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Does A Nudge A Day Keep the Doctor Away? Using A Firm's Digital Marketing Communication to Guide Wellness

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DOES A NUDGE A DAY KEEP THE DOCTOR AWAY?

USING A FIRM’S DIGITAL MARKETING COMMUNICATION TO GUIDE WELLNESS

BY

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ACCEPTANCE

This dissertation was prepared under the direction of the *Orhan Bahadır Doğan*'s Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

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Wearable fitness trackers (wearables) (e.g., Apple Watch, Fitbit) are taking the wellness industry into the age of big data that is accessible at a customer level. The devices are popular but evidence for their effectiveness in driving customer behavior is surprisingly limited. Wearables are shown to be facilitators, not drivers, of wellness. To achieve the intended goal of promoting wellness, firms often send motivational or informational digital marketing interventions (i.e., digital nudges) to encourage customers in achieving their health goals. Studies rooted in behavioral economics demonstrate overwhelming evidence for nudging to influence customer decision-making; however, research is yet to examine digital nudges' influence on wellness, which can be facilitated by wearables. Combining the technology of wearables with behavioral research could help firms design interfaces that will be more effective. Additionally, the existing studies orbit around the public health domain and cater to specific groups (e.g., individuals with obesity and diabetes). Wearable effectiveness in our everyday lives from a marketing perspective remains unearthed.

Through panel data obtained from multiple wearable brands, the study investigates the effectiveness of digital nudges on customer wellness using a mixed model specification. Data includes the timing and content of the digital nudges, along with customers' subsequent physical activity behavior in the form of steps taken and exercise duration. These variables are observed daily over four months for 517 global customers. We find that type of nudge the firm sends matters in driving behavior; further, firms should be careful when sending too few or too many nudges. Recommendations on the interaction effects of focus area with nudges are also provided. We provide an alternative approach to measure habitual behavior in a sub-analysis using a recent modeling approach MBG/CNBD-k to measure and predict wearable usage behavior.

The use of rich archival data could not only shed light on how digital nudging can encourage healthy behavior but also offer solutions to sustain this outcome. The study provides insights for practitioners to improve their product's features (e.g., mobile app notifications) and to identify churn based on wearable usage regularity. Academic research can also benefit from this study since it enriches the recent research priorities in customer wellness, identified by top marketing journals. Further implications can be indirectly derived through the preventative nature of wellness, including avoidance of depression and cancer as well as proactively lowering health expenses for customers.

Dedicated to the memory of my sister, Zeynep.

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1. INTRODUCTION

Wearable technology, also referred to as wearable trackers, is broadly defined as "*products featuring a combination of sensors and/or computing devices embedded in apparel and fashion accessories,*" and has become increasingly popular in our daily lives (Friedman, 2017). According to a recent survey, one in five adults in the United States currently use health apps or wearable trackers (McCarthy, 2019; Vogels, 2020). The adoption of this nascent technology is not only limited to the United States. Wearable technology has gained an unprecedented interest worldwide and has been named the highest-ranked trend in the fitness industry three times in the past five years (Thompson, 2021). Further, this adoption can be observed globally where nearly 50% of smartphone users have installed at least one health or fitness app (Business of Apps, 2016). This global interest in wearable technology is also reflected in actual sales. Beating market expectations, a total of 445 million units of wearable devices were shipped in 2020 with a projected market potential of over 776 million units by 2026 (Business Wire, 2021; International Data Corporation, 2021). Moreover, according to a recent industry report, people spend about $1.5 trillion annually on consumer health and wellness products and services, and they plan to spend even more (Callaghan et al., 2021).

While this exponential growth well represents people's interest in improving their health, the flip side of the coin is perhaps every marketer's favorite question: "what's in it for the firms?" We know from the literature that the heterogeneity of customer needs is becoming more sophisticated (Zhang and Wedel, 2009), particularly within the digital marketing domain (Kannan and Li, 2017). Demographic variables such as age, gender, and education have limited predictive capability in segmenting individuals in social sciences (Wedel and Kamakura, 2012).

Along with academia, industry standards have also sidelined such variables as predictive tools. Netflix reportedly put geography, age, and gender in the “garbage pile” when predicting taste (Morris, 2016).

At the same time, it is increasingly difficult to measure lifestyle and customer contexts without relying on individual self-report, a data collection method that is prone to error from learning effect, recall bias, selection bias, and measurement bias. Consequently, firms are interested in capturing behavioral measures to predict future actions, and wearable technology allows for the collection of highly granular data while diminishing such biases. Through this technology, firms can extract much more valuable information directly from the observed behaviors of their customers and then marketers can identify patterns and capitalize using this data (AMA Marketing News, 2018). We already see large companies heavily investing in this area. Most recently, Google completed the Fitbit acquisition in 2021 for $2.1 billion (Osterloh, 2021). However, the perception that the technology giant is only interested in a successful company is likely an understatement. The type of data Google already uses focuses heavily on browsing and purchasing patterns, which can be swiftly complemented by wellness data that comes in the form of exercise, steps, and sleep, along with geolocation and demographics data. With Fitbit’s 29 million active users, what Google is really interested in is rich, granular, and accurate data.

The current environment of an everyday customer is more ready than ever to facilitate the integration of technology in wellness. Over the last decade, there has been a tremendous research interest in customer and technology interaction (Ameen et al., 2021; Lamberton and Stephen, 2016; Marketing Science Institute, 2020). A recent study conducted by the American

Marketing Association shows that millennials' primary care doctor is the internet, where they search their symptoms online or consult WebMD rather than going to a physician. Evidently, reliance on technology alone is becoming a feasible option (AMA Marketing News, 2018). Technology-healthcare integration has become an instrumental part of our lives, particularly while everybody was looking for ways to diminish, if not eliminate, physical contact during COVID19-related lockdowns.

Now, with the prevalence of such data streams, wearable devices can even save lives by identifying heart rate abnormalities or detecting unexpected falls and reaching out to emergency contacts. With the involvement of technology in our routines, the definition of customer wellness has also evolved to include remote healthcare services such as personal health trackers, better fitness in the times of the pandemic, and app-enabled sleep trackers (Callaghan et al., 2021). In this recent survey conducted by McKinsey & Company, the shift to digital channels is stated to happen at the speed of "a decade in days" and firms should look for ways to personalize their messaging to target the precise customer segments. Successful targeting should result in increased profits as well, since customers all around the world are willing to spend more on wellness-related products and services. In our study, we specifically look at customer wellness in the form of physical activity (steps taken and exercise duration), complementing the current focus of both customers and firms.

Despite the unprecedented scope of wearable technology, evidence for its effectiveness in driving customer behavior is limited and little evidence exists that activity trackers actually improve health outcomes. Wearables are shown to be facilitators, not drivers, of health behavior change (Finkelstein et al., 2016; Patel et al., 2015). Essentially, one does not become

more “well” by solely using a wearable device. Further, existing studies in wearable technology effectiveness typically focus on individuals with preexisting conditions, such as obesity and diabetes. Such studies also generally include a limited sample size due to the requirement of their experimental approach to recruit people with such conditions. Albeit very helpful, these studies merely present us with a limited picture of how wearables work that may not be generalizable to the whole population. Accordingly, the scalability of internet-of-things has received a significant interest in marketing, especially from the new product development perspective with a call for research in this domain (Bstieler et al., 2018). Scalability can be achieved by using wearables and their ability to capture big data and exploit analytics.

With the amount of data available through wearable technology, there is a need for academic studies to examine and demonstrate the usefulness of this technology at an individual level that also represents the behavior of everyday people. At the same time, behavioral studies demonstrate overwhelming evidence to suggest that nudging influences customer behavior. However, to the best of our knowledge, research is yet to examine the influence of digital nudging on improving wellness in the context of wearable technology. Furthermore, while nudge theory provides us with the perspective that small details in the environment can change the way people behave, literature also shows that certain nudges do not work (Sunstein, 2017). Recently, there has been a growing interest in nudges that are informational and motivational (Bird et al., 2021). The type of nudges can be informational in nature, which provides one with a current snapshot, or they can be motivational, which attempts to push one toward achieving a goal or moving more. It would be useful for the firms to know which type to send (and to not send), to whom, and under what circumstances.

Literature also suggests that people process communication differently based on their focus area and perception of effort advantage (Kim, Shi, and Srinivasan, 2001). Given that information provision must be tailored to the cognitive resources and the message should bear in mind the motivations of the consumer, accounting for heterogeneity will likely improve the managerial actions (Miesler et al., 2017). Accordingly, accounting for the goals and motivations of an individual can help firms with their targeting strategy. In our study, we use nudge theory as underlying mechanism for a customer's wellness behavior.

This study aims to combine wearable effectiveness with the firm's digital marketing communication strategy and demonstrate under which conditions customers can reach their wellness goals. Specifically, this paper aims to address the following questions:

1) Does digital nudging work in improving customer wellness?
2) What nudging strategy should be used by firms that advocate wellness?
3) What is the role of informational versus motivational nudges in driving customer behavior, and is there a synergistic effect of these nudges?
4) Does a customer's focus area moderate the link between a nudge and wellness?
5) What is the benefit of pursuing customer wellness for any firm?

To answer these questions, we propose a mixed modeling specification, using a unique dataset from a mobile app that aggregates data from several wearable technology brands (e.g., Fitbit, Garmin, Google Fit, Apple Health) and guides customers to improve their wellness by providing wellness-related feedback. The dataset includes the number and type of digital nudges that customers receive, customers' consequent behavior in the form of steps taken and exercise duration. Data is collected over the span of four months across 517 customers. From a theoretical standpoint, we examine the effects of informational and motivational messages on

individuals in reaching their wellness goals, and we observe the instrumental role of digital nudges. From an empirical standpoint, using a granular dataset of hundreds of users, we use a mixed effects approach to account for heterogeneity across customers and we jointly model two wellness variables of interest in a seemingly unrelated regression specification. We also seek to understand the effectiveness of the focal firm's digital marketing communication in the form of digital nudges in driving people to move and exercise more.

Our results highlight interesting findings in a firm's digital marketing strategy. We show that when it comes to digital nudges, the common knowledge we have on smartphone notifications that a higher number of touchpoints leads to decreased engagement does not hold for all types of communication (Goldfarb and Tucker, 2011). We show that motivational messages do produce an initial pushback, but the effect turns positive after a threshold, suggesting that firms should persist in sending motivational nudges. On the other hand, informational nudges produce positive outcomes initially, but sending more does not continue to improve physical behavior and may even hinder consequent behavior. We show that the customer's focus area moderates the link between informational nudges and exercise duration positively, but this effect is negative for motivational nudges. Accordingly, firms should be mindful of the type of nudge to send toward people with varying focus areas.

This paper makes three main contributions. First, to the best of our knowledge, it is the first study to demonstrate wearable effectiveness through digital nudging facilitated by objective data. The ongoing global pandemic has taught us that wellness will remain a priority and customers are willing to continue to invest in this domain in a post-pandemic world (Callaghan et al., 2021). Second, it elucidates the everyday user's behavior rather than focusing

only on individuals with preexisting conditions, leading to a more representative sample. There is a need for academic studies that demonstrate a scalable solution to this common topic. Third, it complements the existing survey-based literature by instead studying a unique, real-world dataset. Using our results, firms can segment, target, and deliver the right nudges to the right customers.

The remainder of this work is structured as follows. A literature review is given in the next section. We then elaborate on the theoretical foundations of the study. In the subsequent section, we introduce the data setting we examine, followed by endogeneity corrections and model specification. We include an additional study under further considerations. We then discuss our findings and present academic contributions and managerial implications. We conclude the paper with limitations and provide recommendations for future research. Additional analyses are available in Appendix as robustness checks along with supporting figures.

2. LITERATURE REVIEW

The set of activities in which a firm partakes (e.g., sending catered and timely messages) dictates the customer's decision to engage with the firm. Most notably by the work of Dwyer et al. (1987), a range of studies examined the means to improve a firm's relationship with its customers. Considerable attention was given to the customer relationship management (CRM) through customer duration and customer lifetime value (Reinartz and Kumar, 2003), dynamics of customer relationships (Netzer, Lattin, and Srinivasan, 2008), customer experience (Lemon and Verhoef, 2016), and message content in B2B (i.e., relational vs economic) (Kim and Kumar, 2018). These studies all echo that there cannot be a uniform messaging strategy. Also, much less focus has been directed to the type of firm messaging that has no immediate profit goal.

The intention of no direct profit goal will likely lead to heterogenous customer behavior. A portion of customers may infer the lack of profit goal as a friendlier approach and show better engagement with the communication while other customers will remain guarded since the communication is still conducted by a firm. Accordingly, it will be useful for further scholarly work to unfold this ambiguity in customer reaction. Further, as we elaborate in the next section with customer-technology interaction, mobile app notifications work differently than a firm’s general messaging strategy. Yet, mobile app CRM received far less attention compared to its traditional equivalents. In this study, we investigate such marketing communications that are informational and motivational and their effect on customer behavior, using mobile app CRM. In this regard, our study contributes to three bodies of literature: customer-technology interaction, digital notifications, and customer wellness.

2.1. Customer-Technology Interaction

Technology is reshaping traditional CRM and its marketing functions and particular attention should be paid to the marketer’s role in this ever-changing domain. Over the last decade, there has been a tremendous increase in the topic of marketing and technology interface (Martech) as a research priority (Ameen et al., 2021; Lamberton and Stephen, 2016; Marketing Science Institute, 2020).

Literature has long explored the transformational role of technology in customer behavior, but the breadth of research has been concentrated to limited number of topics. These research areas encompass service settings through examining the convenience effects of technology (Meuter et al., 2000; Makarem and Mudambi, 2009), firms’ decision-making featuring the use of technology in making data-informed decisions (Cui et al., 2021;

Giebelhausen et al., 2014), and the role of technology in perceived intrusiveness by scrutinizing the negative impacts of technology in presence of privacy concerns (Beke et al., 2021; Goldfarb and Tucker, 2011). Recently, this focus has been rerouted to involve customers' everyday activities given how intertwined technology has become in our daily lives. Wearable technology is no longer a nuisance and self-quantification has moved on from being inspirational to an essential part of life. In a recent study, Kalaignanam and colleagues (2020) put marketing agility under the spotlight to be reexamined given the increased number and channels of customer touchpoints. Thomas et al. (2013) examine the effective and ethical consequences of using technology as a communication tool. Similarly, Yadav and Pavlou (2020) invite scholars to help the marketing discipline better understand computer-mediated environments and suggest that technology-enabled interactions can aid healthcare services with increased precision. Against the background of demystifying technology-mediated communications, we attempt to offer marketers an updated impression on the role of firm-initiated interactions in enhancing customer wellness.

2.2. Digital Notifications

On average, Americans devote half their day to screen time, with smartphones being responsible for two and a half hours of this statistic, and an average user checks their phone sixty three times a day (Nielsen Insights, 2018; Karnes, 2021). Even the operating platforms who benefit from intense usage levels fail to diminish these numbers despite numerous attempts (Molla, 2020). While such screen time leads to negative consequences such as obesity risk in a variety of age groups (Gentile et al., 2014; Powell, 2015), paradoxically, this reality could be used to prevent such undesirable outcomes if screens were used to encourage physical activity.

Nevertheless, with the heavy smartphone usage, people are overwhelmed by push notifications (i.e., pop-up information that appears on smart devices). An average smartphone user receives 46 push notifications everyday (Business of Apps, 2022). Smartphone firms began strategizing to avoid the plethora of notifications their users receive by introducing a summary of notifications in bulk instead of buzzing the user on each occasion. At the same time, targeted communication is a crucial component to an effective app-based marketing strategy. Using profile and behavioral data to segment customers leads to better engagement, with twice the open rate and thrice the conversion rate compared to non-targeted communication such as broadcast (Localytics, 2018).

While the race for the firms is to be the first to grab the customer's attention, as discussed above, the real estate value of attention is getting scarcer by the day, and it is important for marketers to know where to draw the line. Not sending enough notifications faces the risk of losing the customer because they may see no value in keeping the relationship. For instance, 95% of new users delete an app within 90 days if they do not receive any notifications (Airship, 2017). The opposite strategy is also likely a precarious one due to its proneness to trigger privacy concerns. With over-targeting, customers are shown to become guarded and think that the firm is trying to manipulate them (Goldfarb and Tucker, 2011). Consequently, customers deactivate notifications or delete the app with no intentions of coming back. We expect that over-targeting will be less pronounced in our setting since (1) consumers are increasingly willing to share their data to get personalized treatment and service in fitness and general health (Callaghan et al., 2021) and (2) the absence of a profit goal will likely reduce the intensity of a possible coping mechanism, as can be inferred by persuasion

knowledge model (Friestad and Wright, 1994). Hence, this study contributes to understanding the change in customer behavior where these mainstream assumptions likely will not hold.

Another threat to notifications is desensitization: the fatigue that one builds over time due to receiving too many notifications (Hravnak et al., 2018). As a result, in a reverse-Pavlovian fashion, notifications begin to go unrecognized. On the flip side, persistence in communication may reverse the negative initial effects as it helps customers to process the information more easily (Robitaille, Mazar, and House, 2021). Accordingly, there is a need to examine these somehow contradictory findings to showcase which one prevails.

2.3. Customer Wellness

Research in customer wellness could benefit from this study in two main ways: generalizability and the use of objective data. First, most of the research on wearables is done in public health literature, which focuses on individuals that are susceptible to diseases and is interested in preventative measures. A few studies include patients with obesity in an experimental design and show the influence of wearables through weight loss programs and counseling (Jakicic et al., 2016; Jo et al., 2019; Pellegrini et al., 2012). Although these field experiments help to explain the effect of wearables for such individuals at risk, they fall short in contributing to the big picture of the role of this technology on the lives of everyday people with more nebulous wellness goals. Further, given the experimental design in which the subjects are aware of their participation in the study, behavior may be altered, and benefits may fade away after the study ends. These studies have been widely criticized for the fact that the changes in behavior may simply be a product of behavioral biases rather than a true effect (Sunstein, 2020).

Second, recent scholarly work outside of public health mainly comes from survey-based studies in computer information systems with an interest in the factors that play a role in smart wearable adoption (Dehghani, Kim, and Dangelico, 2018), perceived value of devices (Chuah et al., 2016), and intention to use smart devices (Choi and Kim, 2016). In another recent study that utilizes survey data, Oc and Plangger (2022) show the effects of demographic variables along with motivational nudges in explaining habitual use of wearables. Perhaps the closest work to ours is a working paper by Hagen et. al (2020), who bring a marketing perspective to the surface. In this study, the authors collaborate with a mobile app to explore the behavioral, progress-based, and demographic factors that drive tracking behavior. Our study is distinct in the following ways: (1) we focus on the behavioral consequences of digital marketing communication initiated by the firm (i.e., digital nudges), (2) our study is less prone to be affected by testing effects since the data gets synched automatically through the wearable device, rather than relying on customers self-reporting their calorie intake and calories burned. Accordingly, this study and the work conducted by Hagen and colleagues (2020) contribute to distinct areas and supplement each other in understanding the customer behavior within the context of mobile apps with a wellness focus. Such studies with archival data can complement experiments in public health and survey work in computer science to help establish a holistic picture.

Little evidence exists that activity trackers can improve health outcomes. However, research is yet to examine the influence of digital channels on wellness. On one hand, wearables are shown to be facilitators, not drivers, of wellness (Finkelstein et al., 2016; Patel et al., 2015). On the other hand, behavioral studies demonstrate the power of nudging to improve

people's decision-making (Guthrie, Mancino, and Lin, 2015; Kácha and Ruggeri, 2019; Lattarulo, Mariani, and Razzolini, 2017; Mirsch, Lehrer, and Jung, 2017; Schneider, Weinmann, and Vom Brocke, 2018). Our study attempts to (1) fill this void in literature by studying the effect of nudges in wellness by leveraging a unique dataset, (2) using objectively collected data to contribute to the existing body of research that showcases subjective measures using survey and self-report data, and (3) provide a roadmap to enrich firms' marketing communication.

