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Social distance "nudge:" a context aware mHealth intervention in response to COVID pandemics

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Abstract

The impact of the COVID pandemic to our society is unprecedented in our time. As coronavirus mutates, maintaining social distance remains an essential step in defending personal as well as public health. This study conceptualizes the social distance "nudge" and explores the efficacy of mHealth digital intervention, while developing and validating a choice architecture that aims to influence users' behavior in maintaining social distance for their own self-interest. End-user nudging experiments were conducted via a mobile phone app that was developed as a research artifact. The accuracy of social distance nudging was validated in both United States and Japan. Future work will consider behavioral studies to better understand the effectiveness of this digital nudging intervention.

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1 Introduction

The COVID-19 pandemic has seriously disrupted societies across the globe with devastating effect. To date, it has claimed countless lives worldwide (Ritchie et al. 2022). Public health agencies face a difficult battle on multiple fronts. Even with the availability of vaccines (Cohen and Travis 2020; Corey et al. 2020), hesitancy toward the vaccination is evident worldwide (Bendau et al. 2021; Cooper et al. 2018; Marzo et al. 2022). Healthcare protocols are complex, economies are in flux, education systems are straining to fulfill their functions, and an air of uncertainty has settled across the populace. These notable obstacles, taken separately, are significant in their own right, but together they present a titanic problem. Although COVID-19 is not the first in a history of pandemics (e.g., Black Death in 1347–1351, Spanish flu in 1918, SARS in 2002–2004, Ebola in West Africa in 2014–2016), the challenge of COVID has caused society to utterly re-structure (Shirani et al. 2020). The economic impacts caused by the COVID pandemic have exceeded the 2006–2009 economic crisis, based on the soaring numbers of unemployment and the sharp drop in GDP growth (Center on Budget and Policy Priorities 2022; Sablik and Schwartzman 2020). The effects of COVID have the potential to persist well beyond its tenure as a pandemic.

The coronavirus mutates and has become more contagious (Benvenuto et al. 2020; Callaway 2020; Licitra et al. 2013; McKinley et al. 2011; Nature 2020; Saha et al. 2020; Sexton et al. 2016) such as BA.5 Omicron subvariant (Centers for Disease Control and Prevention 2022e). The World Health Organization (2020b) has classified such spread as community transmission, providing interim guidance and strategies to urge the communication of risk and community engagement in order to control the virus spread and to minimize impact (World Health Organization 2020a). These guidelines include having adequate healthcare systems in place, educating the public about its role in protecting the community, developing response plans, and ensuring sufficient resources in hospitals. Although numerous approaches have been studied in an attempt to stem active cases, response options to COVID are still limited (Centers for Disease Control and Prevention 2022b) to preventative strategies such as wearing masks, social distancing, quarantine and sanitation of surfaces (Shirani et al. 2020). In this context, social distancing is considered one of the more effective preventative strategies (Centers for Disease Control and Prevention 2022d). If a community adopts the practice of social distancing, the spread of the virus will be controlled, and herd immunity can be reached. Improving the community response begins with influencing individual decision-making. As we actively seek solutions to protect individuals and the community as a whole, our research question arises naturally: *Can social distance nudging theory be developed as a practice using ubiquitous technology*? (Kosters and Van der Heijden 2015) *Can we computationally "nudge" individuals to alert them when they are approached by others*?

This article is outlined as follows. Section 2 discusses the significance of social distancing during the COVID pandemic. Section 3 reviews related works on nudging theory. The nudging theory is conceptualized to provide users with an adaptive intervention. Related work further includes the efficacy of mobile health (mHealth) behavioral intervention, as well as the groundwork for using Received Signal Strength Indication (RSSI) signal strength to gauge the distance between users. Section 4 describes the study framework of the conversion of RSSI signal strength to physical distance, and a "choice" architecture that can provide context-specific reminders as an intervention that can help users make decisions. Section 5 describes the method, and two experiments that calibrate and validate the accuracy of "nudging" based on "unsafe" distance (within 6 feet). A user experience survey was conducted and is discussed. Section 6 provides more detailed study discussion. Section 7 elaborates on the implications of this work in term of the long-term impact of social distancing, the future of machine learning and potential bias in mHealth behavioral interventions, and the impact of a social distancing nudge on COVID pandemic. Section 8 concludes the study with research contribution and future work.

2 Significance of social distancing during the COVID pandemic

As of this writing, the total number of coronavirus infection cases has exceeded 610 million globally, with the United States ranking number one in total infections as well as deaths (Worldometer 2022). Coronavirus hotspots started in major cities with international airports (Kanno-Youngs 2020), but community transmission (World Health Organization 2020b) has made almost every state a coronavirus hotpot in the United States (Hernandez et al. 2020; The New York Times 2020). Over 95.5% of the reported coronavirus deaths are over age 50 (Centers for Disease Control and Prevention 2022a). While older adults are a group at risk, the effect on the younger population is also significant, as younger adults are more likely to contribute to community transmission (Centers for Disease Control and Prevention 2022a). The median age of coronavirus infection has shifted to younger populations in the United States as well as in Europe (Boehmer et al. 2020; Centers for Disease Control and Prevention 2020a; Pastorino et al. 2022). As such, younger adults face unique challenges, such as maintaining proper social distancing measures without fully evolved emotional control mechanisms. Those with preexisting conditions have experienced the illness as being exacerbated, often making it chronic and deadlier.

