#### The Last JITAI?

# The Unreasonable Effectiveness of Large Language Models in Issuing Just-in-Time Adaptive Interventions: Fostering Physical Activity in a Prospective Cardiac Rehabilitation Setting

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## **Abstract**

We explored the viability of Large Language Models (LLMs) for triggering and personalizing content for Just-in-Time Adaptive Interventions (JITAIs) in digital health. JITAIs are being explored as a key mechanism for sustainable behavior change, adapting interventions to an individual's current context and needs. However, traditional rule-based and machine learning models for JITAI implementation face scalability and reliability limitations, such as lack of personalization, difficulty in managing multi-parametric systems, and issues with data sparsity. To investigate JITAI implementation via LLMs, we tested the contemporary overall performance-leading model 'GPT-4' with examples grounded in the use case of fostering heart-healthy physical activity in outpatient cardiac rehabilitation. Three personas and five sets of context information per persona were used as a basis of triggering and personalizing JITAIs. Subsequently, we generated a total of 450 proposed JITAI decisions and message content, divided equally into JITAIs generated by 10 iterations with GPT-4, a baseline provided by 10 laypersons (LayPs), and a gold standard set by 10 healthcare professionals (HCPs). Ratings from 27 LayPs indicated that JITAIs generated by GPT-4 were superior to those by HCPs and LayPs over all assessed scales: i.e., appropriateness ( $M|SD_{GPT-4} =$ 5.47 | 1.26;  $M|SD_{HCP} = 4.60$  | 1.67;  $M|SD_{LayP} = 4.47$  | 1.53), engagement ( $M|SD_{GPT-4} = 5.94$  | 0.90;  $M|SD_{HCP} = 4.58|1.66$ ;  $M|SD_{LavP} = 4.35|1.54$ ), effectiveness ( $M|SD_{GPT-4} = 5.85|0.96$ ;  $M|SD_{HCP} =$ 4.58|1.58;  $M|SD_{LavP} = 4.36|1.51$ ), and professionality ( $M|SD_{GPT-4} = 5.86|0.91$ ;  $M|SD_{HCP} =$  $4.74 \mid 1.55$ ;  $M \mid SD_{LayP} = 4.54 \mid 1.37$ ). This study indicates that LLMs have significant potential for implementing JITAIs as a building block of personalized or "precision" health, offering scalability, effective personalization based on opportunistically sampled information, and good acceptability.

## Introduction

Retaining adherence after transitioning back from settings with intensive in-person support is a major challenge in promoting long-term health behavior change. E.g., patients going through cardiac rehabilitation typically transition through different phases from initial clinical to ambulatory settings with more sparse healthcare professional (HCP) support, and eventually should return to living fully independent everyday lives<sup>1</sup>. However, health behaviors like regular physical activity (PA), which is a central part of a successful cardiac rehabilitation program<sup>2</sup>, are strongly determined by contextual influences such as the social environment, structural opportunities for integrating PA, or momentary affect<sup>3,4</sup>. That means, when support fades out after patients transition back to living their regular lives, many people quickly fall back into their old, often sedentary habits<sup>5</sup>. This is the point where digital health tools such as Just-in-Time Adaptive Interventions (JITAIs) can support the maintenance and perpetual habitualization of health behavior change introduced during the first rehabilitation phases<sup>6</sup>.

JITAIs are a concept that has many use cases across a broad range of digital health interventions<sup>7</sup>. Nahum-Shani et al.<sup>8</sup> conceptualized that JITAIs are designed to adjust to the dynamic needs and contexts of individuals, harnessing technological advancements to provide personalized health interventions when they are needed most. As opposed to common "one-size-fits-all" models in healthcare, JITAIs have potential as a valuable tool offering more "precise", context-sensitive, and time-relevant health interventions that consider the individual's unique circumstances. JITAIs can have many use cases, especially in digitally accompanying people outside of stationary or in-practice routine care, e.g. in offering support with achieving PA or other health behavior change goals throughout daily living.

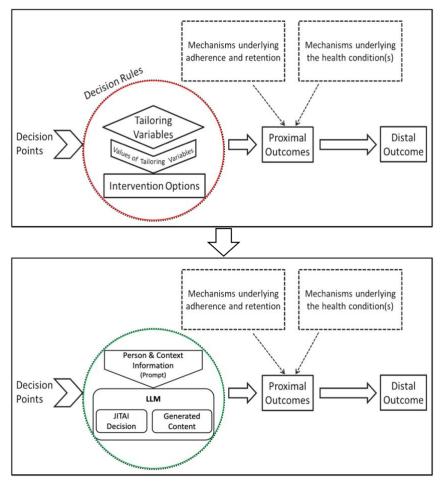
However, the two main approaches currently used to implement JITAIs – *rule-based systems*<sup>9</sup> and *machine learning models* (MLM) – are lacking behind visions of what JITAIs could be – a "personal coach in your pocket". *Rule-based JITAIs* function based on a preestablished set of rules or algorithms. They often implement, clear-cut intervention guidelines that can be conveniently modified when needed. However, appropriate models describing the contextual dependencies of the respective health behaviors are not yet available<sup>3,12</sup>. Therefore, setting up an effective set of rules requires time- and cost-intensive optimization processes, such as micro-randomized trials (MRTs)<sup>13</sup>. Additionally, these systems become exponentially more complex with rising numbers of tailoring variables. This makes them hard to manage and potentially leads to error-prone outputs. Rule-based systems also lack the ability to personalize interventions in the sense of tailoring to an individual's unique needs and preferences as they dynamically change over time<sup>14</sup>.

While such personalization could be achieved through MLMs, e.g., using reinforcement learning (RL)<sup>10,11</sup>, such models face extensive requirements regarding the amount of data they need to start working effectively, also referred to as the "cold start"

problem<sup>15</sup>. This can quickly leave users annoyed by ill-placed interventions, which might cause them to abandon the use of their digital health tool, entirely<sup>14</sup>. Additionally, both rule-based and MLM-based JITAIs face limitations in effectively dealing with missing or sparse data or with not firmly pre-defined types of data<sup>16</sup>, which are very common in real-world applications.

Additionally, the concerns above are only considering JITAI tailoring in terms of whether a message should be sent in a given moment, not the content of messages, which is also a core intervention element with JITAIs. Currently, most state-of-the-art systems merely aim to support choosing the most appropriate option for a given situation out of a static list of intervention options with only pre-structured or no personalization. This limits variability in personalization and contextualization and can quickly lead to JITAIs being repetitive, potentially disrupting the user's impression of receiving personalized support and possibly leading to reduced efficacy and increasing disengagement<sup>21</sup>. Overcoming this limitation requires a different approach that offers the opportunity to generate flexible, personalized, context-aware, and ever-unique health interventions in real-time. Such qualities might be offered by generative artificial intelligence (GenAI), including large-language models (LLMs)<sup>22–24</sup> that have seen a ubiquitous rise over the last year and have reached prominent public discourse<sup>25</sup>. This begs the question if these models might present a viable solution for the challenges named above and thus be the next step in JITAI evolution.

