Lived experience in dialogue: co-designing adaptive support in large language models for youth well-being

Kathleen W. Guan[1,*], Easha Jadnanansing[2], Mohammed Amara[3], Kirmina Rezk[1], Bernard J. Jansen[4], Mark de Reuver[1], João Fernando Ferreira Gonçalves[5] and Caroline A. Figueroa[1,6]

[1]*Delft University of Technology, Delft, The Netherlands*
[2]*University of Applied Sciences Utrecht, Utrecht, The Netherlands*
[3]*University of Oxford, Oxford, United Kingdom*
[4]*Qatar Computing Research Institute, Doha, Qatar*
[5]*Erasmus University Rotterdam, Rotterdam, The Netherlands*
[6]*Stanford University, Palo Alto, USA*

Abstract

Youth increasingly turn to large language models (LLMs) for well-being support, yet existing adaptive strategies often fail to reflect the diverse lived experiences and circumstances shaping youth's daily needs. This work contributes human-centered foundations for adaptive user modeling and personalization in youth well-being LLM systems through community-grounded dialogue strategies. We conducted a participatory study with youth, parents, and youth care professionals (total N=38). Thematic analysis highlighted how community stakeholders prioritized dialogic scaffolding that supports youth agency. In particular, stakeholders emphasized adaptive LLM strategies such as clarifying support priorities, meaning-oriented reflective inquiry, exploring personal narratives and future aims, and preserving decision-making. Based on these insights, we developed dialogue extracts directly from stakeholder quotations to inform the design and future alignment of LLM-based well-being systems. By framing adaptive support as an ongoing dialogic process, this work offers human-centered guidance for tailoring support to youths' evolving contexts, priorities, and lived experiences.

Keywords

Lived experience, large language models, participatory design, youth well-being

1. Introduction

There is a pressing need for new approaches that can more effectively and proactively promote the well-being of youth aged 15 to 24 [1, 2]. Around three quarters of well-being-related difficulties begin before age 25, and their prevalence continues to increase worldwide [3]. Youth is a pivotal developmental stage characterized by major physical, emotional, and social transitions, which can increase exposure to health risks while also creating important possibilities for early and lasting prevention [4]. Digital platforms provide youth with an accessible route to seek mental well-being support because they can offer both immediacy and anonymity [5, 6]. These platforms are also increasingly integrating custom chatbots, or specialized automated agents, as a means of delivering support [7]. Within preventive mental well-being contexts, chatbots can help by enabling emotional check-ins, offering psychoeducation, and identifying early indicators of distress [8]. Yet despite their wider adoption, many of these chatbots remain insufficiently relevant or responsive to the diverse and complex needs youth encounter in everyday life, which limits their value for preventive well-being support [2, 9, 10, 11, 12].

Joint Proceedings of the ACM UMAP Workshops 2026, UMAP 2026, June 8–11, 2026, Gothenburg, Sweden
*Corresponding author
k.guan@tudelft.nl (K. W. Guan); easha.jadnanansing@student.hu.nl (E. Jadnanansing); mohammed.amara@univ.ox.ac.uk (M. Amara); k.rezk@student.tudelft.nl (K. Rezk); bjansen@hbku.edu.qa (B. J. Jansen); g.a.dereuver@tudelft.nl (M. d. Reuver); ferreiragoncalves@eshcc.eur.nl (J. F. F. Gonçalves); c.figueroa@tudelft.nl (C. A. Figueroa)
0000-0002-0044-0140 (K. W. Guan); 0009-0001-0524-6830 (M. Amara); 0000-0002-6468-6609 (B. J. Jansen); 0000-0002-6302-7185 (M. d. Reuver); 0000-0002-8948-0455 (J. F. F. Gonçalves); 0000-0003-0692-2244 (C. A. Figueroa)
© 2026 Copyright for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).

CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073
published 2026-05-28

CEUR-WS.org/Vol-4206/llm4wellrec-3.pdf

A common solution is adaptive support, though this still does not have a uniformly accepted definition in digital health. Adaptation within digital well-being tools (DWTs) is typically framed as the use of tailored features including goal-setting, feedback, and reminders, to encourage healthier behaviours for an individual user [13, 14, 15]. These features are frequently integrated with evidence-based models such as motivational interviewing, cognitive behavioral therapy, or the Behavior Change Wheel so that interventions can be situated within personal circumstances, including particular emotional states or times of day, with the aim of improving effectiveness [16, 17, 18].

Notwithstanding, current approaches may miss the complexity of lived experience and the shifting nature of everyday situations, which is especially important given youth's changing identities and contexts. More specifically, one major limitation across many DWTs, including specialized chatbots, is their dependence on rule-based adaptation, where adaptive support is delivered through fixed groupings such as sociodemographic profiles, symptom cut-offs, and/or preset decision pathways [19, 20, 21]. Although such if-then approaches can be efficient, they may be insufficiently meaningful for youth, as they can inadequately capture the nuances of emerging well-being challenges. Proponents of precision health argue that adaptive well-being strategies depend not only on what support is offered, but also on when, how, and with what boundaries it is offered [22, 23].

In contrast to rule-based chatbots, large language models (LLMs) can produce responses shaped by the user's ongoing conversation, drawing on patterns learned from large-scale training data. This allows for more open-ended exchanges that can try to recognize stressors and respond in ways informed by conversational signals, such as shifts in language or sentiment [20, 24, 7], which may make interactions feel more fluid and, in turn, more adaptive. At the same time, because these systems are still relatively new, there remains limited guidance on how to implement artificial intelligence (AI) tools such as LLMs in ways that are relevant to users' lived experiences while also reducing potential harms. Further, current systems pose notable risks for youth well-being, including overreliance, as well as broader concerns around hallucinations, algorithmic bias, marginalization, and unpredictability [9, 25, 26].

Indeed, an increasing number of youth are using publicly available LLMs as a source of well-being support. Recent survey findings from the United States and the European Union indicate that up to three-quarters of youth have used an LLM-powered messaging tool, such as ChatGPT or personified chatbots, at least once [27, 28]. Many of these interactions occur on commercial platforms without oversight and outside systems intentionally developed to support digital well-being. Reported cases show that vulnerable youth may turn to these platforms during acute mental health crises, which has prompted serious concerns about whether such interactions are appropriate [29, 30]. Important questions therefore remain unresolved regarding what adaptive strategies in LLMs used by youth should involve, including their proper scope, depth, and limits, especially because expectations often differ substantially across youth, caregivers, and professionals.

