Gurugram University Business Review (GUBR)
Volume 6 • Issue 1 • January–June 2026
ISSN: 2582-9718 (Online)

Paywalls, Peace, and Perception

How Monetization Shapes User Experience in Mindfulness Apps

Anchal Malhotra[1] & Ajay Solkhe[2]

ABSTRACT

The mindfulness applications are now a days increasingly as scalable mental health apps; however, limited very less evidence exists on how monetization architectures shape the end user experience. This research paper investigates how freemium business models and fully free business models influence user evaluations of mindfulness applications using large scale app review. Python-based scraping tools were used for user reviews and metadata was extracted from Google Play Scraper and App Store Scraper libraries. A total of 9,03 reviews of Medito and Calm App were collected, from which 7,530 reviews were sampled and systematically preprocessed. The corpus which was textual in nature was analyzed using sentiment annotation through NVivo software, LDA (Latent Dirichlet Allocation) based modeling and thematic synthesis. Results showed that Medito is primarily evaluated through themes of therapeutic effectiveness and content accessibility. Whereas, Calm is praised for content quality and criticized for monetization related friction. This friction constitutes the dominant source of negative sentiment in the freemium model. Findings highlight business model design as a higher-order antecedent of user experience and offer actionable implications for sustainable, user-centered mindfulness app design.

Keywords: Mindfulness Applications, Digital Mental Health, Sentiment Analysis, Topic Modeling, Monetization Architecture

INTRODUCTION

The accelerated growth of mobile health (mHealth) technologies has transformed and reshaped the way well-being and mental health services are delivered, offering more accessible, scalable, and user-focused digital interventions (Torous et al., 2020; Olawade et al., 2024). Among these technologies, mindfulness apps have emerged as one of the most adopted forms of digital mental health support, providing guided meditation, sleep facilitation, breathing exercises and self-regulation programs to broad populations (Kabat-Zinn, 2003; Bakker et al., 2016; Mani et al., 2015). The evidence indicates that such mindfulness applications significantly reduce anxiety, and symptoms of depression and improves emotional regulation, positioning them as feasible complements to conventional mental health care systems (Flett et al., 2019; Huberty et al., 2019; Jayawardene et al., 2017). The usage of mindfulness applications has grown rapidly worldwide, as more individuals turn to flexible, stigma free, and cost-effective options in place of conventional mental health services (Grist et al., 2017; Lipschitz et al., 2019; Larsen et al., 2019).

One of the hallmark feature of the digital platform economy is the existence of freemium models, where the users can access core services without any charge, but premium functionalities are available through paid subscriptions (Saura et al., 2019). And at the same time, a significant number of application platforms operates on entirely free open -access principles, to penetrate the larger user base. Prior studies indicate that such monteziation strategies play a crucial role in shaping user trust, perceived benefits, and intentions to continue using the platform in the domain of health and well-being (Sama et al., 2014; Meyer & Okuboyejo, 2021).

[1] Research Scholar, University School of Management, Kurukshetra University, Kurukshetra. E-mail: anchalmalhotra09@gmail.com
[2] Associate Professor, University School of Management, Kurukshetra University, Kurukshetra. E-mail: ajaysolkhe.kuk@gmail.com; asolkhe@kuk.ac.in

Randomized Control Trials and observation studies demonstrate the app-based mindfulness interventions can reduce anxiety, stress and depressive symptoms and enhance emotional regulation (Huberty et al., 2019; Jayawardene et al., 2017). Additional research on this topic further indicates that persistent engagement is essential for reaping these benefits, with content useability and personalization evolving as critical determinants of continues use (Mani et al., 2015; Donkin et al., 2019). In parallel, systematic investigation of digital mental health applications usually assess commercially available apps across major marketplace; the Apple App store and Google Play store, using established mobile health quality criteria such as authority, complementarity, confidentiality, validity, technological functionality, usability, general information quality, and intervention characteristics (Mani et al., 2015; Lagan et al., 2020; Plaza et al., 2021).

In this study, the PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses) Model (Page et al., 2021) was used to systematically search major app marketplaces and identify two prominent mindfulness applications—one fully free and one freemium—for a better comparative analysis. Credibility and App quality were further evaluated using the Heath On the Net (HONcode/mHONCode) principles to ensure acceptable standards and ethical information provision (Ahmed et al., 2022). To advance analytical rigor, the study adopts a mixed qualitative–computational approach for large-scale examination of app review comments. Topic modelling – an automated machine-learning technique based on probabilistic models (Latent Dirichlet Allocation); was employed to uncover latent semantic structures within user-generated text (Blei et al., 2003; Jelodar et al., 2019). The reviews taken underwent thematic analysis approach which follows established qualitative procedures (Braun & Clarke, 2006), which involves systematic data cleaning, clustering of reviews into positive, negative and sentiment group validation of making clusters with accuracy by team of co-authors (Pang &Lee, 2008). Subsequent examination of dominant topics was extracted from each cluster, which were then organized into higher-order themes with sub-themes (Roberts et al., 2014; Abdelrazek, 2023). NVivo software was used for qualitative coding. For sentiment annotation, methodological transparency, and analytical reliability again NVivo was used. This study adopts a three-step study design.

Study 1: A PRISMA-guided systematic search and screening process was employed to identify prominent mindfulness applications across major app marketplaces, ensuring reliable app selection (Page et al., 2021).

Study 2: The user opinions and satisfaction were investigated through large-scale sentiment analysis of user reviews, enabling comparison between a fully free mindfulness application (Medito) and a freemium application offering both free and premium features (Calm).

