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Interacting with an AI-generated Future Self to Promote Healthy Food Choices - A Study Proposal

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INTERACTING WITH AN AI-GENERATED FUTURE SELF TO PROMOTE HEALTHY FOOD CHOICES - A STUDY PROPOSAL

Short Paper

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Abstract

Self-control, the ability to resist immediate temptations, is among the core capabilities to successfully navigate modern obesogenic environments. Addressing impulsivity and self-control using behavioral interventions can contribute to alleviating the global obesity epidemic. Episodic Future Thinking (EFT) interventions, that prompt users to simulate self-related future events, have shown promise in reducing impulsive choice tendencies and inducing dietary behavior changes in laboratory contexts. However, more research is needed to develop tools that make EFT applicable in real-world settings. In this study proposal, we describe a novel EFT intervention based on an AI-powered conversational agent that allows users to interact with a hypothetical future version of themselves. We outline a pre-registered research plan to test its effectiveness for reducing choice-related impulsivity and ameliorating food choice. The results are expected to provide initial evidence for an actionable tool that promises to aid individuals with self-controlled decision making in the dietary domain and beyond.

Keywords: Conversational Agents, Episodic Future Thinking, Impulsivity, Self-Control, Dietary Choice

1 Introduction

Obesity and overweight are among the most pressing health challenges of the 21st century, with far-reaching implications for patients, healthcare systems, and society at large. Between 1990 and 2022, the global prevalence of overweight and obesity has more than doubled, now affecting 43% and 16% of adults, respectively (World Health Organization, 2024). Changes in environmental factors such as the omnipresence of calorie-dense, nutrient-poor food options play a significant role representing a challenge for human self-control in everyday dietary decision making. While many individuals are aware of the risks of overeating and unhealthy diets, their awareness often does not transfer into corresponding dietary behaviors, a phenomenon referred to as the intention-behavior gap which reflects the difficulty of exercising self-control in the face of immediate temptations (Sheeran & Webb, 2016).

Recently, the rapid developments in generative artificial intelligence (AI) and Large Language Models (LLMs) in particular, allow individuals to ask questions and receive personalized responses, which enables active assistance with pursuing their health goals in everyday life (Abbasian et al., 2024; Fang et al., 2024; Kusal et al., 2022). Recent research highlights chatbots' effectiveness in dietary interventions by leveraging real-time feedback and personalized recommendations (Prasetyo et al., 2021; Zhang et al., 2020). This research-in-progress paper represents a study proposal, in which we outline the design of a pre-registered randomized controlled trial to test a novel digital behavioral intervention tool that combines novel LLM-based chatbots with recent theoretical and empirical advances in Psychology on behavioral interventions to reduce impulsivity and support healthy dietary choices. During the intervention, our study participants will interact with Future You, a system developed by Pataranutaporn et al. (2024) that generates a hypothetical future version of an individual and allows for a conversation about episodic future events. Such episodic future thinking (EFT) interventions (Schacter et al., 2017) have proven effective in reducing choice-related impulsivity in laboratory tasks (Rösch et al., 2022; Rung & Madden, 2018b) and in real world settings (Persson et al., 2024) and have shown promise for improving healthy dietary choices (Daniel et al., 2013, 2015; Sze et al., 2015, 2017). Future You provides the possibility to realize such interventions in an immersive and playful way to make them applicable to real-world decision-making interventions.

The proposed study sets out to lay the groundwork for such an applicable intervention by testing a low-resolution but easily scalable version of Future You on choice-related impulsivity and food choice behavior, using Delay Discounting and Food Choice Tasks in a large sample of study participants on Prolific. The results are expected to provide first insights into the mechanisms and effectiveness of a digital future self-intervention based on generative AI to ameliorate dietary decisions. The system including the intervention has been developed. In the next step, we will run a pilot study with 30 participants and improve the system based on our initial findings. When the system is ready for final deployment, we will conduct the full data collection with 300 participants. The results will be presented at the conference in June 2025.

2 Theoretical Background

2.1 Conversational Agents

Conversational agents, also known as chatbots or virtual assistants, have a longstanding presence in IS and neighboring fields (Diederich et al., 2019), dating back to the early implementations of rule-based systems in the 1960s, such as ELIZA (Weizenbaum, 1966). These early agents relied on predefined responses, but with advances in generative AI, they evolved to handle complex queries (Kusal et al., 2022) and support dynamic functions across customer service (Gnewuch et al., 2017), health care (Car et al., 2020), education (Khosrawi-Rad et al., 2022), and e-commerce (Alnefaie et al., 2021).

