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Understanding User Perceptions of Personalized Feedback in Digital Health Tools

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ABSTRACT

This study aimed to explore how users perceive and emotionally respond to personalized feedback in digital health tools. A qualitative research design was employed using semi-structured interviews with 20 adult participants from Mexico who had experience using digital health tools with personalized feedback features. Participants were selected through purposive sampling, and data collection continued until theoretical saturation was achieved. Interviews were audio-recorded, transcribed, and thematically analyzed using NVivo 14. The coding process followed three stages: open coding, axial coding, and selective coding, ensuring a comprehensive understanding of user experiences and interpretive patterns. Analysis revealed four core themes: perceived effectiveness of feedback, personal relevance and cultural fit, communication and design quality, and trust, privacy, and emotional resonance. Participants valued motivational and positively framed feedback that aligned with their health goals, but criticized messages that were overly generic, intrusive, or lacking emotional intelligence. Users expressed a preference for customizable settings, culturally and linguistically appropriate messages, and visual formats such as graphs or summaries. Trust in the system was strongly influenced by the tone, clarity, and perceived transparency of the feedback, while overly frequent or robotic messages sometimes triggered negative emotional reactions or disengagement. User perceptions of personalized feedback in digital health tools are multifaceted and shaped by emotional, cultural, cognitive, and technological factors. For feedback systems to be effective and engaging, they must be adaptive, empathetic, and contextually relevant. Incorporating user control, emotional intelligence, and cultural sensitivity into feedback design can enhance trust, increase adherence, and ultimately improve digital health outcomes.

Keywords: *Personalized feedback, digital health tools, user perceptions, qualitative research, health communication, cultural fit, emotional engagement*

1. Introduction

The rapid evolution of digital health technologies has revolutionized the healthcare landscape, transforming how individuals interact with health information, monitor physiological indicators, and manage chronic conditions. Central to this transformation is the integration of personalized feedback mechanisms—adaptive systems designed to provide users with tailored suggestions, alerts, and behavioral nudges based on real-time or cumulative data inputs. These tools are increasingly embedded in mobile health (mHealth) applications, teleconsultation platforms, wearable devices, and AI-driven patient engagement systems, redefining both the scope and intimacy of healthcare delivery in the digital age (1, 2).

Personalized feedback in digital health tools refers to dynamic, user-specific messages that guide behavior, offer encouragement, report progress, and sometimes warn of potential health risks. These systems draw on an individual's health metrics, self-reports, and contextual factors to deliver adaptive content, aiming to improve health literacy, adherence, and self-management outcomes (3, 4). Research shows that personalization not only enhances user engagement but also fosters a sense of agency and accountability in health-related decision-making (5, 6). However, the effectiveness of such tools depends significantly on how users interpret and emotionally respond to these feedback systems.

Numerous studies have demonstrated that user-centered design is pivotal to optimizing the efficacy of digital feedback tools. For instance, systems that offer emotionally intelligent, visually engaging, and linguistically accessible feedback are more likely to build trust, foster behavioral compliance, and reduce cognitive overload (7-9). Despite these advances, gaps remain in understanding the nuanced perceptions of users, particularly in diverse cultural contexts. As Strandberg et al. (10) argue, feedback systems must be co-designed with end-users to ensure cultural, emotional, and functional fit, especially when targeting vulnerable populations or chronic disease cohorts.

In line with this, the Mexican context presents a particularly rich setting for studying digital health feedback mechanisms. Mexico has witnessed rapid growth in smartphone penetration and digital literacy, yet it continues to grapple with healthcare inequalities, access gaps, and varying levels of health education (11, 12). These contextual complexities influence how users engage with and evaluate personalized digital interventions. For example, while many users value motivational and behavioral feedback, others may interpret repetitive prompts or clinical language as intrusive or patronizing (13, 14). This underscores the need to examine not only the functionality but also the subjective experience of users interacting with these tools.

Emerging technologies such as AI, IoT, and digital twins have further expanded the possibilities for hyper-personalization in digital health. AI-driven platforms are now capable of adjusting feedback based on real-time physiological signals, location data, and even sentiment analysis derived from voice or facial expression recognition (15-17). These systems attempt to replicate aspects of human empathy and coaching by offering context-aware interventions. For instance, Verma et al. (1) introduce the "HEALTHIFY" platform, which employs AI and MERN architecture to provide predictive and personalized healthcare support based on dynamic user data. Similarly, Priyadharshini et al. (18) highlight the use of IoT in designing individualized nutritional plans, while Pasupuleti (19) discusses AI-enhanced bionic feedback in prosthetics. However, while the technological capabilities are expanding rapidly, the psychosocial reception of such feedback remains underexplored.