Study 3: Topic modelling and thematic analysis was applied to identify latent thematic structures within user discourse. This reveal how content quality, accessibility, technical performance, monetization, and perceived value form user experience (Braun & Clarke, 2006; Elliott, 2022).

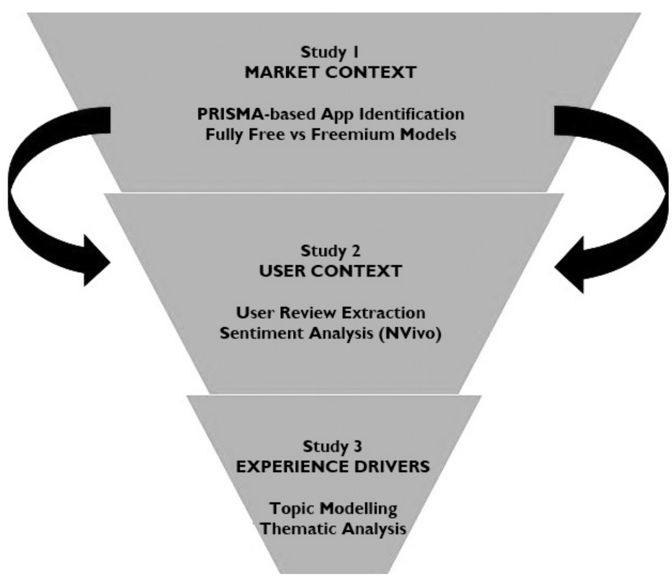

Figure 1: Multi-Stage Analytical Funnel for Comparative Evaluation of Mindfulness App Business Models
Source: Authors

LITERATURE REVIEW

The Rise and Efficacy of Mindfulness Apps

Mobile mindfulness applications have become a channel for delivering brief, scalable mental-health interventions. These apps offers guided meditation, sleep programs, and stress-reduction modules that are accessible outside clinical settings (Aydin et al., 2021). Randomised Control Trials provided evidence that these app-delivered mindfulness interventions can reduce perceived stress and improve mood in nonclinical populations; for example, a rigorously designed wait-list randomized control trial of the Calm app showed significant reduction in stress among college students following an eight-week intervention (Huberty et al., 2019). Subsequent trials have reported similar benefits for anxiety and varying symptoms of depression in the target population.

Business Models and Their Psychological Implications

On the opposite side of coin, these apps operate within a commercial app economy dominated by various strategies that are monetized; which majorly includes, principally freemium subscriptions, in-app purchases, and advertising that shape both product design and user experience (Appel, 2020).

The freemium model is one in which basic functionalities are free of cost. Advanced content is accessible via subscription cost which is a normative model for mindfulness platforms. These mindfulness apps have clear economic advantage for scaling and revenue capture. Evidence highlights few drawbacks of freemium models. Paywalls and subsequent subscription cost prompts may hamper trust of users. This sometimes leads to frustration or feelings of exclusion among the users. (Appel, 2020; ACM study on freemium harms).

User-Generated Reviews as High-Value Evidence

The reviews on app marketplaces offer a valuable source of real-world insight. The app users reflect valuable feedback from diverse background users across different devices and contexts. These reviews have been widely used to identify usability concerns, future needs, and risks in health apps (Hudson et al., 2022; Ahmed et al., 2022).

NVivo assisted computational pipelines like topic modelling, and thematic coding; automated sentiment classification. It can reliably surface both – sentiment polarity and deeper thematic drivers. This is done from large comment corpora available as datasets. NVivo is been used in research like telemedicine and other mHealth review analyses to visualize word frequencies and extract themes (Nurfikri 2022; Zhai et al., 2022). These approaches offer an appropriate balance between scalability and interpretive rigor for studying how monetization architecture affects user perceptions.

Topic Modelling and Thematic Extraction in App-Review Research

Topic Modelling couples with the human centred thematic analysis. For latent concerns and benefit in app reviews it has now emerged as a preferred approach (Ahmed et al., 2022). Previous researches examining mental-health chatbots, telemedicine platforms, and broader in mHealth portfolios show that topic models reliably separate function concerns like crashes, payments, and refund issues and from experiential themes like efficacy, embodiment ad perceived trustworthiness which can be qualitatively validated and refined through NVivo style coding (Ahmed et al., 2022; Zhai et al., 2022). This is particularly important for distinguishing monetization related complaints. The content quality or usability problems which is a key analytical need when comparing freemium versus free models.

RESEARCH GAP

Collectively, previous researches explains that mindfulness apps can deliver measurable psychological benefits and that user generated app review provide valuable insights into real world user experiences. Further, advances in text analytics such as topic modelling have enabled researchers to systematically extract sentiments and themes from large scale review datasets. However, while these studies illuminate the efficacy of mindfulness apps and methodological approaches for analysing feedback from users less attention has been paid to how different monetization architectures influence user perception and experiences. This major gap becomes particularly important given the rapid commercialization of dgital mental health platforms.

RESEARCH MODEL

This study adopts a multi stage analytical framework that integrates systematic app identification, large scale user review mining, sentiment classification, machine-learning based topic modelling and qualitative thematic analysis to examine how monetization architectures shape user experiences in mindfulness applications.

Combining computational text analytics with qualitative interpretation is increasingly recognised as a robust approach for examining large scale user generated data in mHealth research (Guzman & Maalej, 2014; Zhai et al., 2022; Ahmed et al., 2022). The overall workflow is presented below in Figure 2.

