CUSTOMER SATISFACTION THROUGH MOBILE APPLICATIONS: CONCEPTUALIZING MOBILE ATMOSPHERICS USING STRUCTURED TOPIC MODELLING

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ABSTRACT

Despite the rapid growth of mobile health applications, their evaluation has remained fragmented, often focusing on technical or clinical outcomes while overlooking experiential dimensions. This study introduces the concept of mobile atmospherics, the experiential space created by app design and interaction cues and empirically identifies its evaluative variables through Structured Topic Modelling (STM) of user reviews from leading physical and mental health apps.

By integrating metadata such as review polarity and star ratings, STM enables us to uncover how people, activity, and technology-centric evaluators influence user satisfaction, differentiating between positive and negative experiences. Our findings reveal that mental health apps are primarily evaluated through emotional support and engagement, whereas physical health apps are judged more on functionality, accuracy, and reliability.

The central contribution of this study is a validated, experience-based framework that bridges fragmented app evaluation approaches with a user-driven, data-grounded methodology. This framework not only enriches mobile marketing and consumer behavior theory but also provides actionable insights for app developers and marketers to improve personalization, feedback mechanisms, and user retention strategies. Our main contribution is extending mobile atmospherics theory by empirically identifying and validating user-driven evaluators of health apps using Structured Topic Modelling (STM).

INTRODUCTION

Mobile health applications (mHealth apps) have become central to how individuals manage physical and mental well-being. While prior research has primarily focused on technical or clinical outcomes, less attention has been paid to the experiential and atmospheric factors that shape user satisfaction and engagement. To address this gap, we conceptualize mobile atmospherics: the digital experiential space created by app design and interaction cues, and examine how its evaluative attributes influence user satisfaction.

To investigate these dynamics, we employ Structured Topic Modelling (STM). This advanced natural language processing method extends Latent Dirichlet Allocation (LDA) by incorporating document-level metadata such as review polarity and star ratings into topic prevalence estimation (Roberts et al., 2014). Prior applications of STM in consumer research (e.g., Sánchez-Franco et al., 2021) have demonstrated its value in capturing nuanced user sentiments, but its potential in the context of health applications remains underexplored. We build on this methodology to analyse user reviews of both physical and mental health apps, allowing experiential themes to emerge directly from consumer narratives.

This article contributes by (a) offering a novel application of STM to evaluate health app experiences, (b) conceptualising mobile atmospherics through the integration of retail and digital atmospherics literature, (c) empirically comparing experiential differences between mental and physical health apps, and (d) developing a practical framework for app developers and marketers to enhance personalisation, feedback, and user satisfaction. The central contribution of this paper is the empirical validation of mobile atmospheric variables using STM, positioning user reviews as a robust source for theory-driven consumer insights.

Guided by atmospherics theory, which investigates how environmental elements shape consumer experiences, our framework explores the multifaceted factors that contribute to mobile atmospherics and their consequences for satisfaction. Specifically, we address three research questions:

1. What are the key issues that affect customer satisfaction in mobile applications?
2. What are the critical variables of mobile atmospherics across physical and mental health apps?
3. How do these variables influence satisfaction, and what roles do personalization, feedback, and privacy play?

By answering these questions, this study integrates mobile atmospherics theory with empirical analysis of user reviews, identifying experiential attributes ("evaluators") that drive satisfaction with health apps. In doing so, it bridges fragmented app evaluation frameworks with a user-driven, data-grounded approach, offering both theoretical and managerial implications.

The remainder of this article is structured as follows: first, we conceptualize mobile atmospherics and review relevant literature; second, we present STM as the methodological approach; third, we analyze findings and build a theoretical framework; and finally, we discuss implications and conclude.

LITERATURE REVIEW AND THEORETICAL BACKGROUND

What is Mobile Atmospherics?

Kotler (1973) was among the earliest scholars to emphasize the significance of atmospherics in shaping consumer behavior. He conceptualized atmospherics as the strategic design of retail environments aimed at eliciting specific emotional responses from consumers, ultimately influencing their decision-making processes. This marked a pivotal shift in marketing thought, positioning the retail environment as an active and influential component of the marketing mix, beyond the traditional focus on product and price.

Subsequent research extended and refined Kotler (1973)'s insights. Turley and Milliman (2000) provided a structured framework identifying various manipulate atmospheric elements, including layout, signage, and visual aesthetics. Complementing this, Mattila and Wirtz (2001) explored the sensory dimensions of atmospherics, particularly the impact of music and scent on consumer mood and purchasing behavior. Much of this scholarship has been grounded in the Stimulus-Organism-Response (S-O-R) model proposed by Mehrabian and Russell (1974), which elucidates how environmental stimuli trigger internal emotional states that influence behavior.

Further studies reinforced the role of atmospheric cues in consumer responses. Oh et al. (2008) and Tönnis and Bolton (2013) demonstrated how intentional environmental design can encourage specific behavioral outcomes. Kaltcheva and Weitz (2006) examined the interplay between consumer motivation and arousal levels, revealing that the same atmospheric conditions may produce divergent effects depending on whether a consumer is goal-oriented or browsing. We adopt the term 'evaluators' to describe the user-perceived attributes of mobile atmospherics. While prior work has used related concepts such as evaluative attributes (Sharma & Stafford, 2000), atmospheric variables (Rayburn et al., 2022), and atmospheric elements (Bigdeli & Bigdeli, 2014), we propose 'evaluators' as a parsimonious term that captures the active role of users in judging app atmospheres. This terminology emphasizes that these attributes are not merely environmental features but are actively evaluated by consumers, The term emphasizes that users actively assess these cues rather than passively encountering them, thus affecting satisfaction and retention.

As retail increasingly migrated online, researchers began applying atmospheric concepts to digital environments. Eroglu et al. (2001) were among the first to examine how website design, particularly navigability and visual presentation, affects online consumer experience. This was followed by Hausman and Siekpe (2009), who found that responsive, user-friendly websites foster trust and drive purchase intention. Dennis et al. (2010) reconnected physical and digital spaces by studying how digital signage can enrich in-store atmospheres, illustrating the emerging convergence of online and offline retail experiences.

With the proliferation of smartphones, the scope of atmospherics has expanded to include mobile platforms. Lee and Kim (2019) explored how elements such as personalization and visual appeal in mobile shopping applications enhance emotional satisfaction and foster continued use. Building on this, Klaus (2022) introduced the OLX framework to explain how luxury retail apps create immersive digital experiences that promote brand loyalty.

Rayburn et al. (2022) advanced this discourse by introducing the concept of mobile atmospherics, or m-atmospherics. Their study applied the S-O-R model to mobile applications, revealing how design features such as intuitive layout, interactive elements, and modern visual aesthetics jointly influence perceptions of utilitarian and hedonic value. Complementing this, Richard (2005) demonstrated how Internet atmospherics shape online surfer behavior, Marriott and Williams (2018) explored perceived risk and trust in mobile shopping contexts, and Kaatz (2020) extended service quality theory into mobile commerce. Together, these works underscore the need to reconceptualize digital consumption spaces as atmospherically rich environments. These findings underscore the importance of thoughtful design in sustaining user engagement within mobile environments.

This evolving body of literature reframes mobile apps as experiential environments rather than mere transactional tools. The implications are particularly relevant in sectors like mobile health, where the design and experiential dimensions of applications remain underexplored. Despite the increasing use of mobile health (mHealth) apps, most evaluations have focused primarily on technical and clinical efficacy, often overlooking how users emotionally and experientially interact with these platforms. To bridge this conceptual gap, Table 1 synthesizes existing literature, consolidating key characteristics, evaluators, and outcomes of mobile atmospherics to guide both theoretical development and practical application.

Table 1
Synthesis of Existing Literature on Mobile Atmospherics

Retail Atmosphere	Evaluators	Theory Used	Outcome	Reference
Perceived Atmosphere	Perceived Organisation, perceived modernism, perceived style	Perceived Value	Hedonic & Utilitarian Shopping Value	(Rayburn & Voss, 2013)
Mobile Atmosphere	Hedonic shopping orientation	uses and gratification theory	Intention to reuse mobile applications	(Lee & Kim, 2019)
Offline and Online Atmosphere	Graphic Design information design	S-O-R Model	positive emotions and loyalty intentions	(Loureiro & Roschk, 2014)
M-atmospherics	organization, layout, modernism, and style	S-O-R Model	Customers' utilitarian and hedonic value affect return and flow	(Rayburn et al., 2022)
Phygital retailing	Hedonic factors- mental imagery, entertainment and aesthetics	Social exchange theory	Customer decision satisfaction	(Banik, 2021)
Luxury Retail Atmospherics	Identifying the purists, opportunists, and e-lux.	Online Luxury Experience - OLX framework	Customer experience	(Klaus, 2022)
Retail Atmosphere	Design factors Ambient factors, social factors Trialability factor	DAST framework	Shopping Behaviour	(Roggeveen et al., 2020)
Virtual Reality Retail Environment	Shopping orientation, product knowledge and involvement	Mental Imagery	Consumers product knowledge	(Zhang et al., 2024)
Experiencing Atmospherics	Moderating effect of mall experience	Hedonic, utilitarian, material and social mall experiences	In-store spending behaviour and mall loyalty	(Vilnai-Yavetz et al., 2021)
Online Atmospherics	Animated Images	Extended S-O-R Model	Emotion, cognition, processes and purchase intention	(Laroche et al., 2022)
Branded App atmospherics	Experiential Emotions	Pleasure, arousal and dominance (PAD) model	Continuous usage intention and brand loyalty	(Hsieh et al., 2021)
Mobile Apps	Extrinsic and Intrinsic Motivators		Continued willingness to use (CWU)	(Meena & Sarabhai, 2023)
Retail Atmosphere	Colour scheme, lighting, music	S-O-R framework	Desire to stay, word of mouth, shoppers' satisfaction, patronage intentions	(Elmashhara & Soares, 2022)

Reviews by Hensher et al. (2021) and Lagan et al. (2021) highlight this gap, pointing out that users place high value on features such as emotional support and personalization. After four years of research on mobile applications yet these factors are frequently marginalized in both research and design practice.

