Natsukashii: A Sentiment Emotion Analytics Based on Recent Music Choice on Spotify

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***Abstract*—Natsukashii offers a delightful platform for users to seamlessly connect with their Spotify accounts and delve into cherished musical moments, fostering a profound emotional connection with their recent experiences. This platform harnesses the power of Spotify's data, facilitating a secure connection to users' accounts while ensuring that no Spotify data is stored locally. Its array of features includes captivating data visualizations, such as display cards, radar charts, and area charts, elegantly showcasing both recent favorites and top-listened tunes. However, the crowning jewel of Natsukashii lies in its ability to provide users with a heartfelt insight into their current mood, derived from the audio features of their recent playlist selections. By meticulously preparing and analyzing the audio features provided by Spotify, Natsukashii delivers a personalized sentiment analysis, offering users a poignant glimpse into their emotional state through the lens of their musical preferences. Moreover, this enriching experience is seamlessly accessible across desktop and mobile platforms, compatible with popular web browsers like Google Chrome, Firefox, and Microsoft Edge.**

Keywords—Spotify; sentiment analysis; data preparation; data visualization; web development

I. Introduction

Spotify stands as the foremost digital music streaming service globally, granting users the freedom to indulge in on-demand music listening while fostering the creation and exchange of playlists. Employing cutting-edge recommender models, Spotify pioneers personalized music suggestions tailored to each user's listening habits. By seamlessly integrating these recommendations into the user experience, the platform continually introduces fresh content aligned with individual preferences. At its core, this innovation revolves around an algorithmic framework meticulously designed to curate top-tier recommendations, drawing insights from categorized groups, track metadata, and collaborative user-generated content [1].

The importance of delivering personalized analytics directly to consumers is frequently underestimated. Often, analytics are predominantly prioritized by upper management, with a focus on algorithms and recommendations geared towards the consumer. Nevertheless, integrating low-level analytics directly to users would prove significantly advantageous in terms of feature implementation.

Research indicates that over the long haul, algorithmic recommendations tend to narrow the spectrum of user listening habits in contrast to those driven by user choices. However, platforms experience heightened user retention rates with greater content diversity [2]. This underscores the importance of accessible analytics for end-users, empowering them to discern the types of content they engage with. Moreover, such insights aid upper management in gauging user retention following the introduction of novel features.

Recognizing the dynamic nature of users' listening preferences, Spotify continuously refines its algorithms to align with their ever-changing moods and behaviors [3]. Nonetheless, while Spotify Wrapped offers a comprehensive annual insights package, it limits users' freedom to explore beyond the confines of a yearly cycle. Consequently, Spotify misses out on the potential benefits of implementing personalized, time-sensitive analytics.

Investigating individual-level data reveals a treasure trove of insights into human behavior. Research has illuminated a strong correlation between music preferences and listening habits with personality traits. Existing literature underscores the importance of recognizing that personalized analytics offer both tangible and intangible advantages to both users and brands [3].

II. Literature Review

A. Music Streaming Platforms and Music Consumption

Music, as a medium of consumption, holds a profound sway over individual mood regulation, mirroring the ebb and flow of emotional energy within. Scholars underscore that music consumption stands apart from conventional text-centric social media engagement. As shown in Fig. 1, this is owing to its unique capacity to not only reflect an individual's present emotional state but also to shape their desired emotional experience [4]. Such nuanced insight empowers platforms to leverage algorithms in forecasting and delivering desired moods through tailored musical selections. Consequently, music platforms are keenly invested in refining their recommendation systems by manipulating content consumption patterns. The real-time data feedback loop inherent in music streaming services represents a pivotal departure from traditional modes of music consumption, conferring a distinct competitive edge. It underscores the strategic significance of the music streaming landscape amidst the ongoing digitization of music consumption [5].

The trailblazers of the music streaming realm, exemplified by industry giants like Spotify and Apple Music, have profoundly reshaped this landscape. These titanic platforms have effectively transformed the social fabric surrounding music consumption, turning it into a potent form of social interaction. Merely amassing a vast content library no longer guarantees an edge over rivals, as sheer volume alone fails to captivate users' attention. Platforms are tirelessly refining their recommendation algorithms to provide personalized experiences under the broad umbrella of customization [5]. Nevertheless, fixating solely on winning the recommendation race represents just a fraction of what a streaming platform entail.

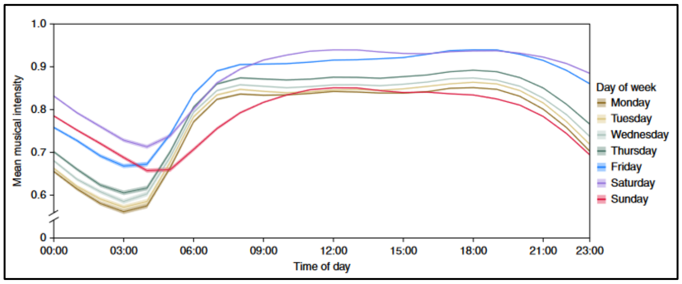

Fig. 1. Music consumption on a diurnal basis [2].

In a comprehensive study conducted by Park et al. (2019), the timely consumption of music streaming through Spotify across fifty-one countries was examined using a random stratified sampling method [4]. Spotify, with its ambitious goal of tailoring recommendations to users even before their preferences crystallize, capitalizes on the wealth of data availability for analytical insights. Notably, Spotify's provision of track analysis, encompassing eleven audio attributes, furnishes invaluable information conducive to enhancing user comprehension of their listening experience.

