Design Tradeoffs in Health Interfaces for Behavior Change

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Abstract

Large language model (LLM)–based chatbots are emerging as persuasive interfaces in digital health, yet their advantages relative to established mobile apps remain uncertain. We present a comparative field study (N = 167) evaluating two smoking-cessation tools: QuitBot, an LLM-driven conversational coach, and quitSTART, a structured mobile app. Participants selected one system, used it for a week, and reported on usability, engagement, and perceived effectiveness. Quantitative findings showed that QuitBot was experienced as easier and more natural to use, while quitSTART prompted more frequent daily engagement and a greater proportion of users to plan a quit date. Qualitative analysis revealed parallel strengths: QuitBot fostered empathy, motivation, and social presence, whereas quitSTART reinforced predictability, goal-setting, and progress tracking. Together, the results highlight a potential trade-off between relational adaptivity and structural scaffolding in persuasive health interfaces, suggesting that hybrid intelligent systems integrating both dimensions may better sustain engagement and support long-term behavior change.

Keywords

Conversational Agents, Large Language Models (LLMs), Human-AI Interaction, Human-Centered AI, Engagement

1. Introduction

Intelligent user interfaces increasingly mediate how people access, interpret, and act on health information, integrating adaptive reasoning and natural interaction to personalize guidance and decision support [1, 2, 3, 4]. In the health domain, intelligent interfaces manifest as relational agents, adaptive mobile applications, and conversational coaches that combine persuasive design with empathic communication to support adherence, motivation, and self-management [5]. The diffusion of large language models (LLMs) and conversational agents represents a major leap in adaptive interface design, enabling systems that simulate natural dialogue, infer user intent, and personalize feedback in real time [6, 7, 8]. These systems can dynamically adjust tone, vocabulary, and persuasive strategy to user context, embodying a long-standing vision of human-centered intelligence in computing that integrates affective, adaptive, and contextual responsiveness [9, 10, 11]. In persuasive health technologies, this capacity for contextual adaptation extends beyond usability to relational communication, allowing systems to mirror motivational tone, empathy, and self-regulatory feedback traditionally provided by human support [10, 12, 13, 14].

At the same time, mobile health (mHealth) applications remain the most prevalent vehicle for delivering behavior change and self-management interventions, leveraging smartphones' ubiquity to enable real-time monitoring, personalized feedback, and persuasive engagement strategies [15, 16, 17, 18, 19, 20, 21]. In smoking cessation alone, hundreds of mobile applications offer features such as reminders, craving trackers, and progress dashboards to support quitting, reflecting the rapid proliferation of digital cessation tools over the past decade [22, 23, 24, 19]. Yet despite their broad reach, many apps show modest engagement and mixed quit outcomes, a pattern repeatedly linked in reviews to limited interactivity and personalization, such as reliance on static content and simple reminders, and limited implementation of evidence-based features [19, 24, 18, 17, 23]. Human-computer

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interaction and persuasive-technology researchers have argued that systems offering only static content, scripted prompts, or one-way messages face disadvantages in sustaining user engagement and delivering perceived relevance, because they lack the responsive feedback and personalization that keep users motivated over time [17, 25, 26, 27].

LLM-based chatbots such as *QuitBot* introduce a conversational paradigm that may overcome these limitations by offering empathy, immediacy, and contextual tailoring. However, there is little comparative evidence of how users experience conversational systems versus more common and structured mobile apps. In fact, recent work on mHealth adoption further suggests that users' engagement is shaped by interface familiarity and feature expectations, with prototypical app designs that provide clear feedback and tailored support perceived as more trustworthy and easier to use [28, 29]. Understanding these trade-offs is central to design of interfaces, where the goal extends beyond intelligent functionality toward meaningful, sustainable interaction that supports user goals and long-term and effective engagement [1, 2, 11, 30, 17]. These questions extend beyond smoking cessation to other domains of mHealth, including mental health support, chronic-disease self-management, and physical-activity promotion, where interactive and adaptive technologies similarly aim to sustain engagement and personalize support for behavior change [13, 31, 32, 33, 34, 14, 8, 35, 36].