In response to this lacuna, the present study adopts a Structured Topic Modelling (STM) approach to analyze user reviews of mHealth applications. Rather than relying on predetermined evaluation criteria, this method allows thematic patterns to emerge from users' own language and experiences. The aim is to reconceptualize mHealth applications not merely as tools for health management, but as digital environments shaped by design choices that meaningfully influence user engagement, affective responses, and sustained usage.

Traditional text analysis methods, such as Latent Dirichlet Allocation (LDA), have been widely used in marketing and consumer behavior research to extract latent themes from unstructured textual data (Lindner et al., 2024). LDA assumes that each document is a mixture of topics, and each topic is a distribution over words. While effective for broad topic discovery, LDA has several limitations particularly in its inability to incorporate document-level metadata such as sentiment, rating, or context. As a result, LDA often treats all documents as context-neutral, ignoring factors that may influence topic prominence or distribution across different types of user experiences.

To address these limitations, Structured Topic Modelling (STM) has emerged as a more flexible approach. Unlike LDA, STM allows researchers to include covariates that affect both topic prevalence and topic content (Roberts et al., 2014). This capability enables a more nuanced understanding of how user characteristics such as star ratings or review polarity influence the themes that emerge from user-generated content. For instance, Sánchez-Franco et al. (2021) effectively used STM to capture user sentiment in reviews of voice-activated personal assistants, showing how different contextual variables shaped consumer perception.

Building on this methodological advancement, the present study applies STM to a large corpus of user reviews from mental and physical health applications. By doing so, we aim to empirically identify the experiential dimensions that users value and critique, what we conceptualize as 'mobile atmospheric variables'. STM's ability to link topic prevalence with review sentiment allows us to differentiate the atmospheric elements that contribute to satisfaction versus dissatisfaction.

To structure this inquiry, the study is guided by the following research questions. First, what atmospheric cues do users mention in positive and negative reviews of health applications. Second, how do atmospheric themes differ across mental and physical health applications. Third, what role does personalization play in shaping user satisfaction with these applications.

To address these questions, we classify mobile atmospherics into three experiential domains: people-centricity (e.g., assistance, responsiveness), activity-centricity (e.g., purpose alignment, clarity), and technology-centricity (e.g., interface design, access). These domains are further moderated by personalization and feedback loops, which shape the intensity and outcome of user experiences across different app contexts.

While prior literature has conceptualized atmospherics in retail, online, and mobile contexts, evaluations of mHealth apps remain fragmented and largely outcome-driven. To capture the experiential variables that users themselves highlight, a method is needed that goes beyond pre-defined criteria and allows themes to emerge from user narratives. Structured Topic Modelling (STM) offers this capability by extracting latent topics while integrating contextual metadata such as review polarity and ratings. Accordingly, we adopt STM to identify and validate the atmospheric evaluators of mobile health applications.

Table 2
Conceptualization of Mobile Atmospherics and Contribution to Theory and Practice

	Framework Elements	Contribution to theory	Practical implications
What is mobile atmospherics?	**Critical Characteristics** • Defines and designs the mobile space consciously. • Produces emotional effects on the consumers. • Provides sensory and peripheral cues to consumers	Presents a comprehensive conceptualization of the mobile space that connects fragmented literature that studied mobile applications in isolation	Identifies the critical characteristics marketers need to remember while creating the mobile application atmosphere.
What are the evaluators of mobile atmospherics?	• People Centricity – Support, Solution, Assistance, Interactions		
	• Activity Centricity – accuracy in the purpose of the mobile application,		
	• Technology Centricity- Interface, Access, latest technology, usage		
What is the consequence of appropriate atmospheric evaluators?	• Review, Responses & Recommendations • Satisfaction, Dissatisfaction • Appreciation and Word of Mouth	The consequences are moderated by personalization and a feedback loop to enhance the mobile application's effects and retention.	Identifies the evaluators that can help marketers create the atmosphere that will help consumers stick to the application for longer and eventually be loyal

With the conceptual foundation in place, the next section outlines the methodological choices made in this study. We explain the data acquisition process, the rationale for selecting health app reviews, and the configuration of Structured Topic Modelling (STM) to capture experiential evaluators.

Theoretical Framework

While prior research has conceptualised atmospherics in retail, online, and mobile contexts, evaluations of mHealth applications remain fragmented and largely outcome-driven. Much of the scholarship in this domain has prioritised clinical efficacy or technical accuracy while overlooking how users emotionally and experientially engage with these platforms (Hensher et al., 2021; Lagan et al., 2021). To address this gap, we advance a framework of mobile atmospherics grounded in user evaluation. This framework draws on the Stimulus–Organism–Response (S–O–R) paradigm (Mehrabian & Russell, 1974) and the Pleasure–Arousal–Dominance (PAD) model of emotional states (Russell & Mehrabian, 1977), adapting them to the digital and interactive affordances of mobile health applications.

From Attributes to Evaluators

In traditional consumer behaviour research, concepts such as evaluative attributes (Sharma & Stafford, 2000), atmospheric variables (Rayburn et al., 2022), and atmospheric elements (Bigdeli & Bigdeli, 2014) have been widely used to describe environmental cues. However, these terms often imply a passive reception of stimuli. We introduce the term evaluators to emphasise that users are not merely recipients of mobile atmospheric cues but active judges who interpret, assess, and respond to them in context. This linguistic and conceptual shift underscores the co-construction of experience: app design provides attributes, but meaning emerges only when users evaluate them.

Accordingly, we distinguish three categories of evaluators. People-centricity captures support, empathy, and interpersonal assistance embedded in app design; activity-centricity reflects clarity, accuracy, and alignment of app functions with user goals; and technology-centricity includes interface aesthetics, accessibility, connectivity, and innovative features. Each of these domains interacts with moderators such as personalisation and feedback loops, which can amplify or attenuate user perceptions. The outcome of this evaluative process is expressed in consequences such as satisfaction, dissatisfaction, continued engagement, or recommendations.

Integration of S–O–R and PAD

This framework extends the S–O–R paradigm by specifying evaluators as the “organism” component—internal cognitive–affective appraisals that mediate the relationship between mobile atmospheric stimuli (e.g., design features, layout, interaction quality) and behavioural responses (e.g., satisfaction, loyalty, retention). The PAD model offers additional explanatory depth by conceptualising how evaluators shape emotional states. For example, responsive support in mental health apps may heighten pleasure and reduce arousal associated with anxiety, while accurate tracking in physical health apps may enhance a sense of dominance or control over health routines (Hsieh et al., 2021; Loureiro & Roschk, 2014). Together, the S–O–R and PAD perspectives clarify how evaluators transform app features into affectively charged experiences that shape behavioural outcomes.

Figures 1 and 2 illustrate this conceptual framework in practice. Figure 1 presents the Attributes–Evaluators–Consequences model for mental health applications, highlighting the salience of interpersonal support, interaction, and affective responsiveness as central evaluators. Figure 2 contextualises the framework for physical health applications, where evaluators such as connectivity, accuracy, and technological reliability dominate user judgments. Across both models, personalisation and feedback emerge as moderating mechanisms that intensify user engagement, while satisfaction and dissatisfaction function as core consequences shaping retention and advocacy.

By situating evaluators at the centre of the mobile atmospheric process, this framework provides a systematic means of understanding user-driven judgments in mHealth contexts. It contributes theoretically by clarifying the organismic processes within S–O–R and empirically by specifying how evaluators differ across mental and physical health applications.

