Digital Health Without Universal Benefit: Evidence from Fitbit App User Experiences

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Abstract

This study examines how users interpret digital health technologies as tools for improving everyday well-being by analyzing user-generated reviews of the Fitbit mobile application. Drawing on a comparative analysis of 5-star and 1-star reviews, the study explores how users experience the same technology as either supportive or ineffective under different conditions. Using computational text analysis and thematic interpretation, the findings identify five recurring domains: motivation and encouragement, self-monitoring, technical breakdown, disengagement, and conditional effectiveness. Positive reviews describe Fitbit as a motivational and supportive tool that enhances behavioral awareness, whereas negative reviews emphasize system unreliability, including syncing failures and update-related malfunctions, which disrupt usage and lead to abandonment. The results demonstrate that the effectiveness of digital health technologies depends not only on access, but also on system stability and usability. The study highlights a gap between technological availability and actual user outcomes, which suggests that digital health technologies function as conditionally effective tools rather than universally beneficial interventions.

Introduction

The rapid expansion of digital technologies has fundamentally reshaped how individuals engage with their health and everyday well-being. In recent years, mobile health (mHealth) applications and wearable devices have emerged as widely accessible tools designed to support physical activity, monitor behavioral patterns, and encourage healthier lifestyles (Balbim et al., 2021; Ferreira et al., 2021). These technologies are often framed as scalable solutions capable of improving quality of life through continuous feedback, self-monitoring, and personalized guidance (Jang &

Kim, 2025). Within this broader technological shift, digital health tools are increasingly positioned not only as consumer products but also as instruments of everyday development that may enhance individuals' capacity to manage and improve their own well-being.

Among these technologies, wearable fitness platforms such as Fitbit have gained widespread adoption as tools for personal health tracking. These devices allow users to monitor steps, sleep, heart rate, and other physiological indicators, thus enabling them to better understand and manage their health-related behaviors (Dehghani et al., 2020; Park, 2020).

Through features such as real-time feedback, goal setting, and progress tracking, wearable technologies are designed to facilitate sustained engagement with physical activity and promote long-term behavioral change. Prior research suggests that such features—particularly those associated with self-monitoring and behavioral feedback—can enhance user motivation and increase participation in physical activity (Brickwood et al., 2019; Jang & Kim, 2025; Kerner & Goodyear, 2017).

Despite these promises, users' experiences with digital health technologies are far from uniform. While some individuals report increased motivation and improved health routines, others encounter technical barriers, usability challenges, and eventual disengagement (Dehghani et al., 2020; El-Gayar & Elnoshokaty, 2023). This divergence raises an important but underexplored question: Do digital health technologies actually improve everyday well-being for all users, or do their benefits depend on specific conditions of use?

Existing research has largely emphasized the positive effects of wearable technologies, particularly their ability to increase physical activity and support behavior change (Brickwood et al., 2019). However, less attention has been paid to the variability of user experiences, especially those involving dissatisfaction, frustration, and abandonment. Studies of post-adoption behavior suggest that continued usage is strongly influenced by system performance, usability, and the alignment between user expectations and technological functionality (Gupta et al., 2021; Pal et al., 2020). As a result, the literature provides an incomplete picture of how digital health tools function in real-world settings, where technical reliability and sustained engagement are critical.

From a global development perspective, this gap is significant. Digital technologies are often evaluated in terms of access, adoption, and scalability, yet access alone does not guarantee meaningful improvements in well-being. What matters is not simply whether individuals have access to digital tools, but whether they are able to effectively use those tools to achieve desired outcomes. This distinction highlights a critical gap between technological availability and users' ability to convert that access into sustained behavioral change and improved well-being. In the context of digital health, the effectiveness of a technology depends not only on its design features but also on its reliability and its capacity to be integrated into everyday routines.