To address this gap, we compare two digital smoking-cessation interventions: *QuitBot*, an LLM-based conversational coach, and *quitSTART*, a structured mobile app (Figure 1). In a field study, participants (N = 167) selected one of these apps, used it for a week with the purpose of quitting smoking, and evaluated it at the end. Our analysis focuses on established dimensions of technology acceptance—such as perceived ease of use and perceived usefulness [37, 38, 39, 40] — as well as patterns of engagement with mobile health technology, reflecting models of user adoption and sustained interaction [17, 41]. In line with recent conceptualizations, we consider engagement as encompassing both the depth and quality of interaction with the system, integrating behavioral and experiential dimensions of use [41, 17]. This paper contributes empirical evidence and design implications for the development of hybrid intelligent health behavior change interfaces that combine conversational personalization with structured engagement scaffolds.

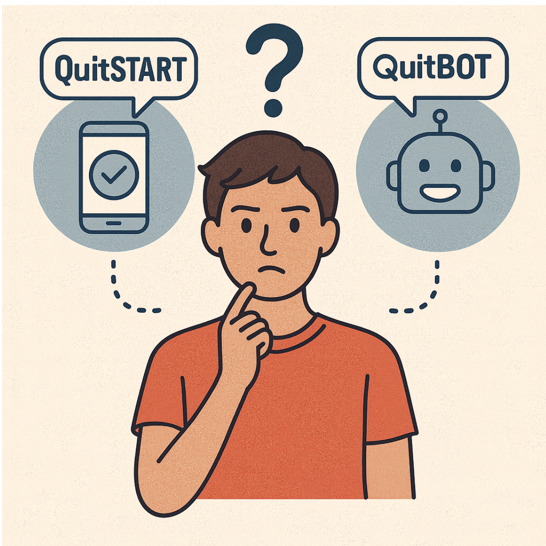

Figure 1: Choosing between an app and a chatbot for smoking cessation

2. Related Work

2.1. Conversational Health Agents and LLM-Based Intelligent User Interfaces

Conversational agents (CAs) and relational interfaces have long served as testbeds for studying social interaction in computing. Early work demonstrated that users apply social and emotional norms to computer-mediated dialogue, responding to relational cues such as empathy, affirmation, and politeness as if they originated from a human partner [12, 3, 5]. These findings inspired a wave of relational agents and health chatbots that employ affective feedback, goal-setting dialogue, and motivational interviewing principles to support adherence and self-management. Within human-computer interaction, this lineage informed the design of IUIs that emphasize dialogue as a channel for persuasion, building therapeutic alliance through empathy and responsiveness rather than static information delivery [5, 13, 42, 35, 43].

Recent advances in large language models (LLMs) have significantly expanded the expressive and adaptive capacity of conversational systems, allowing them to infer user intent, sustain context, and tailor interactions dynamically [7, 8, 32, 44, 36]. This new generation of LLM-based intelligent interfaces can integrate personalization at multiple levels—linguistic, affective, and contextual—creating the potential for more natural and engaging health communication. For example, *HealthGuru* [32] is a recent successful implementation of a multi-agent framework that integrates wearable data and contextual information to suggest tailored interventions to improve sleep. Yet these same design affordances raise critical questions of transparency, trust, and user control [45, 11]. Studies in digital health are beginning to examine these tensions: users often appreciate conversational empathy and immediacy but express uncertainty about accuracy, safety, and the boundaries of automation [46, 47, 48, 42]. Evaluating these trade-offs empirically, as this paper does, contributes to understanding how conversational personalization affects engagement and perceived usefulness and inform future design opportunities [36].