Figure 1
Theoretical Framework for Mental Health Mobile Applications

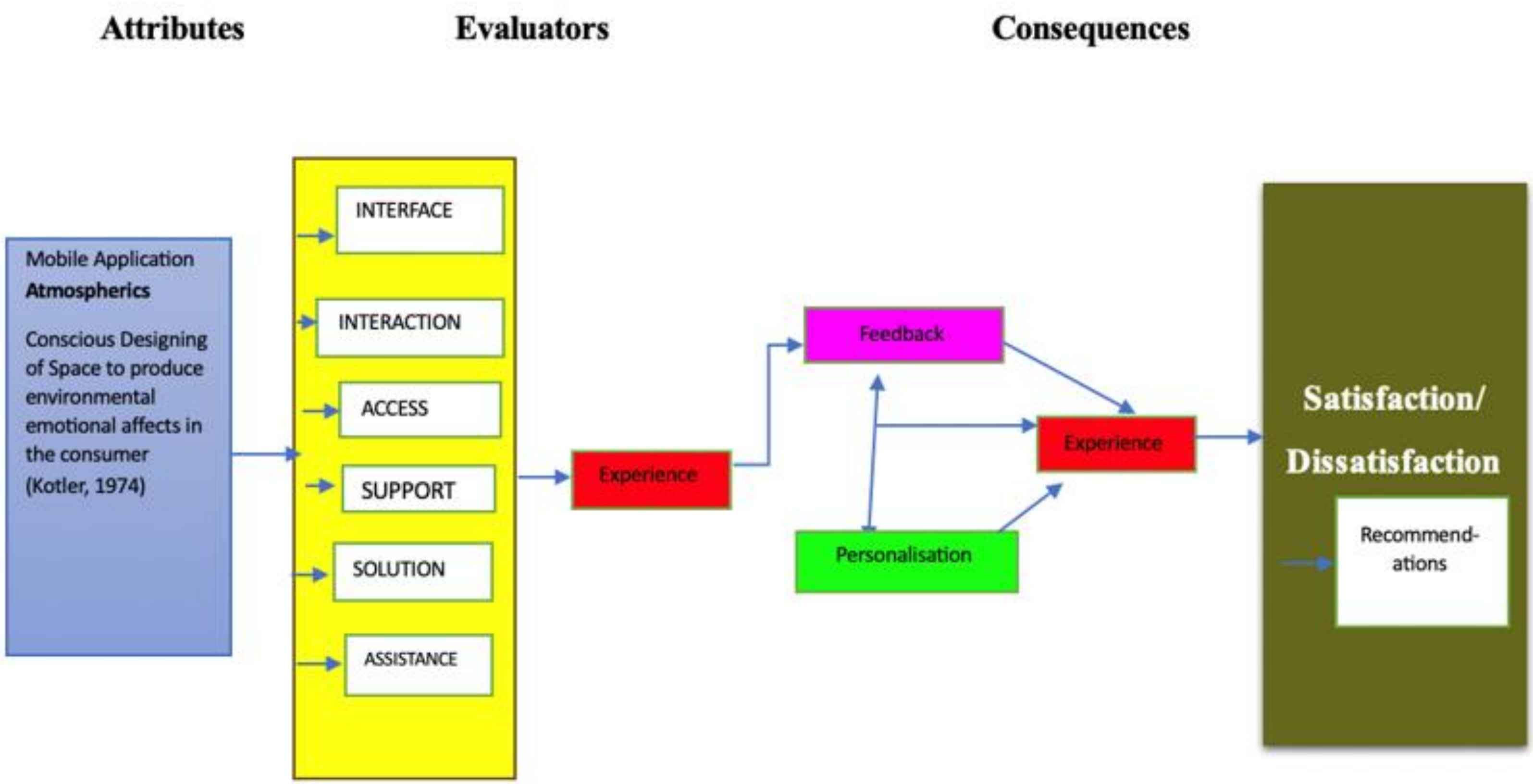
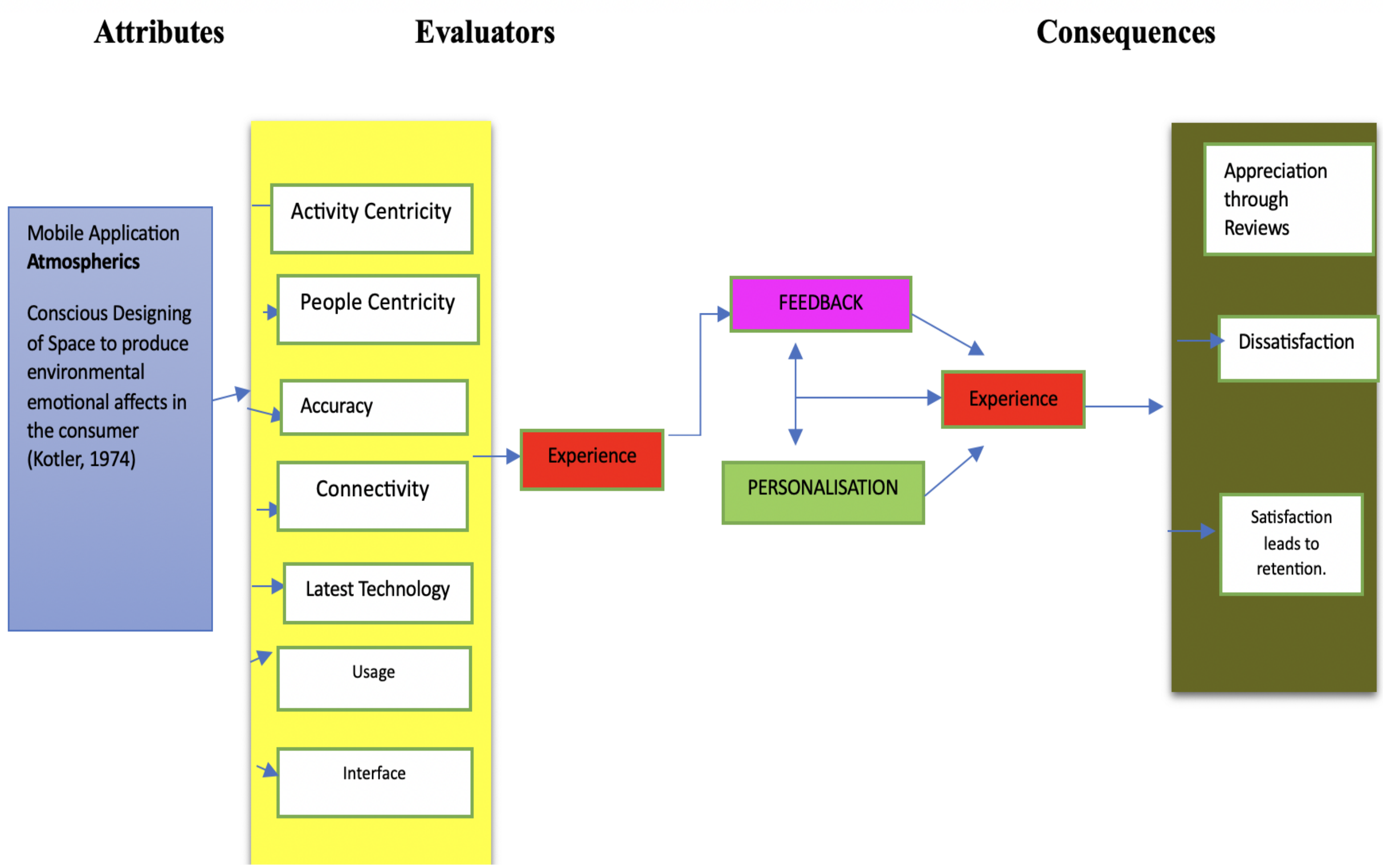


Figure 2
Framework of Mobile Atmospherics for Physical Health Applications



In sum, the proposed framework reconceptualises mobile atmospherics as a user-driven evaluative process, shifting emphasis from static app attributes to active interpretation by consumers. This reframing advances theoretical clarity by positioning evaluators as the mediating organismic states within the S–O–R paradigm, further enriched through the PAD dimensions of pleasure, arousal, and dominance (Mehrabian & Russell, 1974; Russell & Mehrabian, 1977). As illustrated in Figures 1 and 2, the framework specifies how people-, activity-, and technology-centric evaluators, moderated by personalisation and feedback, translate design attributes into behavioural consequences such as satisfaction, loyalty, and sustained usage. Beyond its conceptual contribution, the framework also provides a practical schema for app designers and marketers to align experiential design with user expectations by embedding empathy, clarity, and technological reliability into mobile health environments.

This theoretical foundation directly informs the methodological design of the present study. By applying Structured Topic Modelling (STM) to large-scale user reviews, we empirically identify and validate the evaluators outlined in the framework, enabling us to examine how users interpret mobile atmospherics in both mental and physical health contexts.

Methodology

It is known that most application downloads happen through the Google Play Store (Sensor Tower & Tech Crunch, 2022). Hence, we chose the top-rated five physical and mental health applications from the Google Play Store. Marketers need to understand the customer's perspective because curating any application that does not satisfy the customer will result in failure to achieve the desired results.

The Google Play Store has been the central area for customer reviews, as each application is rated and reviewed by customers who download it. Google Play Store is another marketplace of applications. Customer reviews on the application, in turn, help prospective customers in decision-making. Therefore, we chose the reviews as the data source of this study. Several studies have examined Google Play Store reviews to understand customer expectations of mobile applications (Kumar et al., 2023; Sánchez-Franco et al., 2021). Marketers and researchers must know customer opinions to identify the evaluators of a mobile application that enhances customer satisfaction. This study used natural language processing (NLP) techniques, especially the novel Structural Topic Modelling (STM), to comprehend customer opinion.