For LLMs to realize their promise for adaptive well-being support while reducing potential harms, scholars are increasingly calling for the co-creation of DWTs, including LLMs, with youth and their wider support networks, such as parents and youth care professionals [31, 32]. A central challenge in applying LLMs to youth well-being is ensuring their responses are shaped by the values and lived realities of youth and their communities of support, rather than simply reproducing assumptions from training data or depending only on professional guidance. Addressing this calls for community-grounded alignment, in which the perspectives of youth and other stakeholders help fine-tune LLMs toward greater relevance and appropriateness [33]. Yet, it remains unclear how lived experience can be operationalized in the design of LLM-based digital well-being tools to responsibly support adaptive interactions. In particular, it is not well understood how the ways youth interpret distress, express support needs, and navigate everyday challenges should be translated into concrete dialogue strategies and boundaries for LLM-based well-being support. These epistemic questions also underscore that lived experience can itself be understood as a form of expertise grounded in firsthand knowledge, and that this expertise must be systematically translated into technical design for adaptive LLM support to be meaningfully relevant and responsive to users' personal needs.

To address these gaps in current knowledge, this study works with youth and community stakeholders to draw directly on their insights as experts in lived experience, with the aim of informing how adaptive

LLM strategies can be operationalized in DWTs for youth. We also place particular emphasis on co-creation with youth from marginalized socioeconomic backgrounds, given its importance for both population health and responsible LLM design. Our guiding question is: How can adaptive LLM strategies be integrated into preventative DWTs for youth in ways that remain grounded in the lived experiences of youth, parents, and youth care workers?

Our study specifically centers on preventative well-being, meaning efforts to prevent the onset of acute mental health conditions [34]. As such, clinical mental health challenges, including diagnosis and treatment, were beyond the scope of this current work. Through our qualitative investigation, we offer a person-centered design approach that anchors the co-design of adaptive LLM strategies for preventative DWTs for youth in both individual and community lived experience. Taken together, our study makes three contributions. First, we identify community and lived experience-grounded dimensions of adaptive LLM support for youth well-being, highlighting how support priorities, meaning-making, personal narratives, and agency shape what appropriate adaptation should involve. Second, we translate these themes into concrete dialogue extracts and interaction strategies that can inform the design and future alignment of LLM-based well-being systems. Finally, we offer human-centered guidance for the responsible design of trustworthy and adaptive LLMs in youth well-being support contexts.

2. Background

2.1. LLMs for Well-being Support

LLMs are being incorporated into DWTs with growing frequency to support emotional well-being, strengthen self-awareness, and encourage healthier behavior change [35, 12, 36]. Current examples include MindfulDiary, Wysa, and MindScape, which use behaviour change techniques such as goal-setting to sustain engagement and have shown improved well-being outcomes, including improvements in emotional self-awareness and self-management [37]. Their support mechanisms can be interpreted through persuasive system design (PSD), an established and evidence-based framework that organises features into four forms of well-being support: primary task support, dialogue support, social support, and system credibility support [15, 38]. Despite the existence of these structured LLMs for evidence-based well-being support, they have not yet achieved widespread uptake among youth.

In contrast, increasing numbers of youth are using publicly available, general-purpose LLMs as a source of well-being support [27]. This has generated substantial concern about how youth engage with these commercially available platforms, which were not specifically created as DWTs. Moreover, although human feedback is used during the training and fine-tuning of LLMs on such platforms, such feedback is usually provided by crowdsourced annotators rather than developed in consultation with community stakeholders whose lived experience could meaningfully inform design [33, 39]. Several high-profile news cases have also emerged in which parents have sued companies deploying LLMs, most notably OpenAI and Character.AI, after the suicides of their adolescent children, who had formed parasocial bonds or sought inappropriate guidance during severe mental health crises through these platforms [29, 30]. Taken together, these cases raise serious concerns about the risks of LLM tools whose technical design and deployment do not adequately incorporate community perspectives. They also underscore the urgent need to strengthen LLMs developed for youth-centred DWTs as accessible yet grounded in community perspectives.

Persuasive strategies can strengthen engagement and improve health outcomes in adaptive DWTs. However, when these strategies are delivered through adaptive intelligence such as LLMs, they also introduce ethical concerns and possible risks to youth well-being [31]. AI systems that continually adjust in response to user input may inadvertently influence how youth make sense of their experiences and determine whether to seek help beyond the system. In some cases, this may occur in ways that do not align with developmental needs or established standards of care, thereby increasing the risk of algorithmic overdependence [40]. For this reason, professional psychological organizations and researchers have stressed that such systems should reduce manipulative effects, remain sensitive to developmental context, and be grounded in the actual needs of users [41, 42]. Yet despite rapid progress in generative AI development, including LLMs, there is still little concrete guidance on how to put these principles into practice. Figueroa et al. [31] propose that ethical guidance for AI in youth well-being should be shaped by the lived experiences of youth, particularly those from marginalized backgrounds, together with the perspectives of caregivers and professionals involved in their everyday support. Without this grounding, such tools may become overly restrictive and less useful, or else fail to respond adequately to the realities youth face, while also reinforcing existing inequities in access to well-being support.

2.2. Person-centered Design of Adaptive Strategies

Grounding adaptive LLM support in DWTs in lived experience requires creating space for youth to communicate in their own language, so they can receive support that is responsive to concerns within their lived circumstances. To remain relevant for youth, these strategies also need to reflect the continually changing emotions, relationships, and goals that shape this formative stage of development [4]. This perspective repositions adaptive mechanisms not as forms of persuasion, but as approaches that can adjust over time in response to specific user contexts [22].

Previous research on AI companions has shown how systems that are emotionally engaging and continuously available can weaken the boundary between human and computer interaction and foster dependency among youth [25]. Grounding adaptive strategies in the lived realities and developmental contexts of youth may help reduce these harms by positioning adaptive support as something that encourages agency, rather than overreliance. Achieving this requires participatory and value-sensitive design processes that involve youth and community members in determining what meaningful adaptive support should look like in practice and in everyday life. More specifically, participatory design centers the direct involvement of communities in expressing how DWTs can improve support and relevance, whereas value-sensitive design focuses on systematically identifying and incorporating the values of both direct users and broader stakeholders who may also be affected, including parents and mental health professionals, into system design [43, 44, 45, 46].