2.2. Engagement, Personalization, and Persuasive System Design

Engagement has emerged as a central construct in persuasive and health-interface design, encompassing not only behavioral metrics (e.g., usage frequency) but also experiential dimensions such as attention, affect, and perceived relevance [41, 17]. The persuasive systems design framework [27] and subsequent empirical studies argue that adaptive feedback and interactivity are essential for sustaining engagement in digital interventions [49, 26, 10]. Systems that provide tailored, bidirectional feedback foster a sense of responsiveness and autonomy that static apps struggle to replicate. Moreover, in the design of adaptive interventions for health, personalization goes beyond usability by providing other behavior change mechanisms, such as goal setting, adaptive feedback, self-monitoring, and prompts [50, 51, 25, 20, 52].

Prior research in human-computer interaction and persuasive technology shows that long-term engagement improves when systems adapt to users' goals, routines, and profiles in ways that match their expectations [49, 1, 53, 54, 55]. Specifically, there is a need to allow technologies for behavior change to evolve alongside users' goals and expectations to maintain engagement over time [49]. Conversely, empirical studies and reviews of mHealth applications show that current apps are often too static, with features that rarely adapt to users' and preferences [56, 23, 57, 58]. These insights resonate with the goal of leveraging AI to design conversational agents as empathic and responsive agents for behavior change and health support [8, 59, 47]. This body of work motivates our comparative evaluation of an LLM-based conversational coach (QuitBot) and a structured app (quitSTART), examining how differing modalities shape ease, usefulness, and engagement of digital interventions for smoking cessation.

2.3. Smoking Cessation Apps and Behavior Change Technologies

Digital smoking-cessation tools represent one of the earliest and most studied classes of mobile health interventions. Systematic reviews show that while hundreds of commercial apps claim to support quitting, few implement evidence-based strategies or maintain user engagement over time [22, 23, 19, 56, 60]. Most rely on static educational content, logging features, or push notifications with limited adaptivity—patterns associated with modest effectiveness [24, 56]. Studies on persuasive health apps, such as Quitty and Clickotine, highlight the importance of personalization, real-time feedback, and goal setting in sustaining motivation [61, 62, 63]. Recently, more research is emerging to suggest class of just-in-time adaptive interventions might outperform more traditional apps for smoking cessation [57].

Recent work has explored integrating conversational agents or AI features into smoking cessation interventions. For example, a systematic exploration of prompt-engineering, decoding strategies, and clinician evaluation to optimize LLM–generated smoking cessation messages, showed that well-tuned prompts and decoding schemes can produce messages rated comparably to expert-crafted ones [44]. *QuitBot* was designed to closely mirrors human counseling by covering the full quitting journey—including relapse recovery, coping, and motivation maintenance—while maintaining clinical safety and message consistency [59, 47]. However, little is known about how users choose between traditional mobile apps and AI-based chatbots or how these choices manifest in long-term ease of use, usefulness, engagement, and behavior change outcomes. By comparing QuitBot and quitSTART as part of a field study with real outcomes, our study can help generate design implications for the next-generation behavior change technology, for smoking cessation and other health domains.

3. Methods

3.1. Participants and Procedure

Participants were recruited in June 2025 through the crowdsourcing platform Prolific, which is often used to recruit for addiction science and intervention trials [64, 65]. The platform advertised the study, offering current adult smokers in the US an opportunity to participate in a study that examines preferences for digital smoking cessation interventions with an option to ultimately use an app that can help quit smoking. Participants were first pre-screened by the platform for residing in the US, being current smokers who only use tobacco products and not e-cigarettes (vaping). Eligible participants were provided an information sheet about the study and signed an electronic consent. This study was approved by the Institutional Review Board at Cedars-Sinai Medical Center (STUDY00003690: QuitChoice) [66, 67].

The study involved a more naturalistic choice between apps, that approximate how people choose apps in the wild. Because participants selected their preferred tool rather than being randomized, group differences should be interpreted as associational and may reflect both interface effects and user self-selection. We specifically selected apps for this study that are different from each other in modality (web-based, mobile app, AI chatbot), so that the choice will be informative of preferences. After selecting the app, participants were expected to use this app and complete additional assessments over a period of two months, but this is beyond the scope of the current paper [66]. Of the 167 participants, 87 (52.1%) selected *QuitBot*, an LLM-based conversational smoking-cessation coach, and 80 (47.9%) selected *quitSTART*, a structured mobile app developed by the U.S. National Cancer Institute. Participants downloaded and used their chosen app over a one-week period, during which they engaged with the intervention in their natural environment. Participants were diverse in age (range 19–65 years, mean 39.2, SD 11.3) and gender (58% female, 41% male, 1% other).

