Algorithmic Nudging:
An Application in Curbing Problematic Smartphone Use

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1. Problematic Smartphone Use

We live in an era of digitalization. As a primary approach of Internet Communication and Technologies (ICTs), smartphones are developing and popularizing very fast. The penetration rate of smartphones in the U.S. increased significantly from 20.2 % in 2010 [1] to 91.14% in 2023 [2]. Smartphones toady offer far more than just communication, with a wide range of feature-rich functions. As a result, smartphone users are becoming increasingly addicted to it, making problematic smartphone use (PSU) a growing social technical problem, where PSU refers to the excessive use of smartphones accompanied by malfunctions, withdrawal difficulties, and other characteristics resembling substance addiction (Yang et al. 2020). Evidence shows that PSU is associated with multiple health consequences, including decreased physical activity levels, increased social isolation, and high anxiety levels. A primary consequence of PSU that is chronically harmful but can be easily neglected is sleep deprivation. Persistent shortages of sleep can cause individuals to accumulate sleep debt over time and can deteriorate their brain and other bodily functions.[3]. Therefore, it is crucial to control PSU and optimize the utilization of technology for better outcomes.

Although researchers have been advocating for curbing smartphone use, the time spent on smartphone screens has been increasing. In the U.S., early-twenties Americans used their phones an average of 28.5 hours per week in 2020, up from 25.9 hours per week in 2018, according to research published in 2021 (Wagner et al. 2021). Evidence also shows that Americans averagely pick up their phones 96 times per day. It is easy for smartphone users to become attached to the device as over half of the picking-up actions happen within three minutes of the previous one (Flynn 2022). This motivates us to come up with more creative and efficient ways to reduce smartphone overuse. With the development of artificial intelligence, algorithm-based nudging has been drawing more and more attention.

2. Background

2.1. Algorithmic Nudge

Nudging refers to any aspect of the choice architecture that can predictably alter people's behavior without eliminating any options or significantly changing their economic incentives (Hansen n.d.). A proper nudge delivered at the optimal time to the right individual could benefit the focal person and society (Dalecke & Karlsen 2020). An algorithmic nudge refers to any form of choice architecture in artificial intelligence systems that influences users' behavior in a predictable manner without eliminating options or significantly changing their technological preferences (Ahmad n.d.). With the booming of mobile and wearable technology, massive granular data are increasingly available for designing algorithmic nudges. An algorithmic nudge has the potential to facilitate digital platforms' capacity to deliver highly personalized and accurate nudges. Athey et al advocate that behavioral interventions could be more effective by targeting at certain groups of populations (Athey et al. 2023). Multiple pieces of evidence suggest that algorithmic nudge could help improve individuals' well-being and behaviors. For example, an application of machine learning nudging demonstrates its capacity of facilitating patients with serious illnesses to engage in conversations with clinicians, patients, and their families, which helps improve the quality of care and reduce healthcare costs. Specifically, the study finds that machine learning nudged group of patients has about 10.1% higher engagement rate in serious illness conversations (SICs) (Manz et al. 2023, 2020).