Through a feature-oriented approach rather than a backend model, users can forge connections with their desired musical content based on their emotional context. This approach surpasses conventional computer-based algorithms by acknowledging the significance of human perception, wherein data is presented in easily digestible visual formats. Embracing data analytics as a platform feature holds immense promise for facilitating personalized music discovery and enjoyment.

Variation and diversity of content consumption have moderately significant differences during varying times of the day. In their research [4], the authors posit that Spotify users' musical preferences undergo shifts depending on the nature of their activities, whether it be for relaxation, motivation, stress relief, or winding down. This correlation becomes apparent when specific tracks possess attributes like tempo, valence, danceability, or instrumental quality that resonate with a particular psychological mood within a given time interval [6]. Such findings underscore the invaluable insights gleaned from data analysis, empowering users with the opportunity to deepen their self-awareness.

Spotify diligently gathers data across various dimensions of significance, encompassing stakeholders, societal advantages, and brand perception. Consumption of content occurs on a subconscious plane, often evolving into habitual listening, effortlessly ingrained in users' routines. Consequently, individuals find themselves engaging with music recommended to them, relinquishing active selection of preferred genres. In the evolving landscape where data insights rival sophisticated predictive models in importance, there arises a compelling case for providing users with introspective analytics, including mood analysis. Such an approach fosters a more personalized self-identity, empowering users to curate their musical journey based on individual inclinations, rather than solely relying on algorithmic dictates.

B. Analyzing Emotions in Audio Data

Social media text has emerged as a pivotal data source for comprehensively analyzing mood and emotions at scale, with a nuanced grasp of the temporal dynamics inherent in such data, given its perpetual evolution. As the volume and accessibility of user-generated content burgeon, it has been discerned that both the platform itself and the surrounding community exert significant influence on shaping the overarching emotional landscape of broad target demographics. However, this growth has also engendered a phenomenon wherein predictive models tend to become overly specialized, inadvertently neglecting quieter individuals whose sporadic contributions may not fully encapsulate their experiences [8]. Consequently, when gauging emotional states through historical user data, it becomes imperative to pay heed to the fluctuations in emotions over time. This is crucial due to the manifold external stimuli—ranging from media influences on social connections—which are in a constant state of flux, exerting a profound impact on an individual's mood.

Emotional analysis has transcended mere textual expressions, extending its reach into the realms of audio and video formats. The emergent insight value derived from mining data across semantic audio, music, and soundscapes, previously overlooked by the music industry [9], expands the spectrum of data extraction. This integration of more profound sources enriches comprehensive analyses, fostering deeper comprehension. Yet, achieving such understanding necessitates ongoing development in emotional intelligence, aiming to decipher the influential factors driving human emotions [10].

C. Spotify Track Data

The Circumplex Model, pioneered by James Russell, elegantly captures emotions within a two-dimensional landscape blending cognitive science and psychology. Here, emotions find their place, with valence denoting their positivity or negativity, and arousal signifying their intensity. Positioned in the model, positive emotions reside in the upper right quadrant, while negative one's dwell in the lower left [10]. Illustrated in Fig. 2, Russell's Circumplex Model of Affect holds significant relevance in deciphering Spotify's track data for mood analysis. Spotify's classification of tracks aligns with this model, facilitating the creation of a scoring mechanism. Wei et al. (2021) delved into how emotions, characterized by a blend of valence and arousal, can be extracted utilizing this framework. Their study revealed Spotify's portrayal of valence through a scale of 0.0 to 1.0, where higher values signify a more jubilant emotional state. Arousal, alternatively termed "energy" by Spotify, is also gauged on a scale of 0.0 to 1.0, where elevated scores indicate tracks characterized by speed, volume, and vigor, such as the genre of death metal [11].

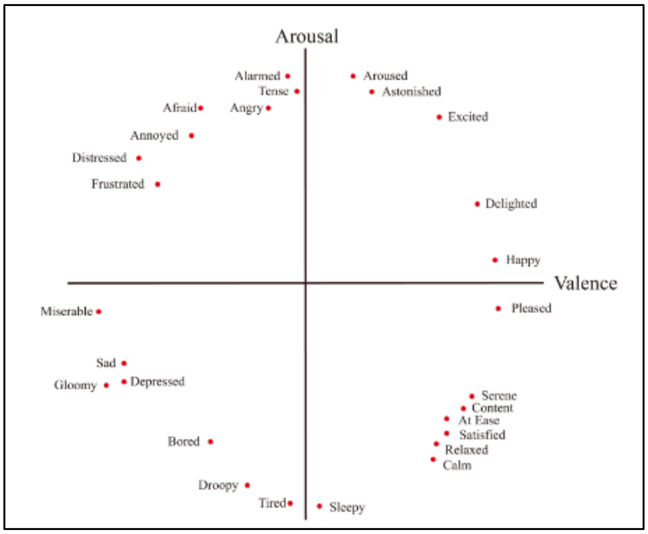

Fig. 2. Russell's circumplex model [3].