In recent years, the marketing discipline has moved from being solely interested in profit goals to accommodating more research studies that focus on wellness. For example, Journal of Marketing released a special issue on "Better Marketing for a Better World" (Chandy et al., 2021) and Journal of Marketing Research had another one titled "Mitigation in Marketing" (American Marketing Association, 2021). In both journals, scholars are encouraged to study the impact of marketing beyond the firm's bottom line, to examine reducing negative outcomes for society at large, and to focus on how marketing can contribute to a better world. Given the impact of the current global pandemic on our world, it is likely that such topics will only become more central to the marketing discipline. Perhaps the most undisputable evidence for this movement can be found in the definition of marketing itself. Accepted by the American Marketing Association, the definition of marketing is: "the activity, set of institutions, and processes for creating, communicating, and exchanging offerings that have value for customers, clients, partners, and society at large" (American Marketing Association, 2017). Stemming from this definition, we aim to contribute to the processes for creating and communicating offerings that have value for customers and society at large. Table 1 summarizes the literature in wearables and how our study contributes to the research stream of wearables and wellness.

Table 1 – Select Literature in Wearables and Wellness

Select Relevant Studies	Discipline	Modeling Approach	Unit of Analysis	Independent Variables	Dependent Variables	Digital MKT Comm.	Heterogeneity	Dynamics
Pellegrini et al. (2012)	Public Health	Causal (Field Exp.)	Patients with obesity	Weight loss counselling, using wearables, or both	Weight loss, Eating behavior, Physical activity	No	No	No
Conroy, Yang, and Maher (2014)	Preventative Medicine	Descriptive	Mobile apps	Instructional vs educational apps	Behavior change techniques	No	No	No
Jakicic et al. (2016)	Public Health	Causal (Field Exp.)	Patients with obesity	In-person vs tech-based weight loss program	Weight loss	No	No	No
Finkenstein et al. (2016)	Public Health	Causal (Field Exp.)	Employees	Using a wearable device (binary)	Physical activity	No	Yes	No
Dehghani et al. (2018)	Computer Information Systems	Partial Least Squares (Survey Data)	Customers	Hedonic motivation, aesthetic appeal, operational imperfection, complementary goods	Smartwatch usage	No	No	No
Brickwood et al. (2019)	Health and Medicine	Meta-Analysis	Customers	Consumer-based wearable activity tracker ownership	Physical activity	No	No	No
Hagen et al. (2020) (W.P.)	Marketing	Empirical Bayesian Forests	Customers	Behavior and progress-based variables, Tracking consistency	Tracking behavior, Weight loss	No	Yes	Yes
Hagen et al. (2021) (W.P.)	Marketing	Ordinary Least Squares	Customers	Freemium vs. Premium App Ownership	App retention	No	Yes	Yes
Oc and Plangger (2022)	Computer Information Systems	Survey	Customers	Relative Autonomous Index, Age, Gender	Habitual use	No	No	No
This study	**Marketing**	**Mixed Effects SUR Model**	**Customers**	**Digital Nudging: Informational and Motivational**	**Steps taken, Exercise minutes, App engagement**	**Yes**	**Yes**	**Yes**

3. THEORETICAL UNDERPINNINGS

In this study, we inspect how a firm's digital marketing communication strategy (i.e., digital nudges) influences customer's consequent wellness-related behavior. One way to impact behavior is through classical conditioning (or Pavlovian conditioning) through a potent stimulus. In our setting of customer wellness, many health insurance firms use this type of conditioning where a customer is evaluated based on certain health-related activities and is rewarded (penalized) for favored (disfavored) health behavior in the form of lower (higher) policy expenditures. While this approach might be effective in the short run, research shows that the effectiveness of external rewards (i.e., both monetary or non-monetary) fades away (Finkelstein et al., 2016). The opposite also holds, more autonomous forms of self-drive triggers physical activity adherence (Silva et al., 2010; Teixeira et al., 2012). Moreover, continuingly providing such incentives will become economically cumbersome to firms and therefore is not a sustainable strategy. Hence, invoking intrinsically driven behavior will both be cost-effective for the firm and have longer-lasting habitual changes for the customers.

Against this background, we find the theoretical associations in digital notifications to facilitate nudges for which a customer can react. Below, we elaborate on how digital notifications are similar to and different from nudges. Further, we examine the influence of the types of nudges on the consequent behavior.

3.1. Nudge Theory

Literature shows that what is chosen often depends on how the choice is presented (Johnson et al., 2012) such that the choice architecture alters people's behavior in a predictable

way (Sunstein, 2020; Thaler and Sunstein, 2008). Accordingly, nudge theory is about small details in an environment that amend one's behavior. This change is anticipated to be a positive one by exploiting heuristics and biases in one's decision making (Hausman and Welch, 2010), albeit negative consequences may also occur (Sunstein, 2017). Accordingly, nudges must consider the complexity over the course of decision-making and the limited capacity of the nudged individual to process the information intentionally (Simon, 1990). As mentioned earlier, information overload will likely defer someone from investing valuable cognitive effort and instead will result in relying on one's intuition to simplify decision making, which is bound to contribute to decision fatigue. Nudging can take the burden of the cognitive load through this simplification and can be particularly useful for longer term rewards by probing an individual in shorter periods about the progress. Nudging can also help concretize longer term goals such as "I am going to lose weight" by making them more specific such as "I am going to lose weight if I take 10,000 steps every day." Subgoal success is shown to be an effective tool in this scenario, which puts the individual to the driving seat in terms of the path in which they are heading (Zemack-Rugar, Corus, and Brinberg, 2019).

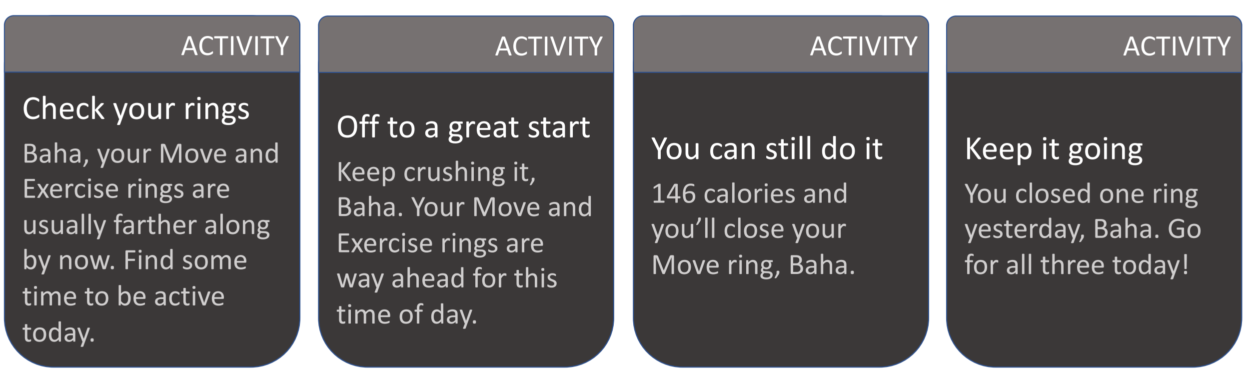
3.2. Digital Nudging and Its Unique Properties

Digital nudging is a subcategory of nudging, and is defined as the aid of user-interface design elements to guide people's behavior (Weinmann, Schneider, and Brocke, 2016). Enabled by the digital footprint, this subcategory of nudges is useful in that they are capable of objectively tracking a customer's reaction. Another distinct property of digital nudges over nudges is that they are more dynamic (e.g., a sign to remind employees to wash hands, or the "look right" sign painted on London streets are less malleable than a real-time communication

established by digital nudging). Coupled with its low-cost properties, digital nudges have become widely adopted to aid firms to influence a customer's decision-making.

As digital nudges became integrated in our lives with the digital transformation, it is worth noting that a digital nudge differs from a push notification (e.g., digital alert received from a mobile app), in that, nudges do not necessarily pursue a direct profit goal. Fittingly, nudges have been termed as "guiding actions in effective and ethical directions" (Thomas et al. 2013). Therefore, push notifications stem from persuasion paradigms which has the assumption that behavior change must be tied to a change in a consumer's deliberate attitude. Nudges, on the other hand, can originate from automatic and intuitive responses (Hansen and Jespersen, 2013; Sunstein, 2016). Therefore, customers are more likely to comply with a message if it helps them, increasing the chances of nudges being perceived as a friendlier type of communication. Researchers are invited to explore the varying consequences of the interplay between automatic and deliberate processes activated by nudges (Miesler et al., 2017), and we aim to provide a perspective on this phenomenon under the lens of firm-initiated communications. For illustration purposes, some examples of digital nudges on Apple Watch are provided in Figure 1.

Figure 1. Digital Nudge Examples



3.3. Types of Nudges and Their Varying Effectiveness

As can be seen in Figure 1, nudges come in different shapes and sizes and we cannot talk about a 'one-size-fits-all' strategy due to expected heterogeneity among the recipients (Jones, 2017; Sunstein, 2017). This notion is supported within the mobile app setting where 85% of the push notifications are segmented in 2017, up from 65% in 2015 (Business of Apps, 2022). When we examine the theories in communication, we see that how one converses has a major influence on the consequent behavior. Speech act theory suggests the differential consequences of assertive (informational), expressive (affective), and directive (call for action) communication types (Villarroel Ordenes et al., 2019; Zhao et al., 2022).

As an extension of the work in communication effectiveness, there has been a growing interest in types of nudges. Nagtegaal et al. (2019) encourage researchers to study the behavioral effects of varying nudges. Further, van Roekel et al. (2021) compare the effectiveness of the types of nudges (environment-related nudges vs. educational boosts), suggesting that while some nudges work better in the short term, others are more effective over time. In another study, Conroy et al. (2014) examine the helpfulness of mobile applications in encouraging physical activity and find that there are two classes of apps: educational and motivational. More recently, Bird et al. (2021) look into how nudging affects campaign efficacy in student loans and consider information-only outreach different than those nudges that attempt to motivate students to seek help. Choudhary et al. (2021) show that performance-based informational nudges may negatively influence safe driving practices while Dhanorkar and Siemsen (2021) show that they positively affect sustainability through energy efficiency. Evidently, nudges that are informational in nature are different from nudges that are

motivational and their effects (in both size and sign) also vary. These studies share the finding that merely presenting a fact may not be enough to influence customer behavior, and the choice architecture plays a prominent role in driving behavior (Miesler et al., 2017). In a similar vein, we examine the type of nudges in the form of informational and motivational firm-initiated messages. It is important to note that some nudges may not be beneficial or even have negative consequences, further highlighting the importance of exploring the effects of types of nudges (Choudhary et al., 2021; Sunstein, 2017).

3.4. The Role of Goal Relevance in Fine-Tuning Nudge Effectiveness

Goal orientation governs people's decision making and consequent behavior (Higgins, 2000). This is because goals provide a reference point and direct one's attention toward relevant behaviors and away from irrelevant ones that are detrimental to the achievement of the task (Miner, 2005). This impression stems from goal-setting theory, which suggests that conscious goals affect action and conscious human behavior is regulated by individual goals (Latham and Locke, 1991). Aptly, research conducted examining the relationship between nudging and consequent behavior suggests that making a pledge (e.g., picking a focus area) is identified as a moderator (Szaszi et al., 2017) because people tend to rely on their regulatory focus area as a filter to process information selectively (Wang and Lee, 2006). Setting a goal is also shown to be a stronger motivator than monetary incentives alone, which would provide an answer to the problem about fading effectiveness of incentives over time (Latham and Locke, 1979). On the flip side, prior planning may reduce the sensitivity toward message responsiveness (Vakeel et al., 2019). Together, these studies suggest that the goals play a role in how an individual processes information and acts upon it. The divergent views of the

helpfulness for types of nudges suggest a need to understand the effectiveness of communication in presence of a focal interest better.

Specific to our context, the effectiveness of health communications is shown to be a function of an individual's focus (Aaker and Lee, 2001; Crowe and Higgins, 1997; Keller, 2006; Lee and Aaker, 2004). We also know that challenging goals lead to better performance as they are associated with higher self-efficacy, valued more by the individual, encourage a tendency to persist on a task, and motivate individuals to focus planning ahead (Locke and Latham, 1990). Taken together, we posit that focus congruence will moderate the impact of both types of nudges on customer wellness. As elaborated above, we expect this moderating role to be more prominent for exercise behavior in comparison to step behavior because exercise goals are more challenging to achieve.

3.5. Conceptual Framework

Against the background of the theoretical underpinnings, we postulate that both informational and motivational nudges should improve customer wellness by serving an individual as reminders to perform physical activity (i.e., steps taken and exercise minutes), and these effects should reverse for the squared terms, resulting in an inverse U shape. This expectation that a message is effective up until a certain point stems from the finding that higher number of touchpoints leads to decreased engagement (Goldfarb and Tucker, 2011).

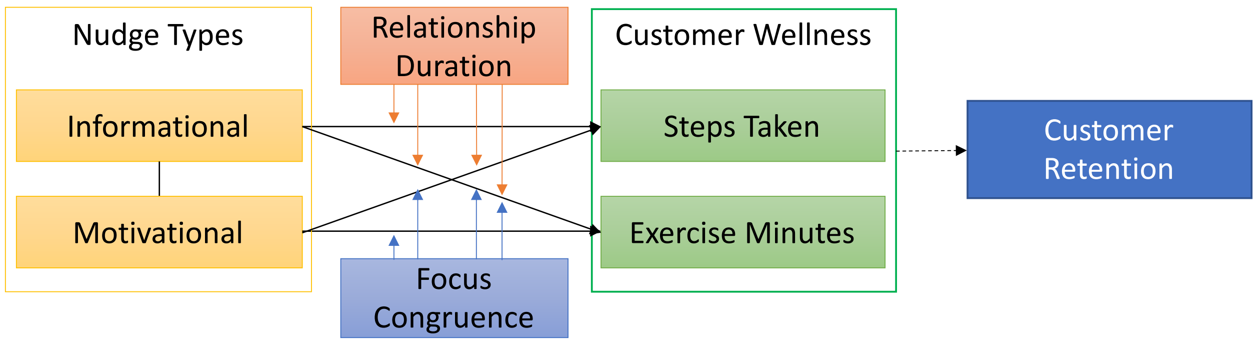
In line with previous research, we expect a negative effect of time on customer wellness. Similar to an effect found in neurophysiology, we anticipate the effects of repeated messages to fade away (Anderson et al., 2016). Since starting a membership within a health coaching app is an attestation of motivation, we posit that motivational nudges should work

better at an earlier stage of the relationship. Similarly, informational nudges should replace motivational ones as the relationship evolves since habits are likely to form over time and informational content will complement these habits.

Effectiveness of message framing depends on the disposition and motivational orientation of the individual, and tailoring the message likely improves the persuasiveness of the message (Covey, 2014; Updegraff and Rothman, 2013). Goal-pursuit is another aspect that should be accounted for in examining the relationship between message effectiveness and behavioral change (Cesario, Higgins, and Scholer, 2008). Focus congruence will likely exhibit the disposition of an individual toward relevant behavior while acting as a proxy for goal pursuit. Accordingly, we consider the focus area of an individual as a moderating factor between a nudge and physical activity behavior, as elaborated in the previous section. Specifically, we believe that self-selecting a focus area already indicates the presence of motivation, and that receiving additional motivational directions may be perceived as irritating and unnecessary for those with competitive goals (i.e., focus to improve exercise duration). Given the likely presence of intrinsic motivation, individuals may not pay attention to motivational communication. We expect the opposite to hold for less challenging goals (i.e., focus to improve step count) since these individuals may need the additional push to be motivated. As it is more achievable to set short-term and more realistic goals (Martin and Pear, 2019; Zemack-Rugar, Corus, and Brinberg, 2019), informational nudges enable more frequent opportunities to update and acknowledge progress. Therefore, informational nudges should serve users as a reminder of their focus area, and lead to actions to improve wellness. Finally, following the finding from Hagen et al. (2020) we expect the improvement in customer wellness to improve

customer retention as this link will demonstrate the usefulness of the service. We show our conceptual framework in Figure 2.

Figure 2 – Conceptual Framework



4. EMPIRICAL SETTING

4.1. Data Source: A Mobile App with Wellness Coaching

Our study explores the influence of digital nudges on customer wellness, accounting for the focus area. Ideally, observing the consequent purchase decisions would provide us with the bigger picture by highlighting a profit point of view. However, it is near impossible that these would be combined in a dataset. We believe what leads to a customer's wellness behavior is timely and unique, and many research streams have long explored profitability. Further, data with such granularity can only be collected by wearable trackers, which can have a higher generalizability if collected through an aggregator. Accordingly, we collaborate with a global mobile application that focuses on helping users reach their health goals by sending them catered push notifications (i.e., digital marketing communication). The app is free of charge, pulls user data from any wearable device with the ability to track health behavior (e.g., Fitbit, Apple Watch, Google Fit, Garmin devices, smartphones), and is available on both iOS and

Android platforms. The collaborating firm chooses to remain anonymous, and we thank the firm and its product development team for providing unique datasets for this research study.

4.2. Data Description

Data includes 517 global customers over the span of nearly 4 months. All customers are new so that there is no left truncation issue. Data granularity is minute-by-minute for steps and on each occasion for firm-initiated digital nudges. We observe the frequency and type of the nudge that any user receives, and customers' physical activity in the form of steps taken and the duration of exercise in minutes, along with demographic variables such as age, gender, device (i.e., Fitbit, Garmin, Apple Health, Google Fit, and Smartphone), and platform used by the customer (i.e., iOS vs Android). We also observe the focus area a customer picks at the time of sign up for the app, which is communicated that it cannot be changed. In line with the wearable adoption statistics, we observe a predominantly female sample (68%) with a good coverage for age (Vogels, 2020; Fried, 2020). The sample includes mostly Apple users, which is in line with the market share stated in industry reports (e.g., Apple's market share in Q3 2021 was 28.8%, more than triple that of the following company Samsung, 9.2%) (IDC, 2021). We provide the sample characteristics in Table 2.

Table 2 – Sample Characteristics

Gender	Male	164	32%
	Female	353	68%
Platform	Android	94	18%
	iOS	423	82%
Data Source[1]	Apple Health	361	69.8%
	Smartphone	311	60.2%

[1] Customers may have multiple data sources. For example, someone using Apple Health may also have a Fitbit wearable device. The algorithm ensures that there is no double counting when a customer has multiple sources.

	Garmin	29	5.6%
	Fitbit	114	22.1%
	Google Fit	38	7.4%
Age	Min	21	
	1st Q	32	
	Median	44	
	Mean	44.4	
	3rd Q	55	
	Max	80	
Focus Area[2]	Exercise	221	43%
	Steps	215	42%
	Other	81	15%

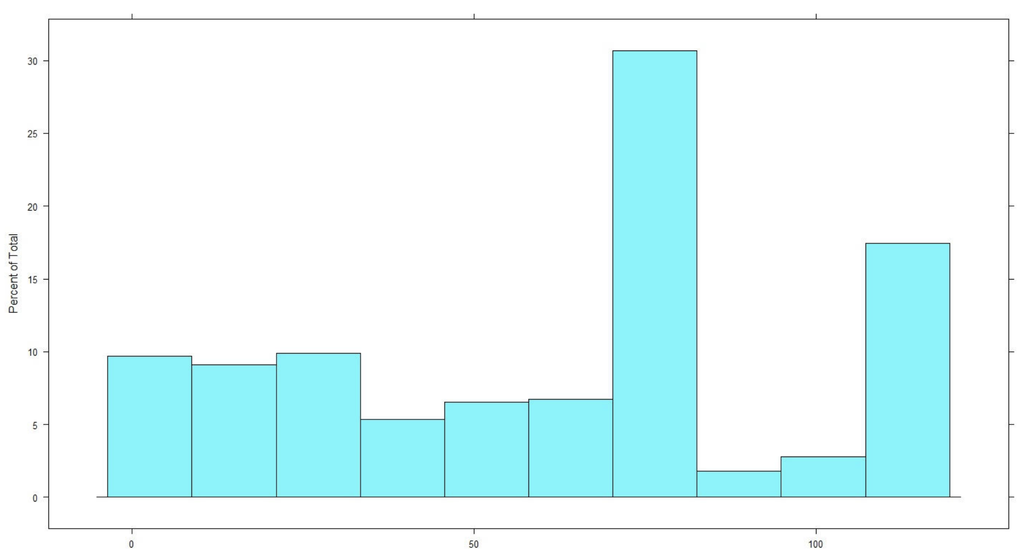
There are over eight thousand unique nudges sent to the customers in the 16 weeks of observation period and the focal firm categorizes them into motivational and informational nudges. They could be motivational, such as, *"Take the time to show up for yourself. Even putting on those sneakers is a small step towards a better you."; "Every day, you have an opportunity to do one thing differently. What will you change today?"; "Keep walking and you'll meet your goal in no time!"* The message could also be informational, such as, *"Just keeping you aware of your progress - you're at [GOAL PROGRESS] steps today."; "Learn about finding the right fit and features for your daily walks."; "It's good to know where you're at. Today you walked [GOAL PROGRESS] steps towards your health."* The firm sends a daily average of 1.285 motivational and 1.680 informational nudges to a customer.

