From User Feedback to Iterative Decision-Making: A Low-burden Multi-Channel Feedback Framework for Mobile Health Applications Targeting Non-Communicable Diseases

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Abstract

Mobile health applications (mHealth Apps) can support the long-term management of non-communicable diseases (NCDs). However, their practical value is commonly limited by low user dropout rates and declining engagement over time. To identify meaningful directions for further improvement, a more comprehensive user evaluation is needed. Existing evaluation methods generally rely on questionnaires and interviews, which can provide valuable quantitative and qualitative evidence. At the same time, studies on user-generated content (UGC) show that free-text feedback can also reveal specific directions for product iteration. Yet these sources of feedback are often collected and analysed separately. Further exploration is required on how to integrate multiple feedback sources while minimising the burden on users with limited time and energy, thereby generating actionable evidence to support subsequent iterations. Therefore, this study proposes a low-burden, multi-channel user feedback framework for NCDs mHealth Apps. It integrates three types of feedback—questionnaires, interviews, and UGC—to obtain more comprehensive user feedback evidence and provide a basis for subsequent iterations. The framework comprises three stages: feedback collection and problem identification, cross-source evidence collation, and iteration-oriented outcome delivery. It aims to gather more comprehensive, timely user feedback, facilitating product iterations that better align with user needs and laying the groundwork for future validation in real-world settings.

CCS Concepts

• **Applied computing** → Life and medical sciences; Health informatics.

Keywords

mHealth applications, user feedback, product iteration, usability evaluation, natural language processing

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1 Introduction

Non-communicable diseases (NCDs), also known as chronic diseases, include cardiovascular diseases (CVD), diabetes, respiratory diseases, and others. They are characterised by their long duration and pose serious health challenges [18]. According to the China Cardiovascular Health and Disease Report (CCHDR)2023, the number of CVD patients has reached 330 million, and the prevalence continues to increase. Individuals with type 2 diabetes mellitus (T2DM) face a significantly higher risk of developing CVD compared to the general population, and CVD remains the primary cause of mortality among both type 1 and type 2 diabetes patients [27]. Multimorbidity (two or more chronic conditions) is rising sharply, with an estimated two-thirds of adults aged ≥65 years expected to live with multiple chronic conditions by 2035 [28]. Although existing epidemiological studies and official monitoring data vary in specific figures, they generally indicate that approximately three-quarters of individuals aged 60 and above suffer from at least one chronic disease [16; 22].

Digital health interventions (DHIs) evolve rapidly, and various digital technologies are constantly being updated. Mobile health applications (mHealth Apps) have the potential to facilitate ongoing management of chronic conditions. This is primarily achieved by strengthening self-monitoring and fostering the implementation of healthy behaviours [19]. As early as 2012, the WHO recognised the important potential of mHealth Apps in the prevention and control of NCDs [29]. The high prevalence of these NCDs is largely due to modifiable lifestyle factors such as physical inactivity, irregular diet, smoking, and excessive alcohol consumption, and is compounded by unalterable physiological changes associated with ageing [18]. Therefore, interventions targeting NCDs place greater emphasis on promoting healthy behaviours and supporting self-management, rather than one-off information delivery [11]. mHealth Apps assist users in progressively establishing and consistently maintaining sustainable self-management behaviour patterns [5]. Furthermore, the market for mHealth Apps is showing a significant growth trend. As of December 2025, approximately 337,000 digital health applications were available globally, with over 360 software-based digital therapeutics and more than 103 digital diagnostic products having achieved commercialisation [30].

Despite the rapid growth of mobile health applications and the accelerating pace of product iteration, sustained user engagement has

become a key factor influencing the effectiveness of interventions and the realisation of product value. The usability of applications and the overall quality of the user experience (UX) are considered to be major factors affecting user adherence [26]. Research in the field of DHIs has also demonstrated that high dropout and attrition rates significantly diminish intervention effectiveness and cost-effectiveness [24]. From the perspective of the implementation and iteration of digital health products, relevant research has shown that the realisation of a product's value depends not only on the tool itself, but also on its selection, implementation, deployment and long-term operation in real-world settings. At the same time, feedback data such as user reviews can provide evidence to help developers continuously identify key issues relating to usability, stability, compatibility and privacy. It can also guide the prioritisation of subsequent updates and enhancements [9; 17].

