Exploring the Relationship Between Intrinsic Motivation and Receptivity to mHealth Interventions

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ABSTRACT

Just-in-Time Adaptive Interventions aim to deliver the right type and amount of support at the right time. This involves determining a user's state of receptivity – the degree to which a user is willing to accept, process, and use the intervention. Although past work has found that users are more receptive to notifications they view as useful, there is no existing research on whether users' intrinsic motivation for the underlying topic of mHealth interventions affects their receptivity. To explore this, we conducted a study with 20 participants over three weeks, where participants interacted with a chatbot-based digital coach to receive interventions about mental health, COVID-19, physical activity, and diet & nutrition. We found that significant differences in mean intrinsic motivation scores across topics were not associated with differences in mean receptivity metrics across topics. However, we discovered positive relationships between intrinsic motivation measures and receptivity for interventions about a topic.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

Digital Health, mHealth, Just-in-time Adaptive Interventions, Receptivity

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1 INTRODUCTION

The ubiquity of smartphones and wearables, coupled with advances in built-in sensor technology, has led to a wide array of research opportunities and applications for mobile health (mHealth). mHealth aims to use mobile and wireless technologies to deliver effective interventions that improve health outcomes. Indeed, researchers have designed various smartphone-based interventions to promote outcomes such as reducing smoking, increasing physical activity, eating healthier, and improving mental health [1, 7, 8, 23, 30].

Recent mHealth studies have used Just-In-Time Adaptive Interventions (JITAIs), which aim to provide the right type and amount of support, at the right time, depending on the individual's changing internal and contextual state [14]. Effective timing depends on states-of-vulnerability (like during a craving for alcohol [14]) or opportunity (such as a period of prolonged inactivity [33]). and on states-of-receptivity, i.e., when someone is able/willing to receive, process, and use the support provided. Prior research has found that factors such as age, personality, location, and device usage, can influence receptivity to interventions [9, 12, 13]. If interventions are not well-timed, they could lead to intervention fatigue, thus reducing the likelihood of continued engagement and effectiveness [5].

Furthermore, the content of mHealth interventions is critical to their success. Prior research on generic phone notifications has demonstrated that people are generally more receptive to notifications they find important, urgent, or useful [4, 11, 19]. However, there's limited research on how *intrinsic motivation* towards the content of mHealth interventions affects their receptivity. the most autonomous form of motivation, involves doing an activity for the inherent satisfaction of the activity itself. Intrinsic motivation and greater internalization of behavioral goals has been associated with better retention and behavioral health outcomes – including greater adherence to medications [34], better long-term maintenance of weight loss among obese patients [35], improved glucose control among diabetics [34], and greater attendance in an alcohol addiction treatment program [29]. In this study we explore whether intrinsic motivation influences receptivity to mHealth interventions. We examine variations in intrinsic motivation across different health topics and within the same topic, assessing whether higher intrinsic motivation corresponds to greater receptivity.

We conducted a 21-day study where participants received three digital coaching interventions daily on topics like mental health, COVID-19, physical activity, and diet & nutrition, delivered at random times during the morning, afternoon, and evening. We used the metrics defined by Künzler et al. to quantify receptivity in terms of response rate, just-in-time response rate, conversation engagement, and response delay [9]. Additionally, we conducted weekly surveys with four subscales of the Intrinsic Motivation Inventory [22, 25, 26]: interest/enjoyment, perceived competence, perceived choice, and value/usefulness for each intervention topic. [1]

We hypothesize:

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[1]Standard IMI has seven possible subscales. Past research has found negligible effects from changing the order of survey items, and from including or excluding various subscales [2]. As a result, experimenters rarely use all items and instead pick the subscales relevant to their research questions [2].

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- H1: When a participant has a higher intrinsic motivation score for an intervention topic, they will be more receptive to messages from that topic compared to other topics.
- H2: The higher a participant's intrinsic motivation score for a topic, the higher the likelihood that the participant will be receptive to that topic.