Spotify presents its data to users in a sleek JavaScript Object Notation (JSON) format, ensuring that structured objects are easily interpretable. JSON stands out as a widely embraced format across various platforms. To access Spotify's data, users have two options. Firstly, they can directly request a download of their data via their profile. Following some processing time, Spotify packages this data and dispatches it to the user's account via email. However, for projects requiring real-time data, tapping into Spotify's web API proves more fitting [12]. Spotify employs an approximate scoring system, assigning nine "audio features" to songs, with scores ranging from 0.0 to 1.0. These features gauge different facets of an audio track's composition. The audio features are as listed below: -

- Acousticness
  - Represents if a track has high confidence in being acoustic.
- Danceability
  - Describes suitability to dance in terms of tempo, rhythm, beat, strength.
- Energy
  - Represents track intensity.
  - Higher scores are tracks that are fast, loud, and noisy.
- Instrumentalness
  - Predicts degree of vocal presence in a track
  - Sounds like “ooh” and “aah” are not vocal content.
  - A higher score represents a higher likelihood of having no vocal content.
- Liveness
  - Detects audience presence if the track artist performed live.
  - A value more than 0.8 has a strong likelihood of live performance.
- Speechiness
  - Detects the presence of spoken words.
  - Values above 0.66 have a high likelihood of the track being made of spoken words such as podcasts or audio books.
  - The value between 0.33 and 0.66 may contain both spoken words and music.
  - Values below 0.33 may be music or other non-speech audio.
- Tempo
  - Estimates the beats per minute (BPM).
  - Represents the pace (speed) of the track.
- Valence
  - Represents musical positiveness.
  - High values represent positive emotions such as happiness and cheerfulness.
  - Low values represent negativity such as sadness and anger.

In instances where Spotify has assigned pre-labelled scores to its track data, the methodology behind the determination of these scores remains ambiguous. A comment in a blog post by Shanahan (2016) indicated that this information is proprietary, with Spotify deriving these scores through their internal algorithms. It was mentioned that these algorithms appear to be aligned with the principles of Echonest's algorithm [11].

D. *Spotify Wrapped Campaign*

The inception of the "Spotify Wrapped" campaign in December 2017 ignited a social media phenomenon, capturing the enthusiasm of users who eagerly shared their listening statistics across various platforms. With its organic growth fueled by word-of-mouth promotion, the campaign swiftly gained traction, serving as a communal celebration of beloved artists [7]. Its resonance reverberated through the digital landscape, spawning a proliferation of news articles and blog posts dedicated to extolling its virtues.

Evolved into an annual tradition, each iteration of the campaign sought to introduce novel features, fostering heightened user engagement with every passing year. Notably, in 2022, the campaign unveiled 16 distinct listening personality archetypes for individual users, alongside a strategic foray into the burgeoning metaverse landscape via Roblox [13]. However, Adenuga (2022) raised poignant ethical concerns regarding the extensive collection and dissemination of users' data, prompting reflection on the justification and inherent value of such surveillance practices.

While businesses often approach data through a macroeconomic lens, emphasizing its monetary utility, users derive personal value from the insights gleaned, facilitating a deeper understanding of their emotions and preferences. Thus, amidst the ethical discourse surrounding data privacy, users find solace in the self-awareness afforded by these analytics.

E. *Similar Systems*

Table I elucidates three contemporary systems available at the time of the study, designed to furnish user listening analytics leveraging Spotify data.

TABLE I. COMPARISON OF SIMILAR SYSTEMS

Features	Systems		
	Spotilyze	Stats For Spotify	Stats.fm (Spotistats)
Desktop Resolution	Yes	Yes	Yes
Mobile Resolution	No	Yes	Yes
Stores Data	No	No	Yes
Has Time Range Filter	No	Yes	Yes
Analysis Infographics and Platform Features	Playlist mood radar chart. Top artists in the playlist. Top genres of the playlist. Track the popularity of songs within the playlist. Distribution of track information within the playlist.	User's top tracks User's top artists User's top genres Recently played activity	A user profile that links to Spotify Integrated "friend" system that allows users to add friends. User's top tracks User's top artists User's top genres Recently played tracks activity. Genre analysis Track content analysis
Pros	Clean and simple user interface design Easily digestible visualization and metrics	Time filter available Mobile responsive	Time filter available with custom time range Mobile responsive Simple user interface
Cons	Not mobile friendly Restricted only to analysis of playlists. No time filter available	Has no visualization and only uses lists. Have limited features	Has limited variations of visualization. Paywalls restrict most of the features. Collects and stores user data which creates privacy risk.

Although existing systems boast robust and dynamic functionalities, they fall short of adequately addressing the specific problem of correlating emotions with individual music preferences. The prevailing limitations of these systems primarily revolve around leveraging the features offered by platforms like Spotify, rather than focusing on solving the fundamental issue while harnessing the data provided by such platforms. Consequently, the rationale behind selecting the proposed research and implementation methods lies in their adaptability and effectiveness in addressing the inherent challenge of connecting emotions with music preferences.

III. TECHNICAL STACK

Table II outlines the chosen technical stacks designated for system development. GitHub, coupled with Git, emerges as a pivotal quality-of-life tool for version control among developers. JavaScript, renowned as the prevailing industrial standard for contemporary web development, stands as the unequivocal choice for system development, owing to its expansive capabilities and user-friendly nature. Given the plethora of community libraries and frameworks available for JavaScript, incorporating additional features or addressing potential compatibility issues within the project's scope and deliverables can be seamlessly adapted, ensuring scalability and flexibility to accommodate evolving requirements.

TABLE II. TECHNICAL STACK

Category	Name
Programming Language (Framework)	ReactJS on NextJS (JavaScript)
Styling Library	MantineUI, ChakraUI
Data Visualizations Library	Recharts
Developer Tools	NodeJS + NPM (Package Manager) GitHub + Git (Version Control)
Design Tool	Figma
Deployment Service	Vercel
Database	None

IV. METHODOLOGY

A. Introduction

The proposed project embodies dual facets, intertwining both software development and data science methodologies, owing to its nature spanning across these two domains. Fundamentally reliant on data to catalyze its initiation, the project necessitates a data science methodology (see Fig. 3). Conversely, the deployment of the platform within a web application necessitates a software development methodology. These complementary methodologies will converge within a hybrid framework, fostering a synergistic workflow and structured project plan. Initiating the project involves delving into data comprehension and domain understanding, for which the CRISP-DM methodology serves as the cornerstone. Transitioning to the data preparation stage, elements borrowed from the waterfall model will be seamlessly integrated into the hybrid methodology. This strategic amalgamation promises to enhance both the understanding of data intricacies and the efficacy of software development within the project. Tables III and IV delineate the phases of these comprehensive approaches.