3.2. Interventions

QuitBot is a conversational coaching program delivered through a virtual coach (“Ellen”) in daily chats that span a pre-quit phase, quit day, and post-quit phase, with optional tracks for users who are not yet ready to quit or who have relapsed [59, 47]. The intervention is designed to strengthen four therapeutic-alliance processes—bond, agreement on goals, agreement on tasks, and the user’s sense that the coach understands their needs—through an empathetic persona, social dialogue, and meta-relational communication. QuitBot proactively messages users at preferred times and provides on-demand support for urges, mood triggers, and lapses. A core feature is a hybrid question-answering engine that draws from a curated library of over 10,000 cessation question–answer pairs (via Microsoft Azure QnA Maker) and escalates out-of-library queries to a fine-tuned GPT-3.5 model. The program content adheres to U.S. Clinical Practice Guidelines and is delivered as an adaptive, ongoing conversation that integrates prior user inputs to personalize guidance and motivation.

quitSTART is a free, interactive smartphone app developed by the National Cancer Institute (NCI) and offered through the Smokefree.gov platform [68]. The app provides personalized tips, motivational messages, and challenges designed to support quitting and relapse recovery. The app includes progress tracking with milestone badges, real-time trigger tagging that delivers context-specific encouragement (including a map-based "drop-a-pin" feature), and a relapse-recovery flow that helps users resume their quit plan after slips. It also offers tools for managing cravings and moods through games, coping exercises, and distractions, as well as a customizable "Quit Kit" that stores preferred tips and resources. The app's design emphasizes self-monitoring and positive reinforcement rather than dialogue, offering tailored but structured interactions guided by user input rather than adaptive conversation. quitSTART is available for iOS and Android devices and has been evaluated in prior studies assessing user engagement and feature utilization [69, 70].

As presented in Figure 2, these two apps represent contrasting designs in persuasive mobile health interventions for smoking cessation and should allow to study the impact of design tradeoffs.

Figure 2: Screenshot of the quitSTART and QuitBot App

3.3. Measures and Analysis

During the follow up survey, participants completed an assessment of current smoking status and quit attempts, engagement with the app, and reported their positive and negative experiences. These assessments were designed to allow for quantitative and qualitative comparison of user experience, based on their choices of an app.

3.3.1. Smoking Status and Engagement

To assess current smoking status, we also evaluated participants' attempts to quit smoking, quit date, and abstinence during this period. All questions asked about the last 7 days, for example, "Have you smoked (even a puff) in the last 7 days?". These types of self-reports questions are common in low-burden trials that evaluate smoking cessation apps [61].

To assess engagement, participants asked whether they signed up for the app they chose at baseline. If they answered "yes", we asked additional questions, adapted from prior research to measure engagement with the app [17, 71] and technology acceptance [37, 38, 39, 40] that included questions such as: "how frequently do you use [name of app]", "how easy to use is [name of app]". We also asked how likely they are to recommend this app to a smoker like them on a scale of 0-10 (Net Promoter Score; NPS), following prior work in human-computer interaction and digital interventions evaluations that have reported NPS alongside usability and engagement outcomes [72, 73].

Group-level comparisons were conducted to assess differences between users of *QuitBot* and *quitSTART*. Independent-samples t-tests evaluated mean differences in perceived ease, usefulness, and NPS, while chi-square tests compared categorical distributions of daily engagement intensity (single vs. multiple daily sessions) as well as smoking-related outcomes (set quit date, attempted to quit). Statistical analyses were performed in *R* version 4.4.2. Effect sizes were computed using Cohen's d for continuous measures and Cramer's V for categorical comparisons to aid interpretability.