2 RELATED WORK

Prior research on receptivity and the related field of interruptibility investigated the associations between the users' contextual factors and receptivity, such as the time of the day and the day of the week [9, 12, 18, 21], location [9, 10, 20, 31], Bluetooth connected devices [18], Wi-Fi connectivity [18, 21], communication (SMS and Call logs) [4, 21], and phone battery status [9, 20]. Other studies investigated activity [9, 16], personality traits [9, 11], and mental states [31] as potential factors influencing receptivity.

There has been, however, a limited understanding of intrinsic motivation and engagement with digital health interventions. Self-Determination Theory (SDT) offers a comprehensive framework for understanding human motivation, behavior, and the contextual factors that support it [27]. Central to SDT is the distinction between intrinsic motivation, which is engaging in activities for inherent satisfaction, and extrinsic motivation, which is driven by external outcomes [27]. SDT posits that fulfilling three innate psychological needs—autonomy, competence, and relatedness—is crucial for enhancing self-motivation and well-being [28]. These needs, when satisfied, lead to the internalization and integration of behaviors, aligning them with one's values and sense of self. In health care, applying SDT has shown that environments supporting patient autonomy, competence, and relatedness significantly improve adherence to treatments and overall health outcomes [15]. Studies demonstrate strong associations between patients' autonomous motivation, their perception of healthcare providers' support, and long-term adherence to treatments, leading to improved health metrics like blood-glucose regulation and weight loss [32, 32, 36]. A meta-analysis of SDT-based studies confirms that autonomy-supportive healthcare environments contribute to higher levels of patient autonomy, competence, and relatedness, thereby predicting better mental and physical health, with some studies indicating long-term benefits [15].

3 METHODS

In this section, we discuss our study goals and design, the smartphone app used to deliver interventions (Elena+), the study description, and the IMI we constructed. We then describe the data collected during the study, and our approach to data analysis.

3.1 Study Design

In our study, we deployed a modified version of the Elena+ iOS app [17]. Elena+, based on the MobileCoach platform [3, 6], is a chatbot-based digital coach that delivers 43 different educational interventions on 7 topics: COVID-19, physical activity, diet and nutrition, sleep, anxiety, mental resources, and loneliness [17]. We present a summary of the various topics in Elena+ coaching sessions in Figure 1.

The original Elena+ app allows users to complete these interventions at their own pace over a period of two months; we modified the app so that users received a generic initiating push notification three times a day, at a random time within a morning, afternoon, and evening interval. The initiating push notification (Figure 2) told the user it was time for a coaching session, but did not specify the topic of the intervention. The digital coach always delivered an intervention in a topic different from the topic in the previous interval.

The interventions in our study were chat-based conversational messages from Elena+, with some messages requiring participants to answer by selecting from pre-defined answer options. We defined the first message requiring a participant answer to be the *initiating message* of the conversation. Metrics for response, just-in-time response, and response delay were calculated based on participants' response times to initiating messages. See Appendix Figure 3 for an example initiating message. If a user did not complete an intervention an hour before the next interval, we sent a push notification reminding them to complete the coaching session. Reminder notifications were sent at 12 pm, 5 pm, and 10 pm EDT. If the user still did not complete the session by the time the next interval began, it was delivered again within the next week. With these modifications, we estimated users would complete all 43 interventions over 15-21 days.

We requested the participants to keep the active for up to 21 days or until they completed all interventions. After completing the interventions, or at the end of 21 days, participants uninstalled the app and completed a post-study usability survey. This survey included questions about the notification system and its perceived impact on their daily routine.Upon completion of the survey, we sent the participants a US$40 Amazon gift card, regardless of how many interventions they completed. Initially, participants were informed that the study was about promoting positive lifestyle changes during the pandemic, but the primary objective was to assess how their intrinsic motivation influenced their receptivity to the health interventions.