Clearly, communities are being severely impacted. The arrival of additional waves severely affects communities on multiple levels (Shapiro 2020). New York City, for instance, was one of the early epicenters for the pandemic (Centers for Disease Control and Prevention 2020b), and still experiences a dynamic challenge in keeping the public school system open. Universities also observed a high number of cases (New York Times 2020). Different educational communities are being disrupted as cases rise (UNICEF 2021), causing longer-term problems such as educational progress being delayed, and childcare issues.

The pandemic has especially put racial and ethnic minority groups at severe risk (Centers for Disease Control and Prevention 2022f). CDC reports that blacks are 2.3 times more likely to require hospitalization than whites, and Indigenous populations are 3.0 times more likely. Hispanic/Latinos Americans are 2.2 times more likely to be hospitalized and 1.8 times more likely to die from COVID (Centers for Disease Control and Prevention 2022f). Even as vaccine distribution has ramped up across the US, coronavirus has been devastating racial and minority groups (APM Research Lab 2022). Underserved populations living in poverty with limited access to health services (Golestaneh et al. 2020; Hill and Artiga 2022) are the most likely to have underlying medical conditions and comorbidities (Holmes et al. 2020). These concerns emphasize the need for community-based interventions that can safeguard populations at risk while also considering social and health inequities (Alcendor 2020; Centers for Disease Control and Prevention 2021). One key to minimizing COVID's impact is to provide an effective and economical mechanism that can remind individuals in these communities to maintain proper social distancing.

3 Related works

We first review nudge theory and its applications of adaptive intervention for influencing user behavior. Due to the ubiquitous nature of mobile technology, we next discuss mobile Health (mHealth) digital adoption and behavioral intervention. We then review the groundwork of RSSI signal strength to better understand the measurement of physical distance based on the RSSI signal strength as our study framework.

3.1 Nudging users via adaptive intervention

The nudge concept was brought to prominence by Thaler and Sunstein (2008) as part of behavioral economics, which emphasizes the psychological aspect of individual decision-making. The work explores how individuals are largely affected by many factors in their environment which tend to be non-obtrusive. The framework was created in order to better understand and analyze many different mechanisms—referred to as '*nudges*'—which can affect an individual's ultimate decisions. The work has been largely promoted by libertarian paternalists who believe that individuals can be '*nudged*' in positive ways without restricting their choices. This is an enabling mechanism to persuade individuals to make better decisions on their own accord, without legislative intervention or forceful measures. This fulfills the goal of influencing and modifying behavior while also respecting individual choice. The model is designed as an influencer—a "choice" architecture—which interacts with and influences users in making decisions. The assertion is that this choice architecture can provide a context in which the individual is better enabled to make decisions for self-benefit.

The nudge theory is commonly applied in economic policy areas (Sugden 2009) as well as in a financial context (Sabbaghi 2011). Sugden (2009) highlighted the

application of occupational pension plans in behavioral economics. Individuals can be 'nudged' to save money and make more substantial contributions to their wealth. Sabbaghi (2011) also emphasized the effects of nudges that can influence an individual's choice to borrow more responsibly and lead healthier lives. Abouzied and Chen (2014) illustrated a technological implementation of the nudge to create a more social environment for users. The authors identified the problem of social interaction in urban areas, where social norms tend to discourage interaction and distant the self from strangers. In order to remove the interaction barrier, a simple technology '*nudge*' (a context-aware profile matching system), was implemented to encourage social interaction while also maintaining user privacy. Wang et al. (2014) (Wang et al. 2013) designed modifications to the Facebook web interface that 'nudges' users to consider privacy implications before online disclosures. Their study reported that while some users found these privacy nudges helpful, others found them unnecessary or overly intrusive. Recently, Lorenz-Spreen et al. (2020) promoted nudging to slow down disinformation and misinformation, and promote truth in the context of online discourse.

Another application worth mentioning is the use of mobile devices for managing personal health. Binns and Low (2017) drew attention to the utility of nudges in public health and health promotion. A 'gentle nudge' to encourage healthy behaviors can contribute to the goal of public health, which is to "deliver health to all" (Binns and Low 2017). Martens (2011) emphasized that public health can be more effective when changes and measures occur "downstream (for individual, clinical, or curative impact), midstream (education and promotion) and upstream (healthy public policy and built environment) (p. 2)." Our study aims to influence individual measures by identifying a suitable application that takes data from sensors and Bluetooth connected devices, and "nudges" users with social distancing context-awareness information. By providing users with context-aware information, we believe the nudge can better inform users regarding the state of their surroundings. Mapping to nudge theory (Thaler and Sunstein 2008), the choice architecture needs to be a system that is widely adopted and can better observe the individual's social distancing measures while providing contextual information to users through data as offered by a mobile device.

3.2 mHealth behavioral intervention

mHealth approaches have increasingly and successfully been used to support a wide range of health interventions (Burke et al. 2012; Marcolino et al. 2018). Systematic review of mHealth interventions have found them to be effective in chronic disease management, improving patient education, facilitating treatment adherence, and improving access to health services (Marcolino et al. 2018; Price et al. 2014). This is particularly relevant during pandemic conditions when access to healthcare facilities and individual mobility is more limited. Riding on the widespread use of digital cellular networks, mHealth has revolutionized clinical research and practices. In particular, telehealth has been widely accepted by both health providers as well as consumers during the pandemic (Lew et al. 2020).