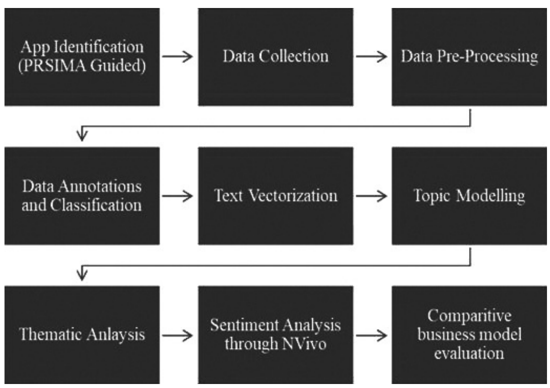

Figure 2: Workflow to Prepare Reviews for Rhematic Analysis – A Conceptual Framework
Source: Authors

App Identification (PRISMA – Guided)

A systematic search was conducted across Google Play and Apple store. Search strings included "mindfulness," "meditation," "mindful living," "calmness," and "mindful awareness." Titles and descriptions were screened for relevance.

Applications were included if they:

(a) explicitly targeted mindfulness,

(b) were available in English language,

(c) had ratings ≥ 4 stars, and

(d) had at least 5,000 user reviews.

Apps unrelated to mindfulness, non-English language apps, or apps with limited user engagement were excluded. This process yielded a set of highly popular mindfulness apps, including Calm, Headspace, Insight Timer, Simple Habit, Balance, Medito, and Smiling Mind. From this pool of apps two apps were selected as they represent contrasting monetization architectures: Medito (fully free) and Calm (freemium).

Data Collection

Following app identification and screening, user reviews and associated metadata were collected for the selected apps. In accordance with the established large scale app review mining studies (Ahmend et al., 2022; Overbode et al., 2020), user reviews were extracted directly from the Google Play Store and Apple App Store. The Python based scrapping tools, the Google Play Scrapper and Apple App Store Scraper libraries were used to extract the relevant data. All publicly available Google Play Store reviews were retrieved for the selected mindfulness applications. In case of Apple Play Store extraction was constrained by platform-imposed limits, permitting a maximum of 500 reviews per application. Reviews were initially collected for a broader set of leading mindfulness apps to establish ecosystem level context; however, in depth computational and thematic analyses were restricted to two focal applications representing contrasting monetization architectures: Medito (fully free) and Calm (freemium). For each application, a corpus of 9,063 recent users' reviews was compiled, yielding a total dataset of 7,530 reviews. Metadata which includes star ratings, review text, and review date were retained for the analysis.

To capture recent user experiences reflecting the current monetization structure of the applications reviews were taken from 1st July-31st Dec, 2025. This ensured methodological rigor and comparability across both the apps. After removing the duplicate entries and incomplete comments, a balanced sampling strategy was applied in which comparable number of reviews were randomly sampled to avoid any kind of selection bias.

Data Processing

Pre-Processing followed established protocols in app reviews mining and computational text analytics (Guzman & Maalej, 2014; Ahmed et al., 2022; Oyebode et al., 2020). Procedures included:

- Text normalization through lowercasing
- Removal of punctuation, digits, emojis and non-textual symbols
- Exclusion of non-English reviews
- Removal of extremely short or semantically vacuous comments

Such cleaning procedures are essential to improve signal-to-noise ratio and enhance topic coherence in subsequent modelling stages (Wallach, 200).

Data Sentiment Annotation and Classification

The App user provided star ratings for each of the app (1-5) as an initial proxy for sentiment polarity, and approach widely adopted in digital health analytics and app-review research (Guzman & Maalej, 2014; Ovebode et al., 2020; Ahmed et al., 2022). Reviews rated 4-5 stars were classified as positive, whereas reviews rated 1-3 were classified as negative.

Data Vectorization

Following preprocessing, reviews were transformed into numerical representations using a Bag-of-Words (BoW) Model with bigram extraction. Vectorization enables probabilistic modelling of latent semantic structures and remains a foundational step in topic modelling workflows (Wallach, 200; Blei et al., 2003). For this we used counter vectorization function from Sklenar's feature extraction module in python. The use of bigrams was done to enhance contextual sensitivity by preserving commonly co-occurring word pairs, thereby improving thematic coherence.

Topic Modelling

Traditional clustering techniques such as k-means partition observations based on nearest centroids are primarily designed for numeric features spaces, limiting their suitability for unstructured textual data (Aggarwal & Zhai, 2012). Likewise, conventional text-mining approaches rely on keyword frequency and count-based representations that often overlook contextual word usage (Silge & Robinson, 2017). Topic modelling overcomes these limitations by performing probabilistic clustering directly on textual corpora to identify latent themes from positive and negative reviews corpora separately. Topic Modelling is widely used in digital health app review analytics to uncover semantic patterns at scale (Guzman & Maalej, 2014; Oyebbode et al., 2020; Ahmed et al., 2022). The optimal number of topics was determined through iterative model estimation and interpretability assessment, balancing topic coherence, and conceptual distinctiveness.

Thematic Analysis

Within each sentiment set thematic analysis was conducted on the four dominant topics extracted from each application within each sentiment set 9positive and negative). For both the apps, taken into consideration the topic outfits were examined. Factors identification contributed positively and negatively to user experience which followed mixed computational-qualitative pipelines used in app review research (Braun & Clarke, 2006; Ahmed et al., 2022; Zhai et al., 2022). Topic labels were assigned first based on high occurring keywords and representative reviews. After these topics were analysed to derive higher order themes and sub-themes which was done through iterative coding and refinement (Braun & Clarke, 2006). This approach enabled a interpretation of how content quality, accessibility, technical performance, and monetization-related features shape user perceptions across the two contrasting business models.