Since our goal was to study how intrinsic motivation related with receptivity to digital health interventions, to prevent any bias, we employed deception and did not tell the participants the true purposed of the study, since that could have affected how participants interacted with the app. Instead, we told the participants that the Elena+ app is used to promote positive lifestyle outcomes during the pandemic. We instructed Participants to treat the Elena+ app as any other app on their iPhone. We did not ask participants to respond to initiating push notifications or to complete the interventions. Even the compensation was not tied completing a specific number of interventions. At the end of the study, we sent a note to the participants updating them with the true goal of the study. The study protocol, along with the use of deception was approved by the IRB.

The recruitment process for the study involved advertising through emails, social media, and physical flyers. Out of 38 initial respondents, 20 participants, comprising 13 females and 7 males with a median age of 20.5 years, completed the study. These participants went through a pre-study questionnaire that included an Intrinsic Motivation Inventory (IMI) for four out of the seven topics covered by Elena+. This was done to reduce the burden on the respondents.

Figure 1: **The Elena+ app can deliver 43 unique coaching sessions about loneliness, anxiety, mental resources, diet & nutrition, COVID-19, physical activity, and sleep.**

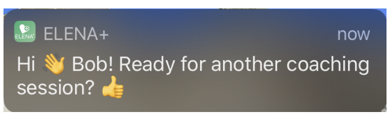


Figure 2: **Example of a generic push notification from Elena+. When a participant tapped the notification, they were navigated to the Elena+ app to view an initiating message.**

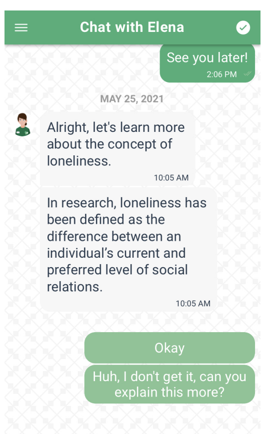


Figure 3: **Example of an initiating message. An initiating message is the first message in an intervention that requires the participant to reply by selecting from provided answer options. Whether or not the participant replied, and when the participant replied was used to calculate receptivity metrics.**

During the study, we asked the participants to complete the IMI surveys and rate their interest and confidence in the coaching topics on a weekly basis. These measures provided comprehensive data on the participants' motivational states and their interactions with the digital interventions, allowing us to study the dynamics between intrinsic motivation and receptivity in the context of digital health interventions. Summary statistics about participant interaction with initiating messages are presented in Table 1.

Table 1: Aggregate Study Stats: Initiating messages are the first messages in the coaching session that require a participant reply, and the receptivity metrics are the same as detailed by Künzler et al. [9]

	Total	Percentage
Initiating Messages Delivered	1236	
Initial Responses	373	30.18%
Just-in-time Responses	96	7.77%
Conversations Engaged	207	16.75%

3.2 Our Intrinsic Motivation Inventory

In our experiment, we constructed an IMI using four subscales: interest/enjoyment, perceived competence, value/usefulness, and perceived choice. We included the interest/enjoyment subscale as it is considered a self-report of intrinsic motivation. Perceived choice and perceived competence are theorized to be positive predictors of both self-report and behavioral measures of intrinsic motivation [24]. We chose the value/usefulness subscale because people tend to be more receptive towards notifications with content they view as important, urgent, or useful [11], and because people internalize motivation for activities they perceive as having value [27]. Our aim is to determine whether receptivity or engagement is correlated with any of these subscale measurements of intrinsic motivation, and whether these measures change over time. Using these four subscales results in a 24-item version of the IMI.

For each intervention topic, we altered the IMI items to focus on the health goal promoted by Elena+ interventions for that topic. For example, the mental health IMI focused on "working on improving mental health," while the IMI for COVID-19 focused on "following COVID-19 guidelines."

To test the internal consistency reliability of our constructed IMIs, we calculated the Cronbach's alpha coefficient for the total IMI and subscales for each topic. The internal consistency measures for the total IMIs were high. As shown in Table 2, while overall internal consistency was high across the four topics, the perceived choice subscale stood out with $\alpha < 0.70$.