Powerful mHealth features include the advent of increasingly sophisticated sensing capabilities which make it possible to deliver just-in-time adaptive interventions (JITAIs) in users' natural environments (Klasnja et al. 2015). mHealth interventions can be used to collect data via self-reporting and sensors to deliver a wealth of information and behavioral cues at opportune times, to which users can optimally respond (Nahum-Shani et al. 2018). The mobility and availability of affordable mobile devices has made mHealth a cost-effective way to improve access to health interventions and resources, particularly among vulnerable and underserved populations. PEW Research Center reports that smartphones have become the primary means for accessing the Internet among low socioeconomic status (SES) communities—one in four blacks use only smartphones to access the Internet, compared with about one in ten whites (Anderson 2019). African-Americans (59%) are also more likely to get news from their smartphones when compared to white adults (Walker 2019). While mHealth interventions can assist in reinforcing healthy behaviors (Newton et al. 2019), the unique issue is how to deploy this instant nudging feature, and design a choice architecture that can effectively remind users of the need to maintain social distance.

3.3 Measuring distance based on RSSI signal strength

Bluetooth technology has been studied and applied in many different areas. Received Signal Strength Indication (RSSI) has become popular as a rudimentary approach for measuring distance. Bluetooth is a protocol used to transfer data wirelessly between devices, with mobile devices being a key area in which it is used. Ionescu et al. (2014), for example, used Bluetooth technology to track objects and find their locations. Bluetooth beacons were used to estimate distances between mobile devices and associated objects. Specifically, the study attached StickNFind beacons to objects which send a signal every 100 ms when paired with the smartphone, using the RSSI value of the Bluetooth signal to calculate distance. Multiple measurements were adopted, and the results demonstrated an improvement of distance estimation with a Kalman filter, which provides a better estimate of the mean, and adds more stability to signal strength.

Chowdhury et al. (2015), on the other hand, proposed a multi-step approach to measure and approximate the distance from RSSI for BLE (Bluetooth Low Energy) devices. That is, they combined the Linear Approximation Model (LAM[1]), the Free Space Friis Model (FSFM[2]) and the Flat Earth Model (FEM[3]), with the low cost RSSI smoothing algorithm. The results minimized the dynamic fluctuation of radio signals received from each reference device when the target device is in motion, and this was able to reduce errors when measuring distance. Given the lack of accuracy in distance estimation through empirical evaluation in RSSI-based state of the art techniques, Palaghias et al. (2015) developed a new machine learning-based solution

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[1] RSSI values great than –44 dBm.

[2] RSSI values between –53 and –44 dBm.

[3] RSSI values less than –53 dBm.

to measure smartphone users' interpersonal distance and relative orientation. The collaborative sensing scheme allowed for the detection and exchange of direction-facing information between users. Their study provided for high accuracy when detecting interpersonal spatial interaction in a real-world environment.

Regarding the COVID-19 context, Google (2020) and Apple (2020) collectively introduced a protocol for privacy-preserving contact tracing, which allows app developers to build applications that can find interpersonal contact events, so that a user can be alerted if one of his contacts has become COVID positive. However, this alert without consent violates the individual's right to privacy. Leith and Farrell (2020) also reported challenges to measuring the BLE-received signal strength for proximity detection, which can vary substantially depending on the relative orientation of handsets, as well as absorption by the human body and reflection/absorption of radio signals in different locations such as buildings and trains. More studies are needed in terms of quantifying the error rates of proximity detection methods using BLE-received signal strength.

4 Study framework

The primary goal of this study is to examine how nudging can help mobile phone users to be mindful of social distancing and other users in the surroundings. The goal is not to estimate risks based on the temporal RSSI values and data. In the following, we describe our framework of converting RSSI signal strength for calculating physical distance while consuming minimal battery power. We further designed a "choice" architecture based on a social science literature—nudge theory—that can influence users in making prudent decisions according to dynamic context information and personal interest.

4.1 RSSI signal strengths to measure distance

The study uses Bluetooth to position and collect RSSI signal profiles received from other devices so as to measure the distance between these devices. The underlying wireless signal used by Bluetooth, known as BLE, is an electromagnetic wave in near 2.4 GHz, and the power of the signal decreases as it traverses through space according the inverse-square law (Bertuletti et al. 2016). Based on the inverse-square law,[4] the signal strength will decrease as the physical distance increases. We use this rule to estimate distance for purposes of social distancing. As RSSI is measured in decibels (dBm) on a logarithmic scale, and displays as a negative number, a more negative number indicates the device is farther away. For example, a value of −20 to −30 dBm indicates that the device is closer than a value of −120 dBm. Obtaining the RSSI value of a Bluetooth signal in an Android device is relatively easy. The Android OS provides the method to get RSSI value of Bluetooth signal starting from

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[4] Inverse-square law: https://en.wikipedia.org/wiki/Inverse-square_law.

API level 21.[5] The full range of RSSI value[6] is [−127, 126] dBm. Social distancing is recommended by CDC guidelines[7] to be at least 6 feet. In our initial estimate, if any device comes within that 6 foot range, the app generates an alert and completes the nudging process.