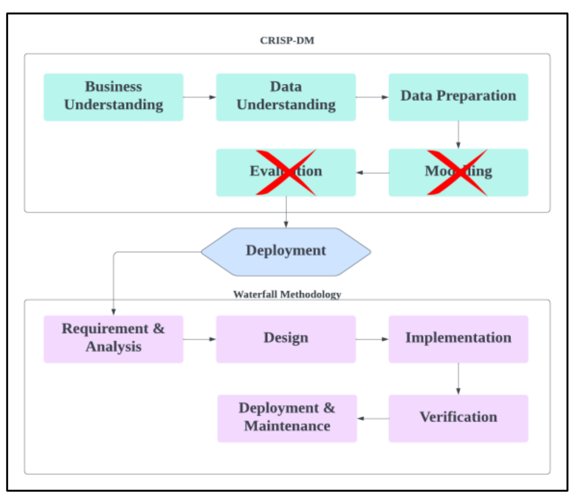

Fig. 3. Proposed mixed methodology framework.

B. Phases of Data Mining Methodology (CRISP-DM)

TABLE III. CRISP-DM PHASES

Phase	Purpose & Outcomes
Business Understanding	Assessing and understanding the current business objectives of Spotify while aligning the project outcomes.
Data Understanding	Explore the capabilities, limitations, and intended use of Spotify data through their Web API.
Data Preparation	This phase is not needed as Spotify has already cleaned their data for usage.
Modelling	N/A – Irrelevant for this project
Evaluation	N/A – Irrelevant for this project
Deployment	This entire phase will be conducted in accordance with the waterfall methodology as listed in the next subsection.

C. Phases of Data Mining Methodology (Waterfall)

TABLE IV. WATERFALL METHODOLOGY PHASES

Phase	Purpose & Outcomes
Requirements & Analysis	Conduct a zero-party data approach of collecting personal opinions of platform features through a questionnaire distributed online. Results of questionnaire are used to validate useful features for the design phase.
Design	Convert the analysis of requirements into low-level visual components through Figma.
Implementation	Develop the designed system with the technical stack proposed. Test plans are also developed within this phase.
Verification	Conduct unit testing and system integration testing with Spotify data.
Deployment & Maintenance	Deploy the system for public usage. Apply for Spotify's extended quota mode to enable all Spotify users to connect to the platform.

V. RESEARCH METHODS

The selected research methodology involved the utilization of an online survey, a strategic means of gathering quantitative data [17] to glean valuable insights from participants regarding the research topic at hand. Leveraging surveys proves advantageous due to its cost-effectiveness and capacity to swiftly engage a sizable cohort of target users [14]. This methodology aligns seamlessly with the envisaged waterfall methodology employed during the requirements phase, facilitating the efficient collection and analysis of project requisites. Streamlining the process further, platforms like Google Forms, Microsoft Forms, and Survey Monkey offer integrated solutions for data collection and analysis, thus optimizing time utilization. Conversely, a qualitative approach is deemed impractical due to its inherent time intensiveness, requisite expertise, and inability to furnish generalizable insights for the target demographic.

Given the nature of the proposed project, which does not necessitate the inclusion of personal viewpoints from participants, the qualitative research methodology is deemed unsuitable for attaining the research objectives. The author faces constraints in conducting qualitative research due to the requisite presence of a skilled moderator, which is currently lacking. Conversely, surveys offer a means to uphold participant anonymity, thereby fostering greater engagement, particularly given concerns regarding data privacy [15].

In the context of system testing, qualitative methodologies present a justifiable approach for gathering opinions and feedback, particularly in instances where quantitative data may not adequately capture user experiences. This phase of research entails soliciting verbal feedback to ascertain the impact of the system on users and any perceived benefits derived from its usage. However, at the onset of research, particularly during the requirements gathering stage, a combined qualitative and quantitative approach may not be appropriate. Qualitative inquiries may inadvertently encroach upon individuals' privacy, particularly concerning sensitive aspects such as emotional states. Thus, initiating with a quantitative focus allows for the establishment of user trust and willingness to engage with the system. Subsequently transitioning to qualitative assessments becomes less intrusive, as users become more receptive to providing nuanced feedback. This progression is rationalized by the integration of emotions and moods into a composite score, which can be presented to users for comparative analysis, rather than intrusively assigning a numerical value to represent their mood.

Unlike qualitative approaches, such as interviews, surveys afford participants a higher degree of privacy, crucial for eliciting candid responses while safeguarding sensitive information. Presented below are tables and figures illustrating the outcomes of primary research conducted among 53 respondents drawn from Malaysian adolescents? The questionnaire encompassed four distinct sections, featuring nominal, linear scale, checkbox, and multiple-choice grid inquiries as shown in Table V, Table VI, Fig. 4 and 5.