Table 2: Cronbach's alpha coefficient (α) for the total IMI score and IMI subscale scores for each topic

Topic	Total	Interest/ Enjoyment	Perceived Choice	Perceived Competence	Value/ Usefulness
Mental Health	0.83	0.83	0.60	0.90	0.96
COVID-19	0.81	0.83	0.62	0.86	0.94
Physical Activity	0.94	0.94	0.63	0.88	0.97
Diet & Nutrition	0.94	0.94	0.55	0.93	0.97

3.3 Data Analysis

In our analysis, we explored how intrinsic motivation inventory scores relate to receptivity towards mHealth interventions both across-topics and within-topics. To prepare for this analysis, we divided the 43 digital coach initiating messages into the four topics used for the IMI surveys. COVID-19, physical activity, and diet & nutrition contained the messages from the similarly named Elena+ coaching session topics. Mental health included messages from the Elena+ coaching session topics of mental resources, sleep, anxiety, and loneliness. As a result, the mental health topic included a little over half of the 43 unique initiating messages delivered to each participant, as shown in Table 3.

Table 3: Division of Initiating Messages into Intervention Topics: Mental health contained initiating messages from Elena+ coaching sessions on mental resources, sleep, anxiety, and loneliness. COVID-19 contained initiating messages from COVID-19 coaching sessions. Physical activity contained initiating messages from physical activity coaching sessions. Diet & nutrition contained initiating messages from diet & nutrition coaching sessions.

Intervention Topic	Number of Initiating Messages	Percentage of Total
Mental Health	22	51.16%
COVID-19	10	23.26%
Physical Activity	8	18.6%
Diet & Nutrition	3	6.98%

Our analysis was guided by the two hypotheses. Hypothesis 1 focused on cross-topic analysis, i.e., with a higher intrinsic motivation score for a certain topic would have greater receptivity to initiating messages about that topic compared to initiating messages about other topics. To test these hypotheses, we employed linear mixed effects models followed by post-hoc analysis for pairwise comparisons across topics, considering both the receptivity metrics and the mean IMI subscale scores. We anticipated a positive relationship between the differences in mean receptivity and the differences in mean IMI scores across different topics, over the study period.

Conversely, Hypothesis 2 focused on within-topic analysis, i.e., within a single topic, higher intrinsic motivation scores would be associated with greater receptivity towards initiating messages for that intervention topic. To explore this hypotheses, we constructed appropriate linear and generalized linear mixed effects models. Our analysis was complicated by the varying times at which participants completed the IMI surveys, which were ideally intended to be filled out at specific intervals (weekly) during the study. Initially, we defined time periods based on the dates when surveys were completed, but this method excluded post-study IMI scores. Therefore, we adopted a partial interpolation method, identifying halfway points between survey completion dates to define our analysis periods. This allowed us to include all IMI scores and calculate receptivity metrics more comprehensively over the adjusted time periods.

4 RESULTS

In this section, we present the findings from our statistical analysis, which revealed mixed outcomes in relation to our hypotheses.

Regarding Hypothesis 1, which predicted a positive correlation between intrinsic motivation and receptivity across different health topics, our findings were inconclusive. While we observed significant differences in the IMI subscales between the different topics (Tables 4, 5, 6), we did not find any significant differences in the key receptivity metrics, such as overall response rate, just-in-time response rate, and average response delay. The one exception was the conversation rate, where COVID-19 topics demonstrated higher engagement compared to diet & nutrition and physical activity (Table 7). However, this was contradicted by lower interest/enjoyment, perceived choice, and value/usefulness scores for COVID-19 guidelines, indicating a complex relationship between intrinsic motivation and receptivity.