User-generated content (UGC), such as app store reviews, has become a vital source of data for understanding UX and needs [27]. The volume of data is vast, and it is updated frequently. Manually analysing large-scale review data to extract valuable insights involves significant labour and time costs [6]. Numerous research studies on natural language processing (NLP) to automate the analysis of user feedback, aiming to enhance the efficiency of large-scale review collation and analysis, whilst offering support for identifying common issues and potential areas for improvement [2; 6; 7; 15]. For mHealth Apps, a systematic understanding of user feedback is particularly important [9]. Continuous feedback analysis helps developers identify usability issues in a timely manner and optimise functionality and interface design.

However, merely relying on UGC makes it difficult to fully understand users' experiences. UGC typically lacks information regarding user background, usage contexts and task objectives, making it difficult to precisely link specific issues to particular user groups or usage scenarios [2; 8]. In contrast, methods such as questionnaires, interviews and experiments can directly capture socio-demographic and contextual information [10]. Yet employing any single source in isolation has its limitations [2]. UGC often lacks the user background and contextual information necessary to understand the problem, whilst pre-arranged evaluation methods such as questionnaires, interviews and tests may place an additional burden on users with limited time and energy [20].

Multi-channel feedback allows users to choose the method that best suits their schedule, communication style and willingness to engage. By minimising the additional effort required of users, this approach assists developers in obtaining more consistent and varied user feedback. Regarding mHealth Apps for NCDs, there remains a lack of a clear organisational framework for integrating multi-source user feedback in real-world usage scenarios and translating it into evidence that can drive product iteration [2]. To address this issue, this paper combines three types of feedback—questionnaires, interviews and UGC—and utilises NLP to organise and analyse unstructured text. The study proposes a low-burden, multi-channel feedback framework suitable for NCD mHealth Apps, providing a more systematic user evidence base for subsequent product optimisation.

2 RELATED WORK

2.1 Mobile Health Application Evaluation Methods and Usability Practices

Usability is widely regarded as a key factor influencing the actual usage and sustained adoption of mHealth Apps [3; 12; 24]. Existing research typically combines quantitative and qualitative methods to evaluate mHealth Apps, with the aim of identifying usability issues, understanding UX and guiding design improvements. Common methods include standardised questionnaires or scales, interviews, usability tests such as task-based testing and think-aloud protocols, expert heuristic evaluations, and objective analyses based on usage logs or behavioural records [25]. Questionnaires and interviews remain the most common methods for evaluating the usability of mHealth applications [8]. Yet existing usability testing samples remain predominantly focused on adult users, with relatively few dedicated analyses addressing age-related factors such as visual acuity, motor dexterity and digital literacy [20].

Different methods have distinct strengths in terms of data type, depth of interpretation and implementation costs. Questionnaires offer advantages including relatively low implementation costs, a high degree of standardisation of results and ease of comparison across versions; consequently, they are frequently used to rapidly gauge overall usability levels [8]. Among various rating scale tools, the System Usability Scale (SUS) is one of the more mature and widely used instruments in usability testing, having undergone extensive validation. It is suitable for evaluating the usability of a wide range of products and services, including mHealth Apps [21]. The scale consists of 10 items and employs a 5-point Likert scale for scoring. According to the standard scoring method, the SUS total score ranges from 0 to 100, with higher scores indicating better perceived usability [4; 14]. Existing research often interprets SUS scores of approximately 70 or above as indicating an acceptable or good level of usability, although specific interpretations must still be considered in the context of the research study [21].