3.3.2. Experience and Qualitative Analysis

In addition to quantitative comparisons, a reflexive thematic analysis [74, 75] was conducted on participants' open-ended responses describing what they found helpful or challenging about their chosen app. The goal was to identify perceived benefits, barriers, and design expectations associated with *QuitBot* (LLM-based chatbot) and *quitSTART* (structured mobile app). This is typical in human-computer interaction research [76] and evaluation of health apps [77, 78].

The research team independently reviewed all textual responses and developed inductive codes capturing recurring ideas related to usability, motivation, personalization, and support. Codes were iteratively refined and grouped into higher-order themes to ensure internal coherence and distinction. Five cross-cutting themes emerged: ease of use, personalization and empathy, engagement routines, technical or functional barriers, and perceived effectiveness. Representative quotes were selected to illustrate each theme while maintaining participant anonymity. Analytic decisions and theme definitions were documented throughout to enhance transparency. The resulting themes were interpreted in relation to quantitative results, providing contextual insight into how users experienced and evaluated the two systems.

4. Results

We first examined differences between *QuitBot* and *quitSTART* on quantitative indicators of smoking status, technology acceptance and engagement, followed by a thematic analysis of open-ended responses.

4.1. Quantitative Results

4.1.1. Engagement

Table 1 summarizes participants' engagement evaluations of *QuitBot* and *quitSTART* across the primary study measures. Overall, participants evaluated both programs favorably, with mean scores above the scale midpoint on ease of use, usefulness, and engagement.

Ease of use. Participants rated *QuitBot* as significantly easier to use than *quitSTART* ($t(165) = 2.43$, $p = .016$, Cohen's $d = 0.38$). The conversational interface was frequently described as intuitive and requiring minimal navigation effort.

Perceived usefulness. Mean usefulness scores did not differ significantly between the two groups ($t(165) = 0.82$, $p = .41$), suggesting that both interventions were perceived as comparably effective in supporting quit-related goals.

Engagement frequency. Daily engagement patterns differed by platform ($\chi^2(1, N = 167) = 4.56$, $p = .033$, Cramer's $V = 0.17$). *quitSTART* users reported more frequent multiple-times-per-day use (46.9%) than *QuitBot* users (30.2%), indicating higher short-term behavioral engagement with the app's structured routines and interactive tools.

Net Promoter Score (NPS). Mean NPS scores were modestly higher for *quitSTART* (M = 7.1, SD = 1.9) than for *QuitBot* (M = 6.5, SD = 2.2), though this difference did not reach statistical significance ($t(165) = 1.57$, $p = .12$, $d = 0.25$).

Across measures, results indicate a trade-off between perceived usability and intensity of engagement. While *QuitBot* was experienced as easier and more natural to use, *quitSTART* elicited more frequent and repeated daily interactions. These complementary strengths suggest distinct engagement pathways—*QuitBot* through conversational motivation and relational immediacy, and *quitSTART* through structured feedback and habit scaffolding.

Table 1
Comparison of engagement measures between *QuitBot* and *quitSTART*. Higher scores indicate greater endorsement or engagement.

Measure	**QuitBot** (M ± SD)	**quitSTART** (M ± SD)	Test Statistic	p-value
Ease of Use (1–5)	4.43 ± 0.71	4.10 ± 0.83	$t(165) = 2.43$	.016*
Usefulness (1–5)	4.11 ± 0.80	4.00 ± 0.78	$t(165) = 0.82$	.41
Daily Engagement (multi/day, %)	30.2%	46.9%	$\chi^2(1) = 4.56$	.033*
Net Promoter Score (0–10)	6.5 ± 2.2	7.1 ± 1.9	$t(165) = 1.57$	.12

Note. $^*p < .05$. Effect sizes: Cohen's $d = 0.38$ for ease of use, 0.25 for NPS; Cramer's $V = 0.17$ for daily engagement.

4.1.2. Smoking Status

We next examined indicators of quit planning and behavior during the one-week study period. Two variables were analyzed: whether participants reported setting a quit date (*QuitDateYes*) and whether they reported having made a quit attempt (*QuitYes*) by the end of the week. Table 2 summarizes these results.