LLMs such as OpenAl's GPT series can generate meaningful responses when faced with opportunistically sampled, very high-dimensional information with many sparse or temporarily unavailable parameters. The adaptability, scalability, and potential for personalization<sup>31</sup> of LLMs could move JITAI systems closer to the envisioned "personal coach in your pocket" concept. Figure 1 illustrates the role that LLMs could potentially take over in terms of the original JITAI conceptualization<sup>8</sup>. In the original concept, decision rules are evaluated at predefined decision points. This means that based on the values of one or more tailoring variables, a decision is made on whether one of the predefined intervention options should be triggered. These interventions aim to improve on a certain proximal outcome (e.g., step count within 30 minutes after intervention), which should, in turn, lead to improvements in a distal outcome (e.g., overall PA level). We propose that LLMs could (1) replace the decision rules in this classic JITAI conceptualization, offering more flexibility in the tailoring of interventions, and (2) augment the intervention options with custom-generated or more strongly adapted content.

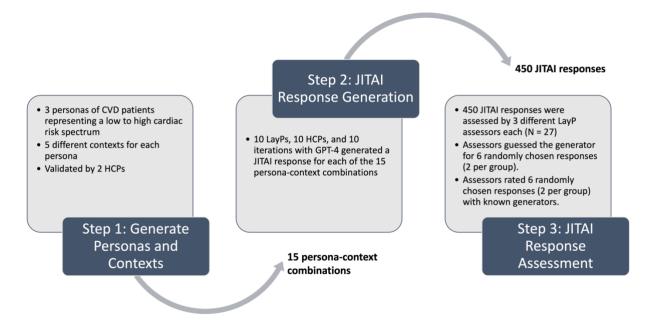


**Figure 1: The conceptual change from rule-based (left) to LLM-based (right) JITAI implementations.** Original figure (top) adapted from Nahum-Shani et al.<sup>8</sup>: In their original concept, decision rules are evaluated at predefined decision points, decision rules are evaluated. This means that based on the values of one or more tailoring variables, a decision is made on whether one of the predefined intervention options should be triggered. These interventions aim to improve on a certain proximal outcome (e.g., step count within 30 minutes after intervention), which should, in turn, lead to improvements in a distal outcome (e.g., overall PA level).

Therefore, our main goal with this study was to explore the viability of employing LLMs, specifically GPT-4, to trigger and generate JITAIs to support engagement with hearthealthy PA in an outpatient cardiac rehabilitation setting. For that purpose, we presented the model with semi-structured information about a persona in outpatient cardiac rehabilitation together with a parameterization of their current context (see <u>Supplement 1</u> for details). For any respective combination of persona and context, the model was tasked with (1) deciding whether the situation indicates a good opportunity for triggering a JITAI and, if so, (2) proposing a fitting motivational text for the potential use case of a push-message intervention. With this task, we aimed to investigate our guiding research question: "Can

LLMs be utilized as a decision-making and personalized message tailoring mechanism in JITAIs for fostering physical activity support messaging in prospective cardiac rehabilitation contexts?"

In order to ground the performance of the LLM in relative terms, we compared the quality of GPT-4 (below abbreviated as GPT) generated JITAI decisions and message content to decisions and intervention messages generated by (1) *laypersons* (LayPs; as a "baseline" of human performance without domain-specific training and since laypersons could arguably be employed for crowdsourced or "human computation" solutions for JITAI decision-making and generation in limited use cases), and (2) *HCPs* (as a "gold standard" – which we would not consider a practical alternative for solving the challenges of personalized JITAIs at scale, but can arguably provide valid anchoring of the LLM performance). To assess the decision and message quality of these three groups of "generators", we collected ratings on the dimensions of assumed appropriateness, engagement, effectiveness, and professionality of LayPs acting as "assessors" (see Figure 2 for a visualization of study flow).



**Figure 2: Study Procedure Flowchart.** The term 'JITAI response' refers to (1) a decision on whether a JITAI should be triggered in the given moment, (2) generating the content of a short smartphone notification (max. 75 characters) if a JITAI should be triggered, and (3) generating the content of a slightly longer message (100 to 300 characters) to display in the JITAI app. CVD = cardiovascular disease; HCP = healthcare professional; LayP = layperson; JITAI = Just-in-Time Adaptive Intervention. Step 3 resulted in a total of 1350 JITAI assessments from LayP. To allow for modeling the assessor as random effect, each of the assessments was entered separately into the linear mixed model.

#### Results

# **Study Participants**

For the second step in our study procedure, as depicted in Figure 2 - the JITAI generation step – we sampled 10 JITAI responses from each generator group (GPT, LayP, HCP) for all 15 combined contexts (3 personas with 5 contexts each). This resulted in 3 x 150 = 450 unique responses, which constituted the *generator outputs sample* for the study. Generally, we recruited HCP generators with the inclusion criteria of working as HCP in the UK (for language consistency), having regular contact with patients, and having regular professional experience with giving PA recommendations, e.g., in the form of creating exercise plans. Out of the 10 HCPs who generated the JITAI responses (6 female, 4 male,  $M_{Age}$  = 34.9 years,  $SD_{Age}$ = 5.67 years), 6 reported to work as clinical exercise physiologists, and 1 each as nurse, cardiologist, physical therapist, and sport scientist. The legitimacy of their professional backgrounds was checked by the study team. None of the LayP JITAI generators (7 female, 3 male,  $M_{Age}$  = 32,  $SD_{Age}$  = 12.73 years, recruited from the UK adult population) reported to have previous experience with giving PA recommendations. For the LLM-based JITAI generation, we used ChatGPT with the GPT-4 model<sup>35</sup>. JITAI response generation was done between the 14th and the 21st of June 2023. Due to the continuous changes that are implemented with these models<sup>36</sup>, our results refer to the model's capabilities at that time. To generate the GPT-4 responses, given the non-deterministic nature of GPT-4 chat instances when presented with identical prompts, we started 10 separate chats with ChatGPT and provided the same instructions as for the human generators (see Supplement 2).