Accordingly, RSSI of a node (e.g., smartphone), depends on the distance away (Lau and Chung 2007).

$$\text{RSSI} = -10 \times n \times \log_{10}(d) + A \tag{1}$$

where n is the signal propagation constant, d is the distance of the node from the sender, and A is the received signal strength at one meter distance. Note that n and A depend on the sender as well as the environment between the sender and node; therefore, accurate distance estimation using RSSI values requires calibration of the parameters. In addition to Eq. (1), other regressive models have also been studied and compared (Bertuletti et al. 2016).

Due to the sensitivity of the wireless channel used by Bluetooth technology (Parameswaran et al. 2009), RSSI values can fluctuate substantially. A common way to deal with such issues is to perform smoothing. For example, by applying averaging and smoothing to the recorded RSSI values, distance estimation error is reduced significantly (Chowdhury et al. 2015). As RSSI values are used to infer close contact risks for effective nudging, accuracy of the distance estimations is not critical as long as the distances reflect this risk.

4.2 Choice architecture for nudging

The "choice" architecture is designed to provide users with the dynamic context-specific information about their surroundings that allows them to make a conscious choice—a decision—to maintain social distance (or not) and to form social "pods". Users first activate the automated scan service on the app. A background service is spawned periodically to check for nearby devices every X minutes (where X is configurable). The architectural design of the choice architecture—the social distance nudge—is illustrated in Fig. 1.

Based on choice architecture, and the estimation of converting RSSI signal strength to physical distance, our research team developed the CV19 SelfDefense[8] android mobile phone app (Ho et al. 2020) with an embedded algorithm called the "social distance nudge". This mobile phone app was developed as a research artifact to conduct user experiments. Next, we will discuss the experiments performed on distance calibration, and social distance nudging.

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[5] Android codenames, tags and build numbers: https://source.android.com/setup/start/build-numbers.

[6] Android developer guide for get RSSI: https://developer.android.com/reference/android/bluetooth/le/ScanResult#getRssi.

[7] CDC Guidelines for social distancing: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html.

[8] CV19 SelfDefense mobile app is free and downloadable at https://isensoranalytics.com.
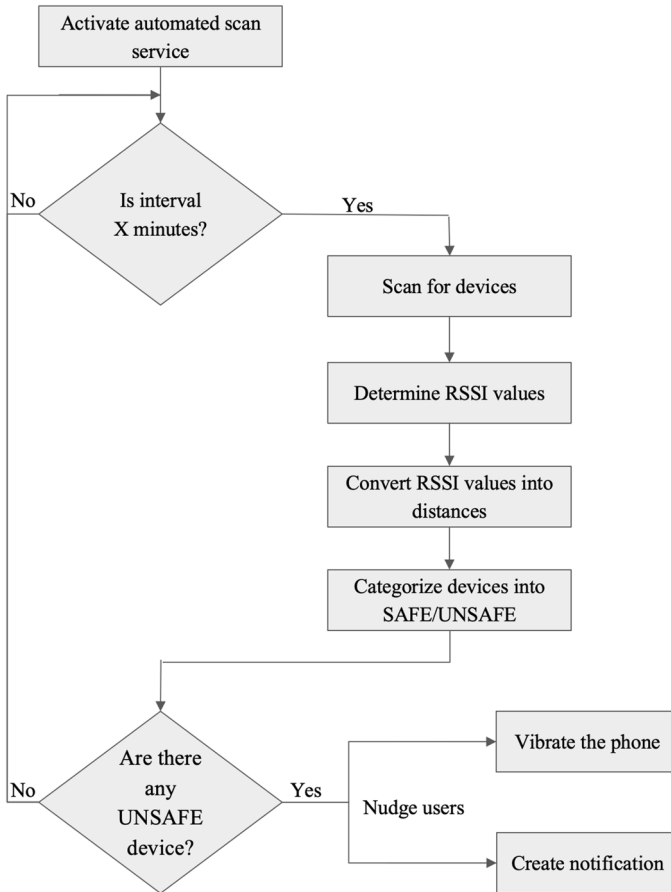
Fig. 1 Choice architectural design

5 Methods

We conducted two separate experiments. The first experiment was designed to calibrate the conversion of physical distance based on RSSI signal strength. In the second experiment, users were paired up to use the social distance nudging algorithm as a research artifact embedded in a mobile phone app (see Footnote 8) for real-time physical environments. Users' physical environment was specified to cover both indoor and outdoor settings. An indoor setting refers to the environment within a building envelope, whereas an outdoor setting refers to an environment where the activities are outside of a building shell. The data collection and validation used to verify nudging accuracy spanned 3 years. Data was collected in Tallahassee, Florida during 2020 and Tokyo, Japan during 2022. We further conducted a user experience survey within a low-income housing community during January–June 2022.

Table 1 Configuration settings for distance calibration

Originator device	Oppo F7 (Android Pie)
Receiver device	Oppo F9 (Android Pie)
Position of the participants	Standing and holding the phone
Environment	Indoor and outdoor

Table 2 Mapping of RSSI values to distance

Distance (feet)	Environment				
	No.	Outdoor		Indoor	
		RSSI	Mean RSSI	RSSI	Mean RSSI
2	1	–50	–50	–39	–38.75
	2	–48		–45	
	3	–52		–35	
	4	–50		–36	
4	1	–57	–56	–45	–47
	2	–55		–46	
	3	–54		–46	
	4	–58		–51	
6	1	–65	–65.25	–65	–54
	2	–63		–51	
	3	–65		–51	
	4	–68		–49	
8	1	–68	–66.5	–53	–59.5
	2	–66		–66	
	3	–66		–61	
	4	–66		–58	
10	1	–69	–67.25	–62	–63.75
	2	–70		–63	
	3	–65		–66	
	4	–66		–64	

5.1 Distance calibration experiment

The first experiment was to understand RSSI signal strength relative to physical distance. Table 1 describes the parameters used for the distance calibration. Table 2 illustrates the measurements of RSSI values when mapped to physical distance.