Data Acquisition and Preparation

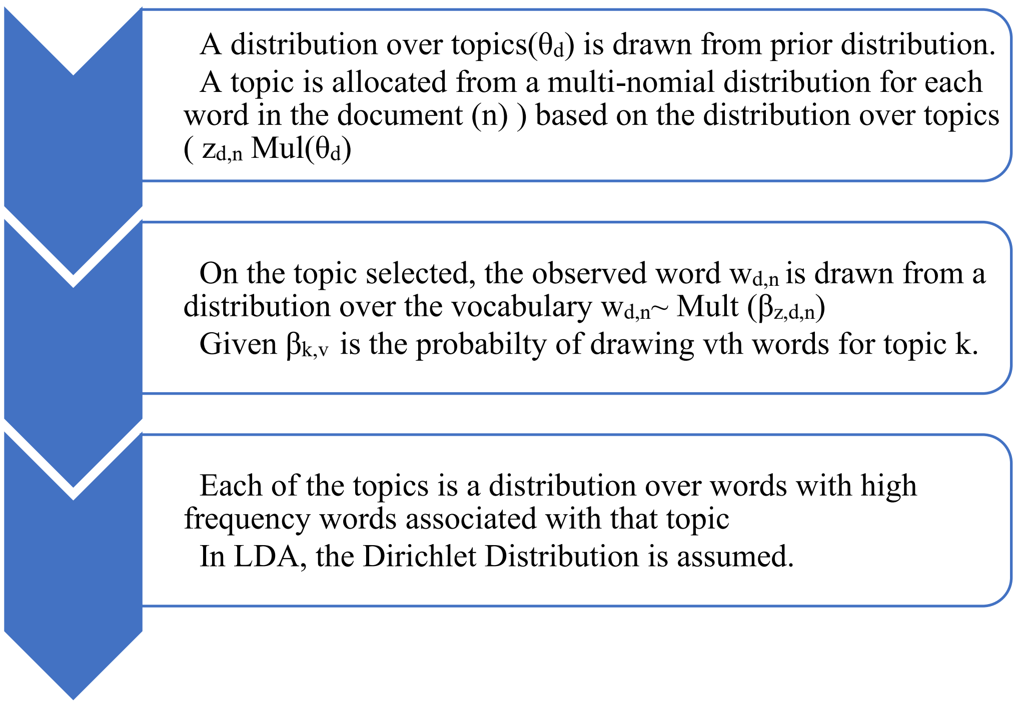
Customer reviews from the top five physical health applications and five mental health applications (as per rating) were scraped using Selenium between May 2022 to July 2024. The data was obtained using Java scripts and was divided into data, textual data and star ratings. Star review ratings were arranged on a 1–5 Likert scale. R language was used to clean and remove duplicate, unstructured data, numbers, arrows and symbols irrelevant to the process. Furthermore, the reviews were filtered for non-English language, and 1,360,000 and 50,000 were finalized for physical and mental health applications, respectively. The next step involved data preparation, including transforming all data to lowercase, tokenizing and lemmatizing the terms, stemming, and removing all stop words, punctuations, and numbers. Lemmatizing refers to grouping words with a similar tree or origin to ensure they are analyzed quantitatively (Sánchez-Franco et al., 2021). The data is cleaned to remove terms shorter than 3 characters. The research followed the methodology suggested by Sánchez-Franco et al. (2021).

Topic Modelling and Justification for STM

Customer opinions are best understood through reviews and ratings (Kumar et al., 2023). Such texts can be analysed through manual content analysis or computer-based text analysis (Hu et al., 2019). With the exponential growth in online customer reviews (OCR), it is increasingly infeasible to process large-scale data manually. Hence, statistical techniques like topic modelling are used to handle and analyze unstructured text.

Traditional text analysis methods, such as Latent Dirichlet Allocation (LDA), have been widely used in marketing to extract latent themes from large volumes of unstructured data (Blei et al., 2003). However, LDA does not accommodate metadata such as user sentiment or review rating, thereby limiting its ability to link topics with context-specific variables (Kumar et al., 2023). Figure 1 visually outlines this limitation by contrasting the basic LDA framework with the enhanced capabilities of Structural Topic Modelling (STM).

Figure 3
Basics of Natural Language Processing



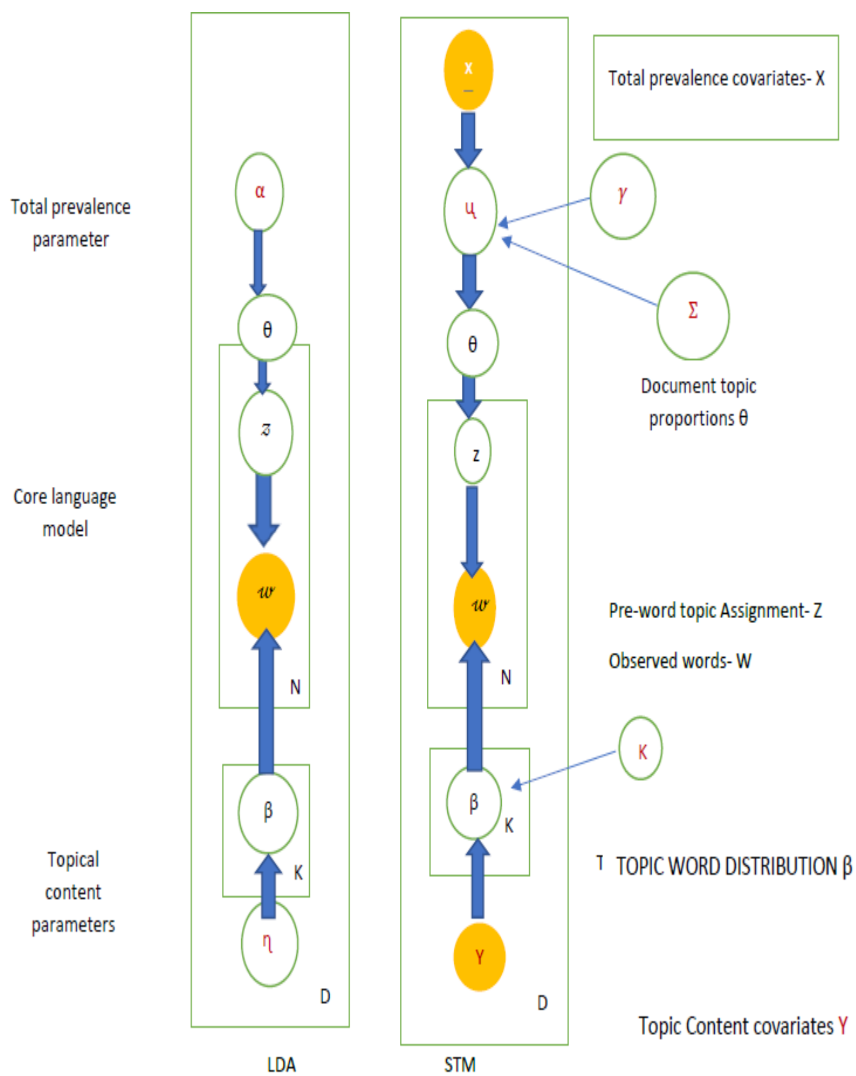
To overcome these limitations, we adopted Structural Topic Modelling (STM), a recent advancement that introduces covariates directly into the topic modelling process (Roberts et al., 2014). STM not only identifies the latent themes within textual data but also estimates how these themes vary across document-level metadata such as sentiment and star rating. This capability makes STM particularly suited for analyzing health app reviews, where differences in tone and content between positive and negative feedback are critical to understanding user satisfaction.

As mentioned above, both STM and LDA are Bayesian generative topic models that assume each topic is a distribution of words and each document is a collection of topics (Blei, 2012). However, STM introduces document-level structure information to influence topic prevalence (also called topic proportion) and topic content (also called topic-word distribution), which assists in unravelling how covariates affect textual data (Hu et al., 2019). Figure 4 illustrates this distinction clearly, contrasting the standard LDA model with the STM approach that integrates covariates such as review rating and sentiment into the estimation process.

This visual clarification reinforces the rationale for choosing STM in this study. It enables us to model how review rating and polarity interact to affect the thematic composition of user reviews, thus uncovering which topics are more likely to appear in positive or negative feedback. This level of granularity would not be achievable with LDA.

With the methodological foundation established, we now explain how STM was configured to reveal user satisfaction patterns across app categories.

Figure 4
Difference Between LDA and STM



STM MODEL SETUP

The topic prevalence parameter is the significant difference between LDA and STM. The STM algorithm allows researchers to discover topics and correlate them to estimate their relationship to document metadata (Sánchez-Franco et al., 2021). Researchers can modulate the topic prevalence parameters by adding covariates to affect the topic proportion of the document (He et al., 2020; Sánchez-Franco et al., 2021).

This research aims to identify the key issues consumers discuss in the reviews. We further identify the proportion of the identified topics in positive and negative reviews. Therefore, we model review extremities, topic words and the topical prevalence parameter μ of STM. Henceforth, the parameter then determines the document-topic proportion θ. STM uses a linear model to determine the relationship between the document-level covariate and topical prevalence parameter μ.

We perform STM to identify the proportion of each topic linked to negative and positive reviews. We introduce a dummy covariate 'Negative' to our data frame: Negative = 0 for a positive review and Negative = 1 for a negative review. Consistent with the literature (Hu et al., 2019), this method helps identify the proportions of a topic; for example, if the proportion of the topic is higher in positive reviews than in negative reviews, such a topic is identified as a positive review. For the benefit of marketers and researchers, we must understand the topics of adverse effects; hence, we identify the negative reviews in this step.

STM extends LDA by modelling topic prevalence as a function of document-level covariates (Roberts et al., 2014). In our case, covariates included review polarity (positive/negative), star rating (1–5), and their interaction. Equation 1 formalises this as a Generalised Linear Model (GLM):

$$Prevalence=g(Negative,Rating,Negative\times Rating)Prevalence=g(Negative,Rating,Negative\times Rating)$$

where gg is the logit link. This allows us to estimate how the likelihood of each topic varies across different sentiment–rating combinations, providing a more nuanced interpretation than unsupervised LDA.

Following Roberts et al. (2014), STM can be expressed as a Generalized Linear Model where topic prevalence is regressed on document-level covariates with a logistic link. In our case, covariates included star rating, review polarity, and their interaction. This specification allowed us to examine not only whether a topic appeared, but whether its probability of appearance shifted systematically between, for instance, low-rated negative reviews versus high-rated positive ones. This covariate-sensitive modelling provides richer interpretability than unsupervised LDA, where all documents are treated as exchangeable and context-neutral.