One way to operationalize these participatory and value-sensitive principles in DWT design is through personas, which we define in this study as fictional profiles representing the needs, contexts, and everyday realities of real youth [47]. In contrast to mere datapoints, personas can portray the whole person by incorporating relationships, values, routines, challenges, and preferences alongside health-related concerns [48, 49]. This makes them especially useful for translating lived experience into actionable design features and for helping stakeholders envision how adaptive support should respond to diverse youth circumstances. Although recent work has begun to explore the use of personas as boundary objects in LLM-supported health contexts [50], guidance remains limited on how personas can inform the design and alignment of LLMs for youth well-being.

Taken together, participatory and value-sensitive design approaches extend existing work on persuasive design by making sure adaptation is shaped together with the people who use and support these systems [31, 44]. These perspectives support a person-centered approach to DWT design that promotes "cooperative inquiry," treating end-users as collaborators whose perspectives, values, goals, and contexts are integral to the development of interventions [51, 52]. Beyond participatory design, person-centered design places particular emphasis on understanding the whole person, including lived experience and socioemotional realities, as a necessary basis for aligning technologies with meaningful support [53].

3. Current study

Using a participatory approach, this study conducted person-centered interviews with community stakeholders to thematically identify adaptive LLM strategies for preventative DWTs for youth. To address ongoing inequities in mental health outcomes experienced by marginalized youth, and their longstanding underrepresentation in research [31], we deliberately recruited through community health organizations that serve these groups, especially youth from low-income and socioeconomically marginalized backgrounds. The study protocol was pre-registered on the Open Science Framework. Drawing on insights generated through the interviews, we then developed a set of dialogue features and conversational strategies that translated stakeholder perspectives into adaptive LLM strategies for preventative youth well-being.

3.1. Community-based Interviews

To directly examine how lived experience can shape adaptive LLM strategies, we carried out semi-structured think-aloud interviews lasting 30 to 45 minutes with 14 community stakeholders, including youth, parents, and youth care workers, defined here as adults who support youth well-being in community settings. In these interviews, we adopted seven personas–created by 24 youth in community workshops as standardized scaffolds–to ground all interviewees' reflections in person-centered LLM adaptation. Specifically, each participant reviewed the seven youth-created personas and answered questions informed by the Persona Perception Scale (PPS) [47]. The PPS is a validated question set designed to assess how representative and relevant personas are for design research across dimensions such as credibility, consistency, and completeness. For this study, we adapted PPS questions for our specific context to explore how personas co-created with youth could inform LLM adaptation in meaningful ways. Participants considered what the personas captured effectively, what they left out, and how an LLM could, or should not, use the information they contained. Example questions included: "What would you want an LLM to know about this persona or other youth that isn't included?" and "What should the LLM ask this persona or other youth to adapt support?"

3.2. Translation to Design

We analyzed the stakeholder interviews in two stages. In the first stage, we used inductive thematic analysis to identify core adaptive strategies for well-being tools that use LLMs, drawing directly on stakeholders' lived experiences. This process followed Braun and Clarke's six-phase reflexive thematic analysis approach [54]. Three researchers independently coded all interview transcripts and generated in vivo codes (i.e. verbatim quotations that captured stakeholders' lived experience perspectives). Through iterative discussion with the broader research team, these in vivo codes were organized into higher-level categories and then refined into overarching themes. Two additional researchers then reviewed the transcripts and confirmed the final themes. ATLAS.ti and Excel were used to support both coding and synthesis.

After thematic saturation was achieved, the resulting themes were converted into exemplary dialogue extracts to help operationalize lived experience insights as concrete adaptive strategies. These dialogue extracts were developed directly from stakeholders' verbatim quotations. Taken together, the dialogue materials generated from the stakeholder themes offer guidance grounded in lived experience. In future research, we plan to examine how the dialogue extracts identified in this study might serve as material for LLM fine-tuning, although that was beyond the scope of the present study.

3.3. Positionality and Reflexivity

Our team brought together expertise from psychiatry, clinical psychology, behavioral science, youth engagement, digital health, public health, computational social science, design, and information systems. We also represented a range of sociodemographic backgrounds and had personal experience with health systems, mental health, and marginalization, all of which influenced how we approached questions surrounding AI and well-being. The combination of lived experience and professional expertise shaped both the design of the study and our aim of capturing youth and community perspectives in ways that could directly inform design decisions.

To support open dialogue and represent participants' perspectives as authentically and respectfully as possible, all co-creation workshops and interviews were led by younger researchers on the team, all under the age of 25, who also contributed to validating the findings. In addition, we piloted the co-creation workshops with youth care workers and design professionals who were not part of the study sample in order to refine the activities and ensure they were appropriate and engaging. Wherever feasible, the present findings seek to report stakeholders' insights anonymously and verbatim to preserve representativeness.

4. Findings

To address our research question, we began the analysis by identifying insights into adaptive strategies in LLMs for DWTs as expressed through the lived experiences of community stakeholders. Complete quotations are provided in Table 1 and are identified by stakeholder group together with a numerical label distinguishing individual participants, for example, Youth 3 or Parent 2.

4.1. Thematic Analysis of Lived Experience Insights

Stakeholders understood adaptive support as a dialogic process that supports youth in making sense of their own situations. In this view, effective adaptation was described as helping youth reflect, interpret, and decide for themselves, rather than directing them toward predetermined conclusions. Four interrelated strategies were identified as central to the core theme of Reflective Dialogue Scaffolds to Support Youth's Agency (Table 1).

First, stakeholders viewed LLM-based DWT tools as needing to begin with "clarifying support priorities," which they saw as critical for matching the scope, tone, and depth of interaction to a youth's developmental stage and readiness while preventing false assumptions. Relatedly, stakeholders described these tools as supporting "meaning-oriented reflective inquiry," enabling youth to express what existing ideas or conditions mean to them personally, in contrast to adaptive strategies that rely on generic or externally imposed interpretations. Stakeholders further highlighted "exploring personal narratives and future goals" as a key scaffold through which stepwise prompts can connect immediate concerns to broader values, hopes, and longer-term directions. Finally, they emphasized "preserving decision-making," noting that adaptive LLM support for youth may be most valuable when it supports reflection and helps youth notice patterns while keeping final choices in their own hands, rather than giving prescriptive or definitive answers.