In the dietary sector, chatbot-based interventions like Foodbot use real-time feedback to encourage healthier eating choices (Prasetyo et al., 2021). Advanced models, like the AI Chatbot Behavior Change Model, further optimize these agents for behavior change, focusing on relational and persuasive capacities (Zhang et al., 2020). The recent integration of generative AI through LLMs further accelerates these capabilities, allowing for context-aware, adaptive interactions that dynamically enhance personalization, user experience, and effectiveness (Schuetz & Venkatesh, 2020).

2.2 Psychology of Self-control, Impulsivity, and Episodic Future Thought

While conversational agents hold great promise for applying behavioral interventions, a deep understanding of the phenomenology and cognitive mechanisms underlying goal-oriented decision making and impulsivity is needed to design effective interventions. In psychology, the ability to act in line with long-term goals in a context full of immediate gratifications, such as consistently adhering to a healthy diet, is often researched under the notion of self-control (Duckworth, 2011; Kable, 2014).

Intertemporal choice tasks are a prominent paradigm for measuring an individual's ability to exert self-control in decision-making or its inverse to fall for impulsive choices (Bickel et al., 2019; Kable, 2014).

In these tasks, individuals are asked to make tradeoffs between a larger reward they would have to wait for (e.g., receiving $25 in 4 weeks) and a reward they could receive sooner but that is smaller in magnitude (e.g., receiving $20 today), allowing researchers to calculate an individual's discount rate, the tendency to discount a reward the further in the future it is expected to pay off (Kirby et al., 1999). The individual discount rate as a trait-like phenomenon has been shown to be a robust marker for several important real-world outcomes associated with impulsivity such as behavioral and substance addictions (see Amlung et al., 2017 for a meta analysis) as well as BMI and the risk of overweight and obesity (Bickel et al., 2021; Jarmolowicz et al., 2014) and is often regarded as an indicator for several pathological and non-pathological maladaptive behaviors (Bickel et al., 2019; Lembert et al., 2018). More recent work also suggests that discount rates can be malleable (Lempert & Phelps, 2016) and several interventions have been shown to effectively reduce them in laboratory settings (Rösch et al., 2022; Rung & Madden, 2018b).

One type of such intervention is episodic future thinking (EFT). EFT interventions encourage individuals to simulate hypothetical but concrete future events referring to the self to promote foresightful decision-making (Schacter et al., 2017) and have been consistently shown to reduce discount rates (Rösch et al., 2022; Rung & Madden, 2018b). Furthermore, Daniel et al. (2013) have shown that an EFT intervention also reduced the amount of food consumed by around 400 calories on average in a sample of overweight women, a finding that was later replicated in overweight children (Daniel et al., 2015). However, EFT interventions are typically highly artificial and challenging to transfer into real-world applications. In many studies applying EFT, participants are usually first asked to simulate a range of episodic events across different time points in the future (e.g., what to eat for breakfast 7 days from now). Then, during a subsequent delay discounting task, they are cued to think about this simulated event while confronted with a tradeoff matching the delay (e.g., $20 today vs. $23 in 7 days). While providing interesting results, such designs lack real-world transferability and are likely subject to the effects of experimenter demand (Rung & Madden, 2018a).

Recently, novel ways to implement EFT into digital tools applicable to field settings have been proposed. Instead of instructing individuals to simulate future events themselves, these interventions aim to induce similar episodic simulation processes by making the future self more relatable, such as showing age-processed renderings of a picture of the self (i.e., Hershfield et al., 2011; Kaplan, Reed, et al., 2016) or interacting with their (hypothetical) future self via letters (Rutchick et al., 2018), social media (Van Gelder et al., 2015), or in virtual reality (Ganschow et al., 2024). Such interventions have been shown to increase financial saving behavior (Hershfield et al., 2011; Robalino et al., 2023), increase physical activity (Rutchick et al., 2018), reduce criminal and cheating behaviors (Van Gelder et al., 2015), and reduce the overall intention-behavior gap (Ganschow et al., 2024). Pataranutaporn et al. (2024) have developed Future You, which uses self-report data on episodic events from a short questionnaire and a picture of an individual to generate a synthetic age-rendered digital twin. It leverages LLMs to allow individuals to chat naturally with their hypothetical future self. In an online study, they have shown the potential of the system to improve self-reported markers of anxiety, emotional valence, and motivation.