To illustrate the granularity of the data, the raw steps data includes around 11 million data points (i.e., each time an individual takes a step aggregated to one minute granularity). However, there are two main issues with using the minute-by-minute data. First, customers set daily goals and all firm communications are directed with this daily goal in mind (e.g., a nudge

[2] Customers are asked to pick one focus area at the beginning of the sign-up process for the mobile app, before the firm sends any nudges. The focus area is a time-invariant categorical variable that has mutually exclusive choices.

such as “a 3-minute brisk walk will help you reach your goal today”). Hence, the effectiveness of any communication will be lost if it is boiled down to a minutely data point since people may decide to partake in physical activity upon receiving a nudge whenever they have their next window of opportunity. For example, the decision to take more steps may occur in the morning but the actual behavior may happen in the evening to compensate for the missed workout. Accordingly, a nudge received might have a delayed effect, which necessitates a more holistic approach. Second, there is a great deal of computational burden in processing this large a data which is exacerbated by the fact that the small intervals will necessarily produce a disproportionate number of zero frequencies, which is bound to significantly skew the results. Consequently, as summing the data values daily makes sense from a managerial and model robustness perspective, we combine data points such that there is one observation per day for each customer. In terms of observation frequency, average number of days a customer is observed is 61.68 with a standard deviation of 35.37. The distribution is given in Figure 3.

Figure 3. Histogram for the Number of Days a Customer Is Observed



5. MODEL

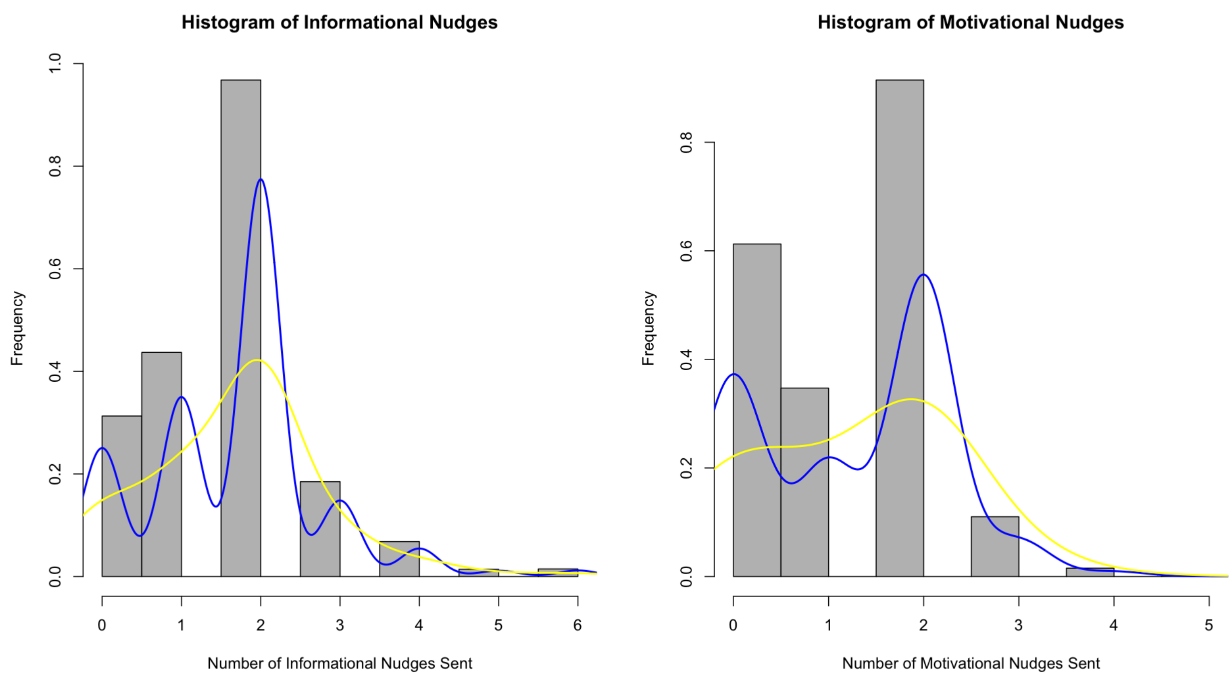
5.1. Accounting for Endogeneity with Gaussian Copulas

Firms communicate with customers based on a set of decisions that are not observable to the researcher. For example, the firm might decide to communicate more with customers that they think are more responsive to such touchpoints. Accordingly, endogeneity is a major concern in such settings. To account for endogeneity, we utilize an instrument-free approach, Gaussian Copula, to flexibly identify relevant endogeneity corrections.

The requirement to use this copula-based approach is for the endogenous regressors not to be normally distributed and have a skewed distribution if these variables are continuous (Park and Gupta, 2012). As can be seen in Figure 4, the assumed endogenous predictors satisfy these assumptions[3]. Since we have more than one endogenous variable (i.e., informational and motivational nudges), we use an augmented OLS copula based on a Gaussian distribution. Necessitated by the inference structure being divided into two stages, we correct for the error term by bootstrapping it with 1,000 iterations as recommended to capture a more robust coefficient. Subsequently, we use the endogeneity-corrected terms in our model for both informational and motivational nudges. Density of informational and motivational nudges against normal distribution, along with the density of the residuals for the model log of steps as a function of informational and motivational nudges are provided in Appendix B.

[3] Additionally, we examine the Anderson-Darling (AD) and Cramer-von Mises (CM) test statistics to test power levels. Reaching a power level of at least 90% requires a minimum value of 67.875 for AD and 12.246 for CM for sample sizes of 2,000 and below. These test scores are 1,870.6 (AD) and 374.44 (CM) for informational nudges and 2,833.9 (AD) and 460.99 (CM) for motivational nudges.

Figure 4. Histograms for Informational and Motivational Nudges



5.2. Model Specification

Given the context of physical activity, we expect a great deal of differences in how customers respond to nudges, which may have contributed to the mixed findings in the literature. As expected, a model with a single trajectory would conceal critical and inter-individual differences. Further, numerous studies show that efforts toward wellness fade away over time, which highlights the importance of accounting for such temporal effects in modeling physical activity behavior.

We specify a jointly estimated mixed effects model to estimate the parameters in the data that relate to both step and exercise behavior. There are two main reasons for this choice. First, panel data introduces a clustered scheme to the observations, which should be accounted for when modeling such a systematic structure naturally built within the data as long as

heterogeneity between groups exists. Second, the two physical activity elements steps taken and exercise minutes by an individual may be correlated in an unobserved manner. We address this phenomenon by jointly modeling the two models of interest (i.e., steps and exercise) using a seemingly unrelated regression, which accounts for this potential correlation.

In addition to the theoretical reasons, we empirically examine whether this mixed modeling choice with a hierarchical specification is necessary. A well-established approach to examine whether clustering is embedded in the data is through intracluster correlation coefficient[4] (ICC), which represents a measure of relatedness of responses within a cluster. ICC values close to zero indicate a homogenous structure while higher values indicate a clustered structure. In our data, ICC equals to 0.553, which indicates that the 55.3% of the total variation in steps occurs between individuals. This result points to the fact that there remains a non-trivial variation in the outcome among individuals which would otherwise underestimate the standard errors. Taken together, a clustered approach is well justified. Furthermore, we use a hierarchical specification because it can accommodate model coefficients at individual levels to be randomly distributed, accommodating heterogeneity.

Accordingly, we define our model with the following specification:

$$(1)\ Customer\ Wellness_{it} = \beta_0{}^{a,b} + \beta_1{}^{a,b} Relationship\ Duration + \beta_2{}^{a,b} Focus\ Congruence_i + \beta_3{}^{a,b} Informational\ Nudge_{it} + \beta_4{}^{a,b} Informational\ Nudge_{it} * Relationship\ Duration_{it} + \beta_5{}^{a,b} Informational\ Nudge_{it} * Focus\ Congruence_i + \beta_6{}^{a,b} Motivational\ Nudge_{it} + \beta_7{}^{a,b} Motivational\ Nudge_{it} * Relationship\ Duration + \beta_8{}^{a,b} Motivational\ Nudge_{it} * Focus\ Congruence_i + \mu_{i1}{}^{a,b} * Informational\ Nudge_{it} + \mu_{i2}{}^{a,b}\ x\ Motivational\ Nudge_{it} + Z'\theta^{a,b} + \upsilon_{it}{}^{a,b}$$

---

[4] $Intracluster\ Correlation\ Coefficient = \sigma^2_{\mu_{0j}} \Big/ (\sigma^2_{\varepsilon_{ij}} + \sigma^2_{\mu_{0j}})$

where $Customer\ Wellness_{it}$ encompasses the logarithmic transformed number of steps taken and exercise duration in minutes and is explained by the number of marketing touchpoints (informational and motivational digital nudges) received by individual *i* at time t[5]. We specify two moderators: relationship duration between the customer and the firm (i.e., the number of days from when a customer joins the mobile app), and a customer's focus congruence (i.e., dummy variable for a focus area chosen by the customer at the time of sign up)[6]. We allow for a random intercept to account for heterogeneity.

As discussed, we estimate these dependent variables jointly, and we use a tobit specification to account for the nature of this variable having non-negative values. We use a logarithmic transformation for the dependent variables due to the extreme right skewness of these variables (skewness: 2.458 and 5.012, kurtosis: 32.826 and 91.167 for steps taken and exercise minutes, respectively). Distributions for both steps, exercise and their logarithmic transformed versions are provided in Appendix C. We add a very small value to both the step count and exercise minutes to get an identified log transformation in occurrences of a zero value. We use clustered errors for each coefficient of the model to reflect the hierarchical nature of the panel data.

[5] We use time t instead of t-1 for the independent variables as the previous day's messages will significantly less likely to affect today's behavior as goals are set daily and nudges are catered with this goal in mind. The majority of the nudges are sent earlier in the day with a median of 10 am, which diminishes the concern that nudges might be sent after the behavior occurs. Additionally, nudges are meant to help customers reach their goals by the end of the day, and we consider the cumulative number of steps by the end of the day to echo this intended structure.

[6] In the steps model (first model in joint estimation), focus congruence is equal to 1 if customers chose steps as their focus area, and is equal to 0 for any other focus area chosen. Similarly, in the exercise model (second model in joint estimation), focus congruence is equal to 1 if customers chose exercise as their focus area, and is equal to 0 for any other focus area chosen.

Finally, Z' denotes the following control variables: number of messages sent by the firm other than nudges (operational messages, weekly routine recaps), lagged reward messages (message on previous day's goal achievement), lagged physical activity (i.e., log of step count for the steps model, log of exercise minutes for the exercise model), wearable used (Fitbit, Garmin, Apple Health, Google Fit, and Phone), platform (iOS or Android), gender, and age. We include the squared terms for informational and motivational nudges in both models as well to understand the effects of these nudges at higher intensity. ${v_{it}}^{a,b} = {\varepsilon_{it}}^{a,b} + {\mu_{i0}}^{a,b}$ represents the errors for steps and exercise models along with the random effects specification for the intercept through a and b superscripts, respectively.

In models that utilize a lagged dependent variable, it may be advised to use Arellano-Bond (AB) estimator, which utilizes an instrumental variable approach through using generalized method of moments (GMM). AB estimator is indeed a viable solution when the problem is that the data has a small timeframe and many individuals (i.e., "Small T, Large N."). However, as T increases (which is the case in this study), dynamic panel bias becomes insignificant, and a less complex and more flexible estimators (e.g., fixed effects) are preferred. Another issue with AB estimator is that "the number of instruments in difference and system GMM tends to explode with T" (Roodman, 2009). Furthermore, GMM was a selection of method in early 1990s with the ease of calculation due to having no iterations. However, the shortcomings of this approach when combined with AB estimator is highlighted, most recently in a study by in a recent article by Allison, Williams, and Moral-Benito (2017) who show that AB estimator suffers from inefficiency since it does not make case of all the moment restrictions implied by the model. There are more methodologically elegant techniques available, including

maximum likelihood-based estimators, which we utilize in this study to obtain robust estimates. Finally, our data does not the meet the sequential exogeneity assumption required by AB estimator, and we provide an alternative approach in Appendix A1 with an autoregressive moving average specification which readily accommodates this assumption while utilizing the efficiencies of maximum likelihood-based methods.

6. RESULTS

Results indicate that although “we are what we repeatedly do,” our behavior can be altered by sending the right type of nudges at the right time to the right customer. Results also show that failing to do so might even end up harming subsequent behavior. Below, we elaborate on each factor that plays a role in guiding physical activity. Table 3 shows covariance parameters and goodness of fit measures, and Table 4 shows the results of our model.

Table 3. Estimates of Random Effects Parameters and Goodness of Fit Measures

Parameter		**Estimate**	**Std. Error**	**95% Confidence Interval**	
Random Effects Parameters	**Individual-level Standard Deviations**			Lower B.	Upper B.
	Steps Model Intercept	0.634	0.020	0.595	0.675
	Exercise Model Intercept	3.197	0.164	2.891	3.534
	Cross-equation Correlation				
	Between Steps and Exercise Models	0.249	0.032	0.186	0.311
	Observation-level Standard Deviations				
	Steps Model Intercept	0.770	0.019	0.733	0.809
	Exercise Model Intercept	4.272	0.135	4.016	4.555
	Cross-equation Correlation				
	Between Steps and Exercise Models	0.613	0.022	0.569	0.654
Information Criteria	**Model Fit Comparison**	**Tobit Model**	**Continuous Model**	**Model with Linear DVs (No Log Transformation)**	
	Log Likelihood	-90,890.6	-122,084.27	-366,154.54	
	AIC	181,885.2	244,284.5	732,425.1	
	BIC	182,331.8	244,782.7	732,923.3	

Table 4. Model Results

	Steps Model					Exercise Model				
Parameter	*Estimate*	*Robust Std. Error*	*Sig.*	*Lower Bound*	*Upper Bound*	*Estimate*	*Robust Std. Error*	*Sig.*	*Lower Bound*	*Upper Bound*
Main Effects										
Intercept	5.452	0.128	0.000	5.200	5.703	-7.347	0.505	0.000	-8.337	-6.357
Informational Nudges	0.090	0.015	0.000	0.061	0.120	0.428	0.084	0.000	0.263	0.593
Motivational Nudges	-0.203	0.024	0.000	-0.250	-0.156	-0.408	0.138	0.003	-0.679	-0.138
Informational Nudges^2	-0.011	0.003	0.000	-0.017	-0.005	-0.057	0.018	0.002	-0.093	-0.021
Motivational Nudges^2	0.070	0.008	0.000	0.055	0.085	0.204	0.046	0.000	0.115	0.293
Relationship Duration	-0.003	0.000	0.000	-0.004	-0.002	-0.041	0.002	0.000	-0.045	-0.037
Focus Area	-0.087	0.030	0.004	-0.146	-0.028	1.971	0.202	0.000	1.576	2.366
Interaction Effects [7]										
Relationship Duration * Informational Nudges	-0.001	0.000	0.000	-0.002	-0.001	-0.008	0.001	0.000	-0.011	-0.006
Relationship Duration * Motivational Nudges	0.000	0.000	0.880	-0.001	0.001	0.001	0.002	0.572	-0.002	0.004
Focus Area * Informational Nudges	-0.008	0.014	0.573	-0.035	0.019	0.328	0.084	0.000	0.164	0.492
Focus Area * Motivational Nudges	0.032	0.022	0.146	-0.011	0.075	-0.333	0.139	0.016	-0.605	-0.062
Informational * Motivational Nudges	-0.016	0.007	0.022	-0.030	-0.002	-0.082	0.041	0.049	-0.163	-0.001
Control Variables										
Platform: iOS	0.279	0.049	0.000	0.182	0.376	1.241	0.234	0.000	0.782	1.700
Lagged Log(Step Count/Exercise Minutes)	0.235	0.016	0.000	0.203	0.267	0.694	0.025	0.000	0.646	0.743
Lagged Reward Messages	-0.026	0.012	0.027	-0.049	-0.003	-0.296	0.064	0.000	-0.421	-0.170
Other Communication	0.134	0.016	0.000	0.102	0.166	0.305	0.072	0.000	0.164	0.446
Apple Health	-0.002	0.053	0.966	-0.106	0.101	-0.879	0.229	0.000	-1.328	-0.431
Device	0.341	0.027	0.000	0.288	0.394	2.077	0.167	0.000	1.750	2.403
Garmin	0.470	0.047	0.000	0.377	0.562	1.538	0.267	0.000	1.015	2.061
Fitbit	0.329	0.038	0.000	0.256	0.403	1.223	0.211	0.000	0.809	1.636
Google Fit	-0.196	0.066	0.003	-0.325	-0.066	1.175	0.338	0.001	0.513	1.837
Gender: Male	0.327	0.026	0.000	0.276	0.378	0.490	0.144	0.001	0.208	0.772
Age	0.003	0.001	0.002	0.001	0.004	0.034	0.005	0.000	0.025	0.043

[7] For the sake of parsimony, we avoid including the interaction effects between the squared terms for the two types of nudges and focus area as well as relationship duration. Doing so yields no significant effects of either type of nudge and time. The interaction between the squared terms of information nudges and focus area is insignificant for both models, while for motivational nudges it is significant and positive for the steps model (0.146) and negative and significant for the exercise model (-0.952).

6.1. Main Effects

The cross-equation correlation is significant (Table 3, $\rho_{steps,exercise} = 0.249\ (0.032)$), justifying the decision to model the steps taken and exercise minutes jointly. Random effects of the individual-level parameters are significant for both models, serving as statistical evidence to support the hierarchical structure. Evidently, there is heterogeneity among the sample members, and failing to account for this intermixture would result in a mismanagement of a firm's communication strategy. We also present evidence for a better model fit (e.g., lower AIC and BIC) for our model choice (i.e., tobit with log transformation) when compared to models with less strict assumptions such as using continuous dependent variables or using step count and exercise minutes as opposed to the logarithmically transformed versions of these variables.

Prior research suggests that time has a negative impact on physical behavior. Although significant, the effect of relationship duration and customer wellness is very small and negative for steps taken (${\beta_1}^a = -0.003, p < 0.001$), and this effect is more than tenfold larger for exercise minutes (${\beta_1}^b = -0.041, p < 0.001$). This contrasting result unearths a lever of how different physical activity measures fade away with different intensities over time, which has not been shown in literature. Interestingly, the results show that users with a step focus ended up taking less steps than ones with other focus areas (${\beta_2}^a = -0.087, p < 0.004$). This effect was flipped for those with an exercise focus, who spend more time exercising compared to users that do not have an exercise focus (${\beta_2}^b = 1.971, p < 0.001$).

We show that when it comes to digital nudges, the common knowledge we have on smartphone notifications that a higher number of touchpoints leads to decreased engagement does not hold for all types of communication (Goldfarb and Tucker, 2011). Informational

nudges positively influence step behavior at lower levels (${\beta_3}^a = 0.090, p < 0.001$) and they diminish it at higher levels (${\theta_1}^a = -0.011, p < 0.001$), hinting that firms should avoid over-targeting when sending informational nudges with a goal of improving step behavior. This finding is echoed for the exercise model, where the lower levels improve, and higher levels diminish exercise duration (${\beta_3}^b = 0.428, p < 0.001;\ {\theta_1}^b = -0.057, p < 0.002$). As elaborated earlier, literature suggests that it is important to revisit goal achievement, and informational nudges likely serve as reminders. This finding illustrates that although people positively react to getting updates about their current stance and progress toward their goal, receiving too many reminders may result in a pushback and ultimately worsens the desired behavior.