4.2. Translating Themes to Dialogue Extracts

Next, we converted stakeholders' insights into a set of exemplary dialogue extracts, which are summarized in full in Table 2. The dialogue extracts and their related reflective dialogue scaffold strategies shown in Table 2 offer preliminary material that can inform future supervised fine-tuning, prompting, and alignment of LLMs for DWTs. For example, rather than immediately offering solutions, the LLM might ask, "Do you want me to listen, help you sort things out, think through options, or help you take a next step?"

In contrast to generic fine-tuning datasets or crowdsourced annotations, the examples developed in this study are rooted in the lived experiences of youth, youth care workers, and parents. As such, they offer a preliminary basis to incorporate community perspectives more directly into DWT design, helping shift LLMs away from generic forms of support or safety-only responses toward strategies that are better able to adapt to the particular contexts of preventative youth well-being.

Table 1
Subthemes, Definitions, and Representative Quotes for Reflective Dialogue Scaffolds to Support Agency

Subtheme	Definition	Illustrative quotes
Clarifying support priorities	Continually invite the end-user to specify what kind of support they want and how far it should go.	"I don't know what she [this persona] does. The LLM should help clarify what exactly she wants to do." – Youth 5
		"Without enough context, advice comes out vague and full of assumptions. I think you should see AI as AI. It either has to be very clear or very general. Then AI can ask you to be more specific." – Youth care worker 3
		"If someone asks me something like what I do in my life, I say kickboxing and school. I do that, but that's not all I actually do in a day. So the LLM should always ask 'what else' right away." – Youth 2
Meaning-oriented reflective inquiry	Use reflective questions to explore how the youth understands their experiences and what those experiences mean to them.	"What matters is not the word 'difficult,' but how the persona saying this finds it difficult." – Youth 1
		"The LLM can use an hourglass model, where you start by asking all sorts of questions until you get to the core. This will help you increase young people's reflective capacity." – Youth care worker 2
		"OCD manifests differently in everyone. Does this mean she has learning disabilities? Trouble concentrating? You don't know what it means for Ashley [the persona]." – Youth care worker 4
Exploring personal narratives and future goals	Guide the conversation step by step so immediate struggles can be connected to broader hopes, values, and longer-term aims.	"This persona says she likes her eyes, but would like to change something about her appearance. How badly does she want that? Is that something that really stands in her way? Or is it something she actually would like, but which she won't do when she really thinks about it? What is the weight like? Everything has a certain weight. How is AI going to recognize that weight without that information?" – Youth care worker 2
		"So that the chatbot is trained well in helping someone, it should determine who, what, where, when, why." – Youth 2
		"It's very black and white: these are challenges, these are goals. But a teenager's life isn't always that simple; it's dynamic." – Youth care worker 3
Preserving decision-making	Encourage reflection and exploration while ensuring that final decisions remain with the youth.	"I wouldn't go to an AI to make a choice about something." – Youth 5
		"It's important to show young people it's okay to make mistakes or to be patient. You don't want to radicalize them into success." – Youth care worker 3
		"It's there to listen to you, but we don't want young people becoming addicted to talking to such a tool." – Youth 1
		"When AI guides them to recognize their problems, they can acknowledge it. But if it starts giving specialist answers, like a doctor would, you could send someone in the wrong direction." – Parent 2

Table 2
From Stakeholder Insight to Dialogue Extracts for Adaptive LLM-based Support in DWTs

Subtheme from prior section	LLM dialogue strategies and extracts
Clarifying support priorities	The LLM should first clarify what kind of help the youth wants, how specific they want the support to be, and what is still missing. Example: "I can help with this in different ways. Do you want me to listen, help you sort things out, think through options, or help you take a next step?" Follow-up prompts can invite elaboration, such as: "What else is important here?" and "Can you tell me a bit more about what this looks like for you?"
Meaning-oriented reflective inquiry	The LLM should avoid interpreting labels or problems right away and instead ask reflective questions about the youth's own experience and meaning-making to probe for underlying experience. Example: "You said this feels difficult. What makes it difficult for you specifically?" "When you say this is a problem, what does that mean in your situation?"
Exploring personal narratives and future goals	The LLM should explore how current struggles relate to the youth's broader values and future aims, while recognizing that priorities may shift depending on context. Example: "How important is this for you right now?" "Is this something that is really getting in your way, or something you sometimes wish were different?" "How does this connect to what matters to you or to what you want for yourself?"
Preserving decision-making	The LLM should support reflection without making decisions or presenting itself as an authority. The LLM should avoid directive or expert-like advice. Example: "I can help you think through the options, but the choice is yours." "Would you like to explore a few possibilities together?" "It is okay if you are not ready yet, and it is okay to take this step by step."

5. Discussion

Adaptive support in digital health is frequently implemented through rule-based categories, but these approaches are often limited in both relevance and responsiveness [19, 20, 21, 23]. The rapid emergence of LLMs marks a critical seachange, as these systems can produce adaptive responses based on conversational patterns, making more open-ended dialogue with end-users possible [20, 24, 7]. At the same time, their emergence introduces major questions about how adaptive LLMs should be deployed responsibly within DWTs. Many commercially available LLMs do not adequately reflect developmental needs and rarely integrate community perspectives into their design [29, 30]. Meanwhile, DWTs that incorporate AI, including LLMs, are making greater use of persuasive design strategies, yet there is still limited guidance on how to ensure such strategies promote well-being rather than manipulate [31, 41]. These overlapping gaps are especially troubling given the increasing number of youth who rely on LLM-enabled tools for personal well-being support [27], prompting calls for participatory and value-sensitive design approaches developed with communities [31, 32].

In response to these concerns, this study examined how adaptive strategies in LLM-based well-being tools for youth can be grounded in the lived experiences of youth, parents, and youth care workers. Our findings show how DWTs that leverage LLMs can begin to respond to ongoing challenges in responsible AI by embedding person-centered co-creation into the design process. In the next section, we discuss the theoretical and practical implications of this work for different stakeholder groups, alongside its limitations and priorities for future research.

5.1. Theoretical Implications: Designing for Person-centered Adaptation

From a recommender systems and personalization perspective, our findings delineate potential human-centered mechanisms for updating user models over time. Beyond inferring needs from static profiles or behavioral inputs, LLM-based wellbeing systems may use reflective dialogue to model shifting priorities, meanings, and goals in context. This positions adaptive strategies in LLMs as an interactional form of personalization grounded in lived experience.