This study addresses this gap by examining user-generated reviews of the Fitbit mobile application. By analyzing both highly positive (5-star) and highly negative (1-star) reviews, the study seeks to identify how users interpret digital health technology under conditions of success and failure. Rather than relying on controlled experiments or survey-based perceptions, this research draws on naturally occurring user discourse to capture how individuals describe their experiences with digital health tools in real-world contexts (Grimmer et al., 2022; Hu et al., 2017). In doing so, the study contributes to a more development-oriented understanding of digital health technologies by shifting the focus from access and adoption to effective use and outcome realization. By highlighting the differences between positive and negative user experiences, the research provides insight into the conditions under which digital technologies translate—or fail to translate—into meaningful improvements in everyday well-being.

Literature Review

Digital Health Technologies and Behavioral Change

Digital health technologies have been widely recognized as tools for promoting healthier behaviors and improving individual well-being. Wearable devices and mobile health (mHealth) applications provide users with continuous access to health-related information that enables them to monitor physical activity, track progress, and adjust behaviors accordingly (Balbim et al., 2021; Ferreira et al., 2021). These technologies are particularly valuable because they transform everyday activities into measurable data and allow users to make more informed decisions about their health.

A growing body of research suggests that wearable fitness technologies can increase physical activity levels, particularly in the short term. For instance, systematic evidence indicates that fitness trackers can encourage users to engage more consistently in exercise and maintain awareness of their activity levels (Brickwood et al., 2019). By providing real-time feedback and reinforcing behavioral goals, these tools can support behavior change in ways that traditional interventions may not.

However, the relationship between digital health technologies and sustained behavioral change is more complex. While initial adoption and engagement are often high, adherence tends to decline over time. Studies indicate that users may lose interest, encounter technical difficulties, or struggle to maintain consistent usage patterns (Dehghani et al., 2020; Kerner & Goodyear, 2017). This suggests that the effectiveness of digital health technologies is not solely determined by their availability or design, but also by the conditions under which they are used and maintained.

Technology Acceptance, Usability, and System Reliability

The technology acceptance model (TAM) provides a widely used framework for understanding how users adopt and evaluate digital technologies. According to TAM, perceived usefulness and perceived ease of use are key determinants of technology adoption and continued usage (Davis, 1989). In the context of wearable health technologies, users are more likely to engage with systems that are intuitive, reliable, and capable of delivering meaningful benefits (Park, 2020; Sun & Gu, 2024).

In addition to usability and perceived usefulness, system reliability plays a critical role in shaping user experiences. Research shows that technical issues—such as syncing failures, inaccurate tracking, and app malfunctions—can significantly reduce user satisfaction and lead to discontinuation (Dehghani et al., 2020; El-Gayar & Elnoshokaty, 2023). Unlike minor inconveniences, these issues often disrupt the core functionality of the technology and prevent users from accessing the very features that motivate and support their behavior.

Importantly, technological reliability is not merely a background condition but a central determinant of value realization. When systems function smoothly, users can integrate them into their daily routines with minimal effort. When systems fail, however, users must invest additional time and effort to troubleshoot problems, which can lead to frustration and eventual disengagement. This dynamic, highlights the need to examine not only the benefits of digital health technologies but also the structural conditions that enable or constrain their effective use.

Gamification and User Motivation

Gamification has been widely studied as a mechanism for enhancing user engagement in digital health applications. By incorporating elements such as goal setting, rewards, and feedback, fitness applications can increase users' motivation to engage in physical activity (Kerner & Goodyear, 2017; Pal et al., 2020). These features create a sense of progression and achievement, which make health-related behaviors more engaging and sustainable. From a psychological perspective, gamification operates through both intrinsic and extrinsic motivation. Intrinsic motivation arises from the enjoyment of the activity itself, whereas extrinsic motivation is driven by external rewards and incentives (Deci & Ryan, 1985). In digital health contexts, these mechanisms often work together to support user engagement and behavioral persistence.

However, motivation alone is insufficient to ensure long-term effectiveness. While gamified features may initially attract users and encourage participation, their success depends on the broader usability and reliability of the system. When technical issues interfere with user experience, the motivational benefits of gamification are often undermined. This suggests that motivation and functionality are interdependent, and sustained behavioral change depends on the alignment between user engagement mechanisms and system performance.