Understanding user perceptions is thus not merely a question of usability but also of digital ethics, cognitive framing, and health communication theory. As Qiao (20) argues, feedback mechanisms must account for signal complexity, frequency, and responsiveness to user behavior over time. When feedback is too generic or not synchronized with user intent, it risks inducing disengagement or mistrust. Moreover, if users perceive feedback as judgmental or surveillance-like, it can trigger psychological resistance and privacy concerns, especially in cultures where digital trust is still being negotiated (21, 22). These concerns are compounded when feedback lacks cultural sensitivity or when language and interface design do not reflect the user's lived context (23, 24).

In a review of mobile health literature, Mizna et al. (25) note that despite technological sophistication, many feedback systems still lack adaptive emotional intelligence and fail to align with users' health goals or mental states.

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This mismatch can result in users either misinterpreting or outright ignoring important feedback. Likewise, Collings and Brennen (26) illustrate how telehealth platforms that incorporate user-preferred communication styles (e.g., visual cues, timing of delivery) enhance comprehension and retention of health information. This is especially important in low-resource settings, where health misinformation and digital fatigue may skew feedback reception (27, 28). This study, therefore, seeks to fill this critical gap by exploring how users in Mexico perceive and experience personalized feedback in digital health tools.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a qualitative research design grounded in an interpretivist paradigm to explore user perceptions of personalized feedback in digital health tools. The design was selected to capture the nuanced, subjective experiences of users and to allow for an in-depth understanding of the meanings they attribute to feedback mechanisms in these technologies. The target population comprised adult users of digital health tools in Mexico who had experience receiving personalized feedback features (e.g., tailored health tips, behavioral suggestions, or goal-based prompts).

Participants were recruited using purposive sampling to ensure diversity in age, gender, digital literacy, and types of digital health tools used (e.g., fitness tracking apps, telemedicine platforms, or mental wellness apps). A total of 20 participants were included in the study, and recruitment continued until theoretical saturation was achieved—defined as the point at which no new themes or significant variations in responses emerged during data analysis.

2.2. Data Collection

Data were collected through individual semi-structured interviews conducted either face-to-face or via secure video conferencing platforms, depending on participant preference and logistical feasibility. An interview guide was developed based on prior literature and expert consultation and focused on key areas such as user interpretation of feedback, perceived usefulness and trustworthiness, emotional responses, and behavioral influence. Interviews were conducted in Spanish, the native language of the participants, by trained bilingual researchers. Each interview lasted approximately 45–60 minutes and was audio-recorded with participant consent. All interviews were transcribed verbatim and then translated into English for analysis purposes, with bilingual validation to preserve contextual and linguistic accuracy.

2.3. Data Analysis

Thematic analysis was used to identify patterns and insights within the data. The analysis followed the six-phase framework by Braun and Clarke (2006): familiarization with the data, generation of initial codes, searching for themes, reviewing themes, defining and naming themes, and writing the report. Transcribed data were uploaded into NVivo 14 software to facilitate systematic coding, category development, and theme mapping. Initial codes were generated inductively from the data and then organized into broader themes reflecting users' experiences and interpretations of personalized feedback.

To enhance the trustworthiness of the findings, several strategies were employed: member checking with selected participants to verify the accuracy of interpretations, peer debriefing with qualitative research experts, and maintaining an audit trail of coding decisions. Reflexivity was practiced throughout the process, with the research team documenting their assumptions and potential biases in analytic memos.

3. Findings and Results

The study sample consisted of 20 participants residing in various regions of Mexico, all of whom had prior experience using digital health tools with personalized feedback features. Participants ranged in age from 21 to 58 years, with a mean age of 37.6 years. The gender distribution included 11 females (55%) and 9 males (45%). In terms of education, 7 participants (35%) held a bachelor's degree, 6 (30%) had completed postgraduate education, 5 (25%) had a high school diploma, and 2 (10%) had vocational or technical training. Employment status revealed that 12 participants (60%) were employed full-time, 4 (20%) were students, 2 (10%) were self-employed, and 2 (10%) were unemployed. Regarding the type of digital health tools used, 9 participants (45%) regularly used fitness tracking apps, 6 (30%) used chronic condition management tools (e.g., diabetes or heart

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monitoring apps), and 5 (25%) used mental wellness or mindfulness applications. The sample demonstrated sufficient diversity in age, education, and health app usage to provide a well-rounded perspective on user experiences with personalized feedback.

