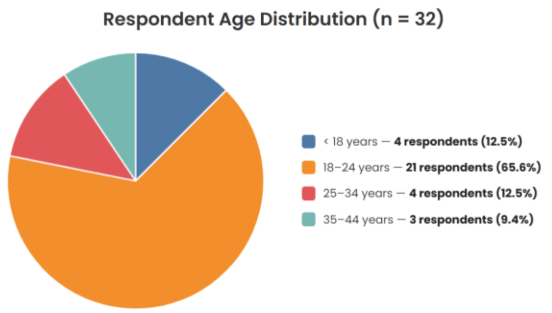

Figure 6. Respondent Age Distribution

Figure 6 presents the age distribution of respondents. The majority of participants (65.6%) were within the 18–24 years age range, followed by 12.5% below 18 years, 12.5% between 25–34 years, and 9.4% between 35–44 years. The dominance of the 18–24 age group aligns with the application's target audience, reinforcing the validity of the respondent selection process.

G. User Acceptance Test

The User Acceptance Testing (UAT) was conducted to evaluate whether the developed system meets user needs and expectations in realistic scenarios. A total of 32 respondents participated by interacting with the application's main features, and their feedback was collected through a structured questionnaire.

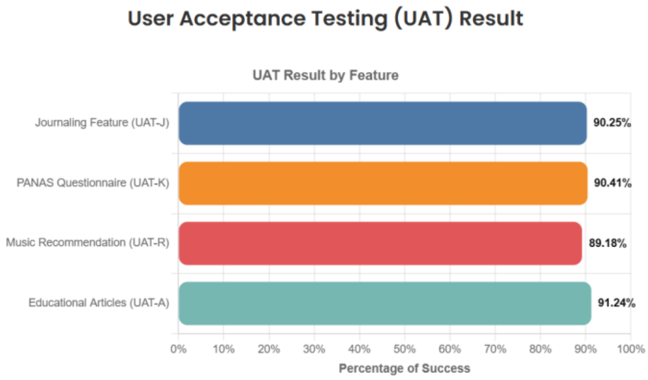

Figure 7. UAT Result

Figure 7 presents the results of the UAT, illustrating a very high level of user acceptance across all tested features [18]. The majority of participants reported that the system was easy to use, responsive, and functionally aligned with their expectations. These findings indicate that the system effectively supports its intended purpose of assisting users in managing mental well-being through music-based recommendations.

H. System Usability Scale

To quantitatively measure the application's ease of use, a System Usability Scale (SUS) evaluation was conducted. The SUS questionnaire, consisting of 10 standard items, was administered to the respondents after they used the system [19]. The final calculation resulted in an average SUS score of 85.00. According to established benchmarks, a score above 80.3 is considered "Excellent" and falls in the top 10% of usable systems. This high score confirms that the "Vibely" application has outstanding usability, with an intuitive interface that is easy to learn and navigate.The detailed scores are shown in Table 10.

TABLE X
SUS RESULT

Respondent	Score
1	90.0
2	85.0
3	87.5
4	82.5
5	85.0
6	80.0
7	87.5
8	90.0
9	85.0
10	82.5
Mean	**85.0**

I. System Performance Test

To complement functional and usability evaluations, performance testing was carried out to measure system responsiveness and stability. The test simulated 100 requests to each endpoint using a benchmark tool, with results shown in Table 11.

TABLE XI
RESPONSE TIME AND LOAD TEST

Page	Total Request	RPS (Request/s)	Time per Request(ms)	Failed Request
/home	100	3.76	2.657	0
/login	100	3.44	2.904	0
/panasresult	100	3.81	2.502	0
/rekomendasi	100	3.41	2.934	0
/panas	100	1.15	5.700	15
/articles	100	3.66	2.736	0

J. Security Considerations

Since the application processes sensitive emotional and mental health information, ensuring data security is critical. The system already incorporates several mechanisms such as password hashing, token-based authentication, HTTPS encryption, and role-based access control to protect user accounts and emotional journals. These mechanisms align with best practices in e-health applications, where safeguarding confidentiality and integrity of data is a primary concern. Recent studies emphasize that the adoption of artificial intelligence and machine learning techniques can further enhance privacy-preserving frameworks in e-health systems, providing proactive monitoring and adaptive security[20].