To increase analytical rigor, the thematic coding process was conducted by 2 independent researchers. These researchers were very much familiar with qualitative analysis methods. Both researchers initially reviewed the topic outputs and a subset of representative reviews. The researchers then independently assigned thematic labels to extracted topics. The experts used NVivo 14. Inter-coder reliability was assessed using Cohen's Kappa coefficient to evaluate coding agreement.

The analysis yielded a kappa value of 0.82, indicating strong agreements establishing reliability thresholds (Landis & Koach, 1977). Discrepancies, if any were discussed and resolved through consensus, resulting in the final set of themes used in the analysis.

Sentiment Analysis

Sentiment analysis was conducted using NVivo 14 to classify user reviews for both the apps.

For Medito App, results indicated a strong predominance of positive sentiment – 1378 comments were categorized as moderately positive, 1315 comments were categorized as very positive, compared to 524 were categorized as moderately negative and 18 comments were categorized as very negative instances.

In contrast, Calm exhibited a polarized sentiment distribution, with 1227 comments as very positive, 1152 comments as moderately positive, 454 comments as moderately negative and 12 comments as very negative. Overall, Medito demonstrated a stronger positive sentiment profile, whereas Calm showed greater monetization-driven dissatisfaction.

Comparative Business Model Evaluation

Finally, sentiment distributions and thematic structures were compared across Medito (fully free) and Calm (freemium). Differences were interpreted considering platform model theory which particularly concerns perceived value, trust formation, accessibility, and monetization tension (Saura et al., 2019; Meyer & Okuboyejo, 2021; Linardon et al., 2024).

This comparative layer enables systematic evaluation of how monetization architecture influencers user experience within digital mindfulness ecosystems.

ANALYSIS AND DISCUSSION

Data Collection, Preprocessing, Annotation, and Vectorization

A total of 9,063 user reviews were initially available across the two focal applications-Medito and Calm. App-store user reviews are widely recognized as ecologically valid and high-value sources for examining real-world user experience and satisfaction in digital health technologies (Guzman & Maalej, 2014; Oyebode et al., 2020; et al., 2022).

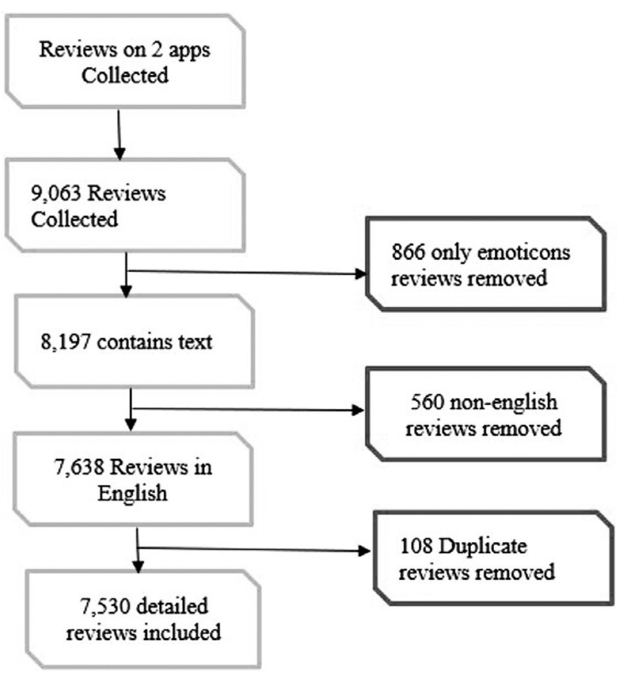

Figure 3: Workflow to Prepare Reviews for Thematic Analysis
Source: Authors

During preprocessing 312 reviews (5.78%) containing only emojis, symbols, or non-textual expressions were removed. From the remaining corpus, 184 (3.66%) written in language other than English were excluded. In addition, 1,104 reviews (21.47%) consisting solely of generic praise (e.g., “good”, “nice,” “great app”) or minimal-content comments were removed, as such reviews do not contribute meaningful analytical value (Ahmed et al, 2022; Oyebode et al., 2020) as shown in Figure 3.

Topic Extraction Model for Positive and Negative Reviews

All cleaned reviews were transformed into numerical representations using Bag-of-Words (BoW) model with bigram extraction. The output of Bow contains document-term matrices for each sentiment subset. Vectorization process enables probabilistic topic modelling by converting unstructured text into analyzable numerical form and is a foundational step in topic modelling pipelines (Blei et al., 2003; Wallach, 2006). These matrices served as the input for subsequent Latent Dirichlet Allocation topic modelling.

Topic Extraction Model for Positive and Negative Reviews for Medito and Cam App

The review corpus was stratified into two sentiment-based meta-themes (positive and negative). Topic modelling was conducted independently on each sentiment subset, as prior research demonstrates that polarity-specific topic modelling facilitates efficient and coherent identification of latent themes in large textual corpora (Piepenbrink & Gaur, 2017; Ahmed et al., 2022; Oyebode et al., 2020). The relative thematic composition of the corpus was estimated by computing document-topic probability distributions. Accordingly, each review received a vector of topic membership probabilities, and the topic with the highest probability value was used to assign the review to its dominant topic. Topics were subsequently labelled based on their most salient keywords and representative reviews. Subthemes were identified by examining recurring semantic patterns with each topic cluster.

Themes Categorization

All subthemes identified within each LDA-derived topic were consolidated under higher-order thematic categories. Although individual topics captured distinct kind of semantic patterns, abstraction into broader themes enabled systematic aggregation and comparative interpretation. Topic model assisted thematic synthesis approaches (Piepenbrink & Guar, 2017; Ahmed et al., 2022), reviews were organized into two meta-themes which were positive theme and negative theme. Lexical salience analysis indicated that "free app" constituted 4.6% of total word frequency, reflecting a very strong orientation toward meditation practice and identity. High-frequency affective expressions such as "really amazing" (1.46%), "helped" (0.75%), "recommend" (0.66%), and "pleasing" (0.60%) suggest predominantly favourable evaluations. The lexical patterns are consistent with sentiment stratification, in which positive reviews outnumbered negative reviews substantially.