In contrast, interviews, focus groups and task-based testing are better suited to revealing users' misunderstandings, operational barriers and usage contexts within specific task flows, thereby complementing the limitations of quantitative scores in explaining underlying causes [20]. Expert heuristic evaluations, on the other hand, are frequently used for rapid checks during the early stages of product development or before and after revisions, to assist teams in identifying potential flaws from the perspectives of interaction principles, information architecture and feedback mechanisms. Overall, the key metrics and applicable methods vary across different development stages. Hence, the choice of evaluation method should align with the product stage and research objectives, rather than relying rigidly on a single approach [25].

On this basis, the use of a combination of methods has become a common practice in mHealth usability evaluation. Existing research indicates that combining different methods, such as questionnaires, interviews, task tests, think-aloud protocols or expert evaluations, enhances the comprehensiveness of evaluation results and facilitates a multi-faceted understanding of user experience and usability issues [1; 8; 20; 21]. However, in rapid iteration scenarios, such methods largely still rely on planned implementation. Whilst interviews, formal testing and expert reviews can provide in-depth

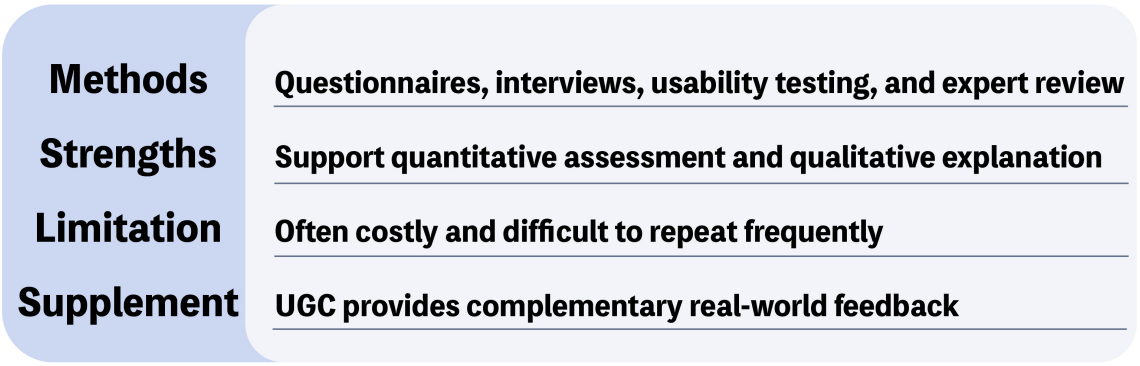


Figure 1: Main evaluation approaches and their role in mHealth usability research

diagnostics, they typically involve high implementation costs and are difficult to conduct frequently. Consequently, alongside formal evaluations, naturally occurring data such as UGC is increasingly being regarded as a vital supplement to traditional methods [12; 13], providing a new source of evidence for the ongoing understanding of user experience in real-world usage contexts (see figure 1).

2.2 NLP-Driven User Feedback Analysis and Its Limitations for Product Iteration

UGC such as app store reviews, in-app feedback channels, and online discussions provide continuously updated textual evidence for understanding real-world usage experiences. Compared to questionnaires or interviews, such feedback typically exhibits greater spontaneity, reflecting users' actual perceptions regarding feature usage, interaction flows, system stability, content quality, privacy trust, and payment experiences [6]. However, the sheer volume of review texts, their fragmented nature, high noise levels, and lack of uniform structure make reliance solely on manual reading and coding challenging to balance efficiency and consistency. Consequently, researchers have begun employing NLP to process unstructured feedback at scale, thereby addressing the limitations of traditional small-sample methods in terms of coverage and timeliness [2; 5; 12].