Table 4: Pairwise comparisons of interest/enjoyment subscale scores across topics

Pairwise Comparisons	Estimate	Std. Error	df	t-ratio	p-value
COVID-19 – Diet & Nutrition	-2.070	0.203	192	-10.217	<.0001
COVID-19 – Physical Activity	-2.197	0.197	192	-11.136	<.0001
COVID-19 – Mental Health	-1.373	0.194	192	-7.087	<.0001
Diet & Nutrition – Mental Health	0.697	0.199	192	3.503	0.0032
Mental Health – Physical Activity	-0.825	0.194	192	-4.258	0.0002

Table 5: Pairwise comparisons of perceived choice subscale scores across topics

Pairwise Comparisons	Estimate	Std. Error	df	t-ratio	p-value
COVID-19 – Diet & Nutrition	-1.0163	0.154	193	-6.578	<.0001
COVID-19 – Physical Activity	-1.2029	0.150	192	-7.995	<.0001
COVID-19 – Mental Health	-1.1564	0.148	192	-7.828	<.0001

Table 6: Pairwise comparisons of value/usefulness subscale scores across topics

Pairwise Comparisons	Estimate	Std. Error	df	t-ratio	p-value
COVID-19 – Diet & Nutrition	-0.861	0.187	192	-4.614	<.0001
COVID-19 – Physical Activity	-0.888	0.182	192	-4.886	<.0001
Mental Health – Physical Activity	-0.488	0.178	192	-2.737	0.0340

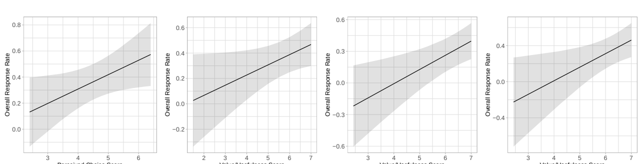
Table 7: Pairwise comparisons of conversation rate across topics

Pairwise Comparisons	Estimate	Std. Error	df	t-ratio	p-value
COVID-19 – Diet & Nutrition	0.14318	0.0501	192	2.856	0.0244
COVID-19 – Physical Activity	0.13774	0.0488	192	2.821	0.0269

For Hypothesis 2, which focused on the relationship within individual topics, we found several significant positive associations between intrinsic motivation scores and receptivity metrics. These were particularly notable in mental health, physical activity, and diet & nutrition interventions, suggesting a more straightforward relationship between intrinsic motivation and receptivity within specific health contexts. However, COVID-19 interventions presented an opposite trend, where increased interest/enjoyment scores were associated with decreased likelihood of response and overall response rate, possibly reflecting the impact of external factors such as pandemic fatigue or changing public health guidelines.

For Hypothesis 3, our analysis revealed a strong correlation between higher intrinsic motivation scores and increased responsiveness within specific health topics. This was particularly noticeable in mental health interventions, where higher perceived choice and value/usefulness scores associated with with an 11.03% and 8.02% increase in overall response rates ($p < 0.05$). We observed a similar trend in physical activity and diet & nutrition interventions, where increases in value/usefulness scores led to significant ($p < 0.05$) boosts in response rates (13.47% and 15.01%, respectively) 4. Additionally, we observed that a one-point increase in perceived competence scores significanty reduced the response delay in diet & nutrition interventions by approximately 54 minutes ($p < 0.05$). These findings highlight that when participants found the intervention content to align well with their personal values or choices, their engagement levels rose markedly, indicating a direct link between intrinsic motivation and participant interaction within specific health domains.

However, we did observe some conflicting associations. For COVID-19, we found a one-point increase in the interest/enjoyment score was associated with a decrease in the likelihood of response by 10.5% ($p < 0.05$). Similarly, a one-point increase in interest/enjoyment



(a) Mental Health (b) Mental Health (c) Physical Activity (d) Diet & Nutrition

Figure 4: **Positive Relationships Between IMI Subscale Scores and Overall Response Rate to Different Intervention Topics**

(a) Likelihood of response to COVID-19 interventions over the course of the study (b) COVID-19 interest/enjoyment scores over the course of the study

Figure 5: **Temporal dynamics for COVID-19 interest/enjoyment score and likelihood of response**

scores was associated with a 12.69% decrease in the overall response rate for COVID-19 interventions ($p < .05$). For the mental health interventions, we observed that higher interest/enjoyment scores associated with longer response delays. These unexpected results imply a complex relationship between interest in a topic and the immediacy of interaction with the intervention, possibly influenced by factors like content relevance, personal mental state, or external circumstances. These findings collectively underscore the intricate dynamics between intrinsic motivation and user engagement within different health intervention contexts.