For the evaluation of the JITAI prompts, we recruited 27 additional laypersons (UK adults, 18 female, 9 male,  $M_{Age}$  = 36.3 years,  $SD_{Age}$  = 12.07 years) to act as raters (assessors). Two of the 27 raters reported previous experience with giving PA recommendations (regularly giving PA advice to friends). Each rater was responsible for assessing 50 responses, ensuring that every generated JITAI received three independent evaluations. The raters served to provide the primary and most secondary outcome measures of the study, with additional auxiliary outcomes being provided by some of the question items that response generators were asked to respond to. Table 1 summarizes the descriptive outcomes for ratings provided for proposed JITAIs by each generator group, and Figure 3 provides an according chart.

Table 1. Descriptive stat	statistics for LayP assessor ratings (on 7-point Likert scales) per generator group.				
Rating scale	Generator group	M	SD	Min	Max
Considering persona and	d context, the decision and m	nessage are			
	GPT	5.47	1.26	1.33	7.00
Appropriate	HCP	4.60	1.67	1.00	7.00
	LayP	4.47	1.53	1.00	7.00
	GPT	5.94	0.90	2.33	7.00
Engaging	HCP	4.58	1.66	1.00	7.00
	LayP	4.35	1.54	1.00	7.00

	GPT	5.85	0.96	2.67	7.00
Effective	НСР	4.58	1.58	1.00	7.00
	LayP	4.36	1.51	1.00	6.67
	GPT	5.86	0.91	3.00	7.00
Professional	HCP	4.74	1.55	1.00	7.00
	LayP	4.54	1.37	1.33	7.00
Considering persona and c	ontext, the decision and	d message would	l leave the r	ecipient	
	GPT	1.71	0.80	1.00	5.67
Angry	HCP	2.19	1.26	1.00	6.33
	LayP	2.09	1.15	1.00	6.00
	GPT	2.09	1.04	1.00	6.67
Annoyed	HCP	2.77	1.49	1.00	7.00
	LayP	2.56	1.34	1.00	6.33
	GPT	2.08	1.05	1.00	6.33
Frustrated	HCP	2.68	1.44	1.00	6.67
	LayP	2.53	1.28	1.00	6.67
	GPT	4.23	1.24	1.00	7.00
Нарру	HCP	3.51	1.49	1.00	7.00
	LayP	3.38	1.28	1.00	6.67
	GPT	1.74	0.72	1.00	3.67
Sad	HCP	2.11	0.98	1.00	5.00
	LayP	2.10	0.99	1.00	5.00
	GPT	1.60	0.69	1.00	4.33
Scared	HCP	1.85	0.90	1.00	6.00
	LayP	1.78	0.79	1.00	4.67
	GPT	2.34	0.88	1.00	4.67
Surprised	HCP	2.71	1.13	1.00	7.00
	LayP	2.68	1.12	1.00	5.67

**Note.** M = Mean; SD = Standard Deviation; Min = Minimum; Max = Maximum; HCP = Healthcare Professional; LayP = Layperson

# **Differences in Response Quality Between Generator Groups**

To analyze the differences in response quality as measured by the respective scales (see Table 5), we used linear mixed models (LMMs), with rating on one of the scales (e.g., appropriateness) as outcome, generator group as fixed, and rater as random effect. The first model, which analyzed the central outcome of a JITAl's appropriateness to the given persona in their current context, revealed that ratings differed significantly by group. Thus, we ran a post-hoc test, which revealed that both lay-person responses ( $\beta$  = -1.02, 95% CI = -1.32 – 0.71, p<.001) and HCP-generated responses ( $\beta$  = -0.88, 95% CI = -1.18 – -0.57, p<.001) were rated significantly less appropriate than the GPT-generated responses. LayP and HCP did not differ significantly regarding prospectively assessed appropriateness. We repeated this analysis for all our scales, with the same directionality to the results throughout. Figure 3 summarizes how JITAls generated by laypersons were prospectively assessed to be less

engaging ( $\beta$  = -1.57, 95% CI = -1.90 – -1.24, p <.001), less effective for fostering PA ( $\beta$  = -1.47, 95% CI = -1.81 – -1.13, p <.001), and less professional ( $\beta$  = -1.29, 95% CI = -1.61 – -0.97, p <.001) than the GPT-4 generated responses. The same applies to the HCP-generatedJITAls, which were also rated less engaging ( $\beta$  = -1.36, 95% CI = -1.66 – -1.05, p <.001), less effective for fostering PA ( $\beta$  = -1.26, 95% CI = -1.58 – -0.95, p <.001), and less professional ( $\beta$  = -1.12, 95% CI = -1.41 – -0.82, p <.001) than the GPT-4 generated responses. Between lay-person and HCP-generated JITAls, while minor differences slightly but reliably favored the HCP responses (see Table 1), we neither found significant differences in engagement, effectiveness, or professionalism.

In the same way as we analyzed the previously mentioned scales, we also investigated how *LayP assessors* thought the personas would feel after receiving the given – or not receiving any – JITAI. These analyses, also visualized in Figure 3, revealed the same results, with GPT-generated JITAIs consistently being rated more positively than those from HCPs or laypersons (see Table 2 for detailed comparisons).

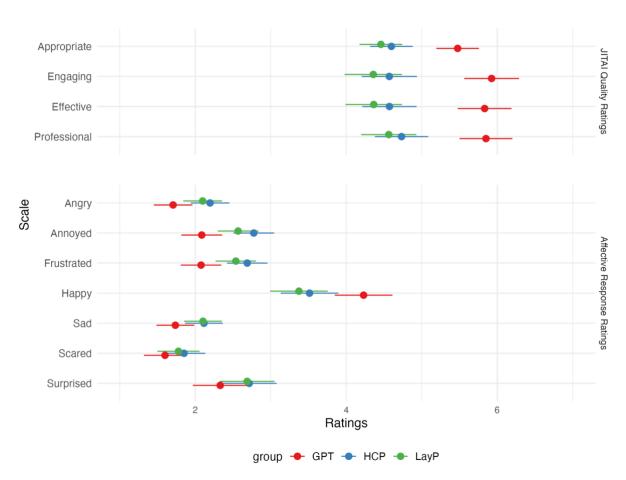


Figure 3: Mean and 95% confidence interval indicators for ratings of JITAI quality and expected affective responses by generator groups.

**Table 2.** Tukey-HSD post-hoc test results for differences in expected affective responses to JITAIs from different generator groups.