Medito App- Review

Review analysis of Medito App (N = 3,630) indicates that user evaluations are structurally anchored in terms like accessibility, usability, and therapeutic outcomes. Whereas, positive themes cluster around the absence of cost barriers, non-intrusive designs, and open access, reinforcing perceived fairness and trust clearly shown in Figure 4. At the outcome level, it is seen discourse is dominated by perceived benefits related to aids in sleeping, calming effects, stress reduction, and anxiety relief, suggesting that users frame Medito primarily as a self-regulatory well-being tool rather than just a content platform.

Overall, Medito app exhibits a value-centric experiential profile in which satisfaction is driven by access and perceived impact, while negative evaluations profile in which satisfaction is driven by access and perceived impact, while negative evaluations profile in which satisfaction is majorly driven by access and perceived impact, while negative evaluations remain confined to functional performance limitations.

Calm App- Review

Review analysis of Calm (N = 3,900) indicates an experiential structure dominated by content-centric value, usability, and monetization cognition. Further "Meditations" (1.1.5%) constitutes the most frequent lexical item, underscoring that content remains the most relevant aspect of evaluation. Simultaneously, the prominence of monetization-related terms such as "subscription" (0.99%) and "premium" (0.60%) indicates that user experience is interrelated with pricing architecture.

Within this context, positive themes cluster around continuous improvements through regular updates and expanding content libraries, perceived value for money. Negative themes, however, are structurally