TABLE V. SECTION 1: PARTICIPANT DEMOGRAPHIC

Question	Results
Gender	52.8% - Male 45.3% - Female 1.9% - Prefer Not to Say
Age	**86.8% - 18 to 25 years old** 5.7% - 26 to 30 years old 3.8% - <18 years old 1.9% - 31 to 35 years old 1.9% - 36 to 40 years old
Occupation	77.4% - Student 22.6% - Working

TABLE VI. SECTION 2: MUSIC STREAMING PLATFORMS

Question	Results
What music streaming platforms that have you used?	84.9% - Spotify 84.9% - YouTube Music 35.8% - Download mp3 files locally 24.5% - Apple Music 22.6% - SoundCloud 9.4% - Tidal 3.8% - Tencent Music 1.9% - Amazon Music

Question	Results
Does your emotional state influence the type of music consumed?	Likert Scale (Multiple Choice) 5 – 26.4% **4 – 47.2%** 3 – 13.2% 2 – 9.4% 1 – 3.8%
Does the type of music consumed influence your emotional state?	Likert Scale (Multiple Choice) 5 – 17% **4 – 49.1%** 3 – 22.6% 2 – 7.5% 1 – 3.8%

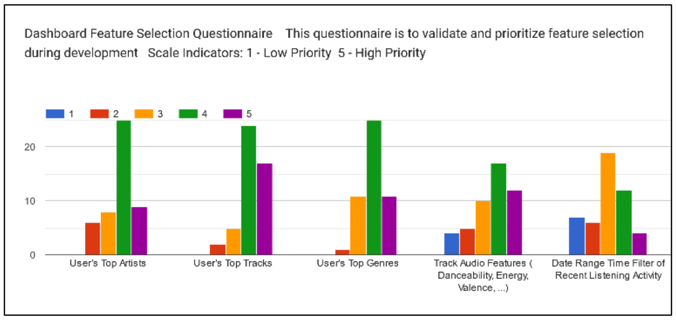

Fig. 4. Dashboard Feature Selection.

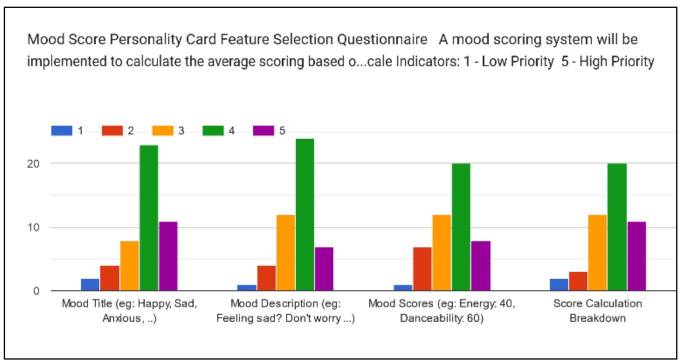

Fig. 5. Mood card content preference.

VI. Data Understanding

The initial exploration of Spotify's Web API delved into its capabilities, potential uses, and inherent limitations regarding the data it provides. Spotify's Web API offers external applications the ability to interact with Spotify's extensive data, encompassing tasks such as retrieving content metadata and accessing account information [16]. Nonetheless, leveraging Spotify's Web API entails adhering to a specific sequence of steps to enable users to access data from their platform. This necessitates the creation of an application within Spotify's developer dashboard to acquire the requisite client credentials. Armed with these credentials, the application gains the ability to initiate Web API calls to Spotify's servers. Within the scope of the proposed project, Natsukashii, integration of a login feature via Spotify facilitates user authorization and seamless data retrieval.

A. Relevant Endpoints

- v1/me
  - Fetch user's account name, display image, and external URL link
- v1/me/top/{type}
  - Fetch user's top tracks and top artists
  - Time range parameters of 1 month, 6 months, and several years
  - Images and metadata must comply with Spotify's design guidelines to obtain approval for Spotify Quota Extension
- v1/audio-features
  - Fetch track's audio features such as valence and energy score
  - Used to build own API endpoint that calculates a mood profile based on Russell's Circumplex Model
- v1/me/player/recently played
  - Fetch the recently played unique tracks with a limit of 50 each API call
  - After and before parameters available to call specific tracks played in a timeframe

B. Data Limitations and Workarounds

It sounds like you're discussing an issue with the Spotify Web API, specifically regarding the before and after parameters for fetching recently played tracks within a certain time frame, such as a week. Despite these parameters being documented, it appears that they are not currently supported based on your research and personal exploration. Additionally, you've found that other developers in the community forum have encountered similar difficulties, specifically with being unable to retrieve more than the initial 50 responses. This limitation might pose challenges for developers who need to access a larger dataset of recently played tracks. If you're looking to address this issue, you might consider reaching out to Spotify's developer support or checking for any updates or announcements regarding changes to the API's functionality. Alternatively, exploring workarounds or alternative methods for accessing the desired data could also be worth investigating.

The issue arises when attempting to use the "before" or "after" cursors in the second response, hindering the retrieval of subsequent responses. Consequently, developers are constrained to fetching no more than 50 responses, thus restricting the available data to only the most recent 50 listened songs [4].

Owing to constraints imposed by Spotify, the component will presently only draw data from the latest 50 tracks played. As a result, the inclusion of a date filter is currently redundant, pending future enhancements from Spotify. Consequently, the initially proposed date picker filter will be replaced with pre-defined time range options, ensuring seamless integration with the bar chart, area chart, and sentiment mood card.

The sentiment mood card and the recently played area chart components retain full functionality, albeit restricted to the fifty most recently played tracks. Notably, these components are no longer influenced by the time range filter located at the top of the page. While this may be perceived as a limitation, it enhances granularity while reducing flexibility in track selection. From a business perspective, this feature encourages frequent visits to the platform, thereby bolstering user engagement. It's worth noting that aside from the recently played tracks endpoint, all other data endpoints are accessible and can be utilized without any constraints or impediments.