Our findings broaden existing conceptualizations of adaptive digital health by framing it as a dialogic, person-centered process that takes shape through continued interaction. Earlier work in digital health has often treated adaptive strategies primarily as tools for increasing engagement, whether through persuasive behavior change techniques or through response adjustments based on predefined behavioral indicators [13, 38]. Drawing instead on situated and value-sensitive perspectives [43, 45], our study suggests that LLM-driven adaptation should be understood as something that emerges through interactional dialogue with end-users, rather than being governed by pre-established if-then rules [55, 56]. More specifically, participants across the co-creation sessions highlighted the value of LLMs as facilitators of narrative exploration through gradual, stepwise questioning. This kind of dialogue was seen as enabling youth to express immediate concerns in meaningful ways while also linking those concerns to broader aspirations connected to their well-being in everyday life. From this perspective, adaptive digital health can move beyond static tailoring and instead function as an interactional process grounded in lived experience and person-centered dialogue. Such an approach may better support individuals in relating what unfolds in conversation with an LLM to their offline circumstances and to the personal meaning those experiences hold.

Importantly, these findings suggest that adaptive support in LLM-based DWTs should not be understood as a form of automated guidance, but rather as a set of mechanisms for dialogic scaffolding that can support self-development. Participants consistently placed greater value on opportunities for self-reflection and personal discovery than on prescriptive advice, imagining LLM-based DWTs that would mainly guide through questioning rather than through reassurance or affirmation. In this sense, support was seen not as something the system delivers on behalf of the individual, but as something that helps individuals develop their own capacity to support themselves.

These kinds of adaptive mechanisms may be especially important in tools designed for youth, who are still developing autonomy, self-management, social understanding, and decision-making skills [4].

At this stage of development, youth may be particularly vulnerable to overreliance on external or problematic forms of algorithmic guidance [25, 41]. This underscores the importance of designing LLM interactions that strengthen reflective capacity, self-efficacy, and social belonging as foundations for long-term well-being, rather than limiting support to the provision of information in response to user prompts. For youth from marginalized communities especially, who often encounter systemic barriers to health access and broader social participation [57], such dialogical scaffolding may play an important role in fostering both agency and belonging. Drawing on the perspectives shared in our interviews, we suggest that dialogic support may help marginalized youth more effectively explore and navigate possible pathways for their mental well-being. Taken together, these findings recast adaptive digital health as a process of co-inquiry that connects digital interaction with reflection and action in everyday life, with the aim of strengthening self-management and well-being.

5.2. Practical Implications for Developing Adaptive LLM Strategies in DWTs

Our findings also point to practical implications for digital health research and development teams seeking to incorporate LLMs into their tools. Extending our broader argument that adaptive strategies can be understood as forms of dialogic scaffolding grounded in lived experience, the study shows how digital health tools, especially those using LLMs, can operationalize adaptation through users' ongoing interactions. The present findings offer concrete examples of this in the form of dialogic scaffolds such as "meaning-oriented reflective inquiry", "clarifying support priorities", and "preserving decision-making". These strategies expand adaptive support beyond established persuasive techniques and identify specific interactional features that future research can examine for their potential to support youth well-being. Although earlier foundational research has offered useful taxonomies of harmful behaviours and psychological risks linked to AI conversational agents [9, 25], our study preliminarily extends this work by contributing exemplar dialogue extracts that can inform future fine-tuning efforts for dialogic scaffolding.

For LLM developers, one of the main implications of our findings is the importance of incorporating the adaptive strategies identified in our interviews into training data and system pipelines. At present, however, existing training practices have notable shortcomings in relation to participatory engagement. Heavy dependence on crowdsourced annotators, who may themselves rely on existing LLMs when completing annotation tasks, can reduce the relevance and appropriateness of LLM applications for youth well-being [33, 58]. As such, lived experience experts, including youth themselves and others who understand the specific challenges surrounding youth mental health, are essential if LLM applications are to move beyond generic support and become more responsive to the needs of youth. The dialogic scaffolds identified in this study can function both as templates for conversation design and as preference signals for reward models, helping ensure that systems prioritize responses that promote agency, as emphasized by our study participants. In addition, the dialogue extracts developed through this work offer material for supervised fine-tuning and hardcoding, supporting more targeted and incremental alignment of LLM behavior with co-created, community-informed preferences and safeguards [59].

5.3. Limitations and Future Directions

An important limitation of the present study is that it has not yet been established whether the adaptive LLM strategies identified here can in fact be learned and reliably expressed by LLMs after fine-tuning on the study outputs. This remains a major direction for future research. Aligning LLMs involves more than creating strong training examples: it requires assessing whether the intended behaviours consistently appear in model responses. In turn, this points to the importance of iterative evaluation cycles that connect participatory design, model training, and real-world testing. Future work should therefore prioritize empirical validation by examining how effectively the current alignment guidelines are reflected in observable model behavior and by refining training approaches on that basis.

In addition, our study involved a relatively small sample drawn from the Dutch community youth care context, and the youth participants were mainly older adolescents rather than younger ones. Although the findings are not intended to be generalizable, the sample brings forward perspectives that remain underrepresented in mental health AI research and application, particularly those of marginalized youth from low socioeconomic backgrounds in community settings. This focus has important implications for the equitable design of DWTs. Our inclusion of multiple community stakeholder groups, namely youth, youth care workers, and parents, also enabled triangulation across perspectives on adaptive strategies and generated insights with broader relevance for youth- and community-centered design. At the same time, although the subthemes were broadly consistent across stakeholder groups, the study did not explicitly examine value tensions or contradictions in how youth, youth care workers, and parents perceived LLM adaptation. That question fell beyond the scope of the present work, but it remains an important area for future efforts to use personas in LLM alignment.

Finally, the scope of this study was confined to general well-being and preventative health, with particular attention to preventing the emergence of severe mental health symptoms because of their importance for public health. Further research is needed to extend these findings to adaptive LLM support in clinical health settings and in more specialized areas, such as disease-related support. Advancing this work will require the involvement of specialist and clinical stakeholders alongside patient communities. The methods used in the present study could also be applied in future research with mental health counselors and psychiatrists to identify how such approaches might be integrated into their professional practice.