Motivational nudges showcase a negative impact on customer wellness at low levels (${\beta_6}^a = -0.203, p < 0.001;\ {\beta_6}^b = -0.408, p < 0.003$), but this effect reverses at higher levels (${\theta_2}^a = 0.070, p < 0.001;\ {\theta_2}^b = 0.204, p < 0.001$). This result is quite counterintuitive as it disagrees with the previous literature on firm-initiated communication and mobile notification literature, which suggests an inverse U shape. These findings insinuate that firms should persist in sending motivational nudges to generate a positive outcome. A perspective worth mentioning originates from health literature focusing on the number of exposures, which states that multiple exposures are more effective than a single exposure (Dijkstra, De Vries, and Roijackers, 1999) and that repetition may improve message recall (Morrow et al., 1999). Similarly, as elaborated before, persistence in communication is shown to reverse the negative initial effects because customers can then process it more easily (Robitaille, Mazar, and House, 2021). We show that motivational nudges replicate these findings while informational nudges do not, which draws a subtle line on what type of nudge the firms should send. Moreover, it is

important to note how much more pronounced the effect size of a nudge is for the exercise model, which demonstrates the importance of nudges in higher intensity physical activity in maintaining wellness. Although at different scales, given the much higher range of the step count variable compared to exercise minutes makes the higher effect size of nudges on exercise more substantial. Figure 5 provides a visual demonstration of the effect sizes of informational and motivational nudges are given with rest of the variables at their mean levels.

Figure 5. Effect Sizes of Nudges at Mean Levels of the Remaining Predictors

Figure 5a. Informational Nudges on Steps

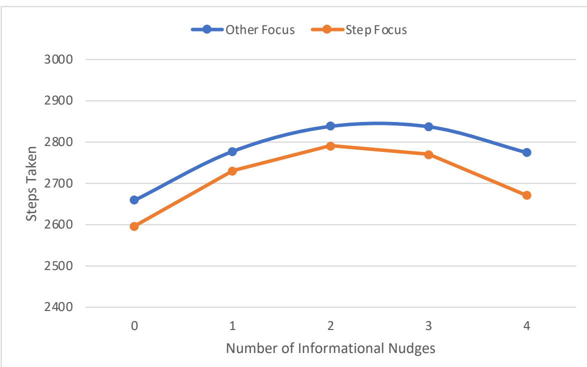


Figure 5b. Motivational Nudges on Steps

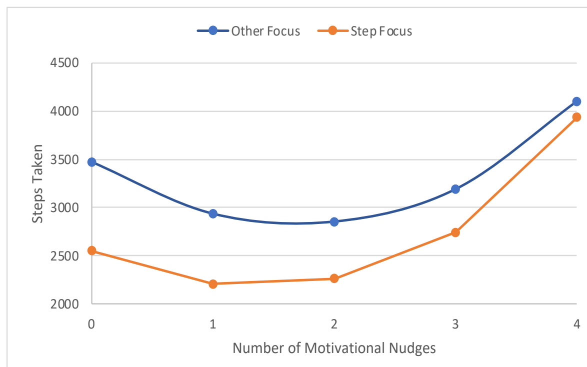


Figure 5c. Informational Nudges on Exercise

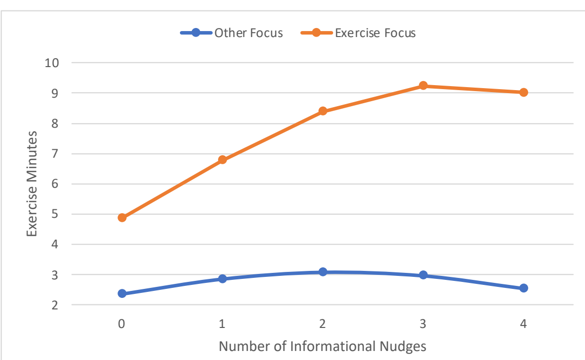
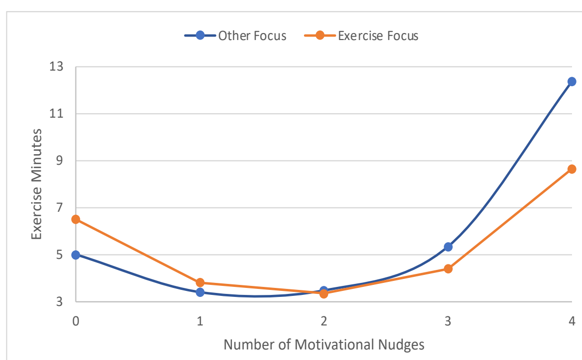


Figure 5d. Motivational Nudges on Exercise



6.2. Interaction Effects

The interaction effects of relationship duration and informational was extremely small despite the significance for both steps and exercise models ($\beta_4{}^{a,b} = -0.001, -0.008;\ p <$

0.001). These effects were insignificant for motivational nudges (${\beta_7}^{a,b};\ p > 0.1$), indicating that time plays to minimal to no role when interacted with either nudge type. Combined with the earlier finding of the minimal effect of relationship duration on either customer wellness measure, we conclude that the customer behavior remains relatively stable over time. This outcome serves as a novel finding and supports our notion that nudges can indeed provide a behavioral solution to the problem of wellness measures suffering over time.

Focus congruence for steps does not moderate the relationship between nudges and step behavior (${\beta_5}^{a} = -0.008,\ {\beta_8}^{a} = 0.032;\ p > 0.1$). For the exercise model, we observe that motivational nudges are now negatively linked to exercise behavior when they are directed toward users with an exercise focus, compared to users with any other focus (${\beta_8}^{b} = -0.333, p < 0.016$). This result confirms the conception that users with an exercise focus do not need the motivation boost as they will likely be already self-motivated and stick to their own agenda rather than the coaching provided by a mobile app. On the flip side, informational nudges do contribute to customer wellness through an increase in exercise minutes (${\beta_5}^{b} = 0.328, p < 0.001$). The contrast in findings highlights the importance of accounting for the mentality difference among the customers and provide additional evidence that the communication strategy can "make or break" the consequent behavior. Finally, we observe detrimental interaction effects when the firm used both informational and motivational nudges in combination for both steps and exercise models (${\theta_3}^{a} = -0.016, p < 0.05;\ {\theta_3}^{b} = -0.082, p < 0.05$). It may then be advisable for the firms to be cautious when they mix and match the type of nudge they send to avoid the detrimental synergistic effects.

6.3. Control Variables

Receiving a reward message the previous day decreased while non-nudge firm communication increased physical activity for both models. These effects demonstrate that the days people reach personal goals are consistently followed by a day off, hinting that people show cyclical physical activity patterns. This result complements the findings of Uetake and Yang (2017), who highlight the positive utility of past short-term goal accomplishments, in that this outcome does not seem to be the case in the context of physical activity. However, we observe partial support for their finding given the positive impact of lagged step count (for the steps model) and exercise minutes (for the exercise model) on the consequent day's wellness measures, which is similar to the finding in Zemack-Rugar et al. (2019). Accordingly, we see that although goal accomplishment may lead to a resting day, taking the previous day's activity as a continuous measure still positively influences the behavior. We believe that these contrasting results may be attributable to the fact that individuals set their own goals, which may not necessarily be challenging. Moreover, evidently, communication other than nudges may not be considered a nuisance as they may also serve as reminders for people to be physically active.

Using Garmin, Fitbit, and smartphone as the data source was associated with an improved step and exercise behavior, while being a Google Fit user had a negative effect on steps taken but a positive effect on exercise duration. Compared to Android customers, those who use iOS as their operating platform have shown a positive effect on steps taken and – a much more pronounced – positive effect on minutes spent exercising. Yet, using Apple Health was linked to a reduction in exercise duration. The contrast in findings stresses that the positive impact of using the iOS operating platform likely originates from Garmin and Fitbit users who

also have an iPhone, and the negative impact is bound to be attributed to Apple Watch users. Given the prevalence of Apple Watch, we infer that although Apple Watch does a better job in reaching to the masses potentially because of its iPhone mirroring capabilities, the customers who opt in for Garmin and Fitbit likely have higher intrinsic motivation, building a niche market. Further, the varying effectiveness between iOS users and Android users may also be a function of the fact that notifications are enabled by default in Android whereas one must actively accept receiving notifications when using an iPhone. Since allowing these notifications is an additional step the customer takes, it is natural to expect an exacerbated wellness outcome from iOS customers. These results are intriguing since they show that there might be systematic differences between individuals who carry different brands of wearables and use a different operating platform, which is a novel finding to the best of our knowledge.

Among the demographic variables, albeit the extremely small effect size, age has a negative and being a male had a positive effect in physical activity. The relatively small effect sizes highlight the significance of the limitations of demographic variables in explaining physical activity behavior. This finding is in line with practice, given that the streaming pioneer Netflix identifies geography, age, and gender as “garbage” to predict preferences (Morris, 2016). A possible explanation to the small effect of age can be that older individuals 1) have more spare time (and less working time) to do physical activity compared to younger individuals, 2) might be more likely to do a walking exercise while younger individuals choose exercise types that are more intense but cover less distance. Hence, although young people can walk longer distances, the reasons above might cancel out this effect.

7. FURTHER CONSIDERATIONS

7.1. Does It Count When You Don’t Wear It? The Role of Physical Activity Habit on App Engagement within Wearable Technology

7.1.1. Habit Theory and Its Influence on Customer Behavior

Habit and physical activity go hand in hand, and it would be an incomplete picture to consider behavior without incorporating the habitual outlook. For instance, about 40% of our daily decisions are not actually decisions, they are automated habits (Neal et al., 2011). Accordingly, habitual behavior has attracted a great deal of attention for scholars from a variety of disciplines given its versatility and relevance to irrational consumer behavior. Despite the popularity of this topic, there are various approaches to define and understand habits. Verplanken and Aarts (1999, p: 104) define habit as “learned sequences of acts that have become automatic responses to specific cues and are functioning in obtaining certain goals.” In a follow up book chapter, Verplanken et al. (2005) elaborate on habit as most of our everyday behaviors to be a function of recurrences or variants of mostly repeated actions. Habitual behavior is also shown to be related to fewer emotions than nonhabitual behavior, hinting that once they are formed, they are likely to stick around for longer (Wood, Quinn, and Kashy, 2002). Social cognitive models show habits to be guided by implicit structures rather than explicit evaluations of behavior, which are activated by relevant cues such as time, location, or internal stimuli (Aarts and Dijkstreshuis, 2000). Taken together, research shows that habits lead to unsupervised behavior which is nurtured by environmental cues, such as nudges. As we establish the benefits of an effective nudging strategy to improve behavioral outcomes, the next step would be to discover efficient ways to sustain this behavior through habits.

A majority of work done in the area of habit measurement has been constrained to survey research that relies on a customer's self-report. There are several measurement scales that aims to capture habit, such as the Self-Report Habit Index, Self-Report Behavioral Automaticity Index, and Habit Index of Negative Thinking (Rebar et al., 2018). However, self-reports are evidenced to harm measure reliability, especially in the context of physical activity where people tend to overreport their behavior to avoid criticism. While the goal of incorporating habitual behavior in econometrics models is to account for customer behavior through its frequency and consistency, studies that use objective measures for habit usually include the mean and standard deviation of past behavior that lack the focus on patterns in behavior (Shah et al., 2014; Hagen et al., 2020).

Physical activity facilitated by wearable technology has also drawn attention to habits. Anecdotal evidence points to a phenomenon that people are reluctant to exercise if they are not wearing their devices because "it does not count if they don't wear it" (Brown, 2019). Scholarly work in this area also supports this opinion. Hagen et al. (2020) show that, among several variables, the strongest effect toward future use for a mobile health app is caused by prior use. Here, it will be important to highlight that although past behavior is a good proxy for future behavior, habits are more complex than the sole past behavior as there needs to be sustained and consistent behavioral patterns (e.g., frequent past behaviors are better predictors of current behaviors ($r=0.47$) compared to nonfrequent past behaviors ($r=0.25$) – Ouelette and Wood, 1998). The patterns of using these devices could reveal insights about future use, which will likely influence the future buying behavior.

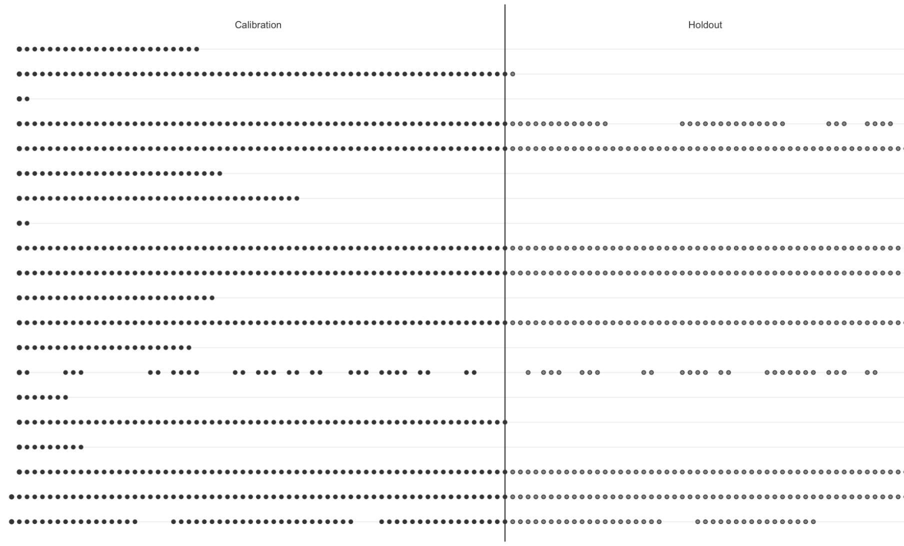
7.1.2. Modeling App Engagement as a Function of Habit

Although there are various approaches to measure habit, there are a few areas of interest that are shared among existing research, such as behavioral frequency, variation, and discontinuity. Accordingly, we investigate models that can accommodate a combination of these prominent features to understand how app engagement works and how it can be proactively identified to take appropriate actions. We follow a recent approach proposed by Reutterer, Platzer, and Schröder (2021) who build on and improve “Buy Till You Die” (BTYD) type models such as NBD, BG/NBD, Pareto/NBD (HB), and Pareto/GGG[8] that are catered to noncontractual settings. These models are interested in describing and predicting customer behavior in such settings by fitting probabilistic models to archival data in an attempt to aid customer-centric managerial interest (Reutterer, Platzer, and Schröder, 2021).

When we examine the lifetime of a random set of 30 customers, we can see a great deal of heterogeneity in frequency, variation, and discontinuity in how people’s wearable use behavior shapes up over time. Exemplified in Figure 6 below, taking the median date in the dataset as a threshold, we see that some customers persist, some churn shortly after the midpoint, and some show an irregular pattern. Accordingly, it will be beneficial for the firm to understand and predict these changes over time to: 1) better allocate valuable marketing resources, and 2) proactively target customers who are likely to churn to prevent this outcome.

[8] These BTYD models are established with Pareto/NBD (Schmittlein, Morrison, and Colombo, 1987), BG/NBD (Fader, Hardie, and Lee, 2005), and the BG/BB (Fader, Hardie, and Shang, 2010), and they continue to be improved by adjusting to behavioral regularities with newer developments such as BG/CNBD-k, MBG/CNBD-k (Reutterer, Platzer, and Schröder, 2020), and Pareto/GGG (Platzer and Reutterer, 2016).

Figure 6. Model Free Evidence for the Change in Customers' Tracking Behavior

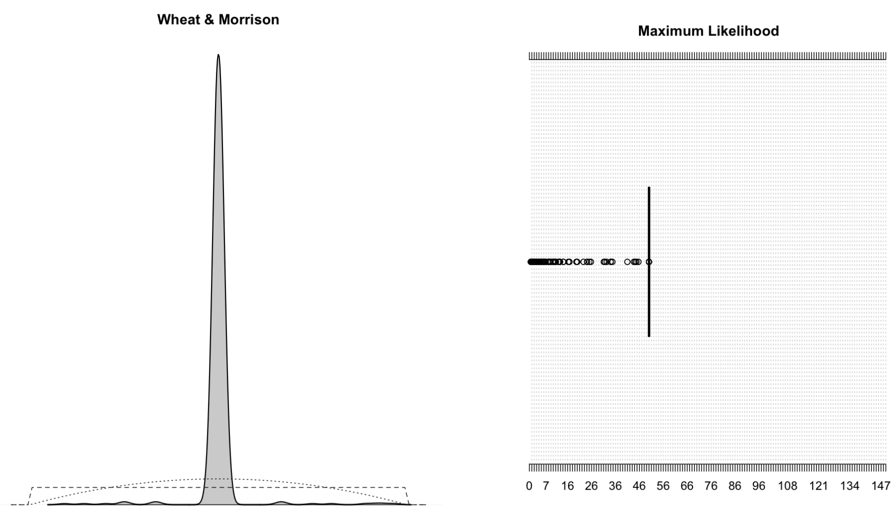


Pareto/NBD variations are interested in customer dropout through a Poisson process which assumes every inter-transaction time to be independent of one another. The independence property also necessitates a memoryless structure in modeling the behavioral outcome. However, this randomness assumption is rarely applicable in practice, especially when the regularity between transactions is intensified. Accordingly, an approach to tackle this challenge is letting the transaction rate vary across customers according to a gamma distribution, which results in a condensed NBD (or CNBD) model. This model is an attractive candidate in such situations since it can combine the highly likely non-Poisson occurrences (e.g., regularity patterns) with latent attrition. Forecast accuracy can be significantly improved by leveraging regularity, given that it is present in the data.

To measure regularity, we use Wheat and Morrison (1990)'s method where the higher the test value, the more regularity there is, and values significantly larger than 1 reveal the presence of regularity. We choose the steps dataset as 1) when the step count is zero, it is a highly likely assumption that a user has not worn the device as it is very unlikely for someone to

take zero steps in a day but the same assumption cannot be made about exercise, 2) steps dataset is more generalizable as everyone takes steps but may not exercise, and 3) we have more users within the steps dataset. With a test value of 38.434, there seems to be an extreme regularity observed within the data, suggesting that models that ignore regularity (i.e., those that assume a random inter-transaction time following a Poisson distribution) will not be a good fit to the data at hand (Figure 7).

Figure 7. Plots for Wheat and Morrison Test and Maximum Likelihood



This expectation is further demonstrated with the tests we run to compare the fit of various models in calibration and holdout periods for our dataset. Specifically, NBD model overestimates the number of occurrences in holdout period by 33.19%. This result hints that a model accommodating regularity, such as BG/CNBD-k and MBG/CNBD-k will fit the data better.