Quit-date planning. A significantly larger proportion of *quitSTART* users reported setting a quit date (74.3%) compared to *QuitBot* users (50.0%) ($\chi^2(1, N = 167) = 9.10$, $p = .0026$, Cramer's $V = .23$). This finding indicates that *quitSTART*'s structured, goal-oriented design was more effective in prompting users to engage in formal quit planning than the conversational approach of *QuitBot*.

Quit attempts. In contrast, there was no significant difference between groups in whether participants reported attempting to quit smoking during the week ($\chi^2(1, N = 167) = 0.06$, $p = .81$, Cramer's $V = .02$). Approximately 69.4% of *QuitBot* users and 72.4% of *quitSTART* users reported making a quit attempt. This suggests that while *quitSTART* facilitated structured planning behavior, both systems were equally effective in supporting users' initial motivation and readiness to attempt quitting.

Together, these findings illustrate a dissociation between planning and action: users of the structured app were more likely to plan a quit date, whereas users of the conversational chatbot were equally likely to initiate a quit attempt despite less formal planning. These patterns align with behavioral models suggesting that motivation and planning represent distinct stages of change, which may be differentially supported by conversational and structured health interfaces.

Table 2
Comparison of smoking-related outcomes between *QuitBot* and *quitSTART*.

Measure	QuitBot (%)	quitSTART (%)	χ^2(1)	p
Set Quit Date (*QuitDateYes*)	50.0	74.3	9.10	.0026*
Attempted to Quit (*QuitYes*)	69.4	72.4	0.06	.81

Note. $^*p < .05$. Cramer's $V = .23$ for quit-date planning; $V = .02$ for quit attempts.

Table 3
Summary of qualitative themes describing user experience with *QuitBot* (LLM-based chatbot) and *quitSTART* (structured mobile app).

Theme	QuitBot (Conversational Coach)	quitSTART (Structured App)
Ease of use and intuitiveness	Conversational flow reduced cognitive effort; users described interactions as intuitive and natural.	Clear navigation and goal-tracking layout supported efficient task completion but required more manual input.
Personalization and empathy	Provided adaptive and motivational dialogue that conveyed empathy and social presence.	Personalization was system-driven through tailored messages, badges, and milestones rather than relational tone.
Engagement routines and motivational triggers	Interaction was emotion-driven and situational, typically during cravings or stress.	Engagement followed predictable daily routines reinforced by challenges, reminders, and visible progress.
Technical or functional barriers	Occasional off-topic or repetitive chatbot responses reduced trust and perceived coherence.	Notification fatigue and limited customization options were common sources of frustration.
Perceived effectiveness and self-efficacy	Users attributed motivation and confidence to the chatbot's supportive dialogue and accountability.	Progress tracking and feedback visualizations reinforced a sense of control and achievement.

4.2. Qualitative Results

Thematic analysis of participants' open-ended responses revealed five overarching themes that characterized user experience across the two digital cessation tools: (1) ease of use and intuitiveness, (2) personalization and empathy, (3) engagement routines and motivational triggers, (4) technical or functional barriers, and (5) perceived effectiveness and self-efficacy. The themes highlight complementary strengths of the conversational and structured interfaces, as well as shared expectations for support and reliability.

Ease of use and intuitiveness. Across both groups, participants frequently described their chosen program as "easy to use" and "simple to navigate." *QuitBot* users emphasized conversational flow and minimal cognitive load ("It felt like texting a real person who already knew my goal"), whereas *quitSTART* users appreciated the organized dashboard and goal-tracking layout ("Everything I needed was on one screen"). Participants associated ease of use with immediate comprehension and accessibility—features that reinforced early engagement and reduced frustration.

Personalization and empathy. A prominent distinction emerged in perceptions of personalization and emotional tone. *QuitBot* users highlighted the chatbot's empathic and motivational responses ("It gave me encouragement when I needed it") and appreciated its conversational adaptability ("It seemed to respond to what I was feeling"). In contrast, *quitSTART* users interpreted personalization primarily through data-driven features such as tailored tips, badges, and milestone messages. While both groups valued feedback, the relational framing of *QuitBot* appeared to foster a stronger sense of social presence and support.