The typical technical pathways for existing application review mining primarily encompass sentiment analysis, topic modelling, text classification, and aspect-level analysis. Sentiment analysis is typically employed to identify the polarity or intensity of emotions within reviews, aiding in the characterisation of satisfaction tendencies. Topic modelling and clustering methods are frequently used to extract recurring themes of concern within reviews. Text classification and aspect-level analysis further attempt to organise reviews into more product-relevant categories such as error reports, feature requests, and experience feedback. Relevant research indicates that NLP not only reduces manual labour costs in large-scale text processing but also provides methodological foundations for identifying user concerns, comparing differences across scenarios, and tracking shifts in prominent themes over time [27].

Within mHealth and related healthcare service contexts, this approach has been applied to identify key factors influencing satisfaction and ratings. Haggag et al. automatically categorised over 5.1 million reviews across 278 mHealth applications, summarising them into 14 dimensions and analysing their relationship with star ratings. They found privacy concerns and login issues were significantly correlated with low ratings, while user experience and multimedia features were more prevalent in highly rated applications [9]. Similarly, Wang et al. employed unsupervised text mining to extract review themes within weight-loss mHealth applications. By integrating statistical models to analyse asymmetric relationships between diverse themes and satisfaction/dissatisfaction, they demonstrated that review texts not only describe user discussions but also identify factors more likely to influence satisfaction [27]. Recent research has begun integrating Transformers or generative large language models into review analysis workflows. Through steps such as text cleansing, sentiment analysis, topic clustering, and LLM-assisted naming, raw reviews are transformed into more interpretable thematic structures. These structures are then employed to analyse key drivers of satisfaction and dissatisfaction [2; 13].

Nevertheless, the outputs of existing comment mining research largely remain at a descriptive level. Typical results often consist of sentiment distributions, lists of themes or aspects, summaries of common issues, and statistical correlations between different themes and ratings. While such findings can address questions like 'What are users discussing?' and 'What is the overall sentiment?', they seldom directly answer 'Which issues should be prioritised?' or 'How can analysis outcomes be translated into actionable items for the next iteration planning?'. In this sense, a distinct operational gap persists between comment analysis and product iteration decisions: textual analysis outcomes remain insufficiently transformed into interpretable, traceable intermediate artefacts conducive to team discussions.

Relevant research has begun exploring ways to embed online comment analysis more deeply within product iteration processes. For instance, one study converts thematic information from reviews

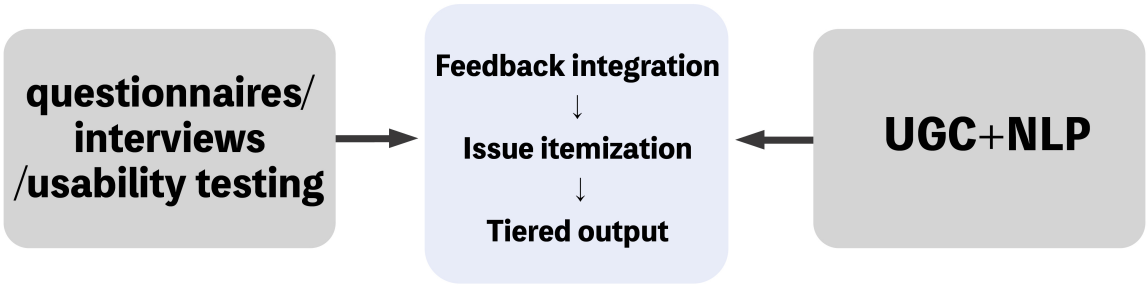


Figure 2: Positioning of the proposed low-burden multi-channel feedback framework.