Following Reutterer, Platzer, and Schröder (2021), MBG/CNBD-k likelihood function is:

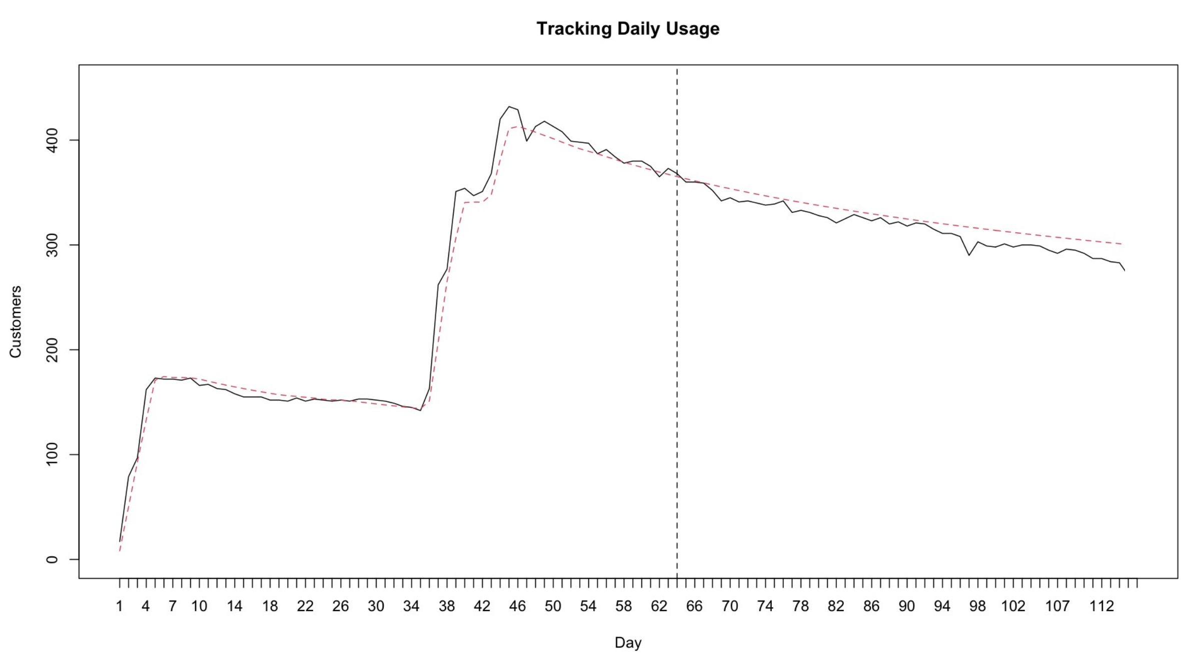
$$L_{MBG/CNBD-k}(k, r, \alpha, a, b|t_1, \dots, t_x, T) = \tilde{t}\frac{B(a+1, b+x)}{B(a,b)}\frac{\alpha^r}{(\alpha+t_x)^{r+kx}}\frac{\Gamma(r+kx)}{\Gamma(\mathrm{r})}$$
$$+\tilde{t}\frac{B(a, b+x+1)}{B(a,b)}\left(\sum_{j=0}^{k-1}\frac{(T-t_x)^j}{j!}\frac{\alpha^r}{(\alpha+T)^{r+kx+j}}\frac{\Gamma(r+kx+j)}{\Gamma(\mathrm{r})}\right)$$

When we examine the models that focus on regularity, we see a significant improvement in model fit, where MBG/CNBD-k yields the highest log-likelihood value. We provide a comparison of parameters and log likelihood for the models BG/NBD, BG/CNBD-k, MBG/NBD, and MBG/CNBD-k in Table 5. Further, in Figure 8, we can see how closely linked the actual customer usage (solid black line) and the model's fit (dotted red line) are over the course of the observation period.

Table 5. Comparison of Model Parameters and Log-Likelihood Values

	k	r	alpha	a	b	Log-Likelihood
BG/NBD	1	22.442	24.121	0.218	15.126	-17768
BG/CNBD-k	12	7.070	0.627	0.345	25.368	-332
MBG/NBD	1	9560.601	10000.000	0.148	6.289	-17447
MBG/CNBD-k	**12**	**59.442**	**5.130**	**0.277**	**15.840**	**144**

Figure 8. Comparison of Model Fit vs Actual Wearable Usage Behavior Over Daily Data



After observing the good fit, we can proceed to calculating the probability of being alive for the whole customer base. For example, among the customers who had 1 to 5 transactions within the first 50 days but remained inactive for the rest of the calibration period, the predicted probability of these customers being alive (p-alive) values are as below. We can see that customers who had less usage are predicted to be alive at a higher likelihood than those who had more usage.

x = 1: 87.48 %

x = 2: 71.07 %

x = 3: 42.40 %

x = 4: 16.21 %

x = 5: 4.36 %

Finally, we can test the predictive power of the model by examining the efficacy of the model's fit in the holdout period. We see that the MBG/CNBD-k we train in the calibration period can predict the number of tracking occurrences as 18,646 where the actual number of occurrences were 18,520 which is less than half a percent off. As expected, MBG/CNBD-k performs the best when we examine the mean absolute error (MAE) as well. MAE values are as follows: NBD: 11.844, BG/CNBD-k: 9.158, and MBG/CNBD-k: 8.786. Using MBG/CNBD-k over NBD leads to a 25.8% lift in MAE.

Another approach to predict churn and usage intensity is MCMC, which provides the coefficients at the customer level. This approach is useful to draw fine-grained inferences on aspects such as p-alive and transaction probabilities. In our case, the predictive capability of MBG/CNBD-k is still superior to the appropriate MCMC models (i.e., Pareto/Gamma Gamma Gamma, Pareto/NBD), as highlighted below in Table 6 (closer to the actual number of

transactions in the holdout period, better the predictive capability). To provide a complete picture, we include the estimated trace and density plots and model fit for an MCMC approach (i.e., Pareto/GGG) in Appendix D.

Table 6. Model Performance Comparison between MBG/CNBD-k and MCMC Models

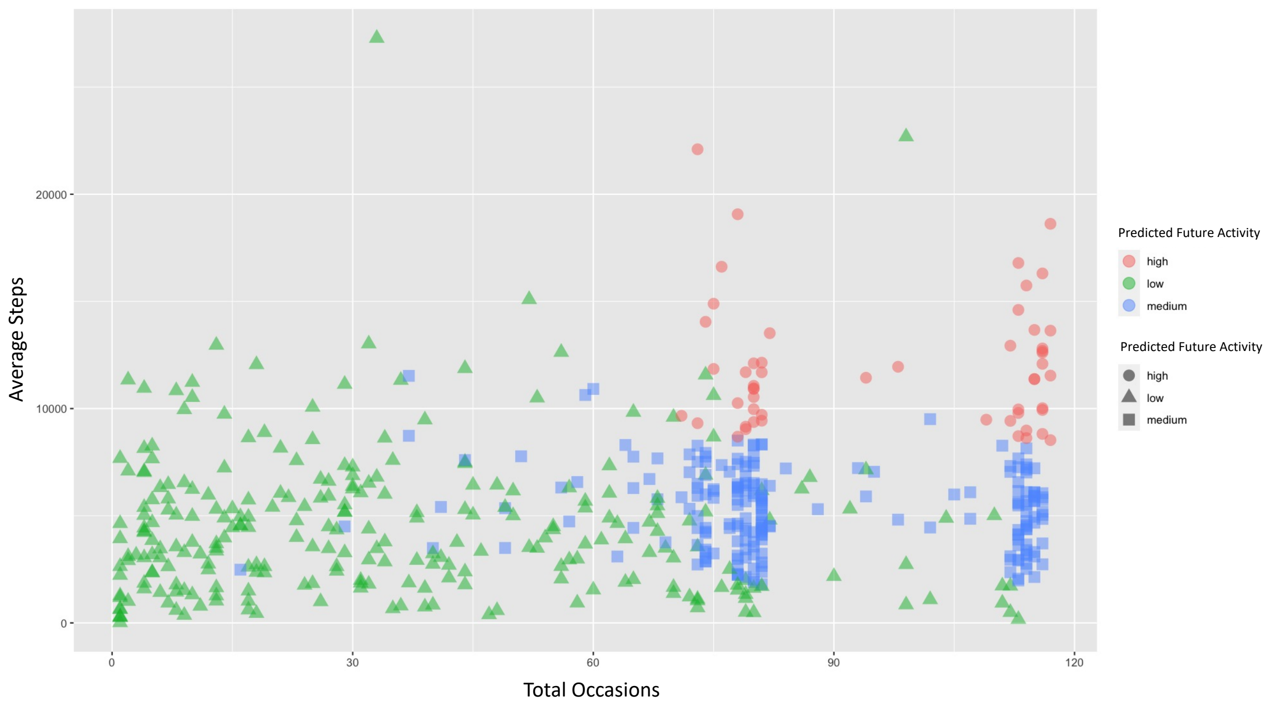
	Number of Occurrences in Holdout Period	Mean Absolute Error
Actuals	18,520	
Pareto/GGG	19,085	10.689
Pareto/NBD (HB)	19,770	11.528
MBG/CNBD-k	**18,646**	10.893

7.1.3. Further Analysis: Predicting Future Customer Behavior

Using the MBG/CNBD-k specification, in a similar vein as predicting CLV, we can also predict the customers' future physical activity behavior. We utilize a two-layered hierarchical model where both the average number of steps taken and the total number of steps taken by each customer will follow a Gamma distribution, creating a Gamma-Gamma spend model. In the below figure, using the expected physical activity of each customer, we group the customers into three activity levels of low, medium, and high using the entire data set with no calibration period (Figure 9). We observe interesting patterns such as customers within the low activity group to demonstrating a high number of steps, as well as customers within the medium and high groups showcasing similar step counts to the group with the lower expected steps. This result occurs because the model integrates how regular customers partake in step behavior along with the number of steps, contributing to a more fine-tuned and accurate picture. The match between this CLV-based categorization and the usage intensity identified

with three groups based on the first two weeks of data is only 55%, which further highlights the importance of incorporating regularity into the model if the goal is predicting future behavior.

Figure 9. Plot of Lifetime Value for Customers with High, Medium, and Low Activity



8. CONCLUSIONS

8.1. Academic Contributions

Interdisciplinary Perspectives

Interdisciplinary insights can be drawn from this work through message effectiveness and app engagement in marketing, wellness in public health, and motivation, goal-relevant behavior and message framing in psychology. Our study also contributes to the academic community by offering an understanding to new product development literature through communication effectiveness. Further, in focusing on wearable technology, we explore an emerging context with an exponential growth and expect future studies to build upon this work

and derive useful insights. We not only enrich the current body of literature within mHealth (mobile health apps), but we also extend the reach of these studies by removing the boundary of focusing on individuals with preexisting conditions and commencing generalizability of the results to everyday people. In a similar vein, we account for multiple wearable brands and present their effects, which improves the representativeness of the results. We provide an angle on behavioral loyalty in the absence of a firm's direct financial gain, which is an often-ignored area in marketing. Future studies could use the results of our work in examining the behavioral response of customers using the right type, frequency, and timing of messaging.

Use of Objective Data in Linking Nudges to Customer Wellness

Explaining customer wellness with digital nudges is a novel approach that has been an under-researched area in academia, especially using a unique real-world data that is likely to complement other research studies that typically utilize an experimental or survey-based approach. While such studies are an excellent means to establish a causal relationship or to quickly obtain data, this study can diminish certain biases (e.g., Hawthorne effect, self-report bias, learning effect) that could arise due to the use of experiments or survey-based research. Our study extends the literature on message effectiveness and showcases unexpected results, such as the need for persistence when sending motivational messages and the need to stop at a threshold for informational messages. We also help unfold the preferred timing of these messages by showing that firms should avoid informational messages as the relationship with the customer matures. Demonstration of dynamic effects (Appendix A2) supports this notion.

Wearable Effectiveness

We contribute to the understudied body of research on the effectiveness of wearables. So far, the few studies that investigate wearable technology show limited effectiveness, while our study shows significant improvement in customer's wellness behavior through the effective use of varying types of nudges. Accordingly, as encouraged by recent calls for papers in top academic marketing journals, we demonstrate a behavioral solution to a common problem, customer wellness. People's physical activity levels fluctuate above and beyond seasonality over time and examining the enduring effects of customer behavior could shed light in improving customer wellness by detecting dormancy and help firms intervene accordingly. Especially given the fact that wearable effectiveness is criticized to fade away over time, bringing in the remedy of nudges in behavioral outcomes enriches the current knowledge and facilitates a foundation for future research studies to extend our findings.

Psychological Underpinnings

Finally, this study can incite relevant conversations on the psychological underpinnings of customer behavior. Holistically put, as suggested by Sunstein in a recent paper (Sunstein, 2017), the reason some nudges may not work could be a function of strong preferences and habits—customers may have a set routine from which they do not deviate despite nudging. Alternatively, it could simply be due to the 'laziness effect,' in which, when we receive a nudge with a motivation attempt, we choose the easier path of not doing anything. However, if we are reminded about our goal enough times, we may choose to take an action. We show that nudges can also have negative effects, such as attempting to motivate to improve exercise duration or inform to increase step count. This finding could be an interesting avenue for future studies, which can examine the reasoning behind this unfavorable outcome and delve into the

emotional aspects of lowered self-esteem, feeling of guilt, self-criticism, and demotivation when reminded about failure to exercise or move. This behavior may have unwanted outcomes such as quitting, which we probabilistically identify and offer ways for firms to proactively take necessary steps before this unsought consequence occurs.

8.2. Managerial Implications

Improving Customer Engagement

By showing not only what drives the desired behavior, but also what kind of messaging strategy harms it, we provide firms with actionable tools to segment, target, and influence customers. Improving customer wellness will likely increase customer engagement, which is an instrumental phase in customer relationship management. Engaged customers are also more likely to upgrade to a newer technology, given that they are satisfied with their progress. Research already shows that customers are willing to increase their spending in personal health and that customers appreciate a targeted communication strategy that helps them reach their health goals. Nudging can be an effective and low-cost vehicle to improve decision-making, which has individual, societal, and environmental impacts.

Revamping Communication to Benefit Firms

Firms can significantly benefit from sending the right nudge to the right customer for the right activity. Evidently, customers enjoy a segmented message (8.8% click through rate) compared to a broadcasted non-tailored message (3.17% click through rate) (Business of Apps, 2022). Effects of incentives are shown to fade away in customer wellness, but firms can improve the longevity of customer relationships by tailoring the message content. We help firms by providing a roadmap to focus on different types of communication strategies at varying

stages of their relationship with the customers. It is shown that premium app adoption within mobile health apps already leads to higher engagement and retention (Hagen et al., 2021). Retained customers are not only much less expensive than acquiring new ones, but are also more likely to purchase the new products from the firm (Gallo, 2014). For example, increasing customer retention rates by 5% leads to 25 to 95% increase in profits (Reichheld, 2001). We also showcase the varying effects of different wearable brands as well as the operating platform on customer wellness (e.g., being a Google Fit customer is linked to a negative step behavior but a positive exercise behavior; iOS users are more active than Android users). Marketers can use this knowledge to better advertise specific brands or products.

Health Improvements

There is overwhelming scientific evidence that suggests quantifiable health improvements of physical activity. 2.5 hours of weekly physical activity is attributed to an increase in life expectancy of 3.5 years and a 31% reduction in mortality and premature morbidity risk (Piercy and Troiano, 2018; Arem et al., 2015; Forberger, Wichmann, and Comito, 2020). We provide policy makers and practitioners with quantifiable estimates of the impact of different nudges on health and how the effects vary over time.

Wearables are increasingly being used by doctors and insurance policies, which is a potential new market for firms to target. Cardiologists review EKGs taken on Apple Watches, some hospitals allow patients to upload data from Apple Health into their electronic medical record (EMR) (Raja et al., 2019), mobile apps (e.g., Rimidi) facilitate an interface that synchronizes and tracks data from wearables and integrates this data within hospital or MD office EMRs (Seelbach, 2021). Other mobile apps (e.g., Paceline) promote physical activity by

rewarding its customers who reach an exercise threshold of 150 minutes per week by providing monetary incentives in the form of gift cards and cashback. Such business models suggest that the mainstream involvement of wearable devices with health insurance is near, and firms can benefit from an enhanced knowledge with big data to define and evaluate risk. Taken together, the plethora of data available can help enrich the decisions within medical system.

Health Expenditures

Customers can reduce their health expenditures by proactively improving their overall wellness. Given the positive consequences of physical activity argued above, at the public level, our study can indirectly help diminish obesity and associated illnesses such as cancer, heart disease, and diabetes (Graff, 2020). These illnesses have heavy costs to the society. For example, the cost of obesity in the United States alone is estimated to range from $147 billion to nearly $210 billion per year (George Washington University, 2013) and body weight is associated with higher health care expenditures across a wide range of body mass index (Ward et al., 2021). Another example is with endometrial cancer, a disease whose survivors show the lowest physical activity among all cancer survivors; however, it is shown that lifestyle interventions such as digital nudges result in improved health outcomes for these patients (Rossi et al., 2018). Similarly, another recent study using wearable technology has shown an improvement in physical activity of breast cancer survivors (Nguyen et al., 2017), which demonstrates the power of technology in improving the lives of those in the most need. On a broader scale, the healthcare costs and scarce assets such as medical professionals trained to treat these illnesses could be better allocated to improve the overall functionality of the health system and society at large.

9. LIMITATIONS AND FUTURE RESEARCH

Our study has several limitations, which could provide fruitful opportunities for future research. First, we do not observe the privacy concerns or reactions of customers. How do customers feel about firms making decisions based on their health data? While technology offers convenience to our lives, also looking into privacy and intrusiveness could extend our findings (Naeem et al., 2022; Beke et al., 2021). Nevertheless, it is worth pointing out that people are less concerned with privacy of their health data than other types of personal data, according to a recent report (Callaghan et al., 2021), and this silver lining will likely make our findings more meaningful.

Second, an important aspect in wearable technology is the social element of befriending people and challenging them to be in competitions (e.g., Apple Watch's weekly competitions between friends that award a digital badge to the winner). This perspective may directly influence the physical activity behavior, and we encourage scholars to bring the social aspects and gamification into future studies in wearable technology. Similarly, we do not observe the monthly challenges that wearable brands create for individuals (e.g., exercise for 2,200 minutes for this month's challenge), and it will affect the customer wellness outcome if people are driven to accomplish these tasks. Additionally, future studies could explore the effects of exact wording on behavior, and state-of-the-art machine learning tools like natural language processing and deep learning methods are available to evaluate the linguistic aspect of digital nudging.

Third, we do not account for the calorie intake of individuals or any dietary measures, which likely influences the outcomes of interest in this study. Luckily, a plethora of previous

studies delve into the link between eating habits and behavior (including a recent study supported by the Marketing Science Institute by Hagen et al., 2020), and our study aims to complement these studies in providing an angle to the under-researched nudge to behavior link in presence of objective measures and contributing to a more informed picture of wellness.

Finally, it is likely that users get nudged both through the mobile app and on their wearable device, but we do not observe the nudges sent from the wearable device or other notifications received that might increase the burden of information overload. However, receiving additional communication would likely diminish the effect sizes in this study, which makes our results conservative and should not harm the generalizability of our work. Another unobserved phenomenon is the fact that people may receive these nudges but not read them. Although we cannot confirm whether someone reads or pays attention to the nudge, having possessed this knowledge would have only increased the effect sizes we report, therefore this lack of knowledge only makes our claims more conservative. Future studies can explore the behavior after confirming that the customer reads or understands the message. Although we did not observe major changes in behavior patterns over time, further research can explore whether the effects remain similar over a longer period since behavioral change may take longer than our observation horizon to sprout.

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APPENDIX

Appendix A. Robustness Checks

A1. An Alternative Modeling Approach Accounting for Sequential Endogeneity: Autoregressive Moving Average Model

Following the findings of our main model, we propose an additional model that can accommodate a more flexible specification to check whether our findings are still supported. Accordingly, we specify a model that accounts for the past behavior as well as the past error term in an autoregressive moving average configuration. This specification provides an improved alternative to the Arellano-Bond estimator due to its property of allowing for both lagged dependent variables and their errors over time to be correlated, using a maximum likelihood specification through mixed modeling. It also accommodates additional complexities such as using the restricted log likelihood as the expectation maximization mechanism and allowing for the random effects variables to covary in a simplified model.

We follow the equation we previously propose and add two random effects for either type of nudge, provided below for convenience:

$$\text{(A1.1)}\ Customer\ Wellness_{it} = \beta_0{}^{a,b} + \beta_1{}^{a,b} Relationship\ Duration + \beta_2{}^{a,b} Focus\ Congruence_i + \beta_3{}^{a,b} Informational\ Nudge_{it} + \beta_4{}^{a,b} Informational\ Nudge_{it} * Relationship\ Duration_{it} + \beta_5{}^{a,b} Informational\ Nudge_{it} * Focus\ Congruence_i + \beta_6{}^{a,b} Motivational\ Nudge_{it} + \beta_7{}^{a,b} Motivational\ Nudge_{it} * Relationship\ Duration + \beta_8{}^{a,b} Motivational\ Nudge_{it} * Focus\ Congruence_i + \mu_{i1}{}^{a,b} * Informational\ Nudge_{it} + \mu_{i2}{}^{a,b}\ x\ Motivational\ Nudge_{it} + Z'\theta^{a,b} + \upsilon_{it}{}^{a,b}$$

where Z' denotes the following control variables: number of messages sent by the firm other than nudges (operational messages, weekly routine recaps), lagged reward messages (message on previous day's goal achievement), wearable used (Fitbit, Garmin, Apple Health, Google Fit, and Phone), platform (iOS or Android), gender, and age. We include the squared terms for informational and motivational nudges in both models. ${\upsilon_{it}}^{a,b} = {\varepsilon_{it}}^{a,b} + {\mu_{i0}}^{a,b}$ represents the error and random effects of intercepts for steps and exercise models, respectively.