As shown in the data collected (Table 2), the RSSI signal strength decreases in accordance with incremental physical distance. We confirmed that the values of signal strength for indoor settings are not the same as for outdoor settings. In indoor settings, the difference between the mean RSSI value of 6 feet and 8 feet is approximately 5.5 whereas in the outdoor settings the difference is only about 1.25. As RSSI values tend to fluctuate, it is not easy to draw a conclusive

Table 3 Configuration settings for user experiments

	08/26/2020	05/31/2022–06/03/2022
Originator device	Oppo F7 (Android Pie)	Oppo A5
Receiver device	iPhone 11 iOS 13.6.1	Huawei Nova 5t
Scanning interval	60 s	60 s
Position of the participants	Sitting and holding the phone	Standing and holding the phone
Outdoor RSSI threshold	−65 dBm	−65 dBm
Indoor RSSI threshold	−55 dBm	−55 dBm

line. However, the estimates of RSSI values can be sufficient, because it serves the purpose of 'nudging' and reminds users without annoying them (Wang et al. 2014).

5.2 User experiment on social distance nudging

The second experiment was purposed to validate the social distance nudge concept with users. In this experiment, we created the CV19 SelfDefense mobile application (see Footnote 8) and utilized the automated scanning process while observing the time lags in social distance nudging. Table 3 describes the parameters used for the social distance nudge. Table 4 illustrates the indoor measurements of nudges, whereas Table 5 illustrates the outdoor measurements of nudges.

The RSSI threshold value for indoor operation was set to −55 whereas the RSSI threshold for outdoors was set to −65 (Table 3). This means that any mobile device sending signals with an RSSI value greater than −55 (indoor) or −65 (outdoor) would be declared an "unsafe" distance, whereas any mobile device with less than −55 (indoor) or −65 (outdoor) would be declared a "safe" distance.

In this experiment, we captured RSSI signals with the range of between 3 to 10 feet. There were 3 datapoints collected per range (e.g., 3, 5, 6, 7 and 10 feet). Data in Table 4 validates the social distance nudge concept in an indoor setting, as the RSSI estimation works well within a 5-foot distance. Anytime the auto scan was activated, the phone would vibrate with a notification alert when a device was within "unsafe" range. Comparing the nudging results of indoor and outdoor settings, the RSSI signal tends to be stable in the indoor environment and will nudge as "unsafe" within 6 feet of distance on average (Table 4). Data in Table 5 also validates the social distance nudge concept in an outdoor setting. The nudging alert for "unsafe" tends to be less than 6 feet on average in an outdoor environment, due to weaker RSSI signal and possible interference by objects or the fluctuations of RSSI signal strength values (Table 5). False positives sometimes occurred at 6–7 feet. Nonetheless, a nudging vibration occurs at 6 feet with the notification alert of "unsafe" in both indoor and outdoor settings.

Table 4 Nudge stimulation and validation in indoor settings

Distance (feet)	No.	Indoor, Tallahassee, FL (8/26/2020)				Indoor, Tokyo, Japan (5/31/2022)				Indoor, Tokyo, Japan (6/3/2022)			
		Start time	Nudge time	Time lag (secs)	Nudge notification	Start time	Nudge time	Time lag (secs)	Nudge notification	Start time	Nudge time	Time lag (secs)	Nudge notification
3	1	1:30:03	1:31:29	86	Unsafe	9:56:34	9:58:08	94	Unsafe	10:23:13	10:23:56	43	Unsafe
	2	1:35:59	1:38:25	146	Unsafe	9:58:37	9:59:23	46	Unsafe	10:24:14	10:24:59	45	Unsafe
	3	1:39:38	1:43:06	208	Unsafe	9:59:40	10:00:21	81	Unsafe	10:25:21	10:26:05	44	Unsafe
5	1	1:59:20	2:00:49	89	Unsafe	10:01:17	10:01:54	37	Unsafe	10:26:29	10:27:18	49	Unsafe
	2	2:01:47	2:03:14	87	Unsafe	10:02:12	10:03:13	61	Unsafe	10:27:42	10:28:26	44	Unsafe
	3	2:03:58	2:07:30	212	Unsafe	10:03:20	10:04:06	46	Unsafe	10:29:19	10:30:18	59	Unsafe
6	1	1:53:20	–	–	Safe	10:04:55	10:05:23	28	Unsafe	10:33:02	10:34:02	60	Unsafe
	2	1:55:25	–	–	Safe	10:05:55	10:06:33	38	Unsafe	10:35:18	10:36:12	56	Unsafe
	3	1:57:26	–	–	Safe	10:06:58	10:07:51	53	Unsafe	10:36:56	10:38:01	65	Unsafe
7	1	2:08:26	2:09:52	86	Unsafe	10:09:47	10:10:27	40	Safe	10:39:11	10:40:15	64	Safe
	2	2:10:35	2:12:03	88	Unsafe	10:11:02	10:11:39	37	Safe	10:40:43	10:41:55	72	Safe
	3	2:12:48	2:14:16	88	Unsafe	10:12:02	10:12:53	51	Safe	10:42:15	10:43:14	59	Safe
10	1	2:15:24	2:16:55	91	Unsafe	10:14:11	10:15:05	54	Safe	10:43:58	10:45:13	75	Safe
	2	2:21:25	–	–	Safe	10:15:47	10:16:17	30	Safe	10:45:32	10:46:43	71	Safe
	3	2:24:50	–	–	Safe	10:16:34	10:17:16	42	Safe	10:47:05	10:48:26	81	Safe