C. Data Driven Implementations

The data under examination will undergo meticulous processing and refinement to align with the intended component implementations. This preparatory phase entails server-side processing within the cloud server, leveraging the project's bespoke API. By employing the Natsukashii application's API for executing the processing logic, the burden on client-side machines is mitigated, ensuring a smoother experience for platform users.

The track audio features data provided by Spotify do not inherently convey the emotional state of a listener. To discern emotions, developers typically employ data preparation techniques, often leveraging models such as Russell's Circumplex Model. This model allows developers to interpret emotions based on metrics like average energy and valence scores. Implementing this approach, developers devise calculations to delineate the boundaries of energy and valence scores. Consequently, they can categorize emotional states into nine distinct profiles. Fig. 6 and Fig. 7 are the diagram and the code snippet accompanying this process.

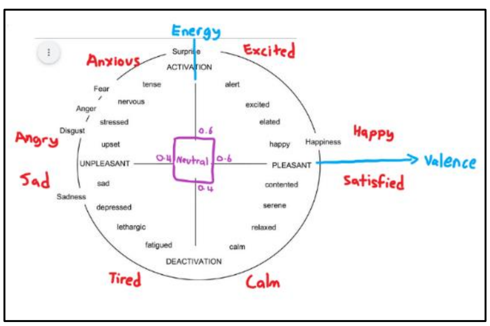

Fig. 6. Russel's Circumplex Model Decimal Point Boundaries.

```
export function getMood({ valence: valence, energy: energy }) {
  // assuming 0.5 is the value of 0,0 on the russell's circumplex model
  // values between 0.4 and 0.6 for both values are considered neutral

  let mood = "neutral";

  if (valence >= 0.6) {
    // positive
    if (energy >= 0.65) mood = "excited";
    if (energy >= 0.5 && energy < 0.65) mood = "happy";
    if (energy > 0.35 && energy < 0.5) mood = "satisfied";
    if (energy <= 0.35) mood = "calm";
  } else if (valence < 0.4) {
    // negative
    if (energy >= 0.65) mood = "anxious";
    if (energy >= 0.5 && energy < 0.65) mood = "angry";
    if (energy > 0.35 && energy < 0.5) mood = "sad";
    if (energy <= 0.35) mood = "tired";
  } else {
    // close to x-axis origin
    if (valence > 0.5) {
      if (energy >= 0.65) mood = "excited";
      if (energy <= 0.35) mood = "calm";
    } else if (valence < 0.5) {
      if (energy >= 0.65) mood = "anxious";
      if (energy <= 0.35) mood = "tired";
    }
  }

  return profiles[mood];
}
```

Fig. 7. Code snippet of mood score calculation.

VII. SYSTEM ARCHITECTURE

After careful examination, it was determined that the project solely requires frontend frameworks, with minimal integration with Spotify's Web API through RESTful connections. Recognizing the paramount importance of data security in accordance with Spotify's developer guidelines, it was decided that no data collection or storage would be undertaken within this project. Instead, real-time data would be continuously retrieved from Spotify's Web API, rendering the necessity for a database redundant within this system.

Upon thorough examination of the system's core functionalities and deliverables, it was determined that a monolithic application, devoid of a database, stands as the optimal choice for the proposed project, tailored for a solitary user. A monolithic architecture encapsulates the entire application within its ecosystem, operating as a cohesive entity with its distinct services and APIs. Conversely, microservices distribute autonomous services to support the application. Given the project's modest scale and the requirement for only a singular communicative service for the user interface, the microservice architecture is deemed unsuitable [5].

In this section, we delve into the high-level architecture of the proposed system, a guiding blueprint empowering developers to seamlessly transition into the developmental phase of our methodology. The design phase emerges as a pivotal precursor to venturing into development within the chosen waterfall methodology. Crafting a user journey and system architecture entails meticulous planning, ensuring developers grasp the fluidity and comprehensive scope of the project. Moreover, a preliminary wireframe design for the user interface has been meticulously sketched to visually illustrate the arrangement of component locations as illustrated in Fig. 8 – Fig. 12.

D. Abstract Architecture

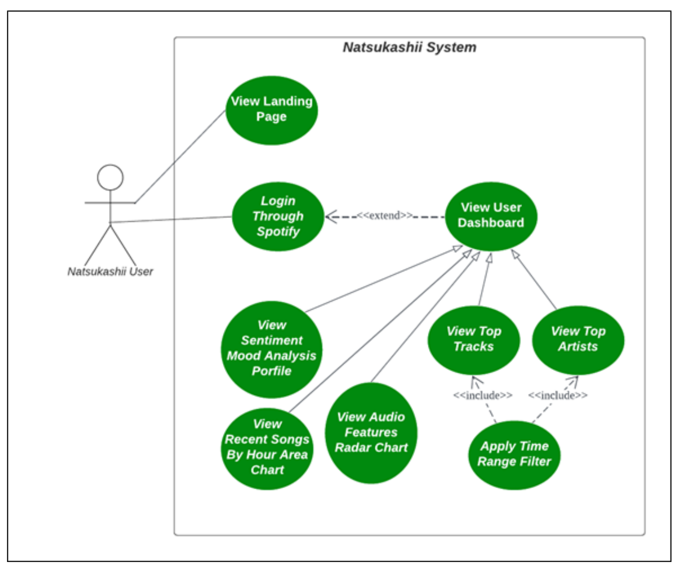

Fig. 8. Natsukashii use case diagram.