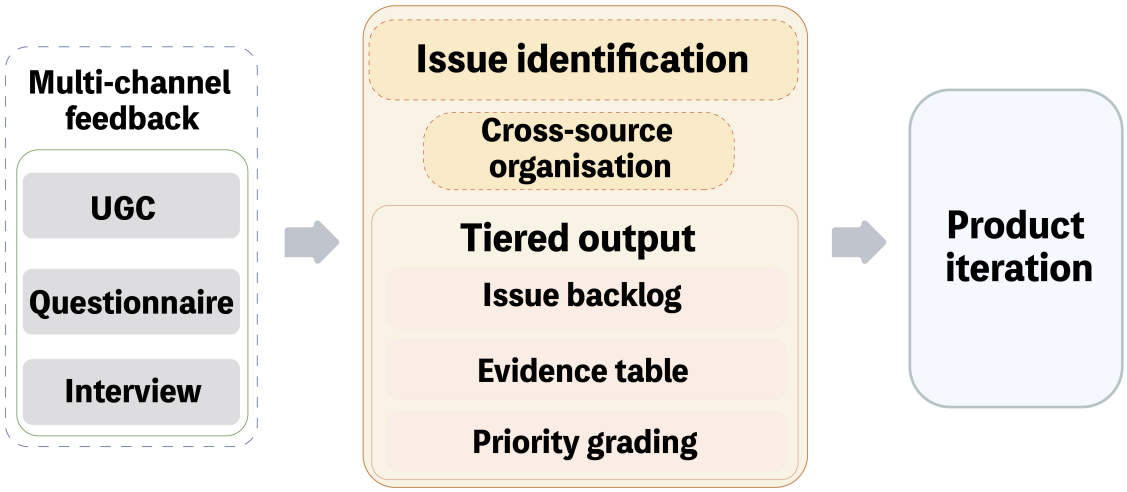


Figure 3: Workflow of the proposed low-burden multi-channel feedback framework for NCD mHealth Apps iteration.

into comparable decision attributes, combining multi-attribute decision methods for requirement screening, weight calculation, and module prioritisation. Another research, after preliminary screening for review credibility, conducts preference analysis at both attribute granularity and design feature granularity to identify key improvement directions [23]. These works demonstrate that the value of user feedback extends beyond mere topic or sentiment identification; it lies in its potential to be organised into comparable, actionable improvement criteria.

3 METHOD

3.1 Framework Overview

This paper proposes a low-burden, multi-channel feedback framework for the routine iteration of NCD mHealth applications (Figure 3). The framework is designed to organise dispersed user feedback into issue items and supporting evidence that can inform product improvement. It consists of three stages: feedback collection and issue identification, cross-source organisation, and tiered output. Its purpose is to support routine product improvement rather than replace specialised assessments of clinical efficacy, safety, or regulatory compliance.

In this study, "low-burden" refers primarily to reducing users' time and effort in providing feedback, rather than reducing the work involved in integrating evidence from multiple sources. The framework does not aim to replace team judgement with automation. Instead, it uses NLP to assist with text organisation, issue identification, and initial consolidation, after which the product team reviews and prioritises the findings considering business goals, resource constraints, and compliance requirements.

Within this framework, an issue item is the basic unit of organisation. It is not a single raw comment, but a specific issue category formed by consolidating multiple pieces of similar feedback. Each issue item records the issue description, source channel, relevant usage context, and representative evidence. In this way, comment text, open-ended feedback, and supplementary evaluation results can be organised into a clearer issue list for later discussion, prioritisation, and tracking.

Table 1: Main outputs of the proposed framework

Output	Description	Use in product workflow
Issue backlog	A structured list of consolidated issue items organised by evaluation domain	Supports sprint planning and problem tracking
Evidence table	Representative evidence, source information, and supporting signals linked to each issue item	Supports team review and traceability
Priority grading	Priority labels such as high, medium, low, or pending verification	Supports iteration discussion and version planning

3.2 Three-Stage Workflow

As shown in Figure 3, the framework progresses through three stages: feedback collection and issue identification, cross-source organisation, and tiered output. Together, these stages generate structured outputs that can support iteration planning and product discussion. Table 1 summarises the three main outputs produced by the framework and their role in product workflow.

3.2.1 Stage 1: Feedback Collection and Issue Identification. This stage gathers feedback from multiple channels while aiming to minimise user participation burden. Feedback sources may vary in the effort required from users, ranging from UGC and brief questionnaires (e.g., SUS) to small-sample semi-structured interviews when deeper explanation is needed.