The first phase of the data analysis involved open coding, which focused on breaking down the interview transcripts into discrete, meaningful units of data. Using an inductive approach, the research team carefully reviewed each transcript line by line in NVivo 14, assigning descriptive labels (codes) to segments that reflected important user statements, concepts, or experiences related to personalized feedback in digital health tools. This process generated a wide array of initial codes capturing participants' interpretations, emotional reactions, behavioral responses, concerns, and suggestions. Codes were refined through constant comparison and collaborative discussion among the coding team to ensure clarity and consistency. A total of 78 distinct open codes emerged, which served as the foundational layer for the subsequent axial coding phase. The table below illustrates the open codes and identifies the participant(s) (P1 to P20) whose narratives contributed to each code.

Table 1

Open Codes and Corresponding Participant References

Open Code	Participants (P#)
Motivated by progress tracking	P1, P5, P8, P12, P17
Confused by feedback wording	P2, P4, P7, P10, P13
Feedback felt judgmental	P3, P6, P9, P15
Positive tone increased trust	P1, P4, P11, P18
Notifications are overwhelming	P5, P8, P12, P19
Prefer visual feedback (graphs/charts)	P2, P6, P14, P17
Emotional reaction to negative feedback	P3, P9, P10, P13, P20
Improved sleep after using app	P1, P5, P16
Distrust in accuracy of feedback	P6, P7, P13, P18
Desire for culturally relevant suggestions	P2, P4, P11, P14, P20
Unclear health terminology	P3, P7, P10, P12
Encouraged by motivational phrases	P1, P4, P9, P17
Too generic to feel personal	P2, P6, P13, P15
App encouraged healthy eating	P1, P5, P11, P16
Data privacy concerns	P6, P7, P12, P18, P20
Tailored goals increased adherence	P3, P8, P11, P14
Preferred daily tips	P2, P9, P10, P15
Feedback aligned with personal goals	P1, P4, P11, P17
App felt like a coach	P5, P6, P8, P12, P16
Annoyed by frequent reminders	P3, P7, P10, P13
Desired more human-like interaction	P4, P9, P14, P18
Felt supported by positive feedback	P1, P5, P11, P17
Wanted feedback in native language	P2, P6, P10, P20
Conflicting messages between modules	P3, P7, P12, P15
Liked feedback celebrating small wins	P1, P8, P11, P16
Lack of feedback customization	P2, P4, P13, P18
Helped track chronic conditions	P5, P9, P14, P19
Prompted doctor visits	P3, P6, P10
App felt impersonal	P2, P7, P13, P15
Preferred audio feedback option	P1, P8, P14, P20
Wanted integration with other apps	P4, P6, P11, P17
Confusion over scoring system	P3, P7, P12
Trusted app because of professional design	P5, P9, P14, P16
Cultural idioms felt awkward	P2, P6, P13
Encouraged by step count feedback	P1, P4, P10, P17
Found feedback intrusive	P3, P7, P15, P18
Desired more control over settings	P2, P5, P12, P20
Became more aware of health patterns	P1, P6, P11, P14

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Frustrated by conflicting data	P3, P8, P13, P19
Needed explanation for feedback recommendations	P2, P7, P10, P18
Wanted reward system for goals	P4, P9, P14, P17
Found visuals motivating	P1, P5, P11, P16
Would like feedback via WhatsApp	P6, P8, P12, P20
Preferred weekly summary format	P2, P4, P13, P15
Liked gamification elements	P3, P5, P9, P14
Wanted option to turn off some feedback	P7, P10, P18, P19
Felt surveilled by app	P6, P12, P15, P20
Feedback matched fitness level	P1, P4, P11, P17
Improved medication adherence	P3, P5, P8, P16
Feedback felt robotic	P2, P6, P10, P13
Became more health-conscious	P1, P5, P9, P14

Following open coding, the second phase of analysis involved axial coding, which aimed to organize and relate the open codes into broader, more conceptual categories. This process entailed re-examining the initial codes to identify underlying patterns, relationships, and causal conditions that connected them. By clustering related open codes under higher-order concepts, we developed a set of axial codes that captured the essential dimensions of participants' experiences with personalized feedback. The axial coding process also helped in constructing the narrative of how users interact with and interpret feedback in digital health tools, revealing both the contextual influences and the perceived outcomes of these interactions.