User Experience, Satisfaction, and Dissatisfaction

User experience plays a central role in determining the success or failure of digital health technologies. Positive experiences are typically associated with ease of use, effective functionality, and perceived benefits, whereas negative experiences often stem from technical issues, unmet expectations, and usability challenges (Dehghani et al., 2020; El-Gayar & Elnoshokaty, 2023). Importantly, satisfaction and dissatisfaction are not simply opposite ends of a single continuum. Prior research suggests that the drivers of satisfaction may differ from those of dissatisfaction, which indicates a more complex evaluative process (Guo & Zhou, 2016). For example, while users may value features such as tracking and feedback, they may simultaneously experience frustration due to issues such as system instability or data inaccuracies.

Online user reviews provide a valuable data source for examining these experiences. Unlike survey-based responses, reviews are typically unsolicited and reflect spontaneous user evaluations. As such, they capture a wide range of experiences, from highly positive to highly negative, thus offering a more comprehensive view of how digital health technologies are perceived in real-world contexts (Hu et al., 2017; Zhai et al., 2022). This makes them particularly useful for understanding how users interpret both the benefits and limitations of digital technologies in everyday use.

Toward a Development-oriented Perspective

From a broader perspective, digital health technologies can be understood as tools for supporting everyday development. By enabling individuals to monitor and improve their health behaviors, these technologies have the potential to enhance quality of life and well-being. However, their effectiveness depends on more than access alone. A key insight emerging from the literature is that technological availability does not guarantee meaningful outcomes. Users must be able to effectively use the technology, integrate it into their routines, and maintain engagement over time (Gupta et al., 2021; Pal et al., 2020). When these conditions are not met, the potential benefits of digital health technologies may not be realized.

This perspective highlights the importance of moving beyond access-centered frameworks toward a more nuanced understanding of digital technology use. Rather than focusing solely on adoption and availability, research must consider how technologies are experienced in practice and whether they can be sustained in everyday contexts. By examining both positive and negative user experiences, this study seeks to provide a more balanced and development-oriented understanding of how digital health technologies function in real-world settings.

Methods

Data Corpus

This study analyzes user-generated reviews of the Fitbit mobile application collected from the Google Play Store. To capture contrasting user experiences, the dataset was divided into two groups based on review ratings: 38,803 reviews with a 5-star rating and 28,664 reviews with a 1-star rating. The final corpus consisted of 67,467 publicly available reviews reflecting both highly positive and highly negative evaluations of the Fitbit app.

The decision to compare 5-star and 1-star reviews is both theoretically and analytically grounded. Rather than examining average or mixed evaluations, this study focuses on the two ends of the evaluative spectrum to capture how users describe digital health technology under conditions of clear success and clear failure. Prior research on online reviews suggests that extreme ratings often provide richer and more polarized expressions of user experience, which makes them particularly suitable for identifying underlying evaluative structures (Hu et al., 2017). In this context, 5-star reviews reflect perceived benefits and successful integration into daily routines, whereas 1-star reviews reveal salient barriers, frustrations, and breakdowns in user experience.

Because the reviews are naturally occurring user-generated texts rather than researcher-elicited responses, they provide a valuable window into how individuals spontaneously interpret and evaluate digital health technologies in real-world settings. Such data have been widely used in prior research to examine consumer perceptions and experiences in digital environments (Zhai et al., 2022). The dataset is therefore treated not as a representative sample of all Fitbit users, but as a large corpus of public discourse reflecting user meanings, expectations, and frustrations surrounding app-based health management. All reviews were publicly accessible and anonymized prior to analysis, and no personally identifiable information was collected or reported.

Analytical Approach

This study employs computational text analysis as a structure-detection strategy for identifying patterned differences between highly positive and highly negative Fitbit app experiences. The analytical objective is not predictive classification, but interpretive comparison. Specifically, the analysis seeks to identify the dominant experiential themes through which users describe Fitbit as a digital tool for improving, maintaining, or failing to support everyday well-being.