*No. 1, 2, 3 denotes 3 data points per range (3, 5, 6, 7 and 10 feet)

Table 5 Nudge stimulation and validation in outdoor settings

Distance (feet)	No.	Outdoor, Tallahassee, FL (8/26/2020)				Outdoor, Tokyo, Japan (5/31/2022)				Outdoor, Tokyo, Japan (6/3/2022)			
		Start time	Nudge time	Time lag (secs)	Nudge notification	Start time	Nudge time	Time lag (secs)	Nudge notification	Start time	Nudge time	Time lag (secs)	Nudge notification
3	1	3:41:13	3:43:20	127	Unsafe	10:25:01	10:25:49	48	Unsafe	10:52:57	10:53:33	36	Unsafe
	2	3:44:32	3:46:00	88	Unsafe	10:26:45	10:27:43	58	Unsafe	10:54:09	10:54:46	35	Unsafe
	3	3:47:42	3:49:11	89	Unsafe	10:28:00	10:28:57	57	Unsafe	10:55:28	10:56:15	47	Unsafe
5	1	3:50:47	3:52:22	95	Unsafe	10:29:12	10:30:21	69	Unsafe	10:56:57	10:57:42	45	Unsafe
	2	3:53:17	3:56:00	163	Unsafe	10:32:25	10:33:32	67	Unsafe	10:58:34	10:59:33	59	Unsafe
	3	3:57:05	3:58:32	87	Unsafe	10:33:45	10:34:59	74	Unsafe	11:00:03	11:00:47	44	Safe
6	1	3:59:23	4:00:50	87	Unsafe	10:35:20	10:36:39	79	Safe	11:01:06	11:02:30	84	Unsafe
	2	4:01:49	4:03:20	91	Unsafe	10:36:55	10:37:34	39	Safe	11:02:58	11:04:03	65	Unsafe
	3	4:03:58	4:06:30	152	Unsafe	10:37:56	10:38:26	30	Safe	11:04:34	11:05:49	75	Safe
7	1	4:07:18	4:09:02	104	Unsafe	10:39:02	10:40:12	70	Safe	11:06:53	11:08:11	78	Safe
	2	4:09:46	4:11:14	88	Unsafe	10:40:33	10:41:33	60	Safe	11:09:23	11:10:26	63	Safe
	3	4:12:15	4:13:52	97	Unsafe	10:41:47	10:42:43	56	Safe	11:13:03	11:14:18	75	Safe
10	1	4:15:05	–	–	Safe	10:43:09	10:44:26	77	Safe	11:14:54	11:16:14	80	Safe
	2	4:19:11	–	–	Safe	10:45:13	10:46:24	71	Safe	11:17:20	11:18:41	81	Safe
	3	4:21:46	–	–	Safe	10:46:53	10:48:15	82	Safe	11:19:52	11:21:23	91	Safe

*No. 1, 2, 3 denotes 3 data points per range (3, 5, 6, 7 and 10 feet)

5.3 User experience survey

Poverty is a condition that correlates highly with the results of decreased health behaviors health outcomes (Pampel et al. 2010). We conducted a user experience survey that focused on poverty populations who may benefit from the use of the social distance nudging. The City of Thomasville in Thomas County Georgia was selected as our target population due to its poverty rate ($27,937 per capita income in Thomas County) being significantly below the average ($66,060 per capita income for the US) (Census Bureau 2021). We further targeted the Federally Qualified Housing (FQH) community because it contains a higher density population that is vulnerable, of a low socioeconomic status, less likely to receive COVID vaccine, and correlated with higher COVID-19 mortality rates. We worked with the Thomasville Housing Authority, which manages six FQH communities in the region, to set up the data collection site for the study.

A total of 60 participants (96% female, 100% all Black/African Americans, and the mean age was 47 years) were recruited during January through June 2022. Most participants had received a high school diploma or general educational development (GED) certificate. There were about 46% among the participants that had received a COVID-19 vaccination. Nearly half of the participants (48%) reported they did not use any type of health app.

Every individual in the study participated in an interview. We collected user experience (UX) feedback on the mHealth app with the social distance nudging feature, and the impact of features on COVID-19 vaccination status. Participants overwhelmingly indicated that the use of the app and any technology that can be accessed using a phone will increase knowledge and awareness of social distancing and COVID-19 vaccination opportunities. Navigation of the mHealth app was reported as easy to use once participants received instructions on its usage. Overall, participants seemed to agree that using a phone app to access and obtain information for COVID-19 vaccinations was most beneficial.