To validate topic quality, we computed two standard coherence metrics: UMass (–0.62) and CV (0.48). Both values fall within acceptable thresholds reported in prior marketing applications of STM (Sánchez-Franco et al., 2021). Beyond statistical validation, we conducted a human coding exercise in which two independent coders reviewed topic-word lists and suggested labels. Inter-coder agreement reached 85%, with disagreements resolved through consensus discussion. This dual validation process, quantitative coherence, and qualitative coder agreement ensure both semantic interpretability and theoretical robustness of the identified topics.

Having established the methodological foundation, we now turn to the empirical findings. The STM analysis generated 30 topics for each of the mental and physical health apps (Tables 3 and 4, respectively), which we interpret using representative keywords and review excerpts. These topics are then organised into experiential clusters to highlight common themes, followed by sentiment-based prevalence shifts and cross-category comparisons.

The following section presents the results of this analysis. We first describe the thematic clustering of topics into experiential dimensions, then identify the topics through STM, and then examine differences across sentiment polarity, and finally compare patterns between physical and mental health apps.

RESULTS

The STM analysis revealed structured patterns in user feedback across both physical and mental health applications, highlighting how users articulate satisfaction and dissatisfaction through experiential attributes. A total of 30 topics were extracted for each category, which were subsequently labelled based on the most representative words and review excerpts. Table 3 and Table 4 present these topics, which were further organised into five overarching experiential dimensions grounded in mobile atmospherics theory and the stimulus–organism–response (S–O–R) framework, thereby linking textual signals with established consumer behaviour constructs.

Topic names were assigned through a dual process of algorithmic clustering and interpretive validation. Discriminating words from STM frequency lists provided statistical anchors, while independent coders conducted interpretive reviews to ensure theoretical alignment. For instance, in mental health apps, Topic 15 (Positiveness) contained high-frequency words such as breathing, amaze, reframing, method, and technique. Drawing on cognitive reframing theory, this cluster was labelled “Positiveness” because it represented strategies for reinterpreting stressful experiences. Similarly, in physical health apps, Topic 28 (Motivation for Fitness) clustered words such as workout, motivation, goal, and track, aligning with motivational framing literature as drivers of persistence.

Beyond individual topics, comparative prevalence patterns emerged. Mental health apps displayed a higher proportion of emotionally framed topics (around 40%), including Panicking, Nervous, and Judgemental. In contrast, physical health apps showed a greater concentration of functional topics (approximately 45%), such as Technical Issues, Workout Tracking, and Goal Customisation. Both app categories prominently featured personalisation-related topics (25–30%), underscoring adaptive functionality as a universal determinant of satisfaction.

Figures 5 and 6 illustrate topic prevalence shifts across positive and negative reviews. In mental health apps, negative sentiment was associated with Interface (Topic 28), Grievances (Topic 29), and Manipulating (Topic 19), while positive sentiment centred on Therapy (Topic 27), Satisfaction (Topic 25), and Positiveness (Topic 15). In physical health apps, dissatisfaction was linked to Accuracy (Topic 3), Connectivity (Topic 4), and Technical Issues (Topic 20), whereas positive sentiment clustered around Appreciation (Topic 25) and Transformation (Topic 26).

Figures 5 and 6 present topic correlation patterns. In mental health apps, Guiding (Topic 21) and Response (Topic 22) were positively correlated, suggesting that effective guidance enhances perceived responsiveness, while Guiding was negatively correlated with Panicking (Topic 6), indicating that personalisation may reduce anxiety. In physical health apps, Data Integration (Topic 15) correlated positively with Fitness (Topic 16) and Consistency (Topic 13), underscoring the importance of synchronised features for reliable fitness outcomes.

Table 2
Topics from Mental Health Apps

Topic Number	Topic Name	Representative Words	Theoretical Underpinning
1	Well-being	Helping, better, really, already, stress, helpful, happiness, totally, amaze, help	Personalisation and Customisation
2	Recommendation	Amaze, helpful, understand, really, situation, sometimes, someone, starting, recommend	Content Quality and Feedback
3	Access	Information, option, personal, anybody, profile, unless, whatever, password, honestly, without	Usability and Navigation
4	Services	Helpful, really, positive, service, access, therapist, memory, mentally, emotionally, deduct	Usability and Navigation
5	Assistance	Talking, penguin, thought, relief, working, person, negative, relief, help	Usability and Navigation
6	Panicking	Burden, communication, express, panic, people, app, emotion, final	Emotional Support and Motivation
7	Annoying	Differ, open, serious, show, scream, annoy, journey, light, weird	Emotional Support and Motivation
8	Doubtful	Could not, book, bed, teenage, esteem, doubt, place, suggest, went, constant	Emotional Support and Motivation
9	Interaction	Helpful, exercise, install, therapist, superb, mental, health, follow, habit	Personalisation and Customisation
10	Feedback	Better, help, experience, though, exercise, helpful, love, intuitive, initially	Content Quality and Feedback
11	Judgemental	Hand, depress, instruct, judge, laugh, told, vent, tired	Emotional Support and Motivation
12	Audio	Long, reduce, explain, sound, work, volume, person, stress, artificial, voice	Personalisation and Customisation
13	Nervous	Quick, guide, frustrate, fear, deep, resource, respond	Emotional Support and Motivation
14	Comprehensive	Ground, breaking, encourage, helpful, comprehensible, initiative	Interface Aesthetics and Design

15	Positiveness	Breathing, amaze, reframing, thought, method, technique	Emotional Support and Motivation
16	Vocalise	Helpful, need, thanks, lovely, friendly, provide, vocalize	Personalisation and Customisation
17	Regret	Purchase, paid, package, confuse, repeat, store, unhelpful	Content Quality and Feedback
18	Useless	Suck, bad, hesitate, bore, anger, useless, worst	Content Quality and Feedback
19	Manipulating	Mindset, push, manipulate, horrible, away, slow	Content Quality and Feedback
20	Reviews	Recommend, helpful, stress, problem, confident, dealing	Content Quality and Feedback
21	Guiding	Listening, judging, whenever, direction	Personalisation and Customisation
22	Response	Helpful, comfort, advice, download, anxiety, problem	Content Quality and Feedback
23	Conversation	Thought, amaze, feeling, thanks, penguin, amount	Personalisation and Customisation
24	Solution	Helpful, decide, YouTube, struggles, suicide, good, thank you	Usability and Navigation
25	Satisfaction	Health, awesome, love, talking, simple, meeting, colours	Content Quality and Feedback
26	Skeptic	Genuine, generic, overwhelmed, doubt, prefer, hate, trust	Content Quality and Feedback
27	Therapy	Activity, therapy, caring, information, person, texting	Emotional Support and Motivation
28	Interface	Download, lock, confuse, provide, access, problem	Interface Aesthetics and Design
29	Grievances	Problem, talking, helpful, perfect, option	Content Quality and Feedback
30	Support	Struggle, focus, engage, everyday, say	Emotional Support and Motivation

Table 3
Topic Names for Physical Health Apps

Topic Number	Topic Name	Representative Words	Theoretical Underpinning
1	Experience	Great, helpful, smooth, progress, really	Usability and Navigation
2	Appreciation	Excellent, thankful, like, enjoy, superb, useful	Emotional Support and Motivation
3	Beginner Friendly	Beginner, easy, start, guide, simple	Usability and Navigation

4	Connectivity	Sync, device, wearable, issue, connection, link	Usability and Navigation
5	Progress	Track, milestone, achieve, measure, consistent	Personalisation and Customisation
6	Accuracy	Accurate, wrong, miscount, error, step, calorie	Content Quality and Feedback
7	Usage	Install, update, usage, crash, bug	Usability and Navigation
8	Transformation	Weight, loss, transform, shape, goal, fitness	Emotional Support and Motivation
9	Latest Technology	AI, innovation, new, advanced, update	Interface Aesthetics and Design
10	Encouragement	Motivate, inspire, goal, positive, keep going	Emotional Support and Motivation
11	Errors in Tracking	Count, error, calorie, misread, inconsistency	Content Quality and Feedback
12	Workout Tracking	Workout, session, log, plan, training	Personalisation and Customisation
13	Motivation	Motivation, fitness, track, energy, push	Emotional Support and Motivation
14	Layout Design	Layout, screen, navigation, clutter, look	Interface Aesthetics and Design
15	Payment Issues	Subscription, billing, refund, charge, hidden	Content Quality and Feedback
16	Functionality	Feature, update, missing, function, crash	Usability and Navigation
17	Goal Customisation	Goal, personal, adjust, level, flexibility	Personalisation and Customisation
18	Transformation 2	Achieve, success, body, motivate, satisfaction	Emotional Support and Motivation
19	Grievances	Complaint, frustrated, bad, poor, disappointed	Content Quality and Feedback
20	Technical Issues	Bug, crash, error, unstable, update	Content Quality and Feedback
21	Feature Update	Update, new, add, option, removal	Interface Aesthetics and Design
22	Adaptive Feedback	Adapt, correct, learn, personalised, adjust	Personalisation and Customisation
23	Reliability	Reliable, stable, smooth, consistent, performance	Usability and Navigation
24	Transformation 3	Fitness, change, progress, weight, lifestyle	Emotional Support and Motivation
25	Beginner Issues	Beginner, hard, confusing, difficult	Usability and Navigation

26	Frustration	Irritate, annoyed, problem, waste, glitch	Content Quality and Feedback
27	Transformation 4	Goal, achieve, proud, fitness, motivate	Emotional Support and Motivation
28	Motivation Fitness	Workout, goal, track, motivate, habit	Emotional Support and Motivation
29	Inefficiency	Slow, lag, unresponsive, inefficient	Usability and Navigation
30	Supportive Tools	Tools, guide, additional, resource, effective	Personalisation and Customisation

Cross Thematic Insights:

Emotional salience is domain-dependent: Emotional support accounts for nearly 40% of mental health topics but only 15% in physical health, suggesting that emotional resonance is indispensable in therapeutic contexts. Personalisation is universally valued but asymmetrically weighted: While both app types show 25–30% prevalence of personalisation, its absence is costlier in physical apps due to goal-tracking expectations. Feedback is interpreted differently: In mental health apps, poor feedback signals a lack of authenticity and empathy, whereas in physical health apps it is primarily a technical shortcoming.