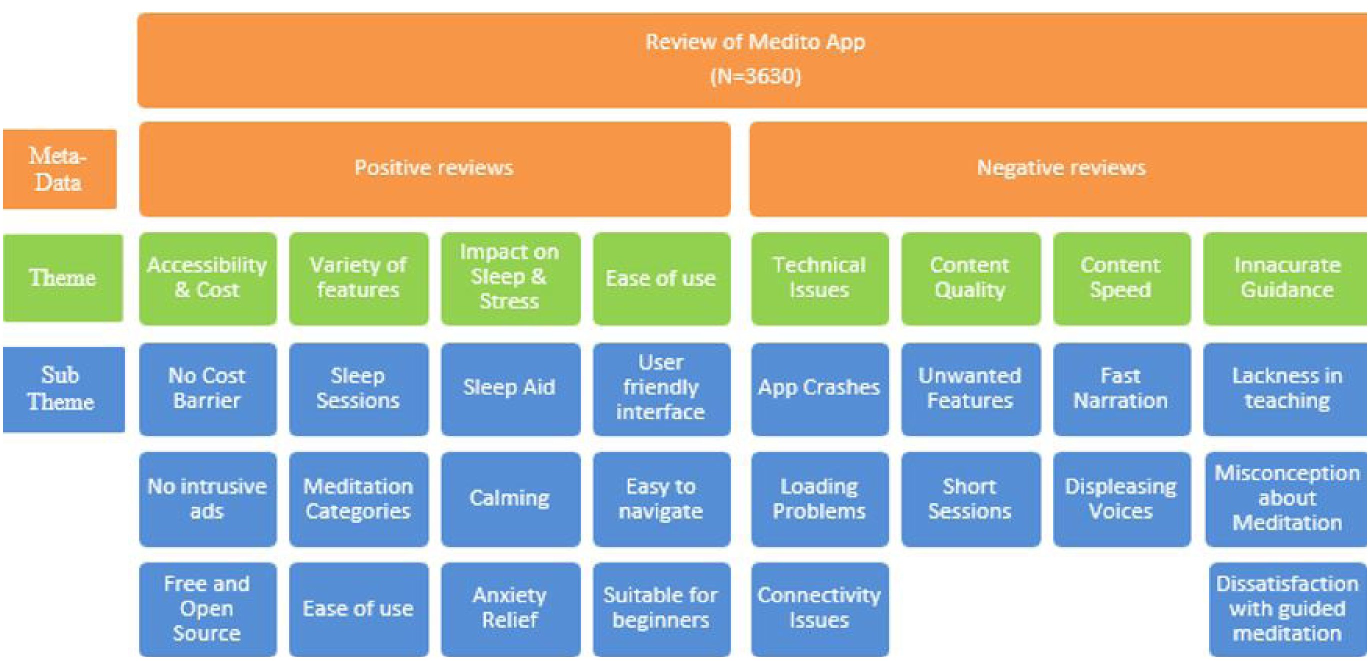

Figure 4: Review of Medito App (Free App)
Source: Authors

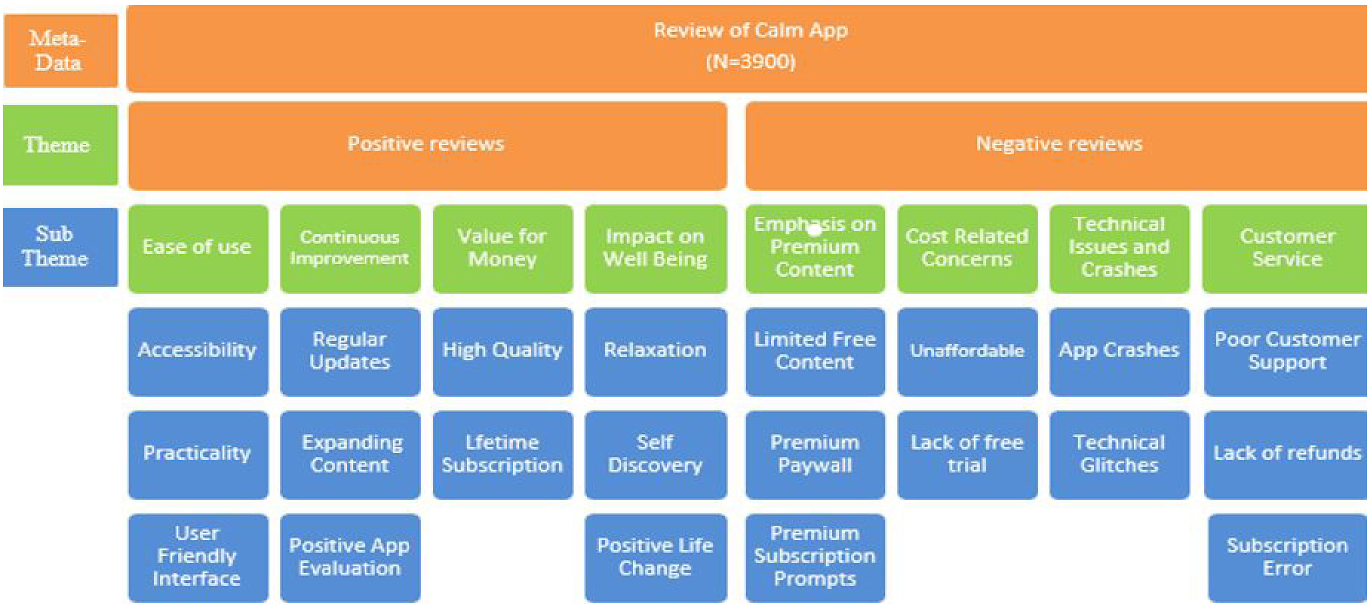

Figure 5: Review of Calm App (Freemium App)
Source: Authors

concentrated around monetization friction and transactional trust as depicted in Figure 5.

Taken together, Calm exhibits a monetization-sensitive experiential profile in which positive evaluations derive from content excellence, whereas negative evaluations are outcome pricing architecture and access constraints rather than by the therapeutic legitimacy of the mindfulness content itself.

CONCLUSION

From this study the mindfulness apps emerge as promising digital interventions. For the individuals who experience stress, anxiety, and sleep disturbances the apps under study showed positive evaluations which are majorly systematically anchored in usability and perceived content value (Flett et al., 2019).

This pattern is consistent with the prior experiential evidence which demonstrates the app-based mindfulness interventions can reduce a major level of anxiety and depressive symptoms while improvements are shown in emotional well-being and sleep quality (Flett et al., 2019; Huberty et al., 2019; Howells et al., 2016).

The identification has been done and four positive and four negative themes for each application through machine-learning-assisted thematic categorization has been done. Further, it also showed the capacity of large-scale review analytics which helped to surface latent experiential structures that extend beyond surface-level sentiment polarity. Positive themes for Medito (accessibility, functional breadth, ease of use, therapeutic impact) and Calm (content quality, usability, continuous improvement, perceived value) coverage on core determinants of digital mental health adoption identified in technology acceptance research (Davis 1989; Venkatesh et al., 2003).

Medito's fully free model appears to amplify fairness and trust. Calm's freemium model introduces cognitive trade-offs between perceived sacrifice. These findings extend perceived value theory by demonstrating that economic friction can attenuate satisfaction even when quality of content is high. (Zeithaml, 1988; Monoroe, 1990; Sweeney & Soutar, 2001).

Negative theme across both platforms is primarily operational rather than ideological in nature. It also centres on technical instability, content delivery limitations, and instructional clarity. This pattern aligns with usability theory, which emphasizes that effectiveness, efficiency, and satisfaction are fundamental conditions for sustained technology use (ISO 9241-11; Brooke, 1996)

Long waiting times, high costs, and stigma continue to constrain access to psychotherapy in many contexts (Kazdin & Blasé, 2011). It is seen that digital mindfulness tools, particularly those without financial barriers, offer a limited remedy by providing immediate but low-threshold support.

Methodologically, this study also demonstrates the value of combining sentiment stratification with probabilistic topic modelling to move beyond surface-level polarity toward theory-relevant experiential dimensions.

The positive signals across mindfulness application Medito and Calm are usability, content quality and therapeutic impact which coexist with negative issues that practical development should be prioritized. Both the platforms observed negative points which include (a) monetization friction which includes premium paywalls, opaque pricing, cancellation diificulty that undermines trust (Larsen et al., 2019; Hudson et al., 2022); (b) technical instability (crashes, connectivity failures/loading issues) that erodes retention; (c) delivery and pedagogical shortfalls (poor voice quality, fast narration, limited teaching depth); (d) customer-service and billing failures; and (e) data-governance and privacy concerns that threaten legitimacy (Torous et al., 2020; Ahmed et al., 2022)

Practically, it is recommended: (1) designing meaningful free tiers that permit therapeutic engagement without mandatory payment. It is recommended that positioning premium content as enhancement rather than gatekeeping (Perceived Value Alignment; Larsen et al., 2019); (2) instituting rigorous performance and usability QA (including SUS-style testing and automated regression checks) to eradicate crashes and loading issues (9Brooke, 1996); (3) improving instructional design and narration/voice quality through user-tested audio UX protocols; (4) ensuring transparent subscription management and accessible cancellation/refund flows; (5) embedding strong privacy-by-design and clear data-use notices to address data-sharing mistrust(Torous et al., 2020); and (6) combining RCTs wiyh ongoing ecological monitoring to evaluate both efficacy and real-world effectiveness (Linardon et al., 2024; Flett et al., 2019). Taken together, these measures will help convert positive short-term uptake into durable, and clinically meaningful engagement.