6. Conclusion

This work shows how co-created dialogue strategies can inform adaptive LLM support in DWTs for youth in ways that strengthen young people's agency. Drawing on stakeholder interviews, we reconceptualize adaptive support not as static tailoring, but as an interactive process that supports agency by helping youth take an active role in making sense of their well-being. Future research should investigate how these strategies can be incorporated into LLM fine-tuning pipelines and assess their effects on mental well-being and quality of life, while also advancing more systematic participatory methods for the responsible development of AI in youth mental health.

Acknowledgments

We would like to thank Sarah Duister, Neslihan Can, Dimpy Gupta, Nic Orchard, and Ruixuan Zhang for their support in data collection and validation, without which this present work would not have been possible. We also thank Niko Vegt and Kayla Green for their insights during early stage co-creation sessions, and Atay Kozlovski for comments on an earlier version of this draft, which strengthened the current methods and interpretation of findings. Most importantly, we thank all youth and community participants for sharing their valuable time and expertise. This research is funded by Healthy Start program, as part of Convergence, the research alliance between Erasmus University Medical Center, Erasmus University Rotterdam, and Delft University of Technology. Additionally, KWG, CAF and MdR are supported through the 'High Tech for a Sustainable Future' capacity building program of the 4TU Federation in the Netherlands.

Declaration on Generative AI

In the present manuscript the authors used generative AI, specifically ChatGPT version 5.2, only for assisting with formatting of tables and editing grammar. No original text was created with generative AI. Authors reviewed all AI-assisted modifications and take full responsibility for the contents of the current manuscript.

References

[1] U. Nations, Youth, 2025. URL: https://www.un.org/en/global-issues/youth.

[2] E. Soubutts, P. Shrestha, B. Davidson, C. Qu, C. Mindel, A. Sefi, P. Marshall, R. Mcnaney, Challenges and opportunities for the design of inclusive digital mental health tools: Understanding culturally diverse young people's experiences, in: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2024, pp. 1–16. doi:10.1145/3613904.3642641.

[3] P. McGorry, C. Mei, N. Dalal, M. Alvarez-Jimenez, S.-J. Blakemore, V. Browne, B. Dooley, I. Hickie, P. Jones, D. McDaid, C. Mihalopoulos, S. Wood, F. Azzouzi, J. Fazio, E. Gow, S. Hanjabam, A. Hayes, A. Morris, E. Pang, K. Paramasivam, I. Nogueira, J. Tan, S. Adelsheim, M. Broome, M. Cannon, A. Chanen, E. Chen, A. Danese, M. Davis, T. Ford, P. Gonsalves, M. Hamilton, J. Henderson, A. John, F. Kay-Lambkin, L.-D. Le, C. Kieling, N. Dhonnagáin, A. Malla, D. Nieman, D. Rickwood, J. Robinson, J. Shah, S. Singh, I. Soosay, K. Tee, J. Twenge, L. Valmaggia, T. v. Amelsvoort, S. Verma, J. Wilson, A. Yung, S. Iyer, E. Killackey, The lancet psychiatry commission on youth mental health, The Lancet Psychiatry 11 (2024) 731–774. doi:10.1016/S2215-0366(24)00163-9.

[4] D. Cicchetti, F. Rogosch, A developmental psychopathology perspective on adolescence, Journal of Consulting and Clinical Psychology 70 (2002) 6–20. doi:10.1037/0022-006X.70.1.6.

[5] C. Pretorius, D. McCashin, N. Kavanagh, D. Coyle, Searching for mental health: A mixed-methods study of young people's online help-seeking, in: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, ACM, Honolulu HI USA, 2020, pp. 1–13. doi:10.1145/3313831.3376328.

[6] J. Huh-Yoo, A. Razi, D. Nguyen, S. Regmi, P. Wisniewski, "help me:" examining youth's private pleas for support and the responses received from peers via instagram direct messages, in: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, ACM, Hamburg Germany, 2023, pp. 1–14. doi:10.1145/3544548.3581233.

[7] X. Zheng, Z. Li, X. Gui, Y. Luo, Customizing emotional support: How do individuals construct and interact with llm-powered chatbots, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2025, pp. 1–20. doi:10.1145/3706598.3713453.

[8] A. Sharma, K. Rushton, I. Lin, T. Nguyen, T. Althoff, Facilitating self-guided mental health interventions through human-language model interaction: A case study of cognitive restructuring, in: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2024, pp. 1–29. doi:10.1145/3613904.3642761.

[9] M. Chandra, S. Naik, D. Ford, E. Okoli, M. De Choudhury, M. Ershadi, G. Ramos, J. Hernandez, A. Bhattacharjee, S. Warreth, J. Suh, From lived experience to insight: Unpacking the psychological risks of using ai conversational agents, in: Proceedings of the 2025 ACM Conference on Fairness, Accountability, and Transparency, Association for Computing Machinery, New York, NY, USA, 2025, pp. 975–1004. doi:10.1145/3715275.3732063.

[10] J. Park, V. Singh, P. Wisniewski, Current landscape and future directions for mental health conversational agents for youth: Scoping review, JMIR Medical Informatics 13 (2025) e62758. doi:10.2196/62758.

[11] K. Kruzan, A. Ng, C. Stiles-Shields, E. Lattie, D. Mohr, M. Reddy, The perceived utility of smartphone and wearable sensor data in digital self-tracking technologies for mental health, in: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2023, pp. 1–16. doi:10.1145/3544548.3581209.

[12] S. Jin, B. Kim, K. Han, "i don't know why i should use this app": Holistic analysis on user engagement challenges in mobile mental health, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2025, pp. 1–23. doi:10.1145/3706598.3713732.