Topic Prevalence and Sentiment Shifts

Figures 5 and 6 present topic prevalence changes when transitioning from positive to negative reviews. In mental health apps (Figure 5), negative sentiment was primarily associated with topics such as interface (Topic 28), grievances (Topic 29), and manipulation (Topic 19). Conversely, themes like therapy (Topic 27), satisfaction (Topic 25), and positiveness (Topic 15) appeared predominantly in positive reviews. Personalisation components (guiding, conversation) were strongly associated with positive sentiment.

In physical health apps (Figure 6), negative reviews highlighted accuracy (Topic 3), connectivity (Topic 4), interface (Topic 8), feature updates (Topic 21), and technical issues. These relate to app malfunctions, compatibility, and poor data syncing. Positive sentiment was more likely in topics such as appreciation (Topic 25) and transformation (Topic 26), underscoring the importance of seamless and consistent app experiences.

Thematic Clusters

Usability and Navigation: Usability-related topics accounted for nearly one-fifth of total discussions. In mental health apps, Access (Topic 3), Services (Topic 4), Assistance (Topic 5), and Interface (Topic 28) highlighted login issues, profile setup, and confusion in connecting with therapists. These were predominantly negative (around 70%), indicating the importance of intuitive onboarding for vulnerable users. In physical health apps, parallel concerns emerged with Connectivity (Topic 4), Usage (Topic 7), and Interface (Topic 28). Here, glitches and syncing failures were emphasised in utilitarian terms (accuracy, speed, device compatibility), reflecting a functional framing of usability.

Emotional Support and Motivation. Emotional dimensions dominated mental health apps, representing nearly 40% of topics. Negative affect was reflected in Panicking (Topic 6), Annoying (Topic 7), Doubtful (Topic 8), Judgemental (Topic 11), and Nervous (Topic 13), often surfacing when apps felt robotic or unempathetic. Positive affect was captured by Positiveness (Topic 15), Therapy (Topic 27), and Support (Topic 30). In physical health apps, emotional resonance was weaker (15%) but present in Motivation for Fitness (Topic 28) and Encouragement (Topic 13), signalling instrumental rather than affective motivation.

Figure 5
Shifts in Positive and Negative Topics in Mental Health Apps

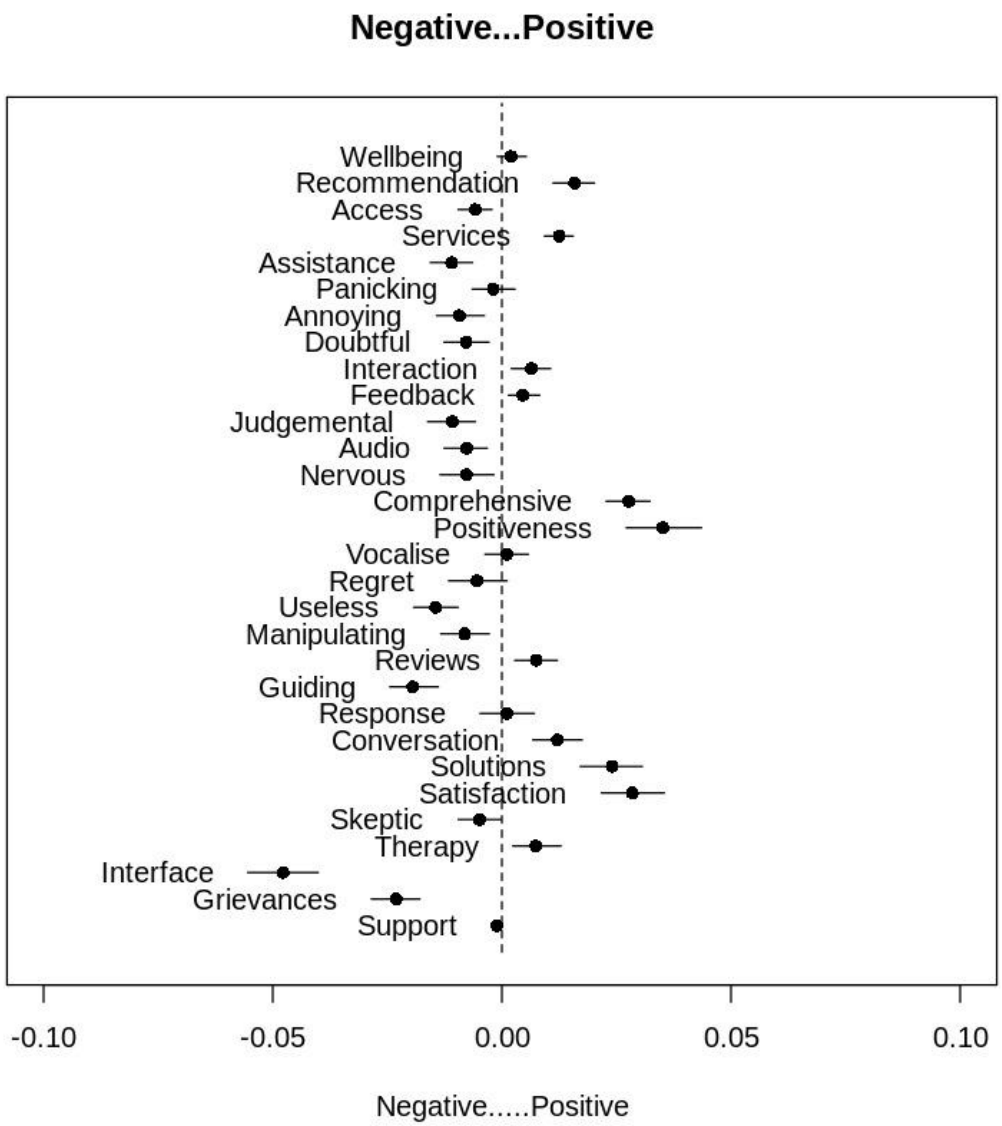
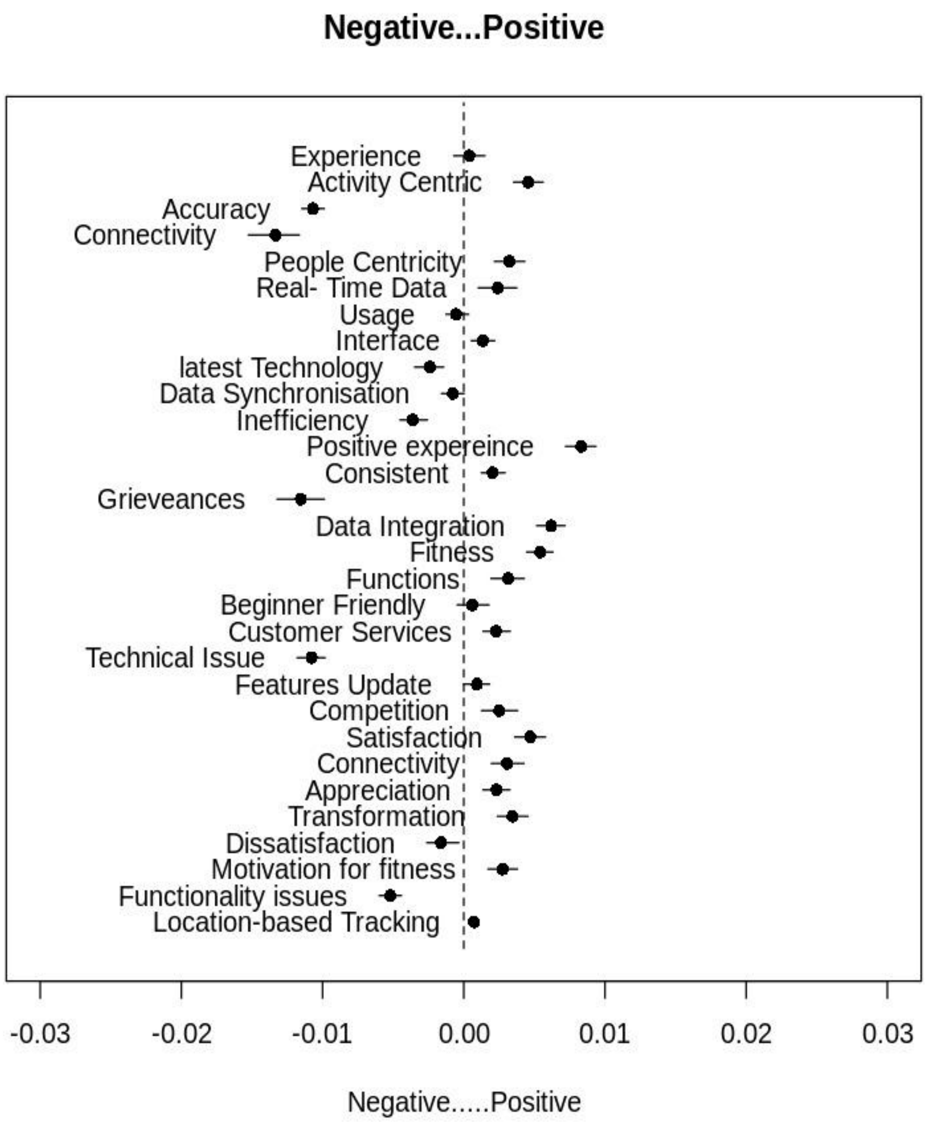


Figure 6
Shifts in Positive and Negative Topics in Physical Health Apps



Personalisation and Customisation. Personalisation was a consistent driver of satisfaction across both app types (25–30% of topics). In mental health apps, this included Audio (Topic 12), Comprehensive (Topic 14), Vocalise (Topic 16), Guiding (Topic 21), and Conversation (Topic 23), which were overwhelmingly positive (about 80%). In physical health apps, Workout Tracking (Topic 12), Goal Customisation (Topic 17), and Adaptive Feedback (Topic 22) were similarly valued, though lapses in tailoring were especially penalising, as they undermined expectations of fitness progress.