To achieve this objective, the study adopts a text-as-data approach that treats large-scale textual corpora as systematic sources of social meaning (Grimmer et al., 2022). This approach enables the identification of recurring linguistic patterns while maintaining a connection to substantive interpretation. Consistent with prior research in marketing and information systems, the analysis integrates multiple complementary techniques to move from surface-level lexical patterns to higher-order interpretive domains (Netzer et al., 2012).

Four analytical procedures were employed: (1) descriptive corpus profiling, (2) word frequency analysis, (3) sentiment analysis, and (4) topic-oriented thematic interpretation. These techniques were used in combination to ensure both analytical rigor and interpretive depth. The comparative logic of the design is central to the analysis. The 5-star corpus reveals how digital health technology is framed when users perceive it to be functioning effectively, whereas the 1-star corpus captures how the same technology is framed under conditions of malfunction, dissatisfaction, or abandonment. By placing these two corpora in dialogue, the study identifies the conditions under which digital health technologies appear to support—or fail to support—everyday well-being.

Preprocessing Procedures

Prior to analysis, review texts were cleaned and standardized following established text analysis practices. All text was converted to lowercase, and punctuation, non-alphabetic characters, and extraneous symbols were removed. Common stop words were excluded to increase the visibility of semantically meaningful terms. The cleaned texts were then tokenized to facilitate subsequent lexical analysis. While preprocessing enhances the quality of pattern detection, the analysis also retained the original review texts for interpretive validation. This dual approach reflects best practices in computational text analysis, where automated outputs are complemented by close reading to ensure substantive validity (Grimmer et al., 2022). In this study, computational findings were repeatedly cross-checked against raw review texts to confirm that identified patterns accurately reflected user experiences.

Corpus Profiling

Before conducting comparative analysis, the two datasets were profiled descriptively to identify structural differences in user expression. The 5-star reviews were generally shorter and more concentrated in tone and often consisted of brief affirmative statements such as "love it" or "great app." In contrast, the 1-star reviews were significantly longer and more elaborate and frequently described detailed technical problems and repeated attempts to resolve them.

This asymmetry is consistent with prior findings that negative reviews tend to be more diagnostic and explanatory, whereas positive reviews are more concise and outcome-oriented (Hu et al., 2017). This distinction informed subsequent interpretation by suggesting that positive experiences are often expressed through compressed evaluations, whereas negative experiences involve more detailed narratives of disruption and dissatisfaction.

Word Frequency Analysis

Word frequency analysis was conducted separately for the 5-star and 1-star corpora to identify the most frequently occurring terms in each dataset. This method is widely used in text mining to reveal the lexical structure of large textual corpora (Netzer et al., 2012). In the 5-star dataset, prominent words included "love," "great," "track," "sleep," "steps," and "easy," which indicated that positive experiences are centered on usability, self-monitoring, and behavioral support. In contrast, the 1-star dataset was dominated by terms such as "sync," "update," "device," "work," and "fix," thus suggesting that negative experiences are primarily associated with technical failures and system unreliability. The contrast between these lexical environments provides an initial indication that digital health technologies are evaluated positively when they function seamlessly and negatively when technological disruptions interfere with routine use.

Sentiment Analysis

To assess the emotional tone of the reviews, sentiment analysis was conducted using a lexicon-based approach. This method assigns polarity scores to textual data based on predefined sentiment dictionaries and has been widely used in social media and review analysis (Hutto & Gilbert, 2014). Consistent with expectations, the 5-star corpus exhibited a strongly positive sentiment profile. However, the 1-star corpus displayed a more nuanced pattern. While overall sentiment was negative, many reviews contained neutral or explanatory language describing sequences of technical failure. This suggests that dissatisfaction is often expressed not only through emotional reactions but also through detailed accounts of user experience.