Importantly, negative evaluations were not directed toward mindfulness as a practice but toward platform design and execution. Underscoring the role of mindfulness as a practice but toward platform design and execution (Larsen et al., 2019; Torous et al., 2020).

PRACTICAL IMPLICATIONS FOR DEVELOPERS AND MENTAL HEALTH PLATFORM PROVIDERS

The findings provide important implications for future researchers, developers, and digital mental health platform providers. First, the results highlight the need of user-centred and accessible design, as sustained engagement with mental health apps depends on usability, meaningful content, and consistent user experience. Secondly, the comparison between with user trust, as excessive paywalls may reduce perceived value and satisfaction. Finally, developers should prioritize evidence-based mindfulness interventions and personalization features to improve long term engagement in digital health platforms.

LIMITATIONS AND FUTURE DIRECTIONS

The future research should move forward beyond cross-sectional review analytics towards longitudinal and multi-method designs that clarify how platforms characteristics translate into engagement and mental health outcomes. Technology integration acceptance framework with psychological mechanisms of mindfulness may help explain perceived usefulness, ease of use, and value shape adherence. (Davis, 1989; Venkatesh et al., 2003; Holzel et al., 2011). Studies should also incorporate behavioural usage logs and outcome measures to examine dosage-response relationships and attrition patterns (Linardon et al., 2024; Flett et al., 2019).

Finally, advanced computational approaches such as dynamic topic modelling could further refine app-evaluation frameworks (Piepenbrink & Gaur, 2017).

First, although this study leverages large-scale app-review analytics to capture real-world experiences, such data reflect self-selected and subjective user expressions, which may overrepresent extreme positive or negative experience and cannot substitute for causal inference. As note in the literature, RCTs remain essential for establishing clinical efficacy, whereas review-based analyses primarily illuminate adoption drivers and friction points rather than treatment outcomes.

Second, the analysis focuses on two highly utilised mindfulness applications-Medito and Calm-representing fully free and freemium monetization architectures. While this comparative design enables theoretical insight into business-model effects, the findings may not generalise to all mindfulness apps or alternative monetization configuration (e.g., ad-supported, or enterprise-sponsored models).

Third, although the study integrates sentiment stratification, probabilistic topic modelling and thematic synthesis, computational models inevitably involve parameter choices and interpretive decisions that may influence topic structures.

Finally, the study relies exclusively on user-generated review data and does not incorporate behavioural usage logs, demographics information, or longitudinal outcome measures. Consequently, conclusions about sustained engagement, dosage effect, and long-term psychological change remains inferential rather than directly observed.

REFERENCES

Abdelrazek, A., et al. (2023). *Topic modeling algorithms and applications: A survey*. Applied Soft Computing. https://doi.org/10.1016/j.asoc.2023.110000

Aggarwal, C. C., & Zhai, C. (2012). A survey of text clustering algorithms. In C. C. Aggarwal & C. Zhai (Eds.), *Mining text data* (pp. 77–128). Springer. https://doi.org/10.1007/978-1-4614-3223-4_4

Ahmed, S., Hossain, M. M., Rahman, S., & Ahmed, H. U. (2022). Mining user opinions of mental health apps from user reviews using machine learning and topic modeling. *Journal of Biomedical Informatics, 127*, 104012. https://doi.org/10.1016/j.jbi.2021.104012

Appel, G. (2020). Monetization strategies in mobile apps: Implications for consumer experience and well-being. *Journal of Interactive Marketing, 50*, 43–56. https://doi.org/10.1016/j.intmar.2019.11.002

Appel, G., Grewal, L., Hadi, R., & Stephen, A. T. (2020). The future of social media in marketing. *Journal of the Academy of Marketing Science, 48*(1), 79–95. https://doi.org/10.1007/s11747-019-00695-1

Aydin, N., et al. (2021). Effectiveness of mobile-based mindfulness interventions on stress and well-being: A meta-analysis. *Mindfulness, 12*(5), 1234–1248. https://doi.org/10.1007/s12671-020-01582-9

Aydin, S., Koçak, O., Shaw, T. A., Buber, B., Akpinar, E. Z., & Younis, M. Z. (2021). Investigation of the effect of social media addiction on adults with depression. *Healthcare, 9*(4), 450. https://doi.org/10.3390/healthcare9040450

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. I. (2016). Burnout and work engagement: The JD–R approach. *Annual Review of Organizational Psychology and Organizational Behavior, 3*, 389–411.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research, 3*, 993–1022.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Brooke, J. (1996). SUS: A "quick and dirty" usability scale. In P. W. Jordan, B. Thomas, B. A. Weerdmeester, & A. L. McClelland (Eds.), *Usability evaluation in industry* (pp. 189–194). Taylor & Francis.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 318–339. https://doi.org/10.2307/249008

Donkin, L., et al. (2019). A systematic review of the impact of adherence on the effectiveness of e-therapies. *Journal of Medical Internet Research, 21*(7), e12566.

Elliott, R. (2022). *Qualitative inquiry and research design: Choosing among five approaches* (5th ed.). SAGE Publications.

Flett, J. A. M., Hayne, H., Riordan, B. C., Thompson, L. M., & Conner, T. S. (2019). Mobile mindfulness meditation: A randomized controlled trial. *JMIR Mental Health, 6*(4), e10844.