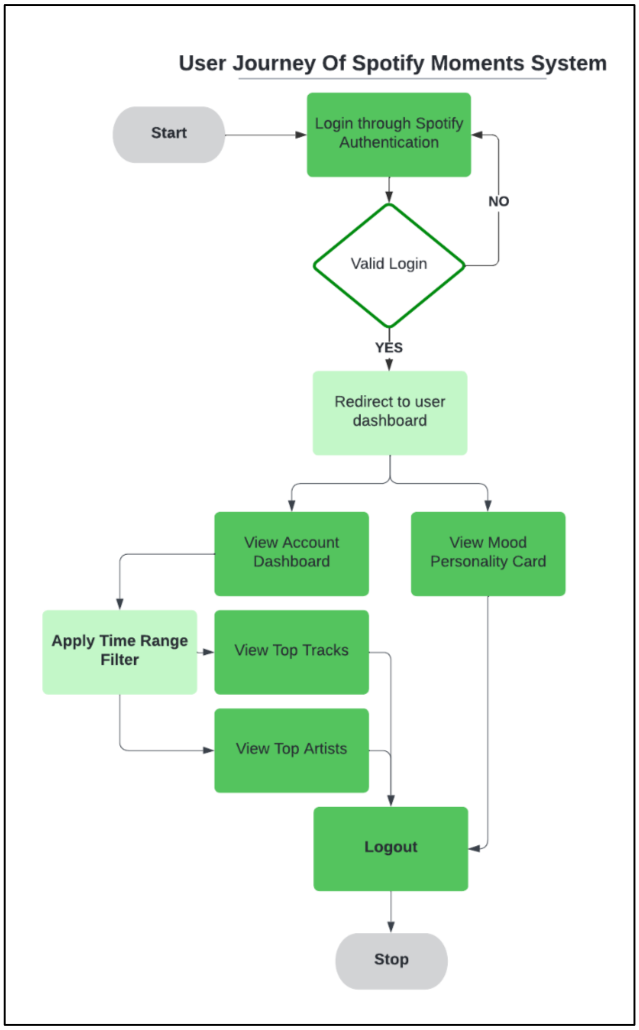

Fig. 9. Natsukashii user journey flowchart.

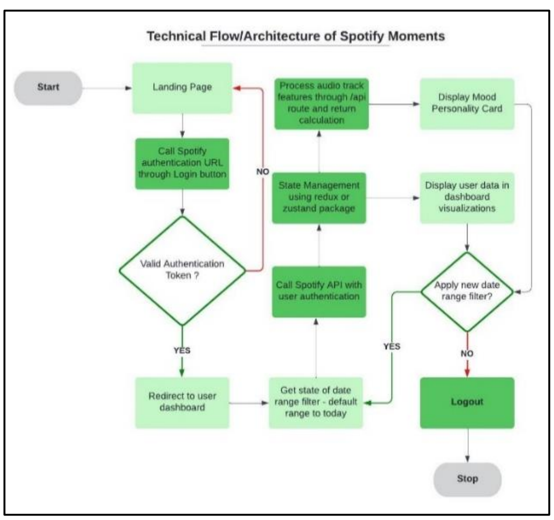

Fig. 10. Natsukashii server-side flow.

E. User Interface Design

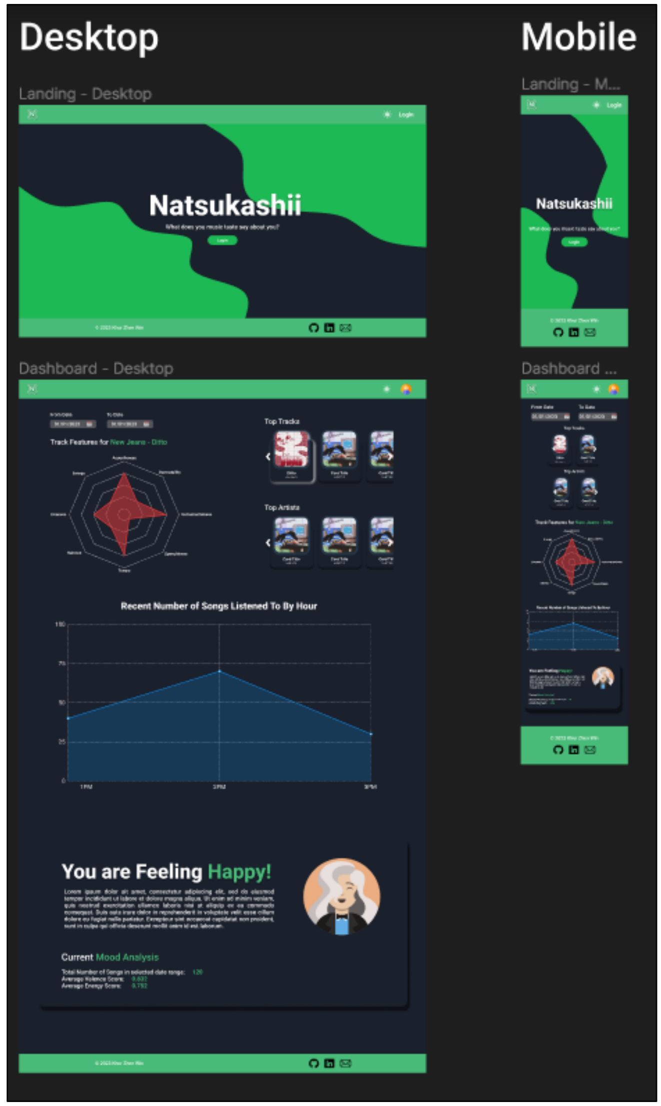

Fig. 11. Natsukashii overall design.