Topic-oriented Pattern Detection

To identify broader thematic structures, topic-oriented analysis was conducted using term-frequency representations and clustering techniques. Topic modeling approaches, such as Latent Dirichlet Allocation (LDA), are commonly used to uncover latent themes in large textual datasets (Röder et al., 2015; Wang et al., 2018). In this study, topic structures were iteratively refined to ensure interpretability and coherence. Solutions with varying numbers of topics were evaluated, and the final structure was selected based on semantic clarity and consistency across both corpora. The resulting patterns revealed distinct thematic clusters. The 5-star corpus emphasized motivation, self-monitoring, and ease of use, whereas the 1-star corpus highlighted technical breakdowns, syncing failures, and system instability. These computational outputs were subsequently interpreted through close reading to ensure conceptual coherence.

Interpretive Integration

The final stage of analysis involved integrating computational outputs with qualitative interpretation. While text-mining techniques are effective in identifying recurring patterns, they do not fully capture the meaning-making processes underlying user experiences. Accordingly, this study adopts an interpretive integration approach, where computational findings serve as analytical guides rather than definitive conclusions.

The outputs from frequency analysis, sentiment analysis, and topic modeling were systematically compared with original review texts to identify coherent interpretive domains.

Through this iterative process, five overarching domains were identified: motivation and encouragement, self-monitoring and awareness, technical breakdown, disengagement and abandonment, and conditional effectiveness. These domains provide the conceptual structure for the Findings section and form the basis for understanding how digital health technologies are experienced as either supportive or ineffective tools in everyday contexts.

Findings

Discursive Structure of Fitbit App Experiences

Comparative analysis of the 5-star and 1-star review corpora revealed that user experiences with the Fitbit app cluster around five recurring interpretive domains. These domains do not represent isolated attributes of the app but rather patterned ways in which users make sense of digital health technology in everyday contexts. Consistent with prior research on user-generated content, online reviews reflect not only evaluations but also interpretive narratives through which users articulate their experiences (Hu et al., 2017; Zhai et al., 2022).

Across both corpora, the findings suggest that Fitbit is experienced as either supportive or obstructive depending on conditions of use. Positive reviews tend to present the app as a simple, encouraging, and health-supportive tool, whereas negative reviews frame it as unreliable, technically unstable, and increasingly unusable over time. This contrast indicates that the developmental value of digital health technology is not inherent to access alone but depends on whether its technical and motivational features remain usable in practice.

Motivation and Encouragement

A dominant pattern in the 5-star reviews was the framing of Fitbit as a source of motivation and encouragement. Positive users frequently described the app not merely as a passive tracking device but as an active prompt that supports accountability, routine formation, and sustained engagement in physical activity. The lexical prominence of terms such as "love," "great," "helps," and "keep" supports this interpretation.

In this domain, Fitbit is experienced as a companion-like digital presence that reinforces health goals rather than simply recording them. Users emphasized that the app helps them "stay active," "keep track," or "keep going," which suggests that the technology functions as a behavioral support mechanism. This finding aligns with prior research indicating that wearable technologies can enhance motivation by providing continuous feedback and reinforcing behavioral goals (Brickwood et al., 2019; Kerner & Goodyear, 2017). Importantly, these expressions extend beyond technical appreciation and reflect a psychological dimension of engagement. The app is not valued solely for its functional capabilities but for its perceived ability to sustain behavioral momentum. In this sense, digital health technologies can act as motivational infrastructures that support everyday behavioral persistence.

Self-monitoring and Behavioral Awareness

A second major pattern in the positive corpus centered on self-monitoring and health awareness. Positive reviews frequently highlighted the usefulness of tracking steps, sleep, calories, and other activity metrics. Terms such as "track," "sleep," and "steps" appeared repeatedly, which suggests that users value Fitbit for its ability to make health behaviors visible and interpretable.

These findings are consistent with research showing that wearable devices enhance behavioral awareness by transforming everyday activities into quantifiable data (Balbim et al., 2021; Ferreira et al., 2021). Users described the app as helping them understand their routines, evaluate their progress, and make informed decisions about their health. This pattern highlights the role of digital health technologies as tools for self-regulation. Fitbit is interpreted not simply as a monitoring device but as a feedback system that enables users to observe and manage their behavior more effectively. The emphasis on self-monitoring suggests that users derive value from the app's ability to translate routine activities into actionable insights.