We allow for a repeated measures specification with a first-order autoregressive moving average covariance structure, ARMA(1,1), to establish a time series configuration, formally specified and elaborated as below.[9]

(A1.2) $Customer\ Wellness_{it} = X'\beta_i + \rho_i * log(Customer\ Wellness_{it-1}) + \varepsilon_{it} + \varphi_i * \varepsilon_{it-1}$

where $Customer\ Wellness_{it}$ denotes $log(Step\ Count_{it})$ and $log(Exercise\ Minutes_{it})$ with the following structure for ρ, φ, and σ^2:

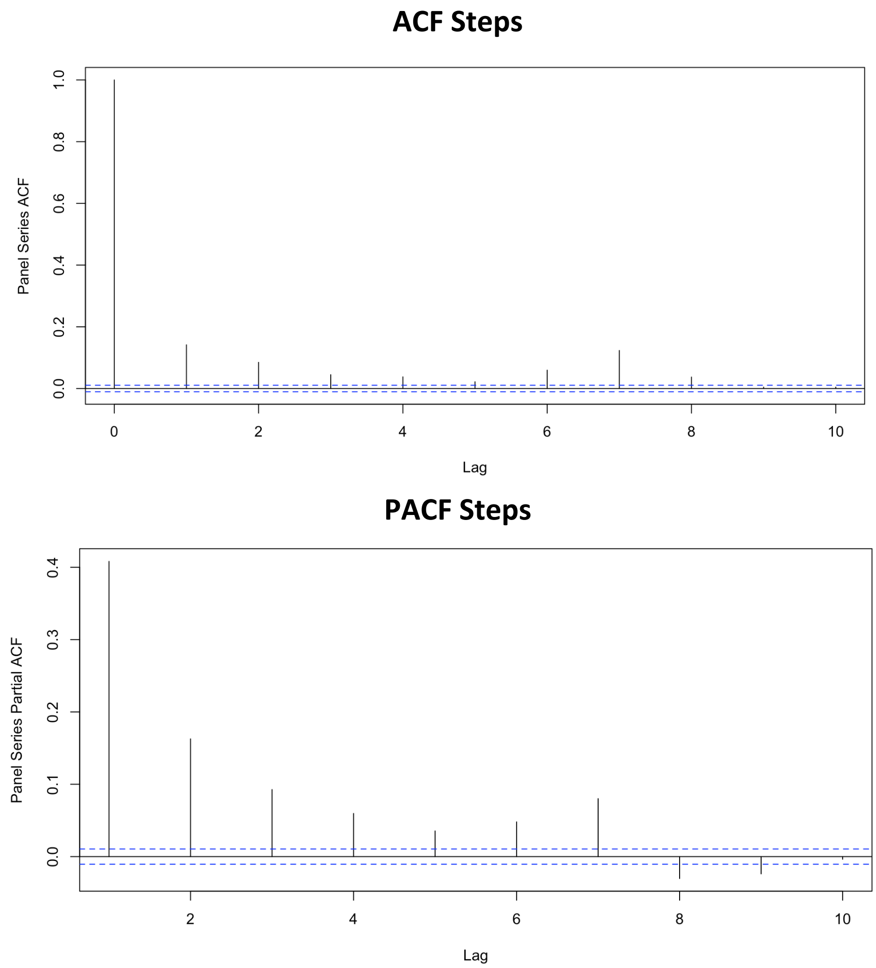
$$\begin{bmatrix} \sigma^2 & \sigma^2\varphi\rho & \sigma^2\varphi\rho^2 & \sigma^2\varphi\rho^3 \\ \sigma^2\varphi\rho & \sigma^2 & \sigma^2\varphi\rho & \sigma^2\varphi\rho^2 \\ \sigma^2\varphi\rho^2 & \sigma^2\varphi\rho & \sigma^2 & \sigma^2\varphi\rho \\ \sigma^2\varphi\rho^3 & \sigma^2\varphi\rho^2 & \sigma^2\varphi\rho & \sigma^2 \end{bmatrix}$$

We define this specification to allow for the dependent variable to be influenced by 1) lagged values of dependent variable in addition to the values at time t, and 2) past error terms, leading to a time series configuration with an autoregressive moving average structure. We ran

[9] We specified a number of error structures for the repeated measures, including Diagonal, Toeplitz, and AR(1) and chose ARMA(1,1) based on the following criteria: convergence, covariance parameter significance, and the lowest AIC and BIC values combined. Same exercise was done to choose the appropriate covariance structure between the random effects.

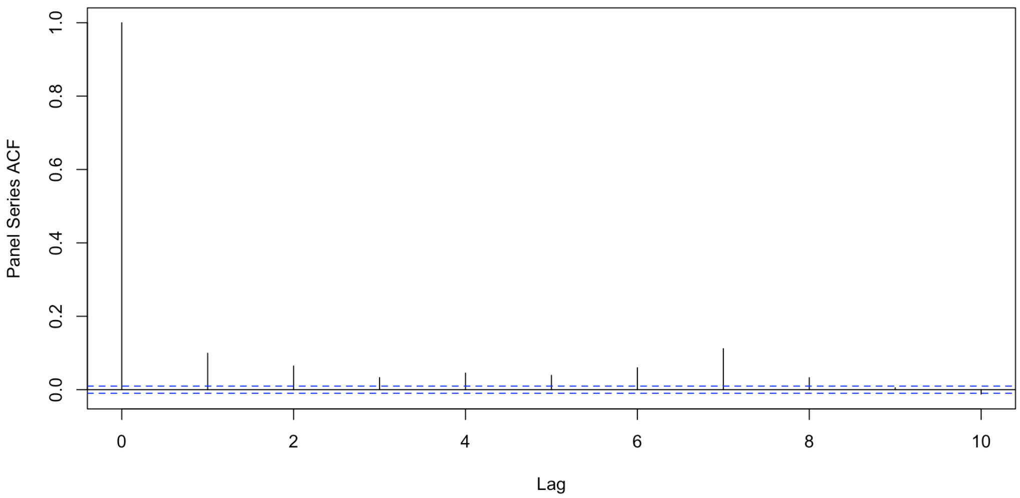
the model with multiple AR and MA configurations and proceed with the specification that converges and yields the lowest AIC and BIC values[10]. Figure A1 supports the non-stationary assumption where the ACF and PACF values both tail off to zero, hinting that differencing (e.g., an ARIMA model) would not be accurate. A tapering pattern of ACF with only the first lag being significant suggests an AR(1) specification and the single spike in PACF calls for an MA(1) specification, together forming an ARMA(1,1) structure.

Figure A1. Autocorrelation and Partial Autocorrelation Function Plots for the Panel Data

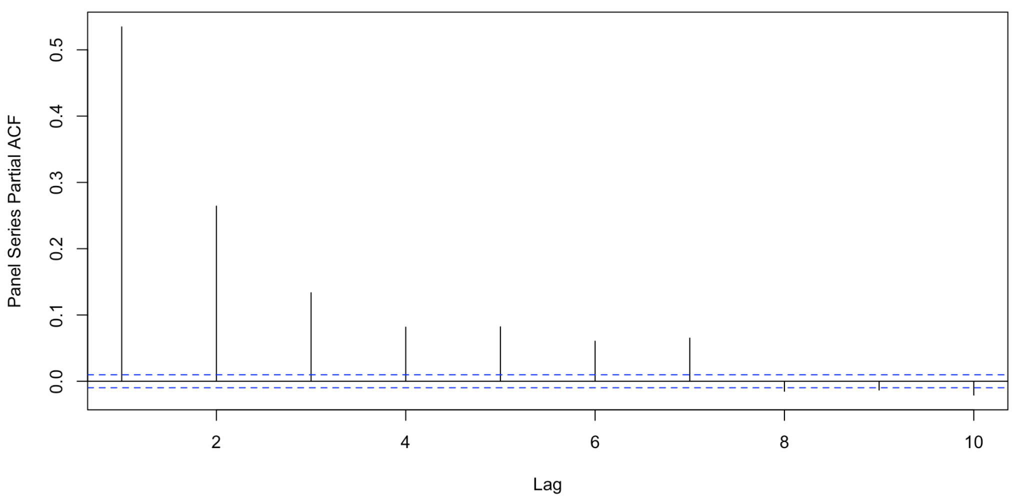


[10] The fit continues to improve up until the second degrees of autoregressive and moving average specifications but the differences in AIC and BIC value are extremely small such that no further insight can be gained from overcomplicating the model. Since they yield visually identical results, we proceed with the more parsimonious equivalent, ARMA(1,1).

ACF Exercise



PACF Exercise



Additionally, random effects are specified for the coefficients of the time-varying variables; namely, intercept, informational and motivational nudge, and relationship duration ($\alpha_{i0t}, \alpha_{i1t}, \alpha_{i2t}, and\ \beta_1$). We also allow these random effects to covary using a first-order autoregressive structure where the correlation between any two elements is equal to ρ for adjacent elements, ρ^2 for elements separated by a third, and so on. We use Restrictive Maximum Likelihood (REML) to fit the model and Satterthwaite Approximation to determine

the effective degrees of freedom, which does not assume equal variances for independent variables, and is shown to provide more robust estimations compared to the pooled method.

Results

Table A1.1 Estimates of Covariance Parameters and Goodness of Fit Measures

		Steps Model				Exercise Model			
Parameter		Estimate	Std. Error	Wald Z	Sig.	Estimate	Std. Error	Wald Z	Sig.
Repeated Measures	ARMA11 diagonal	3.230	0.029	112.898	0.000	6.419	0.198	32.422	<.001
	ARMA11 rho	0.318	0.017	18.746	<.001	0.977	0.001	853.397	0.000
	ARMA11 phi	-0.236	0.005	-51.336	0.000	0.691	0.010	67.633	0.000
Intercept + Informational Nudges + Motivational Nudges + R. Duration | ID	AR1 diagonal	0.051	0.006	8.743	<.001	0.119	0.010	12.199	<.001
	AR1 rho	-0.354	0.063	-5.608	<.001	-0.267	0.066	-4.027	<.001
Information Criteria	-2 Restricted Log Likelihood	135,639.087				151,808.126			
	AIC	135,649.087				151,818.126			
	BIC	135,691.279				151,861.071			

Table A1.2 Random Effects Covariance Structure

	Steps Model			**Exercise Model**		
	Intercept | Id	Info. Nudge |Id	Moti. Nudge | Id	Intercept | Id	Info. Nudge |Id	Moti. Nudge | Id
Intercept | Id	0.051	-0.018	0.006	0.119	-0.032	0.009
Info. Nudge | Id	-0.018	0.051	-0.018	-0.032	0.119	-0.032
Moti. Nudge | Id	0.006	-0.018	0.051	0.009	-0.032	0.119

Table A1.3 Model Results

	Steps Model				Exercise Model			
Parameter	*Estimate*	*Std. Error*	*df*	*Sig.*	*Estimate*	*Std. Error*	*df*	*Sig.*
Main Effects								
Intercept	0.106	0.088	368.430	0.230	-1.114	0.461	660.216	0.016
Informational Nudges	0.134	0.024	2118.138	<.001	0.073	0.032	1496.761	0.020
Motivational Nudges	-0.237	0.031	2422.441	<.001	-0.348	0.046	3353.778	<.001
Informational Nudges^2	-0.030	0.006	9528.676	<.001	-0.032	0.006	25473.359	<.001
Motivational Nudges^2	0.062	0.014	4841.439	<.001	0.103	0.014	11582.873	<.001
Relationship Duration	0.000	0.000	1580.166	0.329	-0.026	0.001	1411.489	<.001

Focus Area	-0.141	0.072	691.025	0.050	0.729	0.148	639.558	<.001
Interaction Effects								
Relationship Duration * Informational Nudges	0.001	0.000	3556.807	0.130	0.001	0.000	26978.169	0.008
Relationship Duration * Motivational Nudges	-0.001	0.000	2973.038	0.038	0.000	0.000	28539.888	0.719
Focus Area * Informational Nudges	-0.071	0.067	758.409	0.284	0.152	0.040	720.183	<.001
Focus Area * Motivational Nudges	0.118	0.072	634.105	0.103	-0.419	0.047	928.367	<.001
Informational * Motivational Nudges	0.029	0.015	3383.468	0.054	0.019	0.015	11485.704	0.199
Control Variables								
Platform: iOS	0.002	0.059	337.885	0.973	0.237	0.314	657.136	0.452
Lagged Reward Messages	-0.124	0.022	12951.394	<.001	-0.053	0.020	32482.973	0.007
Log Lagged DV (step count/exercise minutes)	0.926	0.002	1706.751	0.000	0.056	0.005	39264.667	<.001
Other Communication	0.114	0.025	31361.795	<.001	0.509	0.349	656.873	0.145
Apple Health	0.121	0.067	341.568	0.073	0.569	0.151	636.680	<.001
Device	0.079	0.029	337.241	0.006	1.242	0.408	647.184	0.002
Garmin	0.318	0.078	337.304	<.001	1.261	0.306	657.198	<.001
Fitbit	0.170	0.059	342.267	0.004	1.191	0.438	677.270	0.007
Google Fit	0.157	0.084	357.533	0.061	0.120	0.158	637.451	0.449
Gender: Male	-0.009	0.030	335.908	0.756	0.009	0.005	647.244	0.076
Age	0.002	0.001	341.871	0.029	0.509	0.349	656.873	0.145

The specification of autoregressive moving average errors is significant for both models, which confirms the expectation that the covariates of repeated measures within an individual are intercorrelated (Table A1.1). Random effects coefficients of the intercept, relationship duration, and informational and motivational nudges are also significant (Table A1.2), serving as statistical evidence to identify individual-specific coefficients for these variables. Evidently, there is heterogeneity among the sample members, and failing to account for this intermixture would result in a mismanagement of a firm's communication strategy.

Table A1.3 exhibits that people commit to less exercise minutes over time (${\beta_1}^b - 0.026$, $p < 0.001$); however, we do not observe such an effect for steps taken (${\beta_1}^a = 0.000, p > 0.329$). This finding repeats the results from the main model where the negative effect of time on exercise is prevalent. As expected, the results show that users with an exercise focus participate in increased physical activity compared to users that do not have an exercise focus (${\beta_2}^b = 0.729, p < 0.001$). We observe a negative effect for the steps model (${\beta_2}^a = -0.141, p < 0.050$). All these findings are in line with our results for the main model.

Our main goal is to uncover the varying effects of different types of nudges, which we showcase with the original model where step count and exercise minutes are jointly modeled to provide a holistic picture of customer wellness. This result is repeated with the ARMA specification. People favor informational nudges at lower levels (${\beta_3}^a = 0.134, p < 0.001;\ {\beta_3}^b = 0.073, p < 0.020$) and they disfavor them at higher levels (${\theta_1}^a = -0.030, p < 0.001;\ ;\ {\theta_1}^b = -0.032, p < 0.001$) in improving customer wellness. Accordingly, we are shown again that firms should be mindful of not sending too many notifications to avoid information overload.

Motivational nudges showcase a negative impact on customer wellness at low levels (${\beta_6}^a = -0.237, p < 0.001;\ {\beta_6}^b = -0.348, p < 0.001$), but this effect reverses at higher levels (${\theta_2}^a = 0.062, p < 0.001;\ {\theta_2}^b = 0.103, p < 0.001$). Again, these results are nearly identical to the effect sizes in the main model, where people not only want to be “nudged” enough times to take action when it comes to motivational nudges, but also demonstrate a negative impact toward too few nudges on wellness behavior.

Keeping in mind the extremely small effect sizes, the interaction effects of time and informational nudges were positive (${\beta_4}^a = 0.001, p < 0.001;\ {\beta_4}^b = 0.001, p < 0.004$), indicating that firms have room increase the number of informational nudges later in their customer relationship cycle. This finding agrees with the notion that people are likely to form habits over time and informational content complements this sustained behavior by helping keep track of routines. The interaction between time and motivational nudges is negatively linked to step behavior (${\beta_7}^a = -0.001, p < 0.038$), but this effect is insignificant for exercise behavior (${\beta_7}^b;\ p > 0.719$). The only diversion from the main model is that we do not observe synergistic effects of informational and motivational nudges. Based on these results, we infer that firms should strategize their motivational nudges early in the relationship with its customers and use these types of nudges cautiously as the relationship evolves.

Finally, pledging a focus on exercise negatively moderates the relationship between motivational nudges and exercise behavior (${\beta_8}^b = -0.419, p < 0.001$), while this effect is positive for the link between informational nudges and exercise behavior (${\beta_5}^b = 0.152, p < 0.001$). This result replicates the findings in our main model and confirms the notion that users with an exercise focus do not need the motivation boost as they will likely be already self-motivated and stick to their own agenda rather than the coaching provided by a mobile app. On the flip side, there is no moderating effects of focus area on the link between either informational or motivational nudges to customer wellness for the steps model (${\beta_5}^a = -0.071,\ p > 0.284; {\beta_8}^a = 0.118, p < 0.103$). These repeating outcomes collaboratively support the results in the main model and strengthen our claims about the effectiveness of nudges.

A2. Do Nudges Dynamically Affect Customer Wellness?

Our choice for the main model is a mixed effects approach since it can accommodate several specifications flexibly, such as accounting for the hierarchical nature of the data, allowing for random and fixed effects simultaneously, and parameterizing the effect sizes. We also add to this flexibility by incorporating lagged terms through autoregressive moving average as a robustness check. Having the main model established, we are also interested in examining the dynamic effects for our main variables of interest, informational and motivational nudges along with their squared terms.

Following Li et al. (2017), we use a penalized truncated power spline (p-spline), which uses an automatic tuning penalty to choose the degree of smoothness against the flexibility of the fitted function. The number of knots is chosen by a pseudolikelihood equivalent to an AIC or BIC criteria. In these models, we use the linear terms for the dependent variables for ease of interpretation of the coefficients. We mimic the full models such that the coefficients for informational and motivational nudges along with their squared terms are allowed to vary over time and the coefficients for the rest of the independent variables are time-invariant.

As can be examined in Figures A2.1 and A2.2, changes over time do occur but are not too drastic. Holding both informational and motivational nudges constant, there is no change in step count throughout the data horizon. The impact of informational nudges is relatively constant around 1,000 steps until day 60 but then has a noticeable improvement between day 60 and 120, reaching to nearly 4,000 steps with one unit increase of these nudges. We also observe the reverse effects on the flip side of the coin, where high levels of informational nudges are sent. Day 60 seems to be the cutoff point where the firm must be careful not to

send too many informational nudges. We see a reasonably steadier relationship between motivational nudges and step count, almost to a point of a linear relationship. These nudges are better when the firm persists in sending them and “nudge” the customer enough times.