[13] M. Kaptein, P. Markopoulos, B. de Ruyter, E. Aarts, Personalizing persuasive technologies: Explicit and implicit personalization using persuasion profiles, International Journal of Human-Computer

Studies 77 (2015) 38–51. doi:10.1016/j.ijhcs.2015.01.004.
[14] R. Zhang, K. E. Ringland, M. Paan, D. C. Mohr, M. Reddy, Designing for emotional well-being: Integrating persuasion and customization into mental health technologies, in: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2021, pp. 1–13. doi:10.1145/3411764.3445771.
[15] H. Oinas-Kukkonen, M. Harjumaa, Persuasive systems design: Key issues, process model, and system features, Communications of the Association for Information Systems 24 (2009). doi:10.17705/1CAIS.02428.
[16] A. Thieme, M. Hanratty, M. Lyons, J. Palacios, R. Marques, C. Morrison, G. Doherty, Designing human-centered ai for mental health: Developing clinically relevant applications for online cbt treatment, ACM Trans. Comput.-Hum. Interact. 30 (2023) 27:1–27:50. doi:10.1145/3564752.
[17] O. Oyebode, C. Ndulue, D. Mulchandani, A. A. Zamil Adib, M. Alhasani, R. Orji, Tailoring persuasive and behaviour change systems based on stages of change and motivation, in: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, ACM, Yokohama Japan, 2021, pp. 1–19. doi:10.1145/3411764.3445619.
[18] M. Jörke, S. Sapkota, L. Warkenthien, N. Vainio, P. Schmiedmayer, E. Brunskill, J. Landay, Gptcoach: Towards llm-based physical activity coaching, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2025, pp. 1–46. doi:10.1145/3706598.3713819.
[19] K. W. Guan, M. Amara, S. Gürbüz, I. Khan, C. Adlung, V. Cortiana, R. Ali, C. Iorio, E. Thalassinou, C. R. Smit, A. Vreeker, E. van Roekel, L. Keijsers, M. de Reuver, C. A. Figueroa, Towards participatory precision health with co-designed recommendations for just-in-time adaptive interventions in adolescents and young adults: A systematic review, 2026. URL: https://www.jmir.org/2026/0/e0/. doi:10.2196/84422.
[20] R. Choi, T. Kim, S. Park, J. Kim, S.-J. Lee, Private yet social: How llm chatbots support and challenge eating disorder recovery, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2025, pp. 1–19. doi:10.1145/3706598.3713485.
[21] W. Seo, C. Yang, Y.-H. Kim, Chacha: Leveraging large language models to prompt children to share their emotions about personal events, in: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2024, pp. 1–20. doi:10.1145/3613904.3642152.
[22] I. Nahum-Shani, S. Smith, B. Spring, L. Collins, K. Witkiewitz, A. Tewari, S. Murphy, Just-in-time adaptive interventions (jitais) in mobile health: key components and design principles for ongoing health behavior support, Annals of Behavioral Medicine 52 (2018) 446–462.
[23] E. Hekler, J. Tiro, C. Hunter, C. Nebeker, Precision health: The role of the social and behavioral sciences in advancing the vision, Annals of Behavioral Medicine 54 (2020) 805–826. doi:10.1093/abm/kaaa018.
[24] T. Kim, S. Bae, H. Kim, S.-W. Lee, H. Hong, C. Yang, Y.-H. Kim, Mindfuldiary: Harnessing large language model to support psychiatric patients' journaling, in: Proceedings of the CHI Conference on Human Factors in Computing Systems, ACM, Honolulu HI USA, 2024, pp. 1–20. doi:10.1145/3613904.3642937.
[25] R. Zhang, H. Li, H. Meng, J. Zhan, H. Gan, Y.-C. Lee, The dark side of ai companionship: A taxonomy of harmful algorithmic behaviors in human-ai relationships, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, New York, NY, USA, 2025, pp. 1–17. doi:10.1145/3706598.3713429.
[26] Z. Iftikhar, A. Xiao, S. Ransom, J. Huang, H. Suresh, How llm counselors violate ethical standards in mental health practice: A practitioner-informed framework, Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society 8 (2025) 1311–1323. doi:10.1609/aies.v8i2.36632.
[27] C. S. Media, Nearly 3 in 4 teens have used ai companions, new national survey finds | common sense media, 2025. URL: https://www.commonsensemedia.org/press-releases/nearly-3-in-4-teens-have-used-ai-companions-new-national-survey-finds.

[28] B. I. for Kids, Youth internet monitor 2025, 2025. URL: https://better-internet-for-kids.europa.eu/en/news/youth-internet-monitor-2025.
[29] K. Hill, A teen was suicidal. chatgpt was the friend he confided in., 2025. URL: https://www.nytimes.com/2025/08/26/technology/chatgpt-openai-suicide.html.
[30] K. Roose, Can a.i. be blamed for a teen's suicide?, 2024. URL: https://www.nytimes.com/2024/10/23/technology/characterai-lawsuit-teen-suicide.html.
[31] C. Figueroa, G. Ramos, A. Psihogios, E. Ekuban, P. Bansie, M. de Haas, N. Karnik, O. Ajilore, E. Anderson, C. Stiles-Shields, Advancing youth co-design of ethical guidelines for ai-powered digital mental health tools, Nat. Mental Health 3 (2025) 870–878. doi:10.1038/s44220-025-00467-7.
[32] N. Kurian, Designing child-safe conversational ai: Three dilemmas for responsible design, in: Proceedings of the 7th ACM Conference on Conversational User Interfaces, ACM, Waterloo ON Canada, 2025, pp. 1–5. doi:10.1145/3719160.3737638.
[33] T. McIntosh, T. Susnjak, N. Arachchilage, T. Liu, D. Xu, P. Watters, M. Halgamuge, Inadequacies of large language model benchmarks in the era of generative artificial intelligence, IEEE Transactions on Artificial Intelligence (2025) 1–18. doi:10.1109/TAI.2025.3569516.
[34] C. Arango, C. Díaz-Caneja, P. McGorry, J. Rapoport, I. Sommer, J. Vorstman, D. McDaid, O. Marín, E. Serrano-Drozdowskyj, R. Freedman, Preventive strategies for mental health, The Lancet Psychiatry 5 (2018) 591–604.
[35] V. Das Swain, Q. J. Zhong, J. Parekh, Y. Jeon, R. Zimmermann, M. Czerwinski, J. Suh, V. Mishra, K. Saha, J. Hernandez, Ai on my shoulder: Supporting emotional labor in front-office roles with an llm-based empathetic coworker, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, ACM, Yokohama Japan, 2025, pp. 1–29. doi:10.1145/3706598.3713705.
[36] I. Song, S. Park, S. Pendse, J. Schleider, M. De Choudhury, Y.-H. Kim, Exploreself: Fostering user-driven exploration and reflection on personal challenges with adaptive guidance by large language models, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, ACM, Yokohama Japan, 2025, pp. 1–22. doi:10.1145/3706598.3713883.
[37] S. Giri, K. Kulasinghe, H. Oinas-Kukkonen, Exploring large language model-based mental health interventions: A systematic review with a persuasive system design lense, PACIS 2025 Proceedings (2025).
[38] S. Kelders, R. Kok, H. Ossebaard, J. Van Gemert-Pijnen, Persuasive system design does matter: a systematic review of adherence to web-based interventions, J Med Internet Res 14 (2012) e152. doi:10.2196/jmir.2104.
[39] M. Cheong, G. Bush, M. Wildenauer, "lost in the crowd": ethical concerns in crowdsourced evaluations of llms, AI Ethics 5 (2025) 4407–4413. doi:10.1007/s43681-025-00671-2.
[40] S. Banker, S. Khetani, Algorithm overdependence: How the use of algorithmic recommendation systems can increase risks to consumer well-being, Journal of Public Policy & Marketing 38 (2019) 500–515. doi:10.1177/0743915619858057.
[41] N. Kurian, Ai's empathy gap: The risks of conversational artificial intelligence for young children's well-being and key ethical considerations for early childhood education and care, Contemporary Issues in Early Childhood 26 (2025) 132–139. doi:10.1177/14639491231206004.
[42] A. P. Association, Health advisory: Artificial intelligence and adolescent well-being, 2025. URL: https://www.apa.org/topics/artificial-intelligence-machine-learning/health-advisory-ai-adolescent-well-being.
[43] B. Friedman, P. Kahn, A. Borning, A. Huldtgren, Value sensitive design and information systems, in: Doorn, N., Schuurbiers, D., van de Poel, I., and Gorman, M.E. (eds.) Early engagement and new technologies: Opening up the laboratory, Springer Netherlands, Dordrecht, 2013, pp. 55–95. doi:10.1007/978-94-007-7844-3_4.
[44] E. Ko, R. Landesman, J. Young, A. Arif, K. Davis, A. Smith, Domain experts, design novices: How community practitioners enact participatory design values, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, ACM, Yokohama Japan, 2025, pp. 1–16. doi:10.1145/3706598.3714060.
[45] X. Qi, J. Yu, Participatory design in human-computer interaction: Cases, characteristics, and