Emotion	Comparison	Estimate (β)	95% CI	р
	HCP - GPT	0.49	[0.27, 0.71]	<.001*
Angry	LayP - GPT	0.39	[0.18, 0.61]	<.001*
	LayP - HCP	-0.10	[-0.32, 0.12]	.533
	HCP - GPT	-0.72	[-0.99, -0.44]	<.001*
Нарру	LayP - GPT	-0.86	[-1.13, -0.58]	<.001*
	LayP - HCP	-0.14	[-0.42, 0.14]	.459
	HCP - GPT	0.38	[0.19, 0.57]	<.001*
Sad	LayP - GPT	0.37	[0.18, 0.56]	<.001*
	LayP - HCP	-0.01	[-0.20, 0.18]	.987
	HCP - GPT	0.25	[0.09, 0.42]	<.001*
Scared	LayP - GPT	0.18	[0.01, 0.34]	< .05*
	LayP - HCP	-0.07	[-0.24, 0.09]	.541
	HCP - GPT	0.39	[0.16, 0.61]	< .001*
Surprised	LayP - GPT	0.36	[0.13, 0.59]	<.001*
	LayP - HCP	-0.03	[-0.26, 0.20]	.957
	HCP - GPT	0.69	[0.43, 0.95]	<.001*
Annoyed	LayP - GPT	0.48	[0.22, 0.74]	<.001*
	LayP - HCP	-0.21	[-0.47, 0.06]	.152
	HCP - GPT	0.61	[0.36, 0.87]	< .001*
Frustrated	LayP - GPT	0.46	[0.21, 0.71]	<.001*
	LayP - HCP	-0.15	[-0.40, 0.10]	.345
Note. CI = Confid	ence Interval; HCP =	Healthcare Professi	ional; LayP = Laypers	on; * <i>p</i> < .05

# Consistency of Ratings Across Raters Overall and by Assessed Generator Group

To check the consistency of our response ratings over different raters, we calculated inter-rater reliabilities and compared if they differed between generator groups. Since we had three raters (*LayP assessors*) per JITAI response, we calculated and averaged Cohen's Kappa between each of the rater pairs. This resulted in an overall average of  $\kappa=.53$  indicating a moderate agreement between raters over all our responses. Analyzing this separately for the three different response generators revealed a good level of agreement between raters for GPT-4 generated responses ( $\kappa=.64$ ) and a moderate level of inter-rater reliability for responses from HCPs ( $\kappa=.50$ ) and laypersons ( $\kappa=.42$ ).

# **Possible Interaction Effects with Persona**

To investigate whether the persona – and thus, the approximate degree of aspects either easing or increasing concerns around the extent, intensity and further nature of PA

that is safe and appropriate to propose – moderates the differences in response ratings between the generator groups, we ran a modified LMM, this time including the interaction between the generator group and persona as predictor. We did not find statistically significant interactions between any level of generator group and any level of persona. Instead, the effects observed above hold in the same directionality and separation across dependent variables across the different personas. Hence, there does not appear to be any persona for which the ordering of the relative performance qualities of any rater group changes, which might be assumed, e.g., for a higher-risk persona, or perhaps also for a "middle-ground" persona, as their description and situation leaves more room for interpretation.

To explore this notion, we also analyzed if there were differences between the three personas when comparing how difficult the JITAI generation was perceived to be by the different generators. Using a Kruskal-Wallis test to compare these difficulty ratings over all generators yielded a chi-squared value of 0.07 with 2 degrees of freedom, culminating in a p-value of 0.966. This result suggests a lack of statistically significant differences in the difficulty ratings assigned to the three personas. We found the same result in conducting this analysis separately for the three generator groups: GPT (chi-squared = 1.95, df = 2, p-value = 0.378), HCP (chi-squared = 0.61, df = 2, p-value = 0.736), and LayP (chi-squared = 0.22, df = 2, p-value = 0.895).

# **Qualitative Feedback Analysis**

We also analyzed the qualitative feedback that *assessors* could optionally give for each JITAI response. We received 228 qualitative feedback statements for GPT-generated responses, 203 statements for HCP-generated JITAIs, and 170 statements for JITAIs from LayPs. The first author categorized this feedback into positive, neutral, or negative sentiment. Table 3 shows the counts and respective percentages by category. Comparing the three generator groups by their positive to negative feedback ratio clearly shows that GPT-4 responses received the best feedback, with 4.5 times more positive than negative feedback. HCP responses received 0.2 times more positive than negative feedback, and laypersons received even less positive than negative feedback (P/N ratio:0.74). This is in line with the inferential statistics significantly setting GPT apart from LayP and HCP, as well as with the descriptive statistics indicating slightly but consistently higher response quality for HCP than for LayP within our obtained sample.

Table 3. Valence of feedback on JITAIs by generator group			
	Positive	Neutral	Negative
GPT	170 (75%)	27 (12%)	31 (14%)
НСР	96 (47%)	27 (13%)	80 (39%)
LayP	61 (36%)	26 (15%)	83 (49%)

In an inductive thematic analysis of the qualitative feedback, the first author systematically identified emergent themes by iteratively categorizing the responses into distinct groups. Thereby, we identified reoccurring themes around JITAI timing, content, verbal representation, and affective responses towards JITAIs. Regarding JITAI content, several sub-themes emerged, such as positive reinforcement (e.g., praising users after they adhered to their exercise plan), planning (e.g., incentivizing replanning of a missed activity), offering alternative PA options (e.g., when an outdoor activity is planned, but the weather is bad), encouraging spontaneous PA for mood improvements (e.g., recommending users to go for a short walk to relieve stress), contextualization (i.e. feedback on how well the JITAI was adjusted to a users current context), personalization (i.e. feedback on how well the JITAI was adjusted to the respective user), as well as quality, actionability, correctness, and safety of advice. Notably, regarding the JITAI content sub-themes, positive reinforcement, offering alternative PA options, and encouraging spontaneous PA for mood improvements were perceived as positive over JITAIs from all generator groups. All other content sub-themes contained both positive and negative feedback, with differing distributions over different generator groups.

As mentioned above, GPT-4 JITAIs generally received the most positive feedback. Splitting this up into different themes only corroborated this impression, especially regarding contextualization and personalization. For these central aspects of JITAIs, we received feedback such as: "It came at a good time, Markus was awake and ready to go for a walk, he wouldn't feel angered because he is in a good mood and on his day off, perfect for a walk with his wife" (LayP Rater-14 for GPT-4 JITAI iteration 6, Persona 2, Context 3).HCP-generated JITAIs, on the other hand, received largely negative feedback on the level of personalization and context-sensitivity, e.g., "He has a walk planned so I think this would feel impersonal and not encouraging as it does not relate to the planned activity, and I would think it was automated and not relevant" (LayP Rater-12 for HCP 1, Persona 2, Context 3). The same goes for layperson JITAIs with feedback like, "As the app can see the 'work' location it should not send anything at 9 pm at night. It would be inappropriate and annoying. Sending exercise reminders that late at night should never happen" (LayP Rater-2 for LayP 9, Persona 1, Context 1).