Grist, R., Porter, J., & Stallard, P. (2017). Mental health mobile apps for preadolescents and adolescents. *Journal of Medical Internet Research, 19*(5), e176.

Guzman, E., & Maalej, W. (2014). How do users like this feature? A fine-grained sentiment analysis of app reviews. In *Proceedings of the 2014 IEEE 22nd International Requirements Engineering Conference (RE)* (pp. 153–162). IEEE. https://doi.org/10.1109/RE.2014.6912257

Hölzel, B. K., Lazar, S. W., Gard, T., Schuman-Olivier, Z., Vago, D. R., & Ott, U. (2011). How does mindfulness meditation work? Proposing mechanisms of action from a conceptual and neural perspective. *Perspectives on Psychological Science, 6*(6), 537–559. https://doi.org/10.1177/1745691611419671

Huberty, J., Green, J., Glissmann, C., Larkey, L., Puzia, M., & Lee, C. (2019). Efficacy of the mindfulness meditation mobile app "Calm" to reduce stress among college students: Randomized controlled trial. *JMIR mHealth and uHealth, 7*(6), e14273. https://doi.org/10.2196/14273

Huberty, J., Vranceanu, A. M., Carney, C., et al. (2021). A randomized controlled trial of a mindfulness meditation mobile application for depressive and anxiety symptoms. *Behaviour Research and Therapy, 138*, 103811. https://doi.org/10.1016/j.brat.2021.103811

Hudson, J. L., et al. (2022). Using app store reviews to evaluate mobile health applications: A systematic review. *JMIR mHealth and uHealth, 10*(3), e30141. https://doi.org/10.2196/30141

Jayawardene, W. P., et al. (2017). Effectiveness of mobile-based mindfulness. *JMIR Mental Health, 4*(3), e31.

Jelodar, H., Wang, Y., Orji, R., & Huang, X. (2019). Latent Dirichlet allocation (LDA) and topic modeling: Models, applications, a survey. *Multimedia Tools and Applications, 78*, 15175–15211.

Kabat-Zinn, J. (2003). Mindfulness-based interventions in context. *Clinical Psychology: Science and Practice, 10*(2), 144–156.

Lagan, S., Ramakrishnan, A., Lamont, E., Ramakrishnan, K., Frye, R., & Torous, J. (2020). Assessing mental health apps. *NPJ Digital Medicine, 3*, 1–10.

Larsen, M. E., Nicholas, J., & Christensen, H. (2019). Digital mental health interventions for anxiety and depressive symptoms. *Social Psychiatry and Psychiatric Epidemiology, 54*(7), 863–876.

Linardon, J., Coughtrey, A. E., Farrand, P., & Luberto, C. M. (2024). Effectiveness of smartphone-delivered mindfulness interventions for mental health: A systematic review and meta-analysis. *Clinical Psychology Review, 102*, 102246. https://doi.org/10.1016/j.cpr.2023.102246

Lipschitz, J. M., et al. (2019). Digital mental health interventions. *Psychiatric Clinics of North America, 42*(4), 509–520.

Mani, M., Kavanagh, D. J., Hides, L., & Stoyanov, S. R. (2015). Review and evaluation of mindfulness-based iPhone apps. *JMIR mHealth and uHealth, 3*(3), e82. https://doi.org/10.2196/mhealth.4328

Meyer, M., & Okuboyejo, S. (2021). Digital platform pricing and trust: A systematic study of digital health and wellness services. *Information Systems Journal, 31*(3), 411–437.

Monroe, K. B. (1990). *Pricing: Making profitable decisions* (2nd ed.). McGraw-Hill.

Nurfikri, A. (2022). Sentiment analysis of telemedicine application reviews using NVivo. *Procedia Computer Science, 197*, 580–587.

Oyebode, O., Alqahtani, F., & Orji, R. (2020). Using machine learning and thematic analysis methods to evaluate mental health apps based on user reviews. *IEEE Access, 8*. https://doi.org/10.1109/ACCESS.2020.3002176

Page, M. J., McKenzie, J. E., Bossuyt, P. M., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71. https://doi.org/10.1136/bmj.n71

Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval, 2*(1–2), 1–135.

Piepenbrink, A., & Gaur, A. S. (2017). Topic models as a novel approach to identify themes in content analysis. In *Academy of Management Proceedings* (Vol. 2017, No. 1, p. 11335).

Plaza, I., Demarzo, M. M. P., Herrera-Mercadal, P., & García-Campayo, J. (2021). Mindfulness apps quality assessment. *International Journal of Environmental Research and Public Health, 18*(4), 1602.

Roberts, M. E., Stewart, B. M., & Airoldi, E. M. (2014). Structural topic models for open-ended survey responses. *American Journal of Political Science, 58*(4), 1064–1082.

Saura, J. R., et al. (2019). Digital marketing and freemium models for mobile services. *Sustainability, 11*(17), 4731.

Silge, J., & Robinson, D. (2017). *Text mining with R: A tidy approach*. O'Reilly Media.

Sweeney, J.C., & Soutar, G.N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing, 77*(2), 203–220.

Torous, J., et al. (2020). Digital mental health and COVID-19: Using technology today to accelerate the curve on access and quality tomorrow. *World Psychiatry, 19*(1), 64–77.

Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Wallach, H.M. (2006). Topic modeling: Beyond bag-of-words. In *Proceedings of the 23rd International Conference on Machine Learning* (pp. 977–984). ACM.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing, 52*(3), 2–22.

Zhai, X., Zhang, M., & Chen, X. (2022). Understanding user satisfaction with telemedicine apps: A topic modeling and sentiment analysis approach. *Telemedicine and e-Health, 28*(6), 828–837.