5.4 Section summary

The experiments set the threshold of a safe distance as being 6 feet (Centers for Disease Control and Prevention 2022d). The ability of RSSI signal strengths to represent physical distance was successfully validated with multiple snapshots of datapoints. The "choice" architecture was designed and developed to help users make prudent decisions to maintain social distance at 6 feet. The American Academy of Pediatrics (2021) provides spacial guidelines for elementary and secondary schools; desks should be at least 3 feet apart, and ideally 6 feet apart for indoor spaces. Adult staff and educators are also encouraged to observe 6 feet of distance. To adjust for cases where 6 feet may not be feasible, the application threshold value for the distance can accommodate another value. One component that was not measured in the current experiments is duration of exposure. Centers for Disease Control and Prevention (2022d) describes

close contact as being within 6 feet of an infected person for 15 min over a 24-h period. To include this factor, the mobile device could perform repeated scans and only categorize a contact as "unsafe" when the total time in close contact exceeds 15 min. Current experiments have been based on a snapshot that spans across multiple timeframes in different regions (i.e., Tallahassee Florida and Tokyo Japan). This provides sufficient evidence that the RSSI signal strength can accurately represent the physical distance of 6 feet—even when RSSI values tend to fluctuate. Building on the current work, a great temporal generalizability could be obtained if the duration of a close contact within a predefined SAFE/ UNSAFE category was captured (Centers for Disease Control and Prevention 2022c).

An effective 'nudging' system design should not nudge users too frequently so as not to cause an adverse emotional effect (Wang et al. 2014). The nudging system is most effective when unsafe situations (e.g., grocery shopping in a supermarket, or attending classes or events where people converge)—resulting in multiple nudges within a short time window—are aggregated and calculated as one nudge so as not to skew statistical analysis. Inherently noisy data can be filtered to provide more precise estimates.

6 Discussion

The goal of the choice architecture design for the social distance nudge is to help individuals become more aware and inclined to practice social distancing behavior. Our study defines and conceptualizes nudge theory as adapted in a software context. This choice architecture model is therefore likened to policymaking, but moreover provides dynamic contextual inputs to the users. In addition, disclosure on users' surroundings is controlled by the users, which thus elevates users' right to information privacy. Moreover, as privacy is a major concern for contact tracing apps (Timberg et al. 2020), this approach bolsters users' control over personal contact information. Release of information would require users' voluntary consent, and thus illustrates the potential of voluntary contact tracing for public health.

As the mutations of coronavirus have brought many pandemic waves, the community transmission of coronavirus requires a collective response from the community to protect against massive spread (World Health Organization 2020a). If a community adopts the social distance nudging practice, the spread of the coronavirus can be better controlled. However, the challenge in improving community response begins with the effectiveness of improving each individual's decision-making. The effectiveness of nudging mechanisms to improve individuals' decision-making and behavioral outcomes in maintaining social distance requires further investigation and evaluation. Research on how to evaluate the effectiveness of nudging (from a systems perspective)—as well as the efficacy of shaping users' social distancing and social interaction behavioral change (from a behavioral perspective)—are equally important and required.

7 Study implications

The study has significant implications for social distancing, its direct impact during COVID pandemic, its indirect long-term impact on our social life, and moreover its future application of machine learning in mHealth interventions.

7.1 The long-term impact of social distancing

While practicing social distancing is necessary during a pandemic (Centers for Disease Control and Prevention 2022d), there are significant long-term consequences of social distancing measures, which include the physical difficulties associated with transportation and extended mental stress. Disruptions in employment, social isolation, fear, and feelings of uncertainty all contribute to the psychological effects of the pandemic, making individuals more vulnerable to developing mental illnesses, even among those who have not been previously diagnosed. It is anticipated that the pandemic and its socio-economic consequences will continue to have far-reaching and serious psychosocial effects on health, especially mental health (Javed et al. 2020) (e.g., psychological distress, anxiety, depression, exacerbation of existing mental illnesses, and post-traumatic symptoms), maladaptive coping strategies, and elevated risk behaviors (e.g., alcohol and drug use) (Esterwood and Saeed 2020; Javed et al. 2020). Several studies have reported on the prolonged effects of isolation on psychological state, as social isolation can often lead to undesirable behaviors. Jaspal et al. (2020) reported on compulsive buying behavior, as well as social isolation and fear among religious groups with regards to the pandemic. The COVID pandemic has resulted in psychiatric consequences and mental health-related problems with regards to increased domestic violence and substance abuse (Abdo et al. 2020). Although the evidence was not as strong as expected by the authors, at-risk individuals and vulnerable populations are chronically exposed to elevated anxiety levels, highly stressful environments, and unfavorable economic situations. Use of this social distance nudging app may reduce isolation—and its subsequent mental health problems such as anxiety, stress and/or depression—by offering users an alternative to self-quarantine, in that users can feel some measure of safety in social situations.