Another interesting insight, we can draw from this feedback is that while all the generator groups received about the same amount of negative feedback on the timing of JITAIs – 24 for GPT-4, 24 for HCPs, and 37 for laypersons – these feedbacks contained fewer considerations around negative affect being evoked by bad timing for GPT-4 based JITAIs – 6 (25%) for GPT-4, 10 (42%) for HCPs, and 18 (49%) for laypersons. This could be related to GPT-4 based JITAIs being generally phrased in a more friendly and engaging manner, which was also indicated by feedback such as: "I might be a bit frustrated and groggy because of how early it is but the message would motivate me!" (LayP Rater-6 for GPT-4 JITAI iteration 5,

Persona 3, Context 1). Meanwhile, HCPs and laypersons received largely negative feedback on the verbal representation of their JITAIs, e.g. for HCPs: "The message could be more encouraging rather than factual. The feeling of anxiety may be made much worse if made to feel that not doing at least 30 minutes of exercise will put them at risk of another heart attack." (LayP Rater-7 for HCP 5, Persona 2, Context 1) or for laypersons: "I don't like the message of this one, it doesn't tell me what to do except for move. It's not very encouraging but I would probably need the reminder. maybe the wording needs to be different." (LayP Rater-13 for LayP 5, Persona 3, Context 1).

## **Guessing the Generator**

Before presenting the last six responses that each assessor was asked to evaluate, we revealed that there were three different groups responsible for generating these JITAIs. This gave us the opportunity to additionally ask the raters for a guess on who generated the respective response. The confusion matrix of 'guessed generator' by 'actual generator' in Table 4 indicates how well *LayP assessors* were able to distinguish between the different *generators*. We found that only the GPT-4 responses were recognized with an above-chance probability. For the other groups' JITAIs, the recognition rate was slightly below chance, with a tendency to confuse them for GPT-4 responses. GPT-4 responses, however, were mistaken for being HCP-generated in half of the cases and were very rarely taken for being generated by LayPs. Additionally, we asked the raters how many of the six responses they expected themselves to guess correctly. The ratio of expected to actually correct guesses was 1.74, which means that raters in the sample overestimated their ability to distinguish between the different types of generator groups.

		Guessed Generator		
		GPT	НСР	LayP
Actual Generator	GPT	23 (43%)	27 (50%)	4 (7%)
	НСР	25 (46%)	16 (30%)	13 (24%)
	LayP	31 (57%)	8 (15%)	15 (28%)

## **Differences in Ratings When the Generator is Known**

Lastly, we analyzed how the response ratings differed when raters knew who generated the respective responses. Using a Wilcoxon signed rank test to compare appropriateness ratings provided by LayP for known and unknown conditions, we found no significant differences for GPT-4 generated responses ( $M_{generator\ known} = 5.09$ ,  $M_{generator\ unknown} = 4.85$ ,  $Wilcoxon's\ V = 64.5$ , p = .47), but trend-level differences for HCP ( $M_{generator\ known} = 5.45$ ,

 $M_{generator\ unknown} = 4.75$ ,  $Wilcoxon's\ V = 100$ , p = .1) and layperson generated responses ( $M_{generator\ known} = 3.44$ ,  $M_{generator\ unknown} = 4.2$ ,  $Wilcoxon's\ V = 31.5$ , p = .06). Thus, for GPT-4 JITAIs the primary *appropriateness* rating seems to be unaffected by raters' knowledge about the generator, while slight biases might improve HCP JITAI ratings and worsen layperson JITAI ratings. Figure 4 visualizes this outcome using the difference score between the unknown and the known condition.

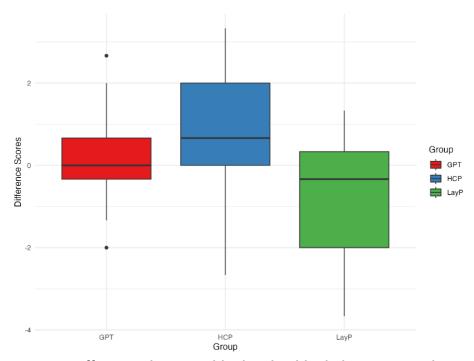


Figure 4: Differences between blind and unblinded JITAI ratings by generator group.

#### Discussion

The results indicate several key insights regarding the potential effectiveness of LLMs as a particular type of generative AI foundation models in generating JITAIs to motivate heart-healthy PA in the prospective setting of cardiovascular rehabilitation: Firstly, JITAIs generated by GPT-4 consistently benchmarked positively compared to those created by HCPs and LayPs in terms of appropriateness, engagement, effectiveness, and professional appropriateness. This finding extends to prospective affective impacts, with GPT-4 JITAIs being assessed as more likely to provoke positive emotions and less likely to elicit negative ones.

Additionally, our analysis showed a higher inter-rater reliability for GPT-4 responses than for responses from HCPs and LayPs, underscoring a more uniform perception of their qualities. Furthermore, GPT-4 demonstrated a consistently high performance across various personas placed on a low-to-high CVD-risk continuum, showcasing its adaptability and reliability of response qualities in diverse contexts. This finding is crucial for the scalability of

JITAI personalization to heterogeneous interests, abilities and needs of the stakeholders, which will also change dynamically over time<sup>14</sup>.

Notably, our raters experienced great difficulties in correctly identifying the source of JITAIs and being made aware of the response generator did not significantly influence the perception of GPT-generated JITAIs by LayPs, formatively representing the target stakeholder group for many nonmedical use-cases. This outcome is noteworthy as it shows that, at least in this aspect, there seems to be no general bias towards AI-generated content or negative suspicion around the capacity of generative AI to inform decision-making and content production in this setting in an automated fashion. For HCP and LayP-generated responses, we observed trend-level biases. As one might assume based on socially learned expectations, we found better ratings for HCP responses and worse ratings for JITAIs from LayPs as compared to blindly labeled persona-context pairings.

Overall, our formative outcomes underscore the considerable potential of LLMs as a form of generative AI for the implementation of effective JITAIs.