Table 2

Axial Codes and Corresponding Open Codes

Axial Code	Corresponding Open Codes
Emotional Responses to Feedback	Feedback felt judgmental; Emotional reaction to negative feedback; Felt supported by positive feedback; Liked feedback celebrating small wins
Clarity and Comprehension	Confused by feedback wording; Unclear health terminology; Confusion over scoring system; Needed explanation for feedback recommendations
Perceived Personalization	Too generic to feel personal; Feedback matched fitness level; Lack of feedback customization; Feedback aligned with personal goals; Tailored goals increased adherence
User Trust and Credibility	Distrust in accuracy of feedback; Trusted app because of professional design; Feedback felt robotic; Conflicting messages between modules
Motivation and Engagement	Motivated by progress tracking; Encouraged by motivational phrases; Encouraged by step count feedback; Found visuals motivating; Liked gamification elements
Notification and Reminder Fatigue	Notifications are overwhelming; Annoyed by frequent reminders; Wanted option to turn off some feedback
Interface Preferences	Prefer visual feedback (graphs/charts); Preferred audio feedback option; Would like feedback via WhatsApp
Desired Control and Customization	Desired more control over settings; Wanted reward system for goals; Preferred weekly summary format
Cultural and Linguistic Fit	Desired more human-like interaction; Cultural idioms felt awkward; Wanted feedback in native language; Desire for culturally relevant suggestions
Perceived Surveillance and Privacy Concerns	Data privacy concerns; Felt surveilled by app; App felt impersonal
Behavioral Impact	Improved sleep after using app; Became more health-conscious; Improved medication adherence; Prompted doctor visits
Role of Feedback as Digital Coach	App felt like a coach; Preferred daily tips; Helped track chronic conditions; Became more aware of health patterns
Integration and Compatibility	Wanted integration with other apps; Conflicting messages between modules
Design and Communication Preferences	Positive tone increased trust; Feedback felt robotic; Confused by feedback wording; Liked feedback celebrating small wins
Barriers to Feedback Acceptance	Found feedback intrusive; App felt impersonal; Conflicting data; Feedback felt robotic

In total, 15 axial codes were derived by grouping the 78 open codes based on conceptual similarity and relational significance. The axial coding phase revealed that participants' perceptions of personalized feedback are shaped by both functional aspects—such as clarity, customization, and format—and emotional and relational aspects, including trust, cultural fit, and the tone of feedback. Notably, Emotional Responses to Feedback and Perceived Personalization emerged as dominant categories, frequently discussed across a broad range of interviews. Meanwhile,

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more specialized themes like Interface Preferences and Integration and Compatibility captured individual variation in user expectations. These axial codes set the stage for the final phase of selective coding, where central themes will be integrated into a core narrative explaining the user experience holistically.

The final stage of data analysis, selective coding, aimed to integrate and refine the emerging theoretical framework by identifying the core categories that encapsulate the essence of user experiences. In this phase, the axial codes were systematically reviewed and organized under broader selective codes, which represent central, overarching themes. These selective codes form the conceptual core of the study and explain how users perceive, engage with, and evaluate personalized feedback in digital health tools. The process involved iterative comparisons across axial categories to determine which ones shared common causal conditions, consequences, or dimensions of meaning, leading to the emergence of four core thematic domains that holistically explain participants' experiences.

Table 3

Selective Codes with Corresponding Axial Codes

Selective Code (Core Theme)	Corresponding Axial Codes
Perceived Effectiveness of Feedback	Motivation and Engagement; Behavioral Impact; Role of Feedback as Digital Coach
Personal Relevance and Cultural Fit	Perceived Personalization; Cultural and Linguistic Fit; Desired Control and Customization
Communication and Design Quality	Clarity and Comprehension; Interface Preferences; Design and Communication Preferences; Notification and Reminder Fatigue
Trust, Privacy, and Emotional Resonance	Emotional Responses to Feedback; User Trust and Credibility; Perceived Surveillance and Privacy Concerns; Barriers to Feedback Acceptance