7.2 The future of machine learning and potential bias in mHealth intervention

The ubiquitous adoption of smartphones creates rich data on user behavior and provides a scalable solution to a fundamental data barrier problem, particularly in behavioral psychology and psychiatry. Observations of user behavior in natural settings can overcome the mismatch between laboratory-controlled conditions and realistic environments. The potential for this work to revolutionize mental health and behavioral interventions is widely recognized (Onnela and Rauch 2016). In particular, digital phenotyping is scalable and a viable path to realizing personalized medicine (Bernardos et al. 2019; Torous et al. 2016). Personality traits can be predicted

using digital activities (Kosinski et al. 2013; Stachl et al. 2020; Youyou et al. 2015); as these traits are indicative of a broad range of life outcomes, while also providing evidence of the effectiveness of smartphones for mHealth applications. However, this requires new machine learning and data science algorithms to overcome the inherent challenges of developing and deploying the full clinical potential of smartphone data (Blease et al. 2019; Huckvale et al. 2019; Onnela 2021). Available open-source platforms such as Beiwe (Torous et al. 2016) can lower the cost of data collection. Understanding and modeling the underlying data generation mechanisms is essential to building robust learning and inference algorithms.

The complexity, the inherent time-varying nature, and limited observations point to the need for new machine learning algorithms. Successfully trained deep neural networks, as enabled by massive parallel computing offered by graphics processing units and huge amounts of data, have led to quantum leaps in artificial intelligence (LeCun et al. 2015; Sze et al. 2017). Such models are establishing a new paradigm for decision-making, and have surpassed human performance in many complex, data-intensive tasks. While such systems and associated learning algorithms are able to "learn" effective predictive models from high dimensional data without manually selected features, their black box nature hinders their adoption in mobile health and other high-stake applications where differentiating spurious correlations from underlying causal factors is required. Furthermore, performance-driven approaches can be blind to fairness. Deep learning models that perform well on validation and test sets typically provide no assurance of impartiality. Ample evidence to the contrary exists, where biases are reported in commonly used data sets (Angwin et al. 2016; Mehrabi et al. 2019; Osoba and Welser IV 2017), and biases and unfairness have been reported in general machine learning techniques, mostly via testing using probes (Mehrabi et al. 2019). In order to address and manage bias, it is imperative to analyze the underlying mechanisms that enable empirical successes and, more importantly, the sources of biases and unfairness beyond those observed in data.

7.3 Impact of social distance nudging on COVID pandemic

Mobile users often voluntarily provide information about themselves. Numerous nutrition and fitness application make use of health consumers' behavioral data to provided courses of action and tailored nutrition or fitness programs. Stachl et al. (2020) use different classes of behavioral data collected from smartphones to predict individuals' "Big Five" personality dimensions. Cruickshank and Carley (2020) used multi-view clustering techniques to analyze users' hashtags on Twitter, so as to better understand and characterize community behavior. Deep consensus neural networks and bidirectional encoder representations (BERT) can be used to predict Twitter users' behavioral tendencies regarding optimism vs. pessimism (Alshahrani et al. 2020; Caragea et al. 2018). However, to what extent is the amount of data required to categorize users' interactive behaviors in a group necessary to prove the effectiveness of "nudges" in protecting users from coronavirus infection? This still requires additional mHealth behavioral intervention research so that coronavirus hotspots can be properly controlled and tamed. More research is required on the

benefits and obstacles of "social distancing nudges" so as to afford individuals more freedom to move about while keeping personal and public health intact.

8 Conclusion, contribution and future work

This paper conceptualizes the social distancing nudge based on 'Nudge theory' (Thaler and Sunstein 2008), and further develops a computational model of a choice architecture for deployment of 'nudging' based on the conversion of RSSI signal strengths to physical distance. The contribution of the study is threefold: first, the novelty of a mobile phone application based on a choice architecture for the 'social distance nudge' was developed specifically to influence and modify user behavior. Second, RSSI signal strengths were successfully calibrated and mapped to physical distance. Experiments were conducted to validate the nudging concept from a technical perspective. Third, by calculating the RSSI signal strength between mobile phones, a nudge was generated via mobile phone as a gentle reminder to the users for social distancing. "Social distance nudging" is an explicit component of 'Nudge theory,' which provides a clear directive to consciously maintain appropriate social distance. The 'social distance nudge' can dynamically construct context by sensing users' surroundings and providing context-aware information that enables users to make choices in their own self-interest.

Future work requires that the 'choice architecture' design be enhanced through customization in a user context. An advanced user behavioral study is required to understand users' experience and adoption of the 'social distance nudge.' A crucial question to ask would be: What percentage of users change their behavior due to an effective nudging system? Discovering whether the nudge can be effective or not will provide data for future iterations of the application with improved performance. Kosters and Van der Heijden (2015) made some distinctions in evaluating the effects of nudges in a variety of settings. Within the software context, more data can be collected for the evaluation process due to the nature of mobile devices to log report usage data. There can be experiments performed that are external to the user—such as observing their behavior within a constructed context, and/or including surveys in which users share their own conscious decision-making process. The next area for exploration is the confirmed functionalities as used by the nudge. Bluetooth signal strength is used only as a measure of distance, meaning that aspects of the application related to Bluetooth—such as how the scanning is performed, data organization and communication, and accuracy tuning of the SAFE/UNSAFE ranges—should be further measured and validated. Furthermore, the variations of smartphone models—and inherent noise in collected mobile phone data—needs to be modeled in order to improve the accuracy and efficacy of social distancing nudging. As the RSSI signal strength fluctuates, it is impossible to estimate distance accurately. Additional sensor data could be considered for future work to allow for a more accurate estimation of physical distance. Moreover, further work can emphasize both software validation and behavioral impact on individuals, as well as collectively on the community for public health.

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