K. Limitation and Future Work

This study has several limitations that should be acknowledged. First, the number of participants in the user evaluation (32 respondents) was relatively small, which reduces the generalizability of the findings. In addition, the demographic profile was dominated by young adults (18–24 years old), which may not fully represent other user groups. Second, while the system was evaluated through usability testing (SUS, UAT), functional verification (Black Box Testing), and performance testing (response time and load test), the scale of performance testing was limited to 100 requests per endpoint. Larger-scale stress testing was not conducted, which leaves questions about scalability in high-demand environments. Third, the effectiveness of music recommendations in directly improving emotional states was not assessed through controlled pre-test and post-test mood measurements, leaving the therapeutic impact of the system unverified. Furthermore, the evaluation was limited to short-term interactions, without longitudinal testing to measure sustained usage or long-term outcomes.

Another limitation concerns the scope of the music database, which was limited to 16 curated tracks across four mood categories (Happy, Sad, Anxious, Angry). This restricted dataset may not fully represent the diversity of user music preferences. In addition, the recommendation engine was designed using a simple rule-based filtering approach, without adaptive personalization.

Future development should integrate artificial intelligence or machine learning techniques to enable more dynamic and personalized music recommendations. Additionally, the music database should be expanded to include a wider range of genres and tracks. Involving a more diverse demographic group and a larger sample size is also recommended to improve the generalizability of the findings.

L. Comparison with Related Work

The findings of this study show that the system achieved high usability scores (SUS = 85, UAT = 90.25–91.24%), demonstrating strong acceptance among users. Compared to similar systems, such as Luminds [4], which primarily provide online consultation and educational content, Vibely offers a more personalized experience by integrating daily emotion journaling, PANAS-based mood classification, and rule-based music recommendations. Previous works on mobile mental health applications mainly focused on mood tracking or cognitive-behavioral interventions [2], [3], with limited emphasis on adaptive therapeutic features. By combining structured mood assessment with therapeutic music recommendations, Vibely provides a unique contribution that enhances user self-awareness and emotional regulation.

IV. CONCLUSION

This study successfully developed a web-based mental health management information system integrated with therapeutic music recommendations. The system utilizes a carefully designed Rule-Based Filtering method that effectively analyzes users' daily emotional inputs and weekly PANAS questionnaire results. It classifies the user's mood into categories such as Positive, Negative, Mixed, or Neutral, and recommends relevant music accordingly. The technical implementation was built using the Laravel framework for the backend and Tailwind CSS for the frontend.

The system demonstrated strong performance across multiple evaluations: functionality achieved 100% based on Black Box Testing; the User Acceptance Test (UAT) indicated highly favorable results, with average scores of 90.25% for UAT-J, 90.41% for UAT-K, 89.18% for UAT-R, and 91.24% for UAT-A; the System Usability Scale (SUS) yielded an average score of 85.00, categorized as "excellent"; the Net Promoter Score (NPS) reached 59.37%, reflecting strong user satisfaction and loyalty within the "good" category. In addition, the performance test showed that the system maintained stable response times of 2.5–3.0 seconds for most endpoints under 100 concurrent requests, though the PANAS module exhibited slower responses and a small number of failed requests.

Despite these promising results, future work should focus on expanding the music database to cover more diverse genres, integrating adaptive recommendation techniques such as artificial intelligence, and conducting larger-scale performance and stress testing to ensure scalability. Furthermore, controlled pre- and post-test mood experiments and longitudinal studies are required to assess the therapeutic impact and long-term effectiveness of the system. Finally, the addition of advanced features such as multilingual support, accessibility improvements, and extended mental health modules (e.g., stress management tips, breathing exercises, and professional consultation links) will help transform the application into a more holistic mental health support platform.

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