#### **Contextualization in Related Work**

It is important to stress that the task of generating JITAIs to motivate PA in cardiac rehabilitation patients, as assessed in this study, is not within the typical scope of responsibilities of HCPs. A large-scale deployment of JITAIs that are custom-generated for every user by HCPs – or even by LayPs – following a crowdsourcing<sup>38</sup> or human computation<sup>39,40</sup> paradigm is not reasonably possible due to scalability limitations and privacy concerns. However, the JITAI implementation through LLMs opens completely new possibilities, and traditional JITAI approaches cannot reasonably compete with the interpretation of complex parameter spaces as they are employed in this study in order to represent broad categories of information that modern multi-device context sensing systems can be expected to integrate during daily living. Thus, we argue that HCP-generated JITAIs are the most appropriate "gold standard" comparison, since we expected that training and experience should allow the HCPs to excel at this task. Even though it is not part of everyday work for HCPs, giving motivational guidance and feedback in a contextualized manner is an occasional part of the work of many HCPs who are regularly involved in issuing PA recommendations or exercise plans. Yet, our results explicitly do not reflect an assessment of LLM capabilities to take over tasks that are currently being handled by HCPs. This formative work to assess the viability of LLMs in the context of JITAIs was also not designed to contrast differences in the ability to offer support in fostering PA between HCP and LayP in a nuanced manner. When considering the integration of JITAIs in healthcare, the role of HCPs might be more aligned with overseeing or validating the content rather than directly creating it. The findings of our study suggest that while HCPs are highly skilled in their traditional roles, crafting digital interventions like JITAIs requires a set of competencies in which generative AI like GPT-4 can offer substantial advantages in terms of personalization based on opportunistically sampled possibly sparse but broadly sampled information inputs, scalability to high-frequency or even continuous support, and adaptability to stakeholder groups of very heterogeneous interests, abilities, and needs, as well as to a broad range of contexts.

Our outcomes indicatively corroborate results from related work on the potential of LLMs. For instance, Kosinski<sup>33</sup> found that GPT-4 displayed strong 'Theory of Mind'-like abilities, being able to solve 95% of the presented false-belief tasks. These are commonly used to measure Theory of Mind<sup>34</sup>, which refers to the human ability to infer and simulate others' cognitive states and processes<sup>32</sup>. Arguably, this ability is essential to the LLM's ability to make empathetic decisions on whether to send a JITAI in a given moment, approximating a "personal coach in your pocket".

The ability of LLMs to make meaningful recommendations has already been determined in the context of recommender systems<sup>41</sup>. To foster PA, such recommender systems could, for instance, be used to recommend PAs that fit a person's preferences<sup>42</sup>. Shin et al.<sup>43</sup> explored a similar direction, indicating their GPT-4-based Al assistant's potential to support users in creating an individualized exercise plan based on their exercise goals, availability, and possible obstacles.

However, to apply such systems to medical contexts, it is extremely important that they adhere to high safety standards and do not pose a risk to patients. In this regard, LLMs have demonstrated the ability to pass various professional qualification tests, including health-relevant ones like the United States Medical Licensing Exam (USMLE)<sup>44</sup> or the MultiMedQA<sup>45,46</sup>. However, Lee et al.<sup>47</sup> also found that GPT-4 produced responses of unreliable quality when asked to answer medical questions and reported an overall relatively low accuracy of GPT-4 in answering these medical questions, and 7% of the responses were even deemed harmful by HCPs. This indicates the need for continued critical debate, consolidation of conflicting outcomes being reported by different research teams, and rigorous empirical testing of LLM outputs' efficacy and safety for each use case<sup>47</sup>.

Given the context of our study within the sensitive realm of health, broader challenges associated with LLMs would, of course, need to be considered and addressed for potential practical use beyond the formative exploration of viability. Issues of privacy, security, inherent biases, and regulatory compliance<sup>52</sup>, notably under frameworks like the EU AI Act<sup>53</sup>, which will particularly regulate AI development and use in sensitive settings, including health, are paramount. Additionally, ensuring accuracy, transparency, fairness, and explainability<sup>54</sup> in these models is critical. Ethical considerations and accessibility also play crucial roles, as highlighted by frameworks such as the European Patients Forum's 2023 principles for AI regulation in healthcare<sup>55</sup>. These challenges underscore the complex landscape of deploying LLMs in healthcare settings and emphasize the necessity for a cautious, well-regulated approach.

From a technical point of view, our findings further corroborate one of the arguably most valuable use cases of generative AI, and particularly LLMs, in fostering transitions between highly structured, possibly well-defined data and rich but not well-defined natural

language representations (see, e.g., emerging databases<sup>56</sup>). As such, in our study, we provided the persona and context information (model input) as the foundation for triggering JITAIs and generating their content (model output). This model input represents, e.g., human- and machine-readable data that might be exchanged from various information collection mechanisms to a central decision-making mechanism in JSON or following other data exchange format specifications. In a digital health context, this can function both ways, e.g., isolating relevant key terms and relations from a subjective expression of self-perceived symptoms, or – as in the case of this study – generating language expressions that feel natural and can serve functions that include human communication nuances. Thus, the encouragement to adhere to planned PA behavior change, as generated in our study, can be seen as an example of computational outputs that are viable to fulfill the principles of reality-based interaction<sup>57</sup>. Similar principles are concurrently being explored in many other application areas, such as robotics and AI-enabled human-robot interaction<sup>58–62</sup>.

#### Limitations

This study is formative and exploratory, and it is therefore crucial to address limitations that frame our findings. Firstly, the generation and assessment of JITAIs were executed based on personas and viable – but artificially composed – context information and the JITAIs were not experienced as part of situated daily living as they would be during an actual deployment. Furthermore, at the current state, our results exclusively display how LayPs perceived the quality of JITAIs generated in our study. Professional perspectives for HCPs are being collected and will be included in the final peer-reviewed publication and updated pre-print versions. Currently, however, the absence of professional perspectives limits the depth and breadth of our evaluation. Especially the professionality ratings should be treated with caution since they were provided by LayPs without specific medical training and experience with making recommendations for exercise activities in the prospective setting of cardiac rehabilitation patients. Thus, the results presented herein require further validation from professional perspectives and based on practical "real-world" deployments.

While our study strongly indicates the viability of using LLMs like GPT-4 for creating JITAIs, this should not be confused with proven effectiveness. The transition from feasibility to real-world efficacy remains an uncharted territory that eventually necessitates rigorous evaluation in practical healthcare settings. Our research lays the groundwork for future studies to explore the actual impact of these AI-generated interventions on health outcomes and can arguably serve to justify a certain degree of efforts, costs and minor inherent dangers in further investigations, e.g., in settings with CVD patients from an ethical perspective.

Based on the comparison with human-generated proposed decisions and content, we also cannot draw conclusions as to how these Al-generated JITAIs compare to current JITAIs implemented via, e.g., rule-based solutions or parameter prediction based on more

traditional machine learning approaches, such as supervised learning from labeled datasets. However, as we lay out above, especially the LLMs' ability to handle sparse and varying contextual variables and transform between structured data and natural language can change the way we think about JITAIs fundamentally, which makes a comparison to rule-based implementations almost impossible. Equally important is the scope of LLMs explored in our study. Focusing solely on GPT-4, we did not evaluate other state-of-the-art LLMs. Particularly, open-source models such as the LLaMA/LLaMA2 model series<sup>27</sup> could be interesting candidates. But also models that are being tailored for local execution "on the edge" and can fully respect crucial privacy sandboxes with federated learning (e.g., MPT-7B<sup>28</sup> or Phi-2<sup>63</sup>) or models trained specifically for the medical context (e.g., Med-PaLM<sup>29</sup>) should be considered.