3 Hypotheses

The current study aims to test the potential of an adapted version of the Future You system to reduce impulsive decision-making and drive healthier dietary behaviors. Specifically, in our online pre-registration(https://aspredicted.org/r8yz-t59f.pdf), we formulate two hypotheses:

H1: First, as suggested by laboratory EFT interventions and future-self interventions, we predict that a conversation with a hypothetical future self via the Future You system will reduce choice-related impulsivity derived from a standard delay discounting task (Kirby et al., 1999) relative to (a) interacting with an off-the-shelf LLM and (b) a non-intervention control group that does not interact with any chatbot.

H2: Second, based on previous findings that EFT and future-self interventions can induce more long-term oriented choices across domains, we expect the conversation with Future You to improve dietary

choices as indicated by an increased probability of choosing the healthier snack food in a hypothetical binary food choice task, again relative to (a) interacting with an off-the-shelf LLM and (b) a non-intervention control.

4 Experimental Design

4.1 Intervention

The future-self intervention is an LLM-enabled (model: GPT-4o) conversational interface that we modified based on the Future You system described in detail by Pataranutaporn et al. (2024). Instead of merely imagining the self in the future and simulating future events as in earlier EFT interventions, the system enables users to chat with their AI-generated future self, incorporating biographical information provided by the user to generate a future-self memory. The system also takes in a picture of the user and renders an aged version of the user's portrait.

The original Future You system focuses on general conversations around topics such as career, finance, and family. As the goal of our study is to investigate the efficacy of EFT on diet-related choices and behavior, we modified the system to discuss health-related topics with the user from the perspective of an aged future self. Specifically, we adjusted the original prompts to (1) nudge users to vividly simulate diet-related future events and (2) incorporate success factors for EFT interventions derived from recent meta-analyses, such as positive emotional valence, high vividness, and content-specificity (i.e., diet) of the future events simulated during the conversation (Rösch et al., 2022; Rung & Madden, 2018b). To provide a realistic future self-experience, we incorporate the user's biographical information including diet-related habits and goals. To protect individuals' privacy, the conversations are under the Zero Data Retention policy and are not retained by the logging system of the LLM provider (i.e., OpenAI). Both "Future You" and "Life Coach" agents are instructed to not respond to any queries irrelevant to their respective roles to prevent harmful or inappropriate use. The participants are informed that they should consult their doctor before acting on any advice provided by AI the chatbots.

4.2 Research Design and Study Procedure

We will test the intervention's effectiveness on choice-related impulsivity and dietary choice quality using a randomized controlled trial (RCT) design. 300 participants (based on power analysis) will be recruited via Prolific and randomly allocated to one of three groups: an intervention group receiving the future-self intervention described above (FY group), an active control group engaging in a conversation with an off-the-shelf LLM-based chatbot that does not involve the generated future-self (LLM group), and a non-intervention control group (Control group).

First, in a pre-intervention phase, the FY group will be presented with questions about personal episodic past events and upload a personal picture. The questions set up the participant-specific synthetic memory of the digital future-self twin, as Pataranutaporn et al. (2024) described. Following, the FY group will be instructed to have a short text-based conversation about future diet-related events. In contrast, the LLM group will have a conversation with an off-the-shelf LLM (i.e., without the perspective of a future-self) with the instruction to get general health advice from the chatbot. The Control group will not receive any intervention. Importantly, LLM and Control groups will not receive the pre-intervention questionnaire used to set up the Future You system in the FY group. While it is important to note that this induces a potential confound (answering self-related questions in the FY group only) impeding the interpretability of our findings regarding the effect's mechanisms, in this experiment, we aim to focus on a first examination of the potential of Future You on improving decision making. Therefore, we compare it against realistic current alternatives such as the untargeted use of an off-the-shelf LLM for health advice or having no intervention at all.

Following, in the post-intervention phase, all groups will perform a delay discounting task and a hypothetical food choice task as described below. Lastly, all participants will answer questionnaires to assess constructs for control analyses, such as trait self-control, dietary behavioral patterns, weight and

height, and manipulation checks. The study will be done entirely online using a web browser. We aim to have an equal split of genders and a diverse representation of age.