Content Quality and Feedback. Feedback-driven topics accounted for about 20% overall. In mental health apps, Feedback (Topic 10), Regret (Topic 17), Useless (Topic 18), Manipulating (Topic 19), Sceptic (Topic 26), and Grievances(Topic 29) reflected frustration with ineffective exercises, hidden paywalls, or misleading practices. These were emotionally charged, with negative reviews outnumbering positives by 3:1. In physical health apps, content quality issues were more functional, focusing on Technical Issues (Topic 20), Errors in Tracking (Topic 11), and Feature Feedback(Topic 22).

Interface Aesthetics and Design: Interface concerns appeared in 10–15% of topics. Mental health app reviews linked Interface (Topic 28) and Comprehensive (Topic 14) with calming layouts and soothing visuals. Physical health app users, in contrast, focused on Feature Updates (Topic 21), Latest Technology (Topic 9), and Layout Design (Topic 14). While mental health users valued minimalist designs for calmness, physical health users evaluated

Cross Thematic Insights.

The results yield three overarching insights. First, emotional salience is domain-dependent: emotional support accounts for nearly 40% of mental health topics but only 15% in physical health, confirming that emotional resonance is indispensable in therapeutic contexts. Second, personalisation is universally valued but asymmetrically weighted: while both app types show 25–30% prevalence of personalisation, its absence is costlier in physical health apps due to goal-tracking expectations. Third, feedback is interpreted differently: in mental health apps, poor feedback signals inauthenticity and lack of empathy, whereas in physical health apps it is judged primarily as a technical flaw.

Figure 6 illustrates Pearson's topic correlation matrix for mental health apps. A strong positive correlation was observed between Guiding (Topic 21) and Response (Topic 22), suggesting that when users perceived clear, structured guidance, they also experienced higher levels of responsiveness. This aligns with the principle of perceived interactivity, where adaptive cues foster trust and engagement (Marriott & Williams, 2018). Importantly, Guiding exhibited a negative correlation with Panicking (Topic 6), indicating that personalised and structured pathways can mitigate anxiety-inducing experiences. This finding resonates with the PAD (Pleasure–Arousal–Dominance) emotional state model (Mehrabian & Russell, 1974), as effective guidance reduces arousal linked with panic and fosters greater user control (dominance).

In physical health apps, Figure 6 shows that Data Integration (Topic 15) was positively correlated with both Fitness (Topic 16) and Consistency (Topic 13). This suggests that seamless synchronisation of data across devices reinforces user perceptions of reliability and consistency, echoing prior findings on the role of technological fluency in shaping satisfaction (Klaus, 2022). Conversely, weak or negative correlations emerged between Feature Updates (Topic 21) and Interface Stability (Topic 14), reflecting a tension between innovation and usability. Users often valued technological modernity but penalised apps when frequent updates disrupted stability.

Together, these correlation patterns highlight how interdependent evaluators coalesce into broader experiential judgments. In mental health apps, emotional and guidance-based cues are mutually reinforcing, while in physical health apps, functional integration and consistency dominate user evaluations. Such inter-topic linkages reinforce the conceptualisation of mobile atmospherics as multidimensional, where satisfaction is shaped not by isolated attributes but by the interplay of emotional, functional, and technological dimensions.

Figure 7
Topic Correlation in Mental Health Applications

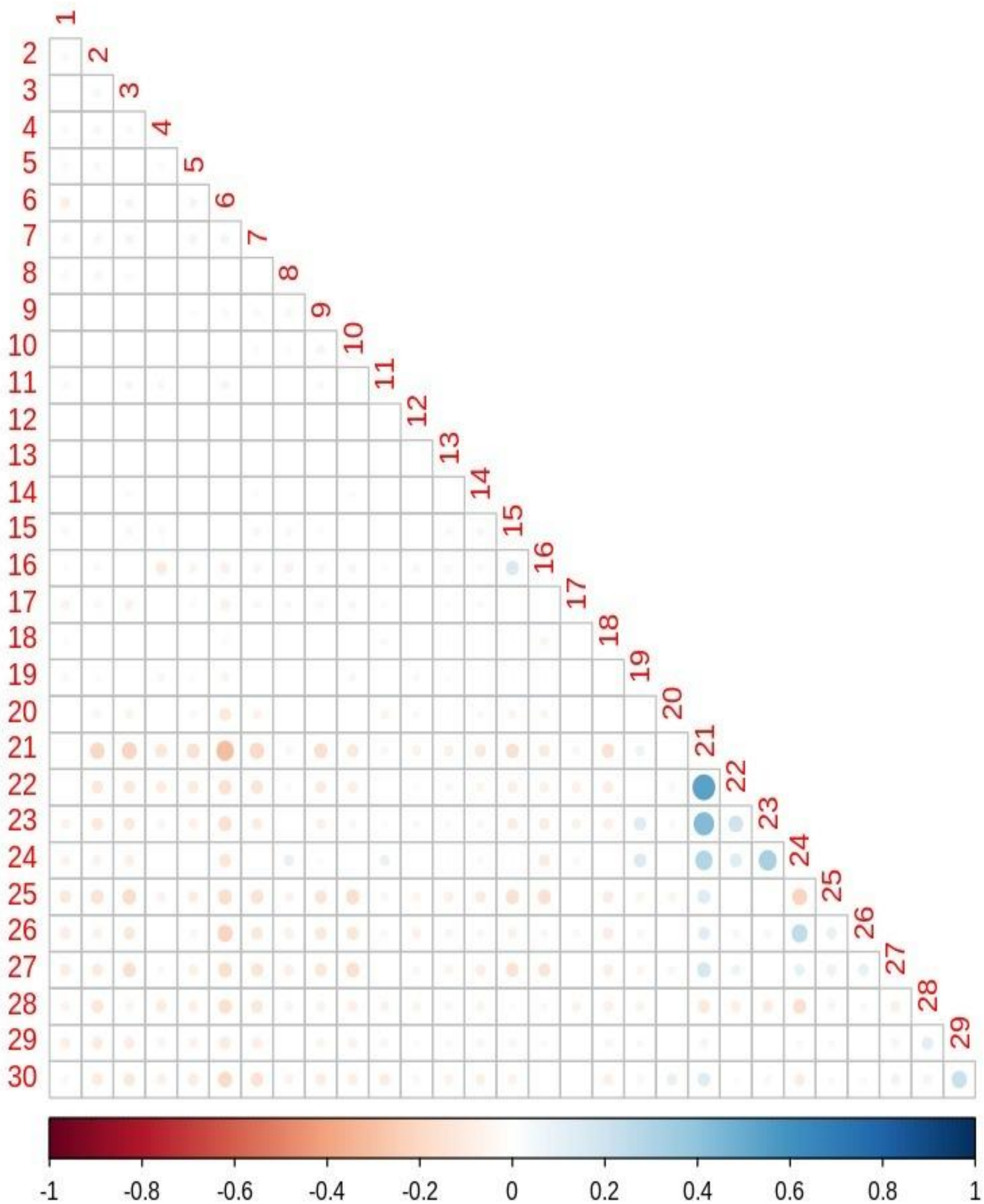
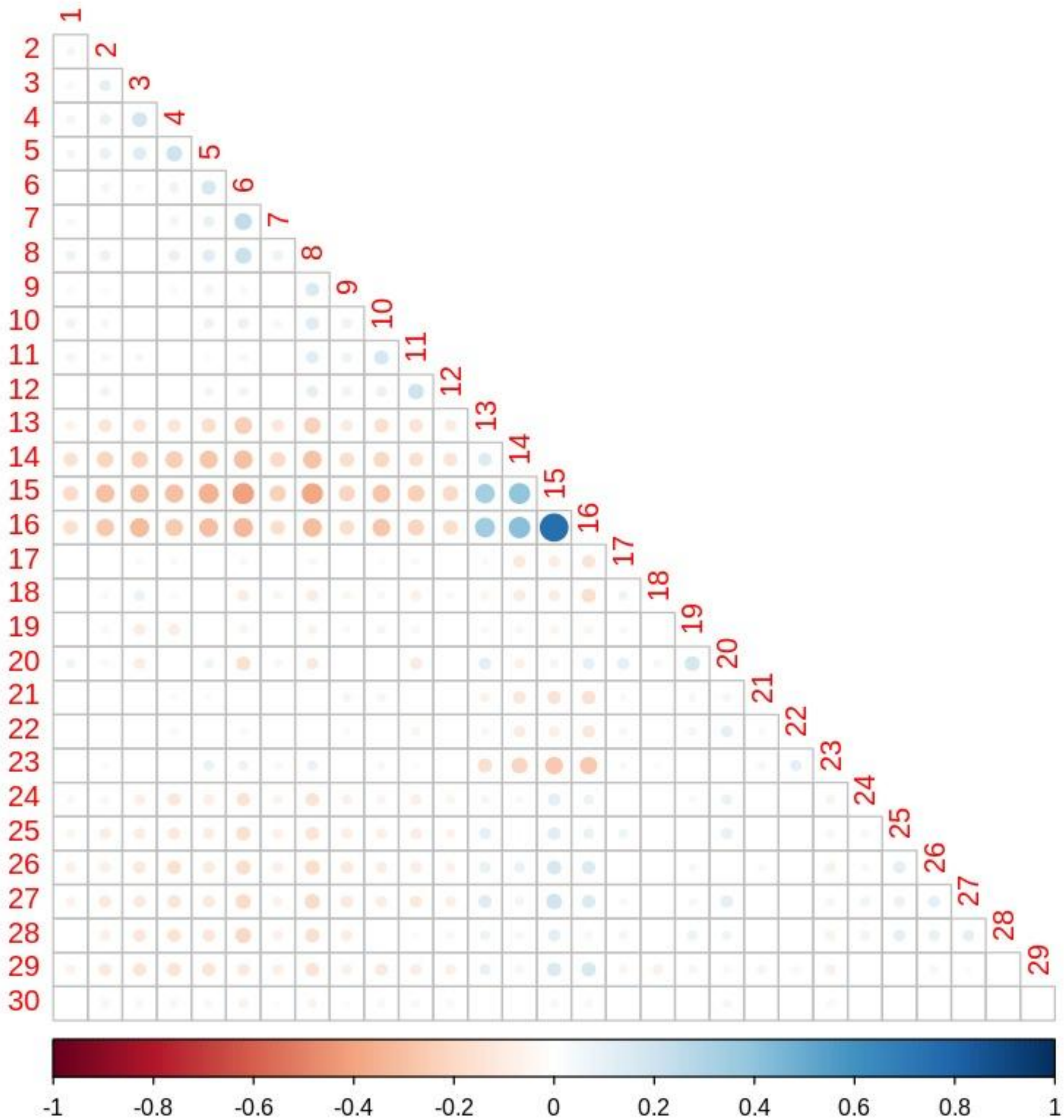