Lastly, although related work is beginning to show that prompting can have a considerable impact on LLM performance<sup>64</sup>, we did not experiment with prompting strategies beyond providing factual and outcome-oriented instructions that were designed to make for meaningful inputs to the LLM and human generators and assessors alike and running feasibility checks with different LLMs and human study participant testers.

## **Implications and Future Research**

Alternative generative AI models could present better solutions in terms of data privacy and could lead to even more precise and effective interventions. Thus, future works should compare these options more closely. Particularly, considering smaller, more domain-specific, and multi-modal models that can more flexibly ingest and produce various input or output data formats, lead to energy savings, and importantly, be reliably and entirely privacy-preserving, e.g., by running on user-dedicated HIPAA and GDPR-conforming secure cloud instances, or even on a user's smartphone<sup>65</sup>. Future studies should also focus on implementing generative AI-enabled JITAIs in practical healthcare settings, allowing for an evaluation of their effectiveness in real-world environments. In settings that potentially involve more severe consequences for triggering flawed JITAIs than fostering PA, it could also be an interesting approach to combine pre-defined rules (e.g., HCPs defining values of tailoring variables in which no JITAIs should be triggered) with the LLMs ability to produce personalized and contextualized JITAI content.

Another intriguing aspect for future research is the exploration of the extent to which personalization and contextualization contribute to the effectiveness of JITAIs. Understanding the relative importance of personalization, e.g., as compared to viable pre-produced building blocks and content of JITAIs could significantly influence how JITAIs are structured and delivered, potentially leading to more efficient health interventions.

Moreover, the concept of incorporating a reinforcement-learning-like mechanism to enhance personalization in JITAIs presents an exciting avenue for research. Such a mechanism could involve feedback loops where patient responses to JITAIs are fed back to

the LLM to continually refine and adapt the interventions based on what works for the individual. Looking beyond contributing personal preferences and feedback as part of an online RL or RL from human feedback<sup>66</sup> loop, further building up and considering user models offers exciting perspectives both for further improved acceptance and effectiveness of interventions. This could, e.g., be enabled by personal health knowledge graphs<sup>67</sup> that a generative AI model can rely on, contribute to, and expand upon. Additionally, this might even allow for scaling research into understanding the complex interplay of the highdimensional parameter spaces that make up the composition of complex, dynamically evolving personalized interventions<sup>14</sup>. Further viable technical steps would include experimentation with LLMs that are fine-tuned based on the scenarios and feedback data collected from this study. For example, our qualitative findings on themes of "positive reinforcement", "offering alternative PA options", and "encouraging spontaneous PA for mood improvements", which received very positive feedback over all generator groups, could inform instruction prompts for JITAI generation. Such refinements should arguably further improve the produced JITAI decision-making and proposed content, moving beyond zeroshot performance in a self-supervised/agentic or weakly supervised manner<sup>68</sup>.

#### Conclusion

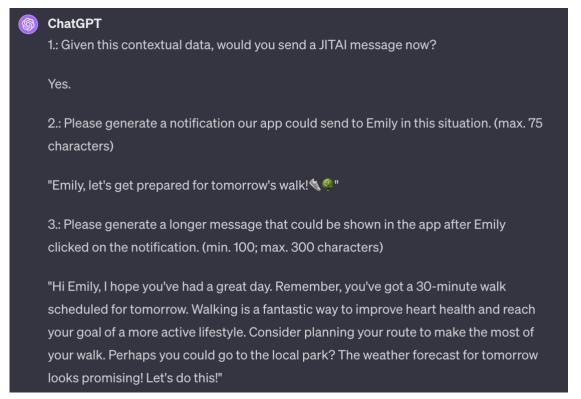
In this formative study, we explored the potential of LLMs - such as GPT-4 - in creating JITAIs for cardiac rehabilitation. Our findings indicate that LLM-generated JITAIs not only surpassed human-generated interventions in terms of appropriateness, engagement, and effectiveness based on layperson assessments, but also demonstrated significant adaptability across various patient personas. Furthermore, the response assessment by laypersons did not differ significantly if the LLM was clearly identified as the producer of the JITAI, indicating an absence of critical biases regarding the potential and viability of AI systems to be the key driver in a JITAI mechanism in the sampled population. Together, these points indicate the relevant potential of generative AI with foundation models in delivering scalable, personalized and contextualized digital health interventions. Despite the identified advantages, the transition from viability to efficacy and acceptability in real-world healthcare settings remains a vital area for future research. In conclusion, this study underlines the transformative potential of LLMs in digital health, particularly in creating effective and personalized JITAIs for fostering behavioral change, clearly warranting investment into further study of the effectiveness of situated and longer-term deployments.

#### Methods

#### **Procedure**

As the first step of the study procedure depicted in Fig. 2, we created three different detailed personas of cardiac rehabilitation patients. With these three personas, we aimed to approximate the spectrum of cardiac health risks commonly found in outpatient CVD rehabilitation, from rather low to rather high. Each persona was crafted with a comprehensive set of variables, including demographics, health metrics, and lifestyle factors, as they may typically be available in healthcare settings. For each persona, we produced five distinct contexts, aiming to vary the advisability of a PA intervention. The contextual variables representing these contexts were selected based on tailoring variables typically used according to JITAI literature<sup>69,70</sup>, previous work from our institute on momentary determinants of PA<sup>71</sup>, and the aktivplan application<sup>72</sup>, in which this exploratory work is grounded for motivation and which produced the original personas that were adapted for this work. Both the personas and contexts were then subjected to a validation process by two HCPs — a cardiologist and a sports scientist — to ensure they depicted a realistic and progressive range of symptom severity.

To generate the JITAI responses we presented, our three *generator* groups—GPT-4, LayPs, and HCPs—with the detailed information on persona and context. We always presented the contexts nested within personas, permuting the order for both, personas, and contexts within each persona. Based on this information, we asked the generators to decide whether a JITAI should be sent in the given situation and to compose two text messages – a short notification (max. 75 characters) and a slightly longer text to display in an exemplary app for physical activity planning and reporting (100 to 300 characters) – if they deemed the situation appropriate for sending a JITAI. If a *generator* decided against sending a JITAI, they were asked to articulate their rationale. To assess the complexity, effort, and mental load perceived by generators, we also asked for feedback on the difficulty of deciding on and crafting a JITAI. Ensuring a standardized task representation across groups, we initially presented instructions that delineated the concept of JITAIs, the functioning of the JITAI-App, and its role in supporting outpatient rehabilitation before starting the JITAI generation. The study materials are available online as <u>supplementary material</u>, and Figure 5 shows an example of a GPT-4 output for this task.