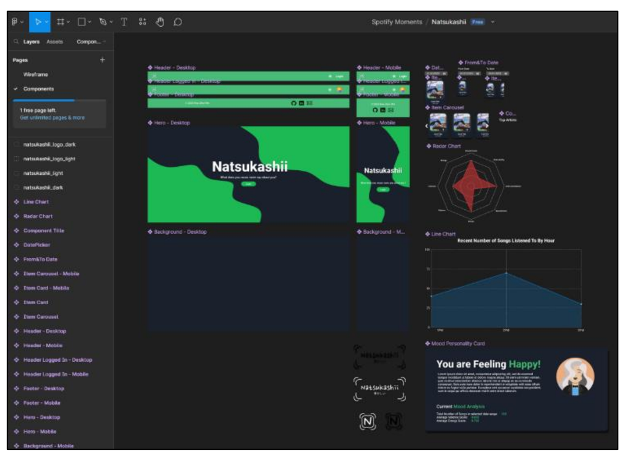

Fig. 12. Natsukashii component level design.

VIII. Implementation

The project Natsukashii has been deployed (see Fig. 13) on https://natsukashii-kzw.vercel.app/ and is freely hosted by Vercel. The application is both available on desktop and mobile browsers alongside light and dark theme modes.

Fig. 13. Natsukashii final system.

IX. System Validation

The testing conducted aimed to ensure the seamless operation of the system both at a granular component level and from the perspective of end users. Unit testing was meticulously performed to assess the functionality and design of each discrete component. Gratifyingly, all unit tests yielded successful outcomes, aligning precisely with the predefined test cases as shown in Table VII. Moreover, a comprehensive system integration testing, serving dually as a user acceptance test, was executed to gauge the platform's efficacy in facilitating the onboarding process for new users. Three proficient testers were enlisted to provide comprehensive feedback and evaluation across four distinct criteria. The culmination of their assessments is encapsulated in the tabulated average score above, wherein all feedback was meticulously addressed, and recommended enhancements were promptly implemented to enrich the overall user experience.

TABLE VII. System Integration Testing Results

Results From System Integration Testing				
Tests	User Interface	User Friendliness	Analytics Insights	Bug-free
Tester 1	4	5	5	5
Tester 2	5	5	5	5
Tester 3	5	5	5	5
Average	4.67	5	5	5

One recommendation remained unfulfilled, namely, the integration of mood with genre types within the sentiment mood profile. This oversight stems from the constraints of Spotify's API, which lacks track genre integration, thereby limiting the ability to analyze diverse song genres effectively.

X. Discussion and Analysis

Throughout the developmental stages of the system, the author conducted comprehensive testing to explore its potential benefits within the scope of personal interests. During data collection, distinct emotional responses were observed across various music genres; for instance, heavy metal music tended to evoke predominantly negative emotions, particularly anger, while classical piano melodies conveyed a sense of calmness. These nuanced insights offer a fresh perspective on how individuals may experience emotions based on their musical preferences. However, it is important to acknowledge the complexity of human emotions, as this correlation may not always hold true universally. Indeed, discussions arose regarding the possibility that certain music genres could simply be a personal favorite without directly influencing one's mood. Nonetheless, such preferences may still provide insights into individuals' personalities, potentially hinting at broader traits such as a tendency towards short-temperedness. This discourse underscores the multifaceted nature of music's impact on human emotions and behaviors, stimulating further investigation into the interplay between musical preferences and personality traits.

XI. Conclusion

Personalized data analytics remains uncommon, largely due to its primary beneficiaries being top-level management. Consequently, research on end-user analytics has been sparse. Exploring the correlation between music and emotional states presents its own challenges, as it's often discussed casually but lacks academic inquiry. However, identifying this gap, the researchers justified the project's significance by drawing upon existing implementations with subtle differences from the proposed system. This process provided the author with insights into bridging industrial contexts with academic research frameworks.

Emotional sentiment analysis through music listening history represents a burgeoning area with promising implications for the medical and psychotherapy domains. By delving into individuals' music consumption patterns, healthcare professionals can access nuanced insights into emotional states, preferences, and potential triggers. This rich reservoir of data empowers the development of tailored treatment plans, thereby enhancing the management of various mental health conditions. In the realm of psychotherapy, leveraging knowledge about patients' musical preferences fosters deeper therapeutic rapport and enables the customization of interventions to align with their unique needs. Furthermore, the longitudinal analysis of emotional trends derived from music listening histories offers clinicians invaluable tools for tracking progress and fine-tuning therapeutic approaches over time. Ultimately, the integration of music listening histories into medical and psychotherapeutic frameworks promises a comprehensive strategy for comprehending and addressing emotional well-being.

Spotify's current web API support, while functional, is not as comprehensive as one might desire, as outlined in their documentation. Nevertheless, ingenious workarounds were implemented to ensure the timely completion of the project. During its development, the author encountered challenges stemming from limitations within Spotify's developer account, particularly concerning the necessity to whitelist testers for system trials. Consequently, seeking a quota extension to increase API call rates and eliminate the need for user whitelisting became imperative to facilitate the platform's successful launch.

In forthcoming system enhancements, we aim to amplify the adaptability of the dual graphs and sentiment mood profile card, leveraging Spotify's [18] Web API upgrades. This enhancement will empower users with the ability to select flexible time ranges, spanning days, weeks, and months, enabling them to gain insights into their mood over broader durations. Moreover, we plan to introduce a comprehensive FAQ page to enrich the platform's usability. This resource will guide users through site navigation and illuminate the platform's purpose, ensuring a seamless and fulfilling experience for all. These enhancements will seamlessly integrate within the maintenance and support phase of our methodology, ensuring continuous refinement and adaptability, particularly in response to any changes in Spotify API endpoints in the future.

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