Figure 8
Topic Correlation in Physical Health Applications



Personalization as a Central Mechanism

Across both mental and physical health applications, personalisation emerged as the most critical experiential determinant of satisfaction. Whether delivered through contextualised feedback, adaptive guidance, conversational agents, or emotionally responsive cues, users consistently rated personalised experiences more favourably. In mental health apps, features such as Guiding (Topic 21), Conversation (Topic 23), and Therapy (Topic 27) fostered perceptions of empathy and individual care, which translated into higher satisfaction and emotional engagement. In physical health apps, personalisation manifested through Workout Tracking (Topic 12), Goal

Customisation (Topic 17), and Adaptive Feedback (Topic 22). These features reinforced users' perceptions of autonomy and progress monitoring.

The absence of personalisation, however, carried disproportionate penalties. In mental health apps, depersonalised or robotic interactions were described as emotionally alienating, undermining trust in the app's therapeutic value. In physical health apps, inadequate tailoring was perceived as demotivating, particularly when progress metrics failed to align with individual fitness levels. This asymmetry underscores personalisation not merely as a desirable feature but as a baseline expectation, consistent with research on adaptive service design (Marriott & Williams, 2018; Zhang et al., 2022).

From a theoretical perspective, these findings reinforce mobile atmospherics as a multidimensional construct that integrates affective, functional, and technological stimuli into cohesive experiences. The PAD emotional state model (Mehrabian & Russell, 1974) further clarifies why personalisation is so powerful: adaptive interactions enhance pleasure, reduce arousal linked to uncertainty, and strengthen users' sense of dominance by reinforcing agency over their health goals.

DISCUSSION

This study demonstrates how user satisfaction with mobile health applications emerges from the interplay of emotional, functional, and atmospheric cues. STM-derived clusters reveal that mental health apps are primarily evaluated through emotional resonance and therapeutic engagement, whereas physical health apps are assessed more on functionality, accuracy, and reliability. These findings extend prior research on mobile app experiences (Gupta & Arora, 2023; Klaus, 2022) by showing that satisfaction is not only an outcome of service delivery but also a reflection of how users emotionally and cognitively engage with digital atmospheres.

The results underscore the relevance of the S–O–R framework in explaining how app features act as stimuli that shape users' internal states and ultimately guide behavioural responses. Emotional clusters such as Positiveness and Support demonstrate that empathetic cues in mental health apps trigger positive affective states, reinforcing satisfaction and continued use. Conversely, negative topics such as Panicking or Manipulating highlight instances where inadequate or inauthentic feedback generates frustration and erodes trust. This aligns with the PAD model (Mehrabian & Russell, 1974), where guidance enhances pleasure and control, while technical glitches increase arousal in negative ways, reducing dominance.

A central contribution of this research lies in conceptualising personalisation as a core mobile atmospheric mechanism. Across both app categories, personalised content, adaptive features, and guided interaction consistently enhanced satisfaction. Yet the asymmetry in consequences is notable: while deficits in personalisation within mental health apps reduced empathy, in physical health apps they undermined goal achievement, producing stronger dissatisfaction. This insight supports evidence that digital interfaces are evaluated through both hedonic and utilitarian logics but are weighted differently across contexts (Zhang et al., 2022).

Equally important is the reinterpretation of the "Satisfaction" topic. While linguistically expressed through terms such as "awesome" or "love," this topic functions as a linguistic marker of satisfaction rather than a theoretical construct. Recognising this distinction avoids tautology in interpreting STM outputs and contributes to a more rigorous conceptualisation of satisfaction in text-based analytics.

IMPLICATIONS

For theory, this study advances the notion of mobile atmospherics by empirically validating its role in shaping health app satisfaction. The integration of STM with consumer behaviour frameworks demonstrates how textual traces of experience can be systematically linked to established theories such as S–O–R and PAD. By showing how emotional, functional, and aesthetic cues converge, the study contributes to a more holistic understanding of digital consumer experiences.

For practice, the findings offer actionable guidance to app developers and marketers. First, mental health app designers must prioritise empathetic feedback loops, conversational agents that mimic human warmth, and calming visual design to strengthen emotional engagement. Second, physical health app developers should focus on technical reliability, wearable integration, and accurate tracking to reduce functional dissatisfaction. Across both contexts, adaptive personalisation is critical. Incorporating AI-driven tailoring of recommendations, workouts, or therapy sessions can directly influence user satisfaction and retention. Marketers, meanwhile, can leverage insights into emotional versus functional framing to tailor communication strategies, highlighting empathy for mental health apps and performance for physical health apps.

LIMITATIONS

Despite its contributions, this study has certain limitations. First, reliance on Google Play reviews introduces potential sample bias, as such reviews disproportionately reflect the voices of highly satisfied or dissatisfied users (Hu et al., 2021). Second, textual reviews capture only verbalised experiences, while non-verbal atmospheric cues such as colours, sounds, or haptic feedback remain underexplored. Third, the study did not integrate demographic data, even though prior research shows that age, gender, and cultural orientation significantly moderate digital satisfaction outcomes (JCSDCB, 2023). Fourth, the cross-sectional nature of the dataset limits inferences about temporal changes in user satisfaction.

FUTURE RESEARCH

Future studies could address these limitations by combining text mining with multimodal analysis of visual, auditory, and haptic cues in mHealth apps. Longitudinal studies of reviews could uncover how satisfaction trajectories evolve with repeated app use. Comparative research across cultural contexts would help examine whether emotional and functional weights differ in collectivist versus individualist societies. Additionally, integrating behavioural usage data with textual reviews could enrich understanding of how expressed satisfaction aligns with actual engagement and retention. Finally, experimental studies could test causal effects of design interventions (e.g., adaptive feedback, empathetic chatbots) on user satisfaction, validating the theoretical mechanisms identified here.

CONCLUSION

This study advances understanding of mobile health applications by introducing and empirically validating a framework of mobile atmospherics through Structured Topic Modelling (STM) of user reviews. The findings reveal that satisfaction in mental health apps is primarily driven by emotional resonance, empathy, and affective engagement, whereas physical health apps are evaluated more on functional accuracy, reliability, and tracking precision. Personalisation consistently emerged as a central determinant across both contexts, though its absence carried asymmetrical consequences, being particularly penalising in physical health apps where progress monitoring is central.

Theoretically, the study contributes to consumer behaviour research by integrating mobile atmospherics with the Stimulus–Organism–Response (S–O–R) paradigm and the PAD emotional state model, thereby illustrating how app-based stimuli shape users' affective states and behavioural outcomes. Methodologically, it demonstrates the value of STM for consumer research, moving beyond sentiment analysis to uncover theoretically meaningful constructs while addressing risks of tautology in linguistic markers of satisfaction.

Practically, the results provide actionable guidance for developers and marketers. Mental health applications should prioritise empathetic design and affective cues to foster trust and comfort, while physical health apps must enhance functional precision, seamless connectivity, and adaptive feedback. Aligning design strategies with user-driven evaluators can enhance satisfaction, sustain long-term engagement, and ultimately improve health outcomes.

Future research could extend this work by incorporating longitudinal review data, examining additional domains of health applications, or exploring cultural differences in how mobile atmospherics influence satisfaction. By integrating user-driven insights with advanced computational methods, scholars and practitioners can better design health applications that foster satisfaction, retention, and well-being.

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