Engagement routines and motivational triggers. *quitSTART* users described building routines around the app's challenges, check-ins, and achievement tracking ("I liked the daily goals and seeing progress"). The structured nature of these features provided predictable, task-oriented engagement that fit within daily schedules. By contrast, *QuitBot* users framed engagement as situational and emotion-driven—turning to the chatbot "when stressed" or "when tempted to smoke." This contrast suggests different engagement pathways: routine-based engagement with structured apps versus context-driven engagement with conversational agents.

Technical or functional barriers. Participants in both groups reported occasional usability issues that disrupted engagement. *QuitBot* users mentioned occasional repetition or off-topic responses, reflecting limits of conversational coherence ("Sometimes it didn't understand my question"). *quitSTART* users described notification fatigue and difficulty customizing reminders ("Too many alerts—it felt overwhelming"). These issues highlight how friction in interactivity—whether cognitive or functional—can reduce sustained engagement even when overall satisfaction remains high.

Perceived effectiveness and self-efficacy. Participants across both programs expressed a general sense of progress and confidence in managing cravings. *QuitBot* users attributed perceived effectiveness to the motivational dialogue and sense of accountability ("It kept me thinking about my goal"). *quitSTART* users emphasized self-tracking and visual progress feedback ("Seeing fewer cigarettes each day was motivating"). These responses align with models of digital engagement that link self-reflection, feedback, and emotional reinforcement to perceived behavior change.

Taken together, the qualitative results illustrate how users evaluate health apps not only by functionality but also by the type of relationship they form with the system. *QuitBot* provided affective and conversational immediacy, while *quitSTART* offered structured reinforcement and habit scaffolding (Table 3). The contrast reveals a core design trade-off between relational adaptivity and behavioral structure, suggesting that hybrid approaches integrating empathic dialogue with routine-building features may yield more sustainable engagement.

5. Discussion

This study compared user experiences with two digital smoking cessation interventions—a conversational, large-language-model (LLM)–based chatbot (*QuitBot*) and a structured mobile application (*quitSTART*)—to examine how interface modality shapes perceived usability, engagement, and smoking-related behavior. The aim was to evaluate how users experience persuasive health interfaces that differ in how relationally adaptive (i.e. adjusting social stance / tone over time) they are, and how much scaffolding (e.g. guided support, hints, workflow structure) they provide, and to identify trade-offs that can inform the design of hybrid intelligent user interfaces for health behavior change.

Quantitative findings revealed a clear trade-off between usability and behavioral engagement. *QuitBot* users rated the system as significantly easier to use, describing its conversational format as natural, intuitive, and low-effort. This aligns with human-computer interaction work suggesting that naturalistic dialogue can reduce cognitive load and increase perceived immediacy [7, 5]. In contrast, *quitSTART* users showed higher daily engagement and more frequent multi-daily use. This is consistent with literature emphasizing the value of structure, routine, and progress tracking in sustaining engagement with mobile health (mHealth) interventions [49, 79]. Smoking-related outcomes further highlight this divergence. Participants using *quitSTART* were significantly more likely to set a quit date, while *QuitBot* users were equally likely to attempt quitting despite less formal planning. The dissociation between planning and action observed here supports prior evidence that behavioral change technologies should integrate both forms of support [49, 27]. These complementary capabilities illustrate how conversational modalities and structural mobile health app design represent distinct pathways to engagement, with one being affective and responsive and the other behavioral and habitual.

Thematic analysis provided qualitative depth to the identified differences. *QuitBot* users highlighted the chatbot's empathetic tone, motivational feedback, and sense of social presence, reflecting relational affordances observed in conversational agents for health and well-being [8, 47, 32]. Conversely, *quitSTART* users valued predictability, goal-setting, and visible progress tracking — qualities known to users' sense of control, competence, and self-efficacy—core drivers of motivation and sustained engagement in behavior change interventions [16, 41, 27]. These findings resonate with prior research on personalization in persuasive technology, which distinguishes between adaptive systems that respond dynamically to context and configurable systems that allow users to self-structure engagement [27, 10]. Together, the results suggest that both relational adaptation and structural consistency can enhance engagement — but through different behavioral mechanisms.