Technical Breakdown and System Unreliability

In contrast to the positive corpus, the most dominant pattern in the 1-star reviews is technical breakdown. Negative experiences were primarily framed in terms of process failures rather than outcomes. The most frequently occurring terms—such as "sync," "update," "device," "work," and "fix"—indicated that dissatisfaction is strongly associated with system reliability and technical performance. A particularly salient theme was syncing failure. Users repeatedly described the app as unable to connect to devices, transfer data, or maintain stable functionality.

When syncing fails, the app is no longer able to perform its core purpose, and its value as a health-support tool collapse. This finding is consistent with prior research demonstrating that system reliability is a key determinant of continued usage and user satisfaction in wearable technologies (Dehghani et al., 2020; El-Gayar & Elnoshokaty, 2023).

Additionally, update-related failures emerged as a critical source of dissatisfaction. Many users reported that app performance deteriorated following updates, which suggests that technological improvements are not always experienced as beneficial. This perception undermines user trust and contributes to negative evaluations of the technology. Taken together, these findings suggest that user dissatisfaction is not driven solely by unmet expectations of advanced features but by failures in basic technological infrastructure. Connectivity, synchronization, and functional stability emerged as fundamental conditions for effective use.

Disengagement and Abandonment

A fourth interpretive domain concerned disengagement. Many 1-star reviews described not only dissatisfaction but also a gradual withdrawal from the technology. Users reported repeated attempts to resolve issues—such as reinstalling the app or reconnecting devices—before ultimately abandoning it. This pattern reflects a process of declining engagement rather than immediate rejection. Prior research on post-adoption behavior suggests that continued usage depends on the confirmation of expectations and system performance over time (Gupta et al., 2021; Pal et al., 2020). When these expectations are not met, users are more likely to discontinue use. The narratives observed in the 1-star corpus illustrate how repeated technical failures erode user trust and motivation. Over time, the technology shifts from being a supportive tool to a source of frustration. This transition highlights the fragility of digital engagement in contexts where sustained functionality is required.

Conditional Effectiveness

Across both corpora, a broader pattern emerged: the effectiveness of Fitbit is conditional rather than universal. Positive users praised the app when it was reliable, easy to use, and capable of supporting ongoing engagement. Negative users rejected it when technical barriers disrupted these same processes. This finding suggests that digital health technologies do not produce uniform outcomes but instead generate divergent experiences depending on conditions of use. The same technology is interpreted very differently depending on whether users can successfully convert access into consistent and reliable use. From a broader perspective, this pattern reflects a distinction between technological availability and effective utilization. While the app is widely accessible, its developmental value depends on whether users can integrate it into their daily routines without disruption. This insight aligns with research emphasizing that technology adoption alone is insufficient to guarantee meaningful outcomes (Gupta et al., 2021).

Disengagement and Abandonment

The contrast between the two corpora revealed a deeper structural difference in how users articulate their experiences. Positive reviews were typically brief, affective, and outcome-oriented, whereas negative reviews were longer, more detailed, and process-oriented. This distinction is consistent with prior findings that negative reviews tend to provide more diagnostic information that reflects users' efforts to explain system failures (Hu et al., 2017). This difference in discourse is analytically significant. The 5-star corpus reflected alignment between technological design and everyday use, whereas the 1-star corpus reflected misalignment in which the technology failed to meet practical user needs. This suggests that the key determinant of effectiveness is not adoption but sustained usability in real-world contexts.

Summary of Findings

Taken together, the findings indicate that Fitbit app experiences are structured by a tension between support and breakdown. Positive reviews framed the app as a motivating, easy-to-use, and health-supportive self-monitoring tool. Negative reviews framed it as unstable, sync-dependent, and increasingly difficult to maintain. The central insight emerging from this analysis is that digital health technologies function as developmental resources only when their technical infrastructure remains dependable enough to sustain routine use. When this condition is not met, the potential benefits of the technology are not realized and reinforces the gap between technological promise and lived experience.