Figure A2.1 Changes in Coefficients Over Time for the Steps Model

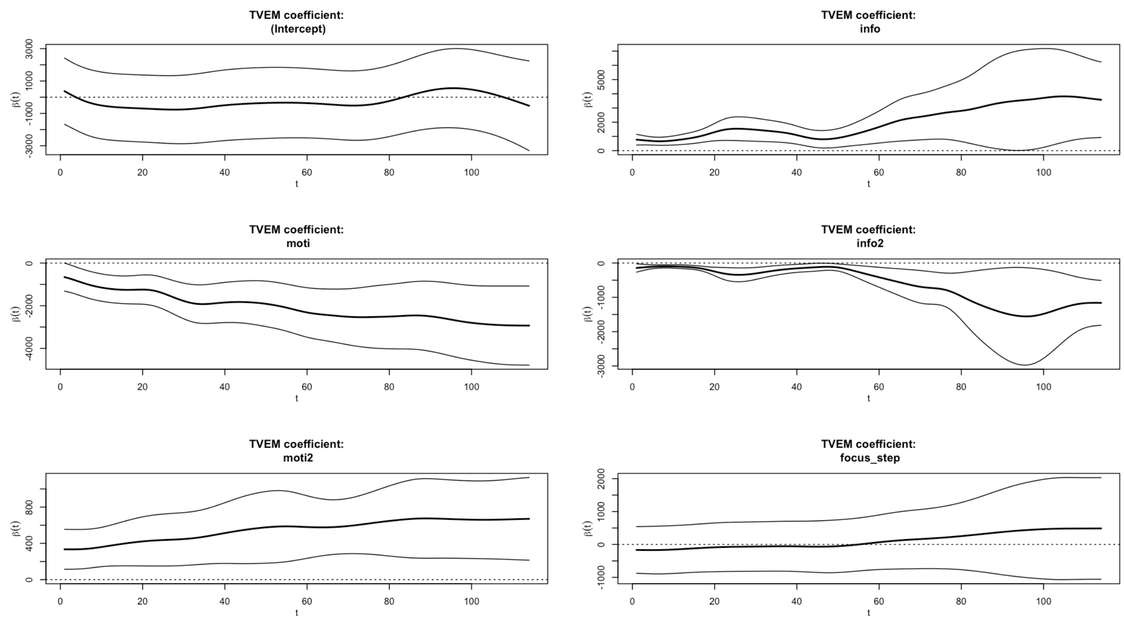
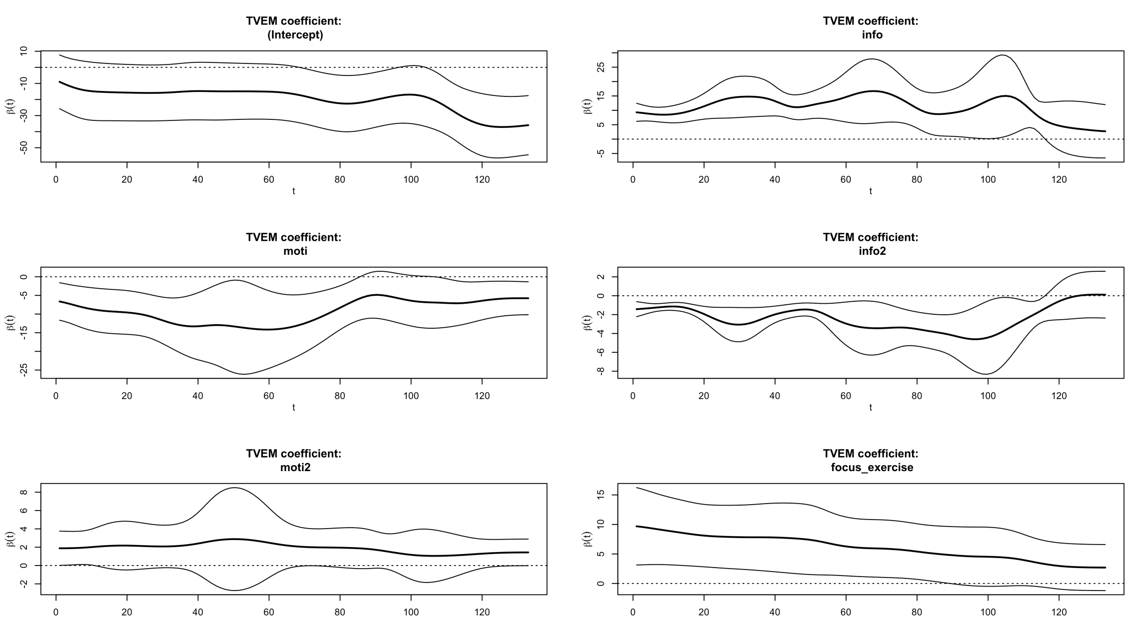


Figure A2.2 Changes in Coefficients Over Time for the Exercise Model



We observe a more cyclical relationship between nudges and exercise behavior. Holding all else constant, this behavior seems to dissipate after day 100, following a long time of plateauing. Informational nudges stay consistently effective over time with certain local peaks (see day 30, 70, and 105), which varies between 10 to 15 minutes of additional exercise minutes for each informational nudge. However, one should also bear in mind that sending too many of these nudges seems to backfire consistently throughout the customer relationship. The negative effects of motivational nudges somewhat recover at day 90, while sending high number of these messages have a steady positive effect throughout the span of data. Interestingly, although the customers with exercise focus have more aptitude to exercise more at the baseline, this effect almost linearly reduces over time. This finding attests to the fact that the pledge to exercise does have an initial impact but this motivation fuel slowly runs out as the relationship evolves.

A3. Accounting for Endogeneity with a Control Function Approach

Control function approach is a robust method to diminish endogeneity concerns (Petrin and Train, 2010). Along with the justified instrument-free Gaussian Copula we use for our main model to correct for endogeneity embedded in the informational and motivational nudges, we use a control function approach as a robustness check. We choose control function over two-stage least squares and instrumental variable approach because it is compatible with accommodating elements from varying distributional families while the other two are not.

We use the number of motivational and informational messages the focal firm sent out at *t-1* to customer *i* as instruments within control function approach for the number of motivational and informational touchpoints the customer *i* received at time *t*. We believe that previous nudges are likely indicators of the firm's recipe in deciding to send the current nudges. Accordingly, while yesterday's nudges influence today's nudges (as the firm is the decision-maker), they likely will not affect the number of steps a customer takes today (as the customer is the decision maker) because goals are set for daily activity and nudges are catered toward the goals within the same day. We also wanted to control for any fluctuations in the focal firm's nudges sent out to all its customers. Accordingly, we use the daily average of nudges received throughout the whole customer base as another instrument[11]. We mean center the instrument variables to adjust for the potential systematic differences between them. Accordingly, a control function approach is formally proposed as below.

[11] Along with the regular variables, we use the mean-centered versions to create residuals for both the motivational and informational nudges to account for any firm-related systematic difference that might occur between them. Both models (with and without mean centered versions) yield directionally the same results with minor differences in effect sizes. We proceed with the version without the mean centering to retain the comparison with the main model as simple as possible.

$$(A3.1)\ Motivational\ Nudge_{it} = \ Motivational\ Nudge_{i,t-1} + Daily\ Motivational\ Nudge\ Average_{t}$$

$$(A3.2)\ Informational\ Nudge_{it} = \ Informational\ Nudge_{i,t-1} + Daily\ Informational\ Nudge\ Average_{t}$$

As can be seen in equations (A3.1) and (A3.2), we regress these two instruments to the two independent variables in the main model (i.e., motivational and informational nudges) that are likely not exogenous in the first step. The resulting R^2_{adj} values are 59% and 24% for equation (A3.1) and (A3.2), respectively, demonstrating that the instruments used are adequate. Additionally, a Durbin Watson test on both equations show no evidence of autocorrelation (DW = 2.481 for Equation (A3.1) and DW = 2.281 for Equation (A3.2), both p-values are insignificant), hinting that lagged variables are appropriate to use as instruments. In the second step, we include the residuals obtained from these reduced form models as two additional variables in the mixed model specification. We term these two variables related to the endogeneity correction as residual 1 and residual 2, representing the variables emerging from equations A3.1 and A3.2, respectively. Results of the full model using control function approach is in Table A3.

Table A3. Model Results with Control Function Endogeneity Correction

	Steps Model			**Exercise Model**		
Parameter	Estimate	Std. Error	Sig.	Estimate	Std. Error	Sig.
Main Effects						
Intercept	2.326	0.527	<.001	-1.982	0.544	<.001
Informational Nudges	0.167	0.064	0.009	0.095	0.064	0.136
Motivational Nudges	-0.515	0.064	<.001	-0.168	0.068	0.013
Informational Nudges^2	-0.032	0.007	<.001	-0.024	0.007	<.001
Motivational Nudges^2	0.079	0.014	<.001	0.088	0.014	<.001

Relationship Duration	-0.017	0.002	<.001	-0.011	0.001	<.001
Focus Area	-0.181	0.180	0.316	1.096	0.181	<.001
Interaction Effects						
Relationship Duration * Informational Nudges	0.002	0.001	<.001	0.002	0.001	<.001
Relationship Duration * Motivational Nudges	0.000	0.001	0.720	-0.003	0.001	<.001
Focus Area * Informational Nudges	0.003	0.025	0.913	0.186	0.024	<.001
Focus Area * Motivational Nudges	0.110	0.040	0.005	-0.575	0.039	<.001
Informational * Motivational Nudges	0.047	0.015	0.002	0.003	0.015	0.823
Control Variables						
Platform: iOS	-0.435	0.358	0.226	0.204	0.365	0.576
Lagged Log(Step Count/Exercise Minutes)	0.425	0.005	0.000	0.052	0.006	<.001
Lagged Reward Messages	-0.141	0.022	<.001	-0.052	0.022	0.021
Other Communication	0.117	0.022	<.001	0.144	0.023	<.001
Apple Health	1.260	0.398	0.002	0.840	0.405	0.039
Device	0.436	0.174	0.013	0.741	0.178	<.001
Garmin	1.852	0.467	<.001	1.479	0.477	0.002
Fitbit	1.174	0.349	<.001	1.592	0.356	<.001
Google Fit	0.363	0.498	0.467	1.511	0.504	0.003
Gender: Male	0.268	0.182	0.141	0.054	0.186	0.771
Age	0.010	0.006	0.113	0.011	0.006	0.088
Residual 1 *	-0.062	0.050	0.217	-0.025	0.050	0.613
Residual 2 *	-0.005	0.040	0.909	-0.130	0.040	0.001

* Residual 1 is the residual captured by Equation A3.1 and residual 2 is the residual captured by Equation A3.2.

Results in Table A3 (full model using control function approach, denoted by $\beta_{n,cf}$) and Table 4 (full model using instrument-free Gaussian copulas, denoted by $\beta_{n,gc}$) are directionally comparable. For example, we observe the inverse U effect of informational nudges (${\beta_{3,cf}}^{a} = 0.167, p < 0.01\ vs\ {\beta_{3,gc}}^{a} = 0.090, p < 0.001;\ {\theta_{1,cf}}^{a} = -0.032, p < 0.001\ vs.\ {\theta_{1,gc}}^{a} = -0.011, p < 0.001$) and the U effect of motivational nudges on step count (${\beta_{6,cf}}^{a} =$

$-0.515, p < 0.001 \; vs \; {\beta_{6,gc}}^{a} = -0.203, p < 0.001; \; {\theta_{2,cf}}^{a} = 0.079, p < 0.001 \; vs. \, {\theta_{2,gc}}^{a} = 0.070, p < 0.001)$. We observe similar results for the exercise model where significant coefficients are directionally identical, with the only difference being the insignificance of the effect of informational nudges at low levels ($p > 0.136$).

For focus congruence, although negative, we do not observe a significant effect for steps (${\beta_{2,cf}}^{a} = -0.181, p > 0.05 \; vs. \, {\beta_{2,gc}}^{a} = -0.087, p < 0.001$) and observe a positive effect for exercise (${\beta_{2,cf}}^{b} = 1.096, p < 0.001 \; vs. \, {\beta_{2,gc}}^{b} = 1.971, p < 0.001$). Among the interaction effects of focus congruence, the significant coefficients are replicated where the moderation for the relationship between informational nudges and exercise minutes is positive (${\beta_{5,cf}}^{b} = 0.186, p < 0.001 \; vs \; {\beta_{5,gc}}^{b} = 0.328, p < 0.001$), and motivational nudges and exercise minutes is negative (${\beta_{8,cf}}^{b} = -0.575, p < 0.001 \; vs \; {\beta_{8,gc}}^{b} = -0.333, p < 0.05$). We observe an additional positive moderating effect of focus area between motivational nudges and step count (${\beta_{8,cf}}^{a} = 0.074, p < 0.05 \; vs \; {\beta_{8,gc}}^{a} = 0.032, p > 0.1$).

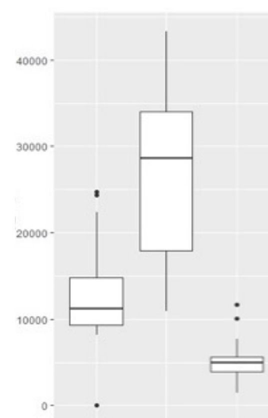
We observe similar effects for customers' relationship duration where the effect sizes are also relatively small and negative, replicating the main findings with the gaussian copula approach. The moderating effects of relationship duration on informational nudges is positive for both steps and exercise models, while this effect on motivational nudges is negative, suggesting a divergent picture from the results for the main model. The fact that the effect sizes are extremely small might be the driving factor for this contrast in findings. In general, these findings altogether show that Gaussian copula method puts forth a more conservative outcome with mostly smaller effect sizes, and that the outcomes of key variables are replicated despite using a different approach to account for the potential endogeneity embedded in the data.

A4. Exhibiting Nudge Effectiveness Using a Finite Mixture Model

Model Description

To compare our original model to another that incorporates heterogeneity through a segmentation approach, we propose a finite mixture model specification to examine the segmented response of customer behavior toward digital marketing communication in the form of digital nudging. As we emphasize throughout the manuscript, customers use wellness coaching apps for varying reasons, and it is critical to account for such heterogeneity in analyzing the data so that the firm understands who to target with which message. As exemplified in Figure A4.1, model free evidence shows three deidentified and randomly selected customers having vastly differing daily step counts.

Figure A4.1 Boxplot of Daily Steps for Three Customers



Finite mixture models are shown to be flexible and convenient ways to model unknown distributional shapes and the expectation maximization algorithm is evidenced to be useful in estimating coefficients for each latent class (Mclachlan, Lee, and Rathnayake, 2019; McLachlan and Peel, 2000). Additionally, the unbalanced panel data at hand includes customers over a four-month period, while some customers have shorter time span of available data, which can

be accommodated through finite mixtures. Finally, the data includes current customers who are expected to be stable in their behavior and we observe no dramatic changes over time. The findings from the main model and the robustness check for endogeneity correction showcase that time plays a limited role in explaining customer behavior. It is likely that although there are models that accommodate the unobserved dynamic elements of data (e.g., a Hidden Markov Model), the data horizon is not long enough for customers to move between latent states and the existing customers do not demonstrate dramatic changes over time. Supporting our main results, Figures A4.2 and A4.3 highlight no major variations of users' daily activity over time.

Figure A4.2 Daily Step Count of Customers Over Time

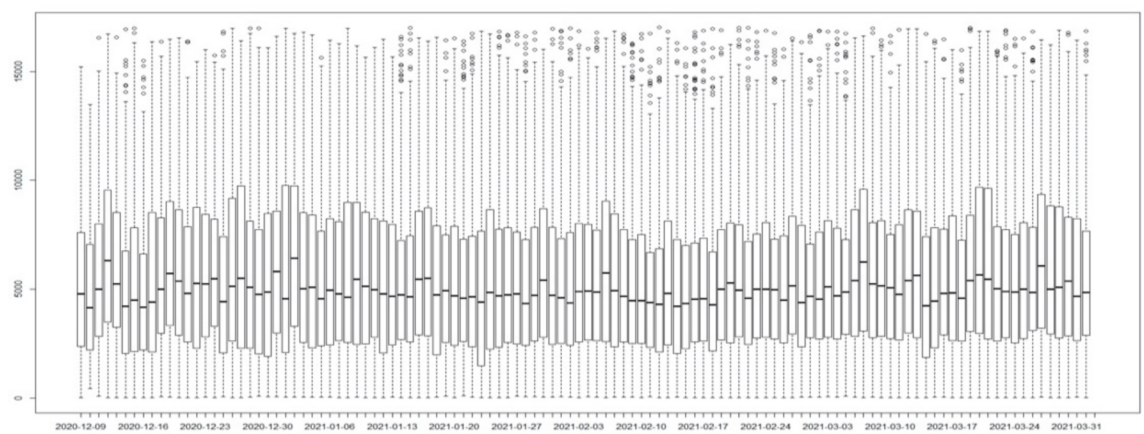
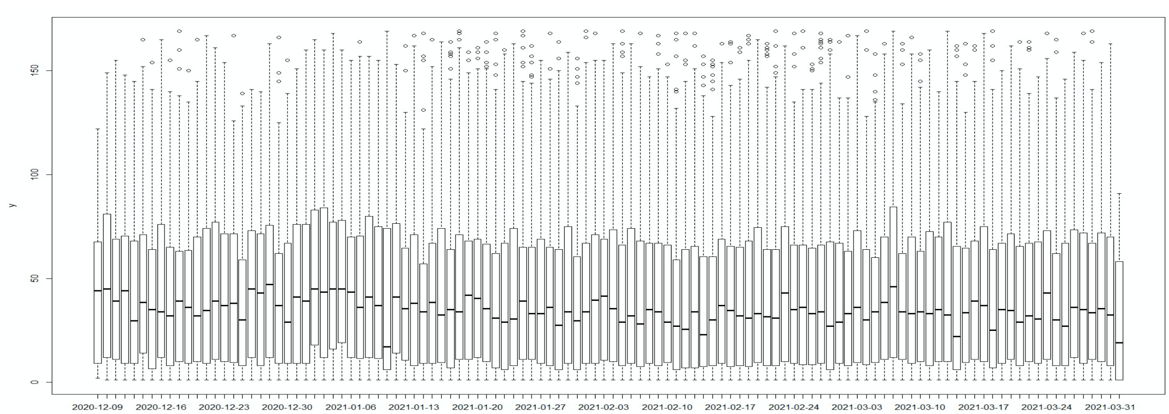


Figure A4.3 Daily Exercise Minutes of Customers Over Time



Our full model specification follows the original model and formally defined below:

$$(A4.1)\ Customer\ Wellness_{it} = \ \beta_0{}^{a,b} + \beta_1{}^{a,b} Relationship\ Duration + \beta_2{}^{a,b} Focus\ Congruence_i + \beta_3{}^{a,b} Informational\ Nudge_{it} + \beta_4{}^{a,b} Informational\ Nudge_{it} * Relationship\ Duration_{it} + \beta_5{}^{a,b} Informational\ Nudge_{it} * Focus\ Congruence_i + \beta_6{}^{a,b} Motivational\ Nudge_{it} + \beta_7{}^{a,b} Motivational\ Nudge_{it} * Relationship\ Duration + \beta_8{}^{a,b} Motivational\ Nudge_{it} * Focus\ Congruence_i + Z'\theta^{a,b} + \varepsilon_{it}{}^{a,b}$$

(A4.2) *X' = [Informational Nudges²*, *Motivational Nudges²*, *Non-nudge Messages, Lagged Reward Messages, Wearable Brand, Operating Platform, Gender, Age]*

In the above model, β_0 indicates the intercept, β_1 captures the effects of the relationship duration between the customer and firm, β_2 represent the effects of the customers who choose the relevant dependent variable (i.e., steps or exercise) as a focus area at the time of signing up for the focal mobile app. β_3 and β_6 denote the magnitude of the effects for informational and motivational nudges on steps taken. β_4, β_5, β_7 and β_8 represent the moderating factors of relationship duration and focus congruence on informational and motivational nudges. θ represents the coefficients for the control variables; namely, effects of over-targeting through motivational and informational messages (respective squared terms), non-nudge messages, lagged reward messages, wearable brand used, age, gender, and operating platform (i.e., iOS vs Android). ε is the random error term. We do not account for the synergistic effects of informational and motivational nudges or consider the lagged dependent variables within the specification since the interpretation of over time effects is difficult with the finite mixture model.

Using the full model above, taking a probabilistic approach, we can account for heterogeneity by placing customers into latent segments based on how similarly they respond to different nudges in a finite mixture model specification defined as below. Using an Expectation-Maximization algorithm, each cluster is assigned an unknown prior probability for a customer from which to originate (Leisch, 2004).

$$\text{(A4.3) } f(Y|x,\ \psi) = \textstyle\sum_{s=1}^{S} \pi_s f(Y|x,\ \beta_s)$$

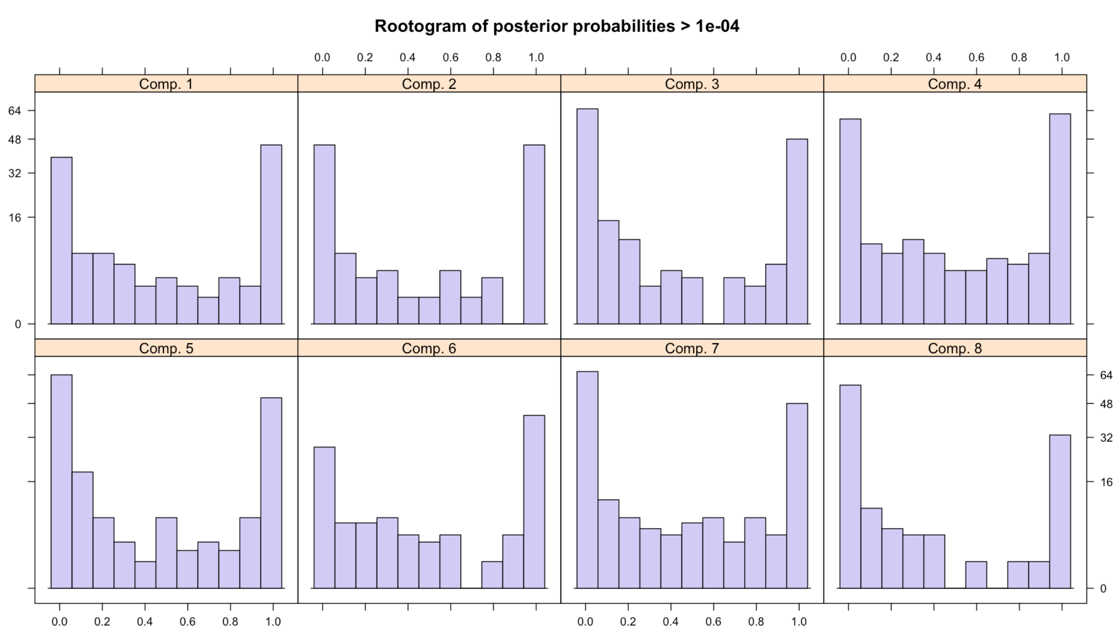
$$\text{(A4.4) } \textstyle\sum_{s=1}^{S} \pi_s = 1$$

Results

Steps Model

Results highlight a heterogenous sample in explaining step behavior where the model with eight segments is identified as the best fitting one. We illustrate the goodness of fit in Figure A4.4, where each end of the rootogram at peak signals a good fit.