For free-text data, NLP is used to support text pre-processing, information extraction, and semantic merging, so that similarly expressed feedback can be consolidated into standardised issue items. Each issue item contains, at minimum, a problem description, relevant functional or task context, triggering scenario, representative evidence snippet, source channel, and temporal information. Representative original text is retained together with its source attribution to support later review and communication.

3.2.2 Stage 2: Cross-Source Organisation. This stage organises and interprets issue items across different sources so that evidence related to the same problem can be compared. To support this process, the framework maps issue items to a set of shared evaluation domains: usability and interaction, technology and functionality, content and support, and trust and risk.

The framework then examines whether an issue is supported consistently across channels. For example, it considers whether a problem appears in UGC, is described similarly in interviews, or is reflected in questionnaire results. Issue items with consistent support across sources are treated as relatively stable issues, whereas items supported only weakly or showing cross-source disagreement may be marked as pending verification. The purpose of this stage is to determine whether an issue has sufficient support to inform later iteration discussions.

3.2.3 Stage 3: Tiered Output. This stage converts the organised findings into outputs that can be used in product workflow. The framework generates three main outputs: an issue backlog, an evidence table, and priority grading results. The issue backlog lists standardised issue items by evaluation domain. The evidence table records representative textual evidence, source channels, and relevant quantitative information for each issue item. Priority grading classifies items as high, medium, low, or pending verification based on their impact, scope, evidence strength, and relevance to continued product use.

This grading is not intended as a mechanical ranking. Instead, it provides a transparent basis for team discussion about which issues should be addressed first. After implementation, the same sources and rules may be revisited in later iterations to observe whether relevant issue items change over time.

To illustrate how the framework operates, Table 2 presents an example of how evidence from UGC, SUS, and interviews can be consolidated into one issue item and translated into a priority judgement. The example is intended to demonstrate the logic of issue construction and cross-source organisation, rather than to report empirical validation.

4 DISCUSSION AND CONCLUSION

This Compared with existing mHealth usability studies, the focus of this paper is not on re-establishing the necessity of multi-method evaluation itself, but rather on discussing how feedback from these different sources can be further organised and utilised in real-world product iterations. Research by Sharma et al. indicates that multi-method designs incorporating questionnaires, interviews, focus groups and think-aloud sessions help to enhance the comprehensiveness of usability insights; however, existing studies still primarily revolve around testing methods, testing environments and specific usability attributes. At the same time, continued usage, engagement and retention are considered to significantly influence the actual effectiveness of mHealth interventions. Consequently, product evaluation and subsequent iterations must extend beyond user satisfaction to identify recurring issues during sustained use, whilst synthesising feedback from diverse sources to inform future improvements.

This paper proposes a low-burden, multi-channel feedback framework tailored to the routine iteration scenarios of NCDs mHealth apps. Its value lies primarily in two aspects: firstly, it attempts to integrate previously disparate quantitative, qualitative and UGC feedback into a single analytical pathway to form more systematic user evidence; secondly, whilst minimising the burden on users, it provides a reference for subsequent version planning that is closer to real-world usage contexts. This study remains, however, a framework-based investigation. Future work could involve validating this framework through its application in the iterative development of real-world NCD mHealth products. Overall, this paper does not seek to propose an automated decision-making solution

Table 2: Illustrative example of issue item construction and priority grading across UGC, SUS, and interview evidence

Evidence excerpt / signal	Source channel	Evaluation domain	Consolidated issue item
"The app logs me out repeatedly and sometimes crashes after login."	UGC	Technology and functionality	Login stability and access problem
"The login process is frustrating and interrupts task completion."	Interview	Usability and interaction	Login stability and access problem
Lower overall SUS score, with less positive responses on ease-of-use and confidence-related items	SUS	Usability and interaction	Login stability and access problem
Evidence status: Multi-source consistent. Priority: High.			

that replaces team judgement with complex modelling but rather offers a framework for organising feedback that can be utilised in routine product iteration.

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