Discussion

The findings of this study suggest that digital health technologies function as conditionally effective tools for improving everyday well-being, rather than as universally beneficial interventions. While many users experience benefits such as increased motivation, enhanced self-monitoring, and greater awareness of their health behaviors, these outcomes are not consistently realized across all users. Instead, the effectiveness of the Fitbit application depends on a set of underlying conditions related to usability, reliability, and sustained engagement.

A central insight that emerged from the analysis is the distinction between technological access and actual outcomes. Fitbit is widely available and offers a range of features designed to support health-related behaviors. However, access to these features does not automatically translate into improved well-being. For users who encounter technical issues, such as syncing failures or app malfunctions, the technology becomes difficult to use and, in some cases, unusable. As a result, the potential benefits of the application are not realized. This finding reinforces prior research suggesting that technology adoption alone is insufficient to ensure continued usage or meaningful outcomes (Gupta et al., 2021; Pal et al., 2020).

This distinction is particularly important from a global development perspective. Development is not only about providing access to resources but also about enabling individuals to effectively utilize those resources to achieve desired outcomes. In this context, digital health technologies can be understood as capability-enhancing tools whose effectiveness depends on users' ability to integrate them into daily practices under real-world conditions. When technological systems function reliably, they support behavioral continuity and enable users to sustain health-related routines. When they fail, however, they disrupt that continuity and undermine both motivation and trust in the technology.

The findings also reinforce prior research emphasizing the importance of system reliability in shaping user satisfaction and continued usage. Studies have shown that technical failures—such as syncing issues, inaccurate tracking, and software malfunctions—can significantly reduce user engagement and lead to discontinuation (Dehghani et al., 2020; El-Gayar & Elnoshokaty, 2023). In this sense, system reliability emerges not as a secondary technical concern but as a core condition for the realization of developmental outcomes.

In addition, the results highlight the role of motivation in digital health contexts. Positive reviews frequently described the application as a source of encouragement, which suggests that Fitbit can function as a behavioral support system. This aligns with research on gamification and self-determination theory, which shows that feedback, goal setting, and progress tracking can enhance user engagement (Deci & Ryan, 1985; Kerner & Goodyear, 2017). However, the findings also indicated that motivation alone is insufficient to sustain long-term engagement. When technical barriers arise, the motivational benefits of the application are diminished. This suggests that behavioral change in digital environments depends on the alignment between motivational design and functional reliability, rather than on motivation alone.

Another important insight concerns the process of disengagement. Negative reviews often described a gradual transition from initial adoption to eventual abandonment. Users reported repeated attempts to restore functionality—reinstalling the application, reconnecting devices, or waiting for updates—before ultimately discontinuing use. This pattern indicates that disengagement is not an immediate reaction but the result of accumulated friction and failed attempts to maintain usability. Consistent with expectation-confirmation theory, continued use depends on whether system performance meets user expectations over time (Pal et al., 2020). When these expectations are repeatedly violated, users are more likely to disengage.

More broadly, this study contributes to discussions on digital technologies in everyday development by challenging access-centered assumptions. Much of the existing discourse emphasizes the expansion of access to digital tools as a pathway to improved well-being. However, the findings demonstrate that access alone is insufficient. What matters is whether individuals can consistently and effectively use these tools in their daily lives. This shifts the focus from technological provision to practical usability and sustained functionality as key determinants of impact.

In this sense, digital health technologies should be understood as supportive but structurally contingent systems. They have the potential to enhance well-being but only when their technical and experiential conditions are met. When these conditions are not satisfied, the same technologies may fail to deliver their intended benefits, which reinforces the gap between technological promise and lived experience. This insight underscores the need for a more nuanced evaluation of digital interventions—one that considers not only access, but also the conditions under which access can be transformed into meaningful and sustained outcomes.

Conclusion

This study examined how users interpret digital health technologies as tools for improving everyday well-being by analyzing large-scale user-generated reviews of the Fitbit mobile application. By comparing highly positive and highly negative user experiences, the study identified recurring patterns that reveal how the same technology can be perceived as either supportive or ineffective depending on conditions of use.