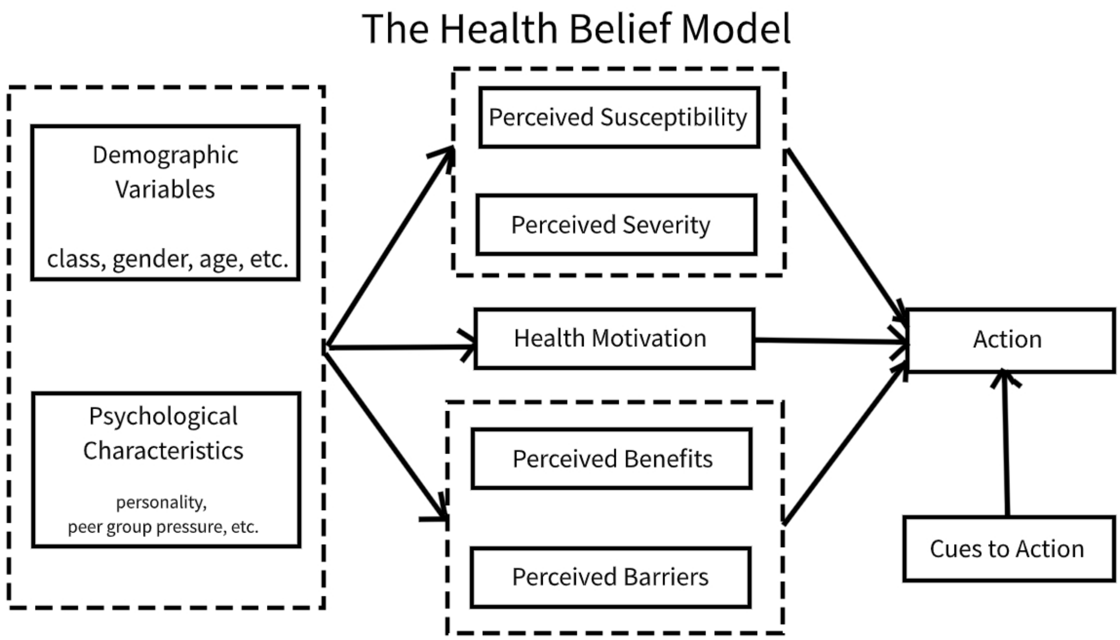
2.2. Design of Algorithmic Nudge

Researchers suggest that with the booming of digital technology, we are having increasingly higher capacity to dynamically build highly personalized nudges based on individuals' real-time information (Dalecke & Karlsen 2020). As a type of digital nudge, the design of an algorithmic nudge may involve four stages: define the goal, understand the users, design and test the nudge (Schneider et al. 2018). Among the four stages, understanding the users and designing the nudge may affect the performance of algorithmic nudges as evidence suggests that delivering the right nudge to the right person may impact its expected outcomes [4]. Evidence also shows that delivering a nudge at the optimal time also significantly impacts its performance (Purohit & Holzer 2019). For example, a late sleep reminder may disturb individual' sleep quality while a too-early reminder may push people to turn the nudge off. To sum up, to assure the performance of the algorithmic nudges, we need to consider three factors: 1) **When?** Identify the optimal time for nudge delivery; 2) **What?** Frame the optimal nudge content to deliver; 3) **Who?** Whom to nudge? Match the right nudge with the right person.

2.2.1. When? Identifying the optimal time for nudge delivery and inference the optimal time for each individual impact the performance of nudging. In this section, we aim to identify and infer the optimal nudge delivery time based on users historical phone use pattern

2.2.2. What? In this section, we discuss a theory-based approach for framing the optimal nudge content for different smartphone users. Since the 1950s, the health belief model (HBM) has been used to explain people's health decision-making behavior and has been applied to improve people's behavior to improve their health (Janz & Becker 1984). HBM states that an individual's behavior change can be affected by perceived susceptibility, perceived severity, perceived benefits, and perceived barriers. The model has been shown to be efficient in changing the improving patients'

Figure 1 **Health belief model**



Notes. (Janz & Becker 1984, Joho 2021).

behavior (Carpenter 2010). The PSU is considered a type of behavioral addiction (Kumar et al. 2021).

Therefore, we build personalized nudges by message framing based on HBM. Based on the theoretical elements we identified by reviewing HBM, we define the constructs related to smartphone use control as follows: 1) **Perceived susceptibility**. The term "perceived susceptibility" refers to a person's perception of the likelihood of having a health issue. 2) **Perceived severity**. The term "perceived severity" refers to a person's subjective evaluation of the seriousness of a health issue and its related side effects. 3) **Perceived benefits.** A person's perception of the value or effectiveness of engaging in an activity that promotes health in order to lower their risk of disease is referred to as perceived benefits. 4) **Perceived barrier.** The term "perceived barriers" refers to how a person perceives the challenges to behavior change (Janz & Becker 1984, Joho 2021). The personalized nudge framing based on the health belief model is as follow:

Table 1 Personalized Nudge Framing Based on Health Belief Model

Nudge Framing Type	Examples
Health Motivation	'Make every day count!'
Perceived Severity/Threats	You have used your screen for four hours, that is, you spent 12 years of your life on
	'Time waits for no one'
	Lost time is never found again.' – Benjamin Franklin.
Perceived Barrier	'You can still do it, put down your phone!'
	You are almost there!'
Perceived Benefits	'Time is the most valuable thing a man can spend.'
	Time is money.' – Benjamin Franklin.

3. Research Objective

In this study, we plan to collect data about smartphone users' individual screen use habits and patterns. With this personal information, we aim to build algorithm-based personalized nudges to custom address individuals' PSU levels. Specifically, we may create personal framed messages to motivate smartphone users to stick to their screen use goals.

4. Experiemnt Design

In this study, our goal is to forecast and reduce smartphone overuse behavior, which is measured by screen time. Understanding the users in the study refers to identifying individuals' smartphone use patterns and identifying the addicted users. Based on the first two stages, we may design personalized and evolutionary nudges based on individuals' historical smartphone use records, which are collected by tracking users' real-time smartphone use behaviors. To do that, we aim to design and develop a mobile application to monitor smartphone use. We plan to track users' smartphone use behavior for one month and use the data for training the algorithm that will be embedded in the nudges. In the last stage, we deploy our algorithmic nudges in our mobile application and test if the nudge could help reduce individuals' daily screen time.

At the beginning of the study, we continuously collect subjects' smartphone use behavior for a certain period, say one month. We measure information like what time individuals are more likely to overuse their phones(daytime vs evening; weekday vs weekend); what type of activities are more likely to exhaust users in using screens (gaming vs communication or browsing). We then build a personal profile for each subject. We take 80% of the profiles as training data sets to train an algorithm that can predict when and on what activities are users going to overuse their phones. We take the remaining 20% data as testing data to test our models. After fine-tuning our models, we expect to build an algorithmic and personalized nudge for each individual.

In the next stage, we ask participants to set their goals of reducing smartphone use time. We install and deploy the customized nudge for subjects to test its performance.

Notes

[1]https://www.statista.com/statistics/201183/forecast-of-smartphone-penetration-in-the-us/.

[2]https://www.statista.com/forecasts/1144749/smartphone-penetration-forecast-in-the-united-states.

[3]https://www.cdc.gov/niosh/emres/longhourstraining/debt.html.

[4]https://www.mckinsey.com/capabilities/operations/our-insights/how-ai-driven-nudges-can-transform-an-operations-performance#/

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