**Figure 5: Screenshot of a JITAI that GPT-4 would have generated for the persona "Emily Thompson".** The response was based on contextual data representing the following situation: "It's Thursday evening, and Emily is sitting in her living room, knitting a new scarf. She's been watching TV for the last couple of hours and has barely moved from her chair." (See online prompt materials: Persona: Emily Thompson, Scenario: 2 for full details.).

To assess the quality of the generated JITAI decisions and content, we asked all three groups of generators to rate the responses on multiple scales described below. We presented the assessors with instructions similar to the generating task, explaining the concept of JITAIs and how their quality should be assessed. For each rating task, instructions contained the same detailed information on personas and their contexts as before, but we additionally included a description of the situation in natural language to ensure the assessors were provided with an accurate representation of the situation as an actual JITAI recipient would have as well. We currently report on the preliminary outcomes based on responses by LayP assessors. The final publication of this study will also contain response ratings from HCPs, which are currently being collected and analyzed. This will allow us to derive more reliable implications driven by multi-stakeholder views, especially regarding the professionality of generated JITAIs, which LayPs can only assess to a limited degree. However, since the main users of such applications would most likely be akin in their assessments to LayP, it is already possible to draw first indications regarding viability of the approach. Therefore, this study can act as an appropriate exploratory step before experimentation in applied health or medical use cases.

#### Measures

The JITAIs were primarily assessed using four key dimensions presented as 7-point Likert scales. Table 5 shows the scales and the items.

Table 5. Dimensions and items assessed via 7-point Likert scales and their respective itemsDimensionItem (What do you think ...)...how appropriate is it to send this JITAI to<br/>the given persona under the given<br/>circumstances?engagement...how engaging are the messages?effectiveness...how effective will this JITAI be in<br/>supporting the user to reach their PA goals?professional appropriateness...how professionally appropriate is the<br/>content of this JITAI?

In addition to the dimensions listed in Table 5, raters gauged the assumed emotional impact of the JITAIs, providing their assessment of how the recipient would feel upon reading the given message under the given circumstances. This assessment included single-item scales for five basic emotions<sup>73</sup> (happiness, sadness, anger, surprise, fear) and additionally for annoyance and frustration, which we considered especially relevant to the JITAI context as they are often related to intervention fatigue<sup>21</sup> and users discontinuing the use of digital health tools<sup>8</sup>. Given the formative and prospective nature of this work and the assessment task, we did not employ validated psychometric questionnaires – which would be firmly implied for possible future practically validating work of this approach – given their complexity and their lack of validity for prospective scenarios.

An optional qualitative feedback section was provided for raters to express their thoughts on the JITAI content and its presentation within the application, which was described as part of the overarching context and framing of the study provided to participants.

The primary outcomes of the study were captured as part of a blinded rating phase. Afterward, raters were informed about the three JITAI-producing parties and asked to guess the *generator* group in a selected subsample of responses. This was followed by a final phase, in which the generator of the JITAI was disclosed before asking for assessment following the scheme as described above on a further subsample of responses. Thus, we were able to analyze whether the evaluations regarding response quality provided by the raters were influenced by their knowledge of the generator group, offering formative insights into potential biases towards AI-generated versus human-generated interventions.

# **Participant Recruitment**

LayP participants for both generation and rating tasks were recruited via Prolific, targeting UK participants to reduce the impact of language barriers. For their contribution, human JITAI generators were compensated with 10 GBP, with an additional 5 GBP bonus awarded for responses deemed to have satisfactory quality. This bonus incentive was aimed at ensuring the collection of thoughtful and relevant JITAIs. LayP raters were offered a higher compensation of 15 GBP, reflecting the longer engagement time of approximately 90 minutes required to complete the ratings. Healthcare professionals were recruited from professional networks within the UK that specialize in physical activity-related fields, as well as via social media and the networks of the study team. Considering their professional expertise as relevant to the context of the study and the nature of their contribution, HCPs were compensated with a 30 GBP Amazon voucher, reflecting approximately twice the monetary value. We selected GPT-4 as the LLM for our study because of its general state-of-the-art performance on most relevant benchmarks<sup>74</sup> and argue that outcomes remain relevant even in comparison to models targeting the medical and health domain, since GPT-4 has been shown to outperform domain-specific models like MedPALM 248 when using case-oriented prompting<sup>64</sup>. We also performed a sanity check comparing the GPT-4 responses to JITAIs generated by Google Bard and BING models available in August 2023 but found GPT-4 responses to display the highest response quality in an informal assessment, providing reasoning to proceed with GPT-4 only for this exploratory work.

# **Data analysis**

The principal analysis of the JITAI response ratings employed LMMs to accommodate the nested structure of our data: multiple, but not all JITAIs evaluated by each rater. Each LMM accounted for the fixed effect of the generator group (GPT-4, LayPs, HCPs) on the ratings, while treating the rater as a random effect to control for inter-rater variability. This approach allowed us to discern the impact of the generator group on the perceived appropriateness, engagement, effectiveness, and professional suitability of the JITAIs. After fitting the LMMs, Tukey's HSD post-hoc tests were conducted for multiple comparisons to determine the significance of the differences between the generator groups. In an additional analysis, we included the interaction between *generator group* and *persona* in the model to investigate if any generator groups would show advantages or shortcomings for different levels of symptom severity. To check if the stability of ratings differed between different generator groups, we calculated and compared average Cohen's Kappa values for responses produced by each of the groups.

## **Acknowledgments**

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#### **Author Contributions**

DH acted as the lead author of the study and implemented and executed most of the study. JS acted as the senior author, together with DK providing mentorship and guidance throughout the project. DK and JS developed the original research concept and collaborated on iterating it throughout the study duration. SG contributed to starting and closing discussions of the project. DH, DK, SG, MS, GT, JN, CB and JS all contributed to drafting and improving the writing of this article. MS and GT contributed to checking the fidelity of personas and scenarios and – together with JN supported writing the medical / health-relevant sections of the draft.

# **Data Availability**

Personas, context descriptions / scenarios, JITAI instructions, analysis scripts, and anonymized outcome data at raw and various processing stages are available online at: <a href="https://doi.org/10.10649386">10.5281/zenodo.10649386</a>

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