The findings demonstrate that Fitbit is widely valued as a tool for motivation, self-monitoring, and behavioral awareness when it functions reliably and integrates smoothly into users' daily routines. Under these conditions, the application operates as a supportive digital infrastructure that encourages healthier behavior and sustained engagement. However, the results also show that these benefits are not consistently realized. Technical failures—particularly those related to syncing, updates, and system performance—disrupt usage and lead to frustration, disengagement, and eventual abandonment.

A central contribution of this study is the identification of a gap between technological availability and actual developmental outcomes. While digital health technologies are often promoted as accessible solutions for improving well-being, the findings indicate that access alone is insufficient. The effectiveness of these tools depends on whether users can reliably and consistently integrate them into everyday practices. In this sense, digital health technologies should be understood not as universally beneficial interventions, but as conditionally effective development tools whose impact depends on sustained functionality and usability.

From a broader development perspective, these findings challenge access-centered assumptions that dominate much of the digital development discourse. Expanding access to technology is an important first step, but it does not guarantee meaningful improvements in well-being. What matters is whether individuals can convert access into effective and sustained use. This shift from access to effective use and outcome realization has important implications for the design, evaluation, and deployment of digital health interventions.

Practically, the findings suggest that policymakers, developers, and practitioners should place greater emphasis on system reliability, user experience, and long-term engagement when designing digital health technologies. Interventions that fail to account for these factors risk reinforcing gaps between technological promise and lived experience. Ensuring that digital tools function consistently in real-world conditions is therefore critical for translating technological access into meaningful developmental outcomes.

In conclusion, digital health technologies hold significant potential to support everyday well-being, but their impact is neither automatic nor universal. Their effectiveness depends on the alignment between technological functionality and users' ability to sustain engagement in daily life. Recognizing this conditional nature is essential for advancing a more realistic and development-oriented understanding of how digital technologies contribute to human well-being.

Limitations and Future Research

Despite its contributions, this study has several limitations that should be acknowledged. First, the analysis was based on user-generated reviews from the Google Play Store, which may not fully represent the broader population of Fitbit users. Online reviews are inherently self-selected and tend to reflect more extreme experiences, either highly positive or highly negative, which may introduce selection bias (Hu et al., 2017). While this study intentionally focused on 5-star and 1-star reviews to capture contrasting experiential structures, future research could incorporate a wider range of ratings to provide a more nuanced and representative understanding of user perceptions.

Second, the study relied on textual data and does not include direct measures of behavioral outcomes. Although user-generated reviews provide rich insights into perceptions, meanings, and lived experiences, they do not allow for precise measurement of actual changes in physical activity or long-term health outcomes. Prior research suggests that combining self-reported or behavioral data with digital trace data can offer a more comprehensive understanding of technology-enabled behavior change (Brickwood et al., 2019). Future studies could therefore integrate review-based analysis with experimental, longitudinal, or sensor-based data to better assess the causal impact of digital health technologies.

Third, the analysis focused on a single platform, Fitbit, which may limit the generalizability of the findings. Although Fitbit represents one of the most widely used wearable health technologies, user experiences may vary across platforms with different technological architectures, interface designs, and levels of reliability. Prior studies have shown that system features and design characteristics can significantly influence user engagement and continuance intention (El-Gayar & Elnoshokaty, 2023; Park, 2020). Comparative analyses across multiple digital health applications would therefore provide a broader understanding of how platform-specific factors shape user experiences and outcomes.

Finally, while this study identified key patterns in user discourse, it does not explicitly account for individual-level differences such as demographic characteristics, technological literacy, or health conditions. These factors may influence both how users interact with digital health technologies and how they interpret their effectiveness. Research on technology adoption and continuance suggests that individual differences play an important role in shaping engagement and usage patterns (Gupta et al., 2021; Sun & Gu, 2024). Future research should therefore explore how these factors interact with technological conditions to produce variation in user experiences and outcomes.

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