lessons, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, ACM, Yokohama Japan, 2025, pp. 1–26. doi:10.1145/3706598.3713436.
[46] M. Sadek, M. Constantinides, D. Quercia, C. Mougenot, Guidelines for integrating value sensitive design in responsible ai toolkits, in: Proceedings of the CHI Conference on Human Factors in Computing Systems, ACM, Honolulu HI USA, 2024, pp. 1–20. doi:10.1145/3613904.3642810.
[47] J. Salminen, H. Kwak, J. Santos, S.-G. Jung, J. An, B. Jansen, Persona perception scale: Developing and validating an instrument for human-like representations of data, in: Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems, ACM, Montreal QC Canada, 2018, pp. 1–6. doi:10.1145/3170427.3188461.
[48] M. Zimmermann, K. Yonkers, K. Tabb, A. Schaefer, E. Peacock-Chambers, C. Clare, E. Boudreaux, S. Lemon, N. Byatt, B. Tulu, Developing personas to inform the design of digital interventions for perinatal mental health, JAMIA Open 7 (2024) ooae112. doi:10.1093/jamiaopen/ooae112.
[49] O. Bhattacharyya, K. Mossman, L. Gustafsson, E. Schneider, Using human-centered design to build a digital health advisor for patients with complex needs: persona and prototype development, Journal of medical Internet research 21 (2019) e10318.
[50] D. Haag, D. Kumar, S. Gruber, D. Hofer, M. Sareban, G. Treff, J. Niebauer, C. Bull, A. Schmidt, J. Smeddinck, The last jitai? exploring large language models for issuing just-in-time adaptive interventions: Fostering physical activity in a prospective cardiac rehabilitation setting, in: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, ACM, Yokohama Japan, 2025, pp. 1–18. doi:10.1145/3706598.3713307.
[51] K. Wong, C. Cloninger, A person-centered approach to clinical practice, Focus (Am Psychiatr Publ) 8 (2010) 199–215. doi:10.1176/foc.8.2.foc199.
[52] M. Guha, A. Druin, J. Fails, Cooperative inquiry revisited: Reflections of the past and guidelines for the future of intergenerational co-design, International Journal of Child-Computer Interaction 1 (2013) 14–23. doi:10.1016/j.ijcci.2012.08.003.
[53] B. Y. Hub, Why ypar? | ypar hub, 2024. URL: https://yparhub.berkeley.edu/why-ypar.
[54] V. Braun, V. Clarke, N. Hayfield, L. Davey, E. Jenkinson, Doing reflexive thematic analysis, in: Bager-Charleson, S. and McBeath, A. (eds.) Supporting Research in Counselling and Psychotherapy, Springer International Publishing, Cham, 2022, pp. 19–38. doi:10.1007/978-3-031-13942-0_2.
[55] T. Oikonomidi, P. Ravaud, J. LeBeau, V.-T. Tran, A systematic scoping review of just-in-time, adaptive interventions finds limited automation and incomplete reporting, Journal of Clinical Epidemiology 154 (2023) 108–116. doi:10.1016/j.jclinepi.2022.12.006.
[56] S. Limpanopparat, E. Gibson, D. Harris, User engagement, attitudes, and the effectiveness of chatbots as a mental health intervention: A systematic review, Computers in Human Behavior: Artificial Humans 2 (2024) 100081. doi:10.1016/j.chbah.2024.100081.
[57] S. Schueller, J. Hunter, C. Figueroa, A. Aguilera, Use of digital mental health for marginalized and underserved populations, Curr Treat Options Psych 6 (2019) 243–255. doi:10.1007/s40501-019-00181-z.
[58] A. Chan, C. Di, J. Rupertus, G. Smith, V. Nagaraj Rao, M. Horta Ribeiro, A. Monroy-Hernández, Redefining research crowdsourcing: Incorporating human feedback with llm-powered digital twins: Incorporating human feedback with llm-powered digital twins, in: Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems, ACM, Yokohama Japan, 2025, pp. 1–10. doi:10.1145/3706599.3720269.
[59] L. Ouyang, J. Wu, X. Jiang, D. Almeida, C. Wainwright, P. Mishkin, C. Zhang, S. Agarwal, K. Slama, A. Ray, Training language models to follow instructions with human feedback, Advances in neural information processing systems 35 (2022) 27730–27744.