5 DISCUSSION AND IMPLICATIONS

The lack of support for Hypothesis 1 suggests that intrinsic motivation's influence on receptivity is more nuanced than initially hypothesized. The higher engagement with COVID-19 interventions, despite lower intrinsic motivation scores, could be attributed to the topic's relevance and urgency during the study period. This finding highlights the potential impact of external factors, such as current events and societal changes, on the effectiveness of health interventions.

Conversely, the support for Hypothesis 2 underscores the importance of aligning digital health interventions with individuals' intrinsic goals and values. The positive relationship between intrinsic motivation and engagement in mental health, physical activity, and diet & nutrition interventions suggests that interventions tailored to individual motivations are more likely to be effective. However, the negative trends observed in COVID-19 interventions caution against a one-size-fits-all approach, emphasizing the need for adaptability and relevance in content, especially in rapidly changing health contexts.

The study's findings also raise questions about the role of intervention fatigue and content relevance. Additional analysis revealed a decreased engagement with COVID-19 content over time (by almost 60 percentage-point), despite increased interest in the topic (Figure 5a), suggesting that the timeliness and perceived usefulness of intervention content are critical for sustained engagement. This highlights the need for continuous evaluation and adaptation of digital health interventions to maintain their relevance and effectiveness.

Additionally, there may also have been other contextual factors that outweighed any interest/enjoyment participants had for that topic. 14.29% of participants selected "Strongly disagree" and 52.38% of participants selected "Disagree" for the statement that "the notifications from Elena were generated at times I was not busy with anything else," showing that a majority of participants were engaged in some activity when receiving initiating messages.

The timing of interventions when participants were engaged with some activity may have decreased the likelihood of response and just-in-time response, as 33.33% of participants selected "Strongly agree" and 38.10% selected "Agree" when asked whether they "responded to notifications with Elena only when I was free or not doing anything else." Delivery when participants were busy may have also decreased the likelihood of conversation engagement, as 42.86% of participants selected "Strongly agree" and 25.57% selected "Agree" when asked whether they "engaged in chat-conversations with Elena only when I was free or not doing anything else." In future research, it would be beneficial to explore how external factors and changing circumstances interact with intrinsic motivation to influence engagement with health interventions. Additionally, considering the temporal dynamics of interest and engagement, as well as the specific content of interventions, could provide deeper insights into the complex relationship between intrinsic motivation and receptivity to digital health interventions.

6 LIMITATIONS

Our study had several limitations, primarily due to the small, and potentially homogeneous, sample size of 20 participants. The general population likely has greater variation in intrinsic motivation both within and across topics. Thus the magnitude of the relationships we found between intrinsic motivation and receptivity could be understated compared to what might be found with a more diverse set of participants.

Another limitation was our approach to measure intrinsic motivation. The IMI survey focused on the underlying topics of interventions rather than on the interventions themselves. This could have led to a disconnect between participants' interest in the topics and their engagement with the specific interventions, potentially skewing the results. Finally, inclusion of COVID-19 as a topic could be another limitation. The evolving nature of the public health guidelines around COVID-19 along with the rollout of vaccinations during the study period may have affected participants' intrinsic motivation and responsiveness to COVID-related interventions, adding complexity to the interpretation of our results.

7 CONCLUSION

In this work, we investigated the relationship between intrinsic motivation for mHealth intervention topics and various receptivity metrics, among a group of 20 university students over three weeks. We delivered interventions on topics like mental health, COVID-19, physical activity, and diet & nutrition. Our analysis evaluated receptivity through metrics like response, just-in-time response, conversation engagement, and response delay. We found that while there was no significant correlation between average intrinsic motivation scores and receptivity metrics across different topics, a positive relationship did exist between intrinsic motivation and the likelihood of response within individual topics. This suggests that while intrinsic motivation levels across various topics might not influence overall receptivity, enhancing intrinsic motivation specific to a topic could improve engagement with interventions, pointing to potential strategies for tailoring content in future JITAIs.

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