4.3 Outcome Measures

Following earlier work (i.e., Dassen et al., 2016; see Rung & Madden, 2018b for an overview), to assess the degree to which the intervention successfully induces changes in individual choice-related impulsivity, participants will be provided with a standard delay discounting task, the 27-item Monetary Choice Questionnaire (Kirby et al., 1999). Herein, participants are asked to repeatedly choose between a smaller but immediately available amount of money (i.e., receiving $15 today) and a larger one available only after a delay period (i.e., receiving $35 in 13 days). Across 27 decisions, the amounts of the sooner but immediate reward (SIR), the larger delayed reward (LDR), and the delay are varied systematically to derive the discount rate k as a proxy for an individual's choice-related impulsivity. Put intuitively, this "impulsiveness parameter" (Kirby et al., 1999, p. 79) describes the steepness with that the subjective value of a reward reduces the further it is to be expected in the future (for details on the calculations see Kaplan, Amlung, et al., 2016; Kirby et al., 1999).

Second, following earlier work on episodic future thinking in the dietary domain (i.e., Segovia et al., 2020) we will use a hypothetical food choice task as a proxy for changes in dietary choice behavior. More specifically, we will use an adaptation of a common computerized food choice task (Hare et al., 2009) which consists of two phases. First, participants evaluate 50 common snack food options (i.e., donut, banana) derived from the Food-Pics_Extended Database (Blechert et al., 2019) with respect to healthiness and taste. Based on these ratings, a reference item is selected that was rated as neutral on both dimensions. Second, the participants are asked to rate each snack food against this reference item in terms of preference while imagining they'd need to eat the chosen item immediately.This task has been suggested being used for a first assessment of intervention success in changing eating behaviors (Foerde et al., 2018) and was shown to be sensitive to state changes of the contribution of healthiness and palatability considerations induced by interventions (Hare et al., 2011). For each participant, we will compute the probability of choosing the healthier snack option as indicated by the share of trials in which the chosen option was healthier than the non-chosen one. ,Third, we will assess further covariate measures related to self-control, future orientation, and general food preferences for exploratory analysis. To assess the risk of the effects of experimenter demand (Rung & Madden, 2018a), we will ask participants to guess the purpose of the current study.

4.4 Analysis Plan

To test the predictions formulated in H1 and H2, we will use Bayesian linear regressions implemented using the brms package in R (Bürkner, 2017). To test H1, the log-transformed individual impulsivity parameter k will be predicted by two (dummy-coded) indicator variables, the first one encoding the contrast between the FY group and the LLM group and the second representing the contrast between the FY group and the Control group. Analogously, for H2, the share of healthy choices will be predicted by two indicator variables, one for the contrast between the FY group and the LLM group and another for the contrast between the FY group and the Control group. We will furthermore include gender, BMI, and age as covariates. H1a and H2a will be accepted when the 95% posterior density interval excludes 0 for the posterior distributions of the FY vs. LLM group parameter. H1b and H2b will be accepted when the 95% posterior density interval excludes 0 for the posterior distributions of FY vs. Control group parameter. In case the 95% posterior density interval includes 0, we will use the Bayes Factor to assess evidence in favor of the null-hypothesis (Kass & Raftery, 1995).

5 Next Steps and Expected Contributions

As of now, we have adapted the Future You system to the dietary context, programmed the outcome measure tasks described above, and we have set up the Bayesian analysis pipeline using simulated data (McElreath, 2019). Next, we will run several small-scale local pilot trials to iteratively optimize the manipulation as well as sensitivity and comprehensibility of the outcome measures. For a first pilot, we

plan to run our experiment with 30 participants. The full data collection with 300 participants is planned for April 2025. We will present a preliminary data analysis of the results from our full sample at the conference in June 2025.

This study aims to make two significant contributions to existing research and practice at the intersection of IS, behavioral science, and AI-driven digital health interventions.

First, this research will assess the effectiveness of conversational AI agents in reducing impulsivity and promoting healthier decision-making in dietary contexts. Specifically, it will examine how these AI agents can bridge the intention-behavior gap by fostering more future-oriented choices, informing both IS research and the design of scalable health technologies aimed at promoting healthy living.

Second, this study will provide empirical evidence for embedding evidence-based interventions—such as EFT—into AI-powered systems like LLM-based chatbots. While EFT has shown promise in controlled laboratory settings, its application within real-world digital health tools remains underexplored. Our research will extend the applicability of EFT by integrating it into conversational AI agents designed for everyday use, offering new avenues for personalized and context-sensitive health interventions.

Future research can build on these findings along two key lines: (1) controlled laboratory experiments to deepen our understanding of the psychological mechanisms driving behavior change and (2) longitudinal field studies to assess the real-world effectiveness of sustained AI-driven interventions in promoting healthier eating habits over time.

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