The selective coding process synthesized the participants' narratives into four central categories that capture the dynamics of their interaction with digital health feedback. The first theme, Perceived Effectiveness of Feedback, emphasizes how users evaluate feedback based on its motivational power and behavioral impact, especially when it functions like a digital health coach. The second theme, Personal Relevance and Cultural Fit, highlights the importance of feedback being contextually appropriate, culturally sensitive, and customizable to users' individual preferences. The third theme, Communication and Design Quality, covers technical and aesthetic dimensions of feedback delivery, including clarity, interface design, and notification frequency—factors that shape ease of use and message comprehension. The final theme, Trust, Privacy, and Emotional Resonance, addresses the emotional and ethical aspects of feedback, including how it is perceived in terms of surveillance, credibility, emotional tone, and data security.

4. Discussion and Conclusion

The aim of this study was to explore how users perceive and interpret personalized feedback provided through digital health tools. Drawing upon thematic analysis of semi-structured interviews with 20 participants from Mexico, the results revealed four core themes: *perceived effectiveness of feedback, personal relevance and cultural fit, communication and design quality*, and *trust, privacy, and emotional resonance*. These findings shed light on the complex and multidimensional nature of feedback engagement and offer several theoretical and practical insights for the future of digital health design.

One of the most prominent findings of this study was the role of *feedback as a behavioral motivator*. Participants often described personalized messages—especially those that were positively framed or visually engaging—as helpful in sustaining health routines such as sleep hygiene, physical activity, and medication adherence. These results echo the findings of (1), who demonstrated how AI-powered personalization platforms, such as HEALTHIFY, significantly improved user retention and adherence by aligning feedback with health goals in real time. The motivational effect was amplified when feedback celebrated small milestones or encouraged incremental improvement, reinforcing the behavioral psychology principle of positive reinforcement in digital intervention design.

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However, participants also noted that *feedback was effective only when it felt personally relevant*. Many interviewees criticized generic or repetitive feedback, perceiving it as impersonal or disconnected from their current goals and lifestyle context. This aligns with (3), who emphasized the importance of integrating patient input and self-reported preferences into algorithmic feedback loops to enhance the personalization of care strategies. Similarly, (4) argued that feedback must be "short, modern, and smart" to resonate with users in a culturally and emotionally meaningful way. In this study, users frequently expressed a preference for feedback that reflected not only their current biometric data but also their cultural norms, language, and emotional tone. These observations support (10), who found that older adults were more engaged with video feedback tools that had been co-designed with their input, thereby ensuring emotional alignment and cultural appropriateness.

Another key theme was *communication and design quality*. Participants frequently referenced issues with the clarity of health terminology, confusing scoring systems, and overwhelming notifications. Such friction points led to disengagement or skepticism toward the feedback. These concerns are consistent with findings by (26), who noted that patients in telehealth education classes benefitted most when feedback was simple, concise, and delivered with multimedia aids. Similarly, (13) emphasized that digital twins should translate real-time health data into intuitive and actionable insights to prevent user confusion and fatigue. This study reaffirms that overly technical, frequent, or poorly designed feedback risks being ignored or misunderstood, undermining its intended impact.

In addition, the issue of *trust and emotional tone* emerged as critical in determining whether users accepted or rejected feedback. Some participants described the tone of automated messages as judgmental or robotic, which decreased their willingness to engage with the application. Others expressed concern over the perceived surveillance embedded in feedback systems, particularly when reminders or nudges occurred with high frequency or without context. These responses reflect findings from (21), who observed that patient trust declined when digital feedback tools lacked transparency in how data was used to generate personalized content. Similarly, (22) highlighted that emotional resonance and perceived empathy—even in AI-generated responses—were essential for engagement, especially among therapy users. These concerns reinforce the importance of balancing automation with human-like interaction in feedback delivery.

Participants also raised privacy and autonomy concerns, particularly when feedback was perceived as overly intrusive. They expressed a strong desire for more control over notification frequency, content types, and delivery modes—preferring, for example, weekly summaries over daily alerts. This finding aligns with (7), who demonstrated that user satisfaction with health recommendation systems increased significantly when interfaces allowed personalization of interaction patterns. Similarly, (6) emphasized that users want health technology to integrate with their lifestyle and environment in real time, rather than dictate behavioral standards from an external authority. The ability to adjust feedback settings contributed to a sense of empowerment and engagement, confirming the value of adaptive, user-driven interfaces in digital health tools.