5.1. Design Implications for Hybrid Intelligent Interfaces

Taken together, these findings underscore a central trade-off in intelligent health interface design: conversational systems, especially with LLM technology, provide relational warmth, empathy, and immediacy, yet may lack the structure required to sustain long-term behavioral routines. In contrast, features of typical health apps offer consistency and self-monitoring but risk losing the social and motivational responsiveness that fosters continued and effective engagement. This pattern mirrors broader conceptualization in the behavior change research, where interactivity, adaptive feedback, and emotional support operate as parallel but interdependent dimensions of engagement and behavior change [41, 17, 29]. The present study extends this literature by empirically comparing these modalities in a real-world smoking cessation context, demonstrating that user preferences and outcomes align with complementary persuasive mechanisms—*social dialogue* in conversational systems and *behavioral reinforcement* in structured ones.

Emerging research on a class of more hybrid and adaptive intelligent systems offers a pathway forward. Studies such as *PITCH* [80] and *HealthGuru* [32] show that evidence-base health behavior change and LLM technology can coexist within the same design, producing more sustainable engagement and better outcomes. The research on just-in-time adaptive interventions [50] similarly demonstrates a way to adapt static features to the user over time, with recent successful examples in smoking cessation as well [57]. For designers of intelligent health systems, this implies the need for *hybrid intelligent interfaces* that combine the empathy, natural language, and contextual adaptivity of conversational agents with the structured feedback loops and progress tracking typical of mobile health apps. Mobile apps and conversational systems should not be treated as competing paradigms, but rather complementary approaches to design more human-centered technology for better health.

5.2. Limitations and Future Work

This study focused on short-term user experience following one week of use. While this period was sufficient to capture early perspectives and short term patterns of engagement [18], long term follow up is needed to evaluate outcomes related to quitting and smoking status. Additionally, self-reported measures of engagement and quit behavior may not fully capture behavioral adherence or the nuances of real-world interaction data. The study team was not involved in the design of any of the apps, which limit access to objective data, but allows for an unbiased evaluation of the technologies. Due to the choice based design, the findings might also be affected by self-selection of users to a specific modality and limit the ability to make causal inferences. However, in natural setting most smokers who attempt to quit select their own app as opposed to being assigned one by a study team, so the study provides ecological validity in that sense. Finally, although *QuitBot* and *quitSTART* were selected by the study team to represent two distinct design paradigms, future research should extend comparisons to hybrid or adaptive systems that dynamically integrate conversational and structured components, such as just-in-time adaptive interventions [50, 57].

6. Conclusion

This study compared a large language model–based chatbot (QuitBot) and a structured mobile app (quitSTART) to examine how interaction modality shapes engagement, usability, and user experience in persuasive health technologies. The findings reveal a clear design trade-off: conversational systems promote ease, empathy, and motivational immediacy, while structured apps foster routine, goal-setting, and more habitual engagement. Users perceived QuitBot as relationally adaptive and emotionally supportive but less structured, whereas quitSTART offered predictable routines and progress feedback that reinforced user control and competence. These complementary strengths underscore that relational adaptation and behavioral scaffolding serve distinct yet interdependent roles in behavior change technology. For designers of intelligent health interfaces, the results advocate for hybrid intelligent interfaces that blend conversational advantages of LLM technology and the structured scaffolds of mobile health apps. Such integration represents a next step toward human-centered, adaptive health technologies that support both effective engagement and better health.

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Declaration on Generative AI

During the preparation of this work, the author used GPT-4o and GPT-5.2 in order to: correct grammar and spelling, and provide suggestions in response to peer review. Further, the author(s) used GPT-4o to generate Figure 1. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

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