The study also adds to the growing literature on *the emotional and cognitive load* that digital feedback can generate. Some users reported feeling anxious, annoyed, or even guilty after receiving repeated or poorly timed messages, especially when they failed to meet predefined health targets. This aligns with (25), who pointed out that artificial intelligence in healthcare must evolve to include emotional intelligence modules that can assess a user's current state and adjust feedback tone accordingly. Similarly, (19) argued that future healthcare devices should not only measure physiological signals but also recognize emotional distress or disengagement, dynamically tailoring content to avoid adverse psychological effects. The users in this study highlighted the need for *empathetic feedback design*—content that not only informs but also encourages without triggering stress or digital burnout.

From a technological integration perspective, participants voiced interest in feedback systems that could communicate across platforms and consolidate data from multiple health apps. Many users found it frustrating that feedback from different tools was uncoordinated or contradictory, leading to confusion about which recommendations to follow. These experiences are echoed in the findings of (5), who proposed DevOps-integrated teleconsultation systems to unify health data streams and improve consistency in feedback.

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Likewise, (20) emphasized that wearable feedback mechanisms should operate with clear data transmission and control protocols to ensure cross-platform usability. The disjointed nature of feedback across apps in this study calls attention to the need for interoperability in digital health architecture.

Furthermore, this study underscores the importance of *socio-cultural grounding* in feedback design. Participants from Mexico emphasized the value of receiving messages in their native language, using culturally appropriate metaphors or health references. This is consistent with (9), who found that the digital proficiency and acceptance of health tools among nursing students was significantly influenced by their ability to relate to the language and content. Similarly, (14) identified cultural adaptation as a key barrier and opportunity in mobile health implementation. These results stress that personalization must go beyond biometrics to include linguistic and cultural sensitivity.

Lastly, the role of AI, blockchain, and wearable technologies in shaping feedback delivery was evident across user narratives. Some participants were aware that their feedback came from AI systems, and their perceptions varied widely—some expressing excitement at the "smartness" of the tool, while others questioned its credibility. These reactions parallel the arguments of (16), who proposed a neuroadaptive incentivization system using blockchain and IoT to ensure transparency, trust, and behavioral motivation. Similarly, (27) highlighted the potential of wearable nanogenerators to deliver real-time, data-driven feedback in health monitoring and rehabilitation. These studies suggest that as technology becomes more sophisticated, understanding *user trust* in the source and mechanics of feedback will be paramount.

While this study offers in-depth insights into user perceptions of personalized feedback in digital health tools, several limitations must be acknowledged. First, the sample size was limited to 20 participants from Mexico, which may restrict the generalizability of findings to broader or more diverse populations. Second, self-reported experiences are inherently subjective and may be influenced by recall bias, social desirability, or prior exposure to health technologies. Third, the study focused only on semi-structured interviews and did not incorporate observational or longitudinal data that could have enriched the analysis. Lastly, while NVivo 14 facilitated thematic coding, the interpretive process remains inherently qualitative and potentially shaped by researcher perspectives.

Future research should consider expanding the demographic and geographical scope of participants to include individuals from rural areas, different age brackets, or low-resource settings where digital health literacy may vary widely. Comparative cross-cultural studies could also illuminate how cultural values and norms shape user engagement with feedback systems. Additionally, mixed-methods approaches that combine qualitative interviews with usage data, emotion recognition software, or eye-tracking could provide a richer understanding of how feedback is processed in real time. There is also a need to examine how the evolution of generative AI and large language models might affect user trust and emotional response to automated feedback in future digital health platforms.

To optimize the effectiveness of personalized feedback, developers and healthcare providers should prioritize customization features that allow users to control the tone, frequency, and format of feedback. Emotional intelligence should be embedded into feedback algorithms to adjust delivery based on user states, minimizing digital fatigue. Cross-platform integration should be implemented to ensure consistency in messaging, and cultural-linguistic adaptation should be central to content design. Finally, transparency in how feedback is generated—particularly when AI or third-party algorithms are involved—should be clearly communicated to build trust and enhance user confidence in the digital health system.

Authors' Contributions

All authors equally contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

The study placed a high emphasis on ethical considerations. Informed consent obtained from all participants, ensuring they are fully aware of the nature of the study and their role in it. Confidentiality strictly maintained, with data anonymized to protect individual privacy. The study adhered to the ethical guidelines for research with human subjects as outlined in the Declaration of Helsinki.

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