Figure A4.4 Membership Probabilities for Each Segment



The output from the finite mixture model (Table A4.1) reveals similar results to that of the base model using mixed effects, as majority of the segments support the main results identified in Table 4. For example, the entire customer base (all eight segments) prefers lower levels of informational nudges and higher levels of motivational nudges, wherever these effects are significant. This finding reiterates on the fact that motivational of nudges will only be successful if the firm persists to send them, however, the strategy should be flipped when it comes to informational nudges where we consistently observe the negative effects of information overload.

Another similar result is the small effect size of relationship duration, which implies that even though literature suggests a significant negative impact of time on physical activity, it may not harm it to the suggested extend. The moderating effects of focus congruence and both types of nudges show varying interaction effects with the most consistent result being the negative effects of informational nudges (for all segments), confirming the original model.

Table A4.1 – Results from the Finite Mixture Model (DV=Log of Exercise Minutes)

	Segment 1 (11.3%)				**Segment 2 (10.8%)**			
	Estimate	**Std. Error**	**z value**	**p-value**	**Estimate**	**Std. Error**	**z value**	**p-value**
Main Effects								
Intercept	7.904	0.061	128.634	0.000	6.914	0.072	95.959	0.000
Informational Nudges	0.062	0.017	3.594	0.000	0.086	0.019	4.441	0.000
Motivational Nudges	-0.014	0.004	-3.519	0.000	0.002	0.005	0.376	0.707
Informational Nudges^2	-0.134	0.020	-6.694	0.000	-0.254	0.022	-11.326	0.000
Motivational Nudges^2	0.041	0.009	4.389	0.000	0.045	0.007	5.988	0.000
Relationship Duration	0.000	0.000	1.434	0.152	0.001	0.000	4.109	0.000
Focus Congruence	-0.238	0.033	-7.312	0.000	0.483	0.023	20.949	0.000
Interaction Effects								
Relationship Duration * Informational Nudges	-0.001	0.000	-2.517	0.012	0.000	0.000	-0.682	0.495

Relationship Duration * Motivational Nudges	0.001	0.000	2.137	0.033	-0.001	0.000	-3.802	0.000
Focus Congruence * Informational Nudges	-0.034	0.018	-1.864	0.062	-0.074	0.018	-4.007	0.000
Focus Congruence * Motivational Nudges	0.036	0.023	1.587	0.113	0.157	0.023	6.952	0.000
Control Variables								
Platform: iOS	0.051	0.060	0.847	0.397	-0.071	0.051	-1.404	0.160
Lagged Reward Messages	-0.003	0.013	-0.256	0.798	0.034	0.015	2.181	0.029
Other Communication	0.144	0.017	8.450	0.000	0.137	0.018	7.462	0.000
Apple Health	0.573	0.034	16.798	0.000	0.966	0.054	17.894	0.000
Device	0.590	0.022	26.566	0.000	0.743	0.021	35.966	0.000
Garmin	0.329	0.047	7.060	0.000	0.183	0.049	3.744	0.000
Fitbit	0.630	0.020	31.867	0.000	0.804	0.045	17.749	0.000
Google Fit	0.570	0.071	8.057	0.000	-0.536	0.060	-8.986	0.000
Gender: Male	-0.373	0.017	-21.778	0.000	-0.263	0.019	-14.038	0.000
Age	-0.003	0.001	-6.696	0.000	0.011	0.001	15.460	0.000
	Segment 3 (12.7%)				**Segment 4 (17.7%)**			
	Estimate	**Std. Error**	**z value**	**p-value**	**Estimate**	**Std. Error**	**z value**	**p-value**
Main Effects								
Intercept	7.272	0.114	63.646	0.000	8.953	0.089	100.111	0.000
Informational Nudges	0.217	0.042	5.225	0.000	0.090	0.026	3.483	0.000
Motivational Nudges	-0.041	0.009	-4.408	0.000	-0.010	0.006	-1.840	0.066
Informational Nudges^2	-0.371	0.058	-6.394	0.000	-0.276	0.031	-8.783	0.000
Motivational Nudges^2	0.104	0.035	2.930	0.003	0.119	0.014	8.781	0.000
Relationship Duration	0.000	0.001	0.373	0.709	0.000	0.000	0.792	0.429
Focus Congruence	-0.491	0.054	-9.074	0.000	0.139	0.024	5.697	0.000
Interaction Effects								
Relationship Duration * Informational Nudges	-0.002	0.001	-1.814	0.070	-0.001	0.000	-2.565	0.010
Relationship Duration * Motivational Nudges	-0.001	0.001	-1.707	0.088	0.000	0.000	0.491	0.623
Focus Congruence * Informational Nudges	-0.017	0.045	-0.387	0.698	-0.057	0.022	-2.619	0.009
Focus Congruence * Motivational Nudges	-0.071	0.046	-1.537	0.124	-0.073	0.025	-2.960	0.003
Control Variables								
Platform: iOS	-0.385	0.069	-5.592	0.000	0.609	0.045	13.579	0.000
Lagged Reward Messages	-0.043	0.036	-1.209	0.227	0.063	0.020	3.105	0.002
Other Communication	0.331	0.041	8.116	0.000	0.079	0.022	3.616	0.000
Apple Health	0.194	0.090	2.153	0.031	-1.574	0.064	-24.729	0.000

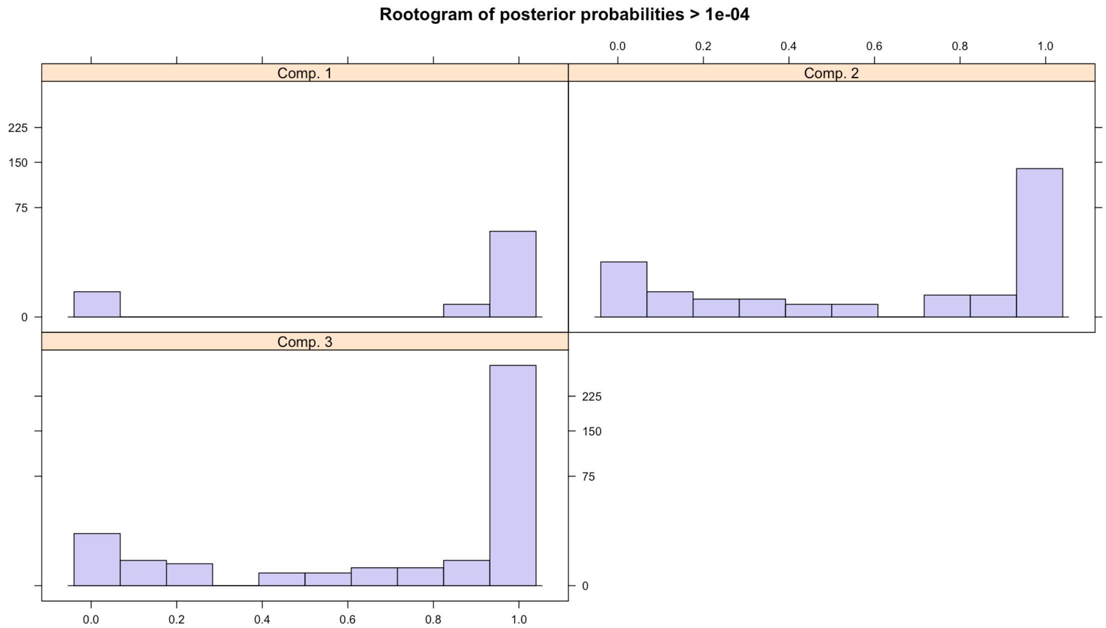
Device	-0.180	0.035	-5.135	0.000	0.370	0.010	36.543	0.000
Garmin	0.602	0.108	5.590	0.000	-0.989	0.063	-15.789	0.000
Fitbit	1.260	0.071	17.729	0.000	-0.985	0.061	-16.110	0.000
Google Fit	-0.680	0.103	-6.589	0.000	-0.701	0.086	-8.111	0.000
Gender: Male	0.792	0.039	20.174	0.000	-0.292	0.024	-12.149	0.000
Age	0.005	0.001	3.767	0.000	-0.002	0.001	-4.077	0.000
Segment 5 (14.0%)					**Segment 6 (11.1%)**			
	Estimate	**Std. Error**	**z value**	**p-value**	**Estimate**	**Std. Error**	**z value**	**p-value**
Main Effects								
Intercept	9.161	0.054	170.561	0.000	7.952	0.122	65.085	0.000
Informational Nudges	0.144	0.028	5.130	0.000	0.022	0.018	1.204	0.229
Motivational Nudges	-0.023	0.006	-3.554	0.000	0.000	0.004	-0.105	0.917
Informational Nudges^2	-0.347	0.033	-10.663	0.000	-0.099	0.025	-4.036	0.000
Motivational Nudges^2	0.080	0.012	6.457	0.000	0.042	0.011	3.862	0.000
Relationship Duration	0.001	0.000	1.705	0.088	0.000	0.000	-0.446	0.656
Focus Congruence	-0.277	0.032	-8.635	0.000	0.030	0.032	0.961	0.337
Interaction Effects								
Relationship Duration * Informational Nudges	0.000	0.001	0.399	0.690	-0.001	0.000	-2.457	0.014
Relationship Duration * Motivational Nudges	-0.001	0.000	-2.995	0.003	-0.001	0.000	-2.566	0.010
Focus Congruence * Informational Nudges	-0.085	0.028	-3.052	0.002	-0.084	0.019	-4.369	0.000
Focus Congruence * Motivational Nudges	0.162	0.031	5.213	0.000	0.005	0.025	0.206	0.837
Control Variables								
Platform: iOS	-0.705	0.069	-10.261	0.000	0.264	0.046	5.705	0.000
Lagged Reward Messages	0.050	0.024	2.101	0.036	-0.014	0.016	-0.836	0.403
Other Communication	0.143	0.027	5.324	0.000	0.053	0.017	3.103	0.002
Apple Health	0.789	0.084	9.410	0.000	-0.232	0.108	-2.146	0.032
Device	-0.983	0.023	-43.663	0.000	-0.150	0.017	-8.648	0.000
Garmin	0.125	0.093	1.348	0.178	0.102	0.114	0.894	0.371
Fitbit	1.347	0.056	24.186	0.000	0.405	0.110	3.672	0.000
Google Fit	0.204	0.076	2.680	0.007	1.052	0.123	8.576	0.000
Gender: Male	0.568	0.032	17.852	0.000	0.141	0.023	6.195	0.000
Age	-0.010	0.001	-8.001	0.000	0.014	0.001	12.746	0.000
Segment 7 (14.3%)					**Segment 8 (8.1%)**			
	Estimate	**Std. Error**	**z value**	**p-value**	**Estimate**	**Std. Error**	**z value**	**p-value**
Main Effects								
Intercept	7.261	0.149	48.715	0.000	7.276	0.679	10.712	0.000

Informational Nudges	0.046	0.058	0.793	0.428	-0.077	0.089	-0.874	0.382
Motivational Nudges	-0.016	0.012	-1.257	0.209	0.014	0.019	0.743	0.458
Informational Nudges^2	-0.244	0.079	-3.083	0.002	-0.591	0.139	-4.252	0.000
Motivational Nudges^2	0.180	0.041	4.447	0.000	0.506	0.087	5.839	0.000
Relationship Duration	0.007	0.001	6.447	0.000	-0.001	0.002	-0.486	0.627
Focus Congruence	-0.167	0.064	-2.629	0.009	0.616	0.120	5.133	0.000
Interaction Effects								
Relationship Duration * Informational Nudges	0.001	0.001	0.850	0.395	0.002	0.002	1.118	0.264
Relationship Duration * Motivational Nudges	-0.003	0.001	-2.810	0.005	-0.004	0.002	-1.952	0.051
Focus Congruence * Informational Nudges	-0.051	0.056	-0.918	0.359	-0.033	0.096	-0.342	0.732
Focus Congruence * Motivational Nudges	-0.020	0.067	-0.300	0.765	-0.247	0.117	-2.119	0.034
Control Variables								
Platform: iOS	0.660	0.100	6.582	0.000	0.555	0.200	2.780	0.005
Lagged Reward Messages	0.123	0.051	2.423	0.015	0.368	0.096	3.820	0.000
Other Communication	0.160	0.053	3.048	0.002	0.418	0.098	4.272	0.000
Apple Health	-0.631	0.115	-5.471	0.000	-1.995	0.620	-3.218	0.001
Device	0.238	0.053	4.477	0.000	0.846	0.099	8.522	0.000
Garmin	0.880	0.122	7.243	0.000	0.124	0.322	0.384	0.701
Fitbit	0.391	0.094	4.175	0.000	-0.374	0.637	-0.587	0.557
Google Fit	0.582	0.132	4.403	0.000	-1.104	0.661	-1.670	0.095
Gender: Male	-0.062	0.065	-0.942	0.346	3.317	0.229	14.455	0.000
Age	-0.004	0.002	-2.149	0.032	-0.012	0.003	-4.202	0.000

Exercise Model

Comparing the number of latent segments based on their goodness of fit suggests three segments to be appropriate. We visualize the segment membership for the exercise model in Figure A4.5 and provide the membership probabilities for each segment.

Figure A4.5 Goodness of Fit for Segmentation



Similar to the steps model, and perhaps even more pronounced, finite mixture model results in Table A4.4 exhibit a strong resemblance to the results from the original model in Table 4. For instance, all three segments dislike motivational nudges initially, but favor them at high frequencies in improving their exercise behavior, which echoes the finding from the original model. Although the first segment reiterates the findings from the original model where lower levels are helpful and higher levels are undesired, informational nudges have mixed results, with the results showcasing mostly insignificant coefficients for either the linear term or the squared term for the same segment. This outcome is not surprising since the effect size for these nudges in the main model is low.

As expected, relationship duration has little to no influence on step behavior show varying interaction effects. Focus congruence shows varying outcomes, where there is a positive relationship between the exercise focus and exercise outcome for the third segment

members while this effect is negative (although much smaller) for the second segment and is insignificant for the first one.

Considering focus congruence as a moderator, the consistent result across all segments is the negative interaction effects of motivational nudges and the positive interaction effects of informational nudges, which is identical to the original model. In summary, these mostly shared findings from both steps and exercise models serve as a tool to support the robustness of our original model despite the finite mixture model specification that deliberately forces these segments to be different from one another.

Table A4.2 – Results from the Finite Mixture Model (DV=Log of Exercise Minutes)

Segment 1 (25.3%)				
	Estimate	**Std. Error**	**z value**	**p-value**
Main Effects				
Intercept	-4.854	0.105	-46.351	0.000
Informational Nudges	0.078	0.034	2.338	0.019
Motivational Nudges	-0.219	0.043	-5.092	0.000
Informational Nudges^2	-0.018	0.008	-2.339	0.019
Motivational Nudges^2	0.098	0.016	6.095	0.000
Relationship Duration	0.001	0.001	1.528	0.127
Focus Congruence	-0.006	0.033	-0.168	0.866
Interaction Effects				
Relationship Duration * Informational Nudges	0.000	0.001	0.115	0.909
Relationship Duration * Motivational Nudges	-0.001	0.001	-1.060	0.289
Focus Congruence * Informational Nudges	0.132	0.030	4.346	0.000
Focus Congruence * Motivational Nudges	-0.361	0.036	-10.019	0.000
Control Variables				
Platform: iOS	-0.300	0.100	-3.011	0.003
Lagged Reward Messages	0.035	0.027	1.283	0.199
Other Communication	0.253	0.032	7.903	0.000
Apple Health	0.283	0.082	3.443	0.001
Device	8.176	0.032	258.398	0.000
Garmin	-0.172	0.119	-1.448	0.148
Fitbit	0.362	0.050	7.202	0.000

Google Fit	-7.755	0.173	-44.787	0.000
Gender: Male	-0.284	0.028	-9.997	0.000
Age	0.006	0.001	5.235	0.000
Segment 2 (44.9%)				
	Estimate	**Std. Error**	**z value**	**p-value**
Main Effects				
Intercept	3.554	0.221	16.070	0.000
Informational Nudges	0.109	0.088	1.245	0.213
Motivational Nudges	-0.212	0.114	-1.863	0.063
Informational Nudges^2	-0.080	0.018	-4.421	0.000
Motivational Nudges^2	0.143	0.040	3.547	0.000
Relationship Duration	-0.003	0.002	-1.700	0.089
Focus Congruence	-0.330	0.091	-3.630	0.000
Interaction Effects				
Relationship Duration * Informational Nudges	0.002	0.002	1.071	0.284
Relationship Duration * Motivational Nudges	-0.006	0.001	-3.974	0.000
Focus Congruence * Informational Nudges	0.862	0.081	10.674	0.000
Focus Congruence * Motivational Nudges	-0.431	0.092	-4.705	0.000
Control Variables				
Platform: iOS	0.026	0.130	0.201	0.841
Lagged Reward Messages	0.840	0.074	11.324	0.000
Other Communication	0.907	0.078	11.664	0.000
Apple Health	-0.804	0.165	-4.870	0.000
Device	-1.125	0.073	-15.398	0.000
Garmin	-0.816	0.162	-5.025	0.000
Fitbit	0.249	0.154	1.614	0.106
Google Fit	0.825	0.200	4.135	0.000
Gender: Male	0.625	0.075	8.320	0.000
Age	-0.068	0.002	-27.226	0.000
Segment 3 (29.8%)				
	Estimate	**Std. Error**	**z value**	**p-value**
Main Effects				
Intercept	-7.297	0.237	-30.804	0.000
Informational Nudges	0.076	0.074	1.031	0.303
Motivational Nudges	-0.538	0.096	-5.594	0.000
Informational Nudges^2	-0.037	0.015	-2.391	0.017
Motivational Nudges^2	0.219	0.036	6.101	0.000
Relationship Duration	-0.001	0.001	-0.559	0.576
Focus Congruence	1.863	0.078	23.914	0.000

Interaction Effects				
Relationship Duration * Informational Nudges	-0.001	0.001	-0.968	0.333
Relationship Duration * Motivational Nudges	0.000	0.001	0.056	0.956
Focus Congruence * Informational Nudges	0.325	0.065	5.011	0.000
Focus Congruence * Motivational Nudges	-0.933	0.070	-13.335	0.000
Control Variables				
Platform: iOS	0.856	0.159	5.372	0.000
Lagged Reward Messages	-0.011	0.056	-0.187	0.851
Other Communication	0.251	0.064	3.901	0.000
Apple Health	0.255	0.155	1.648	0.099
Device	-0.979	0.064	-15.259	0.000
Garmin	2.312	0.186	12.431	0.000
Fitbit	0.023	0.121	0.191	0.848
Google Fit	4.876	0.179	27.195	0.000
Gender: Male	-1.359	0.067	-20.382	0.000
Age	0.151	0.002	64.007	0.000

Appendix B. Density Plots of Nudges and Residuals

Figure B1. Density of informational and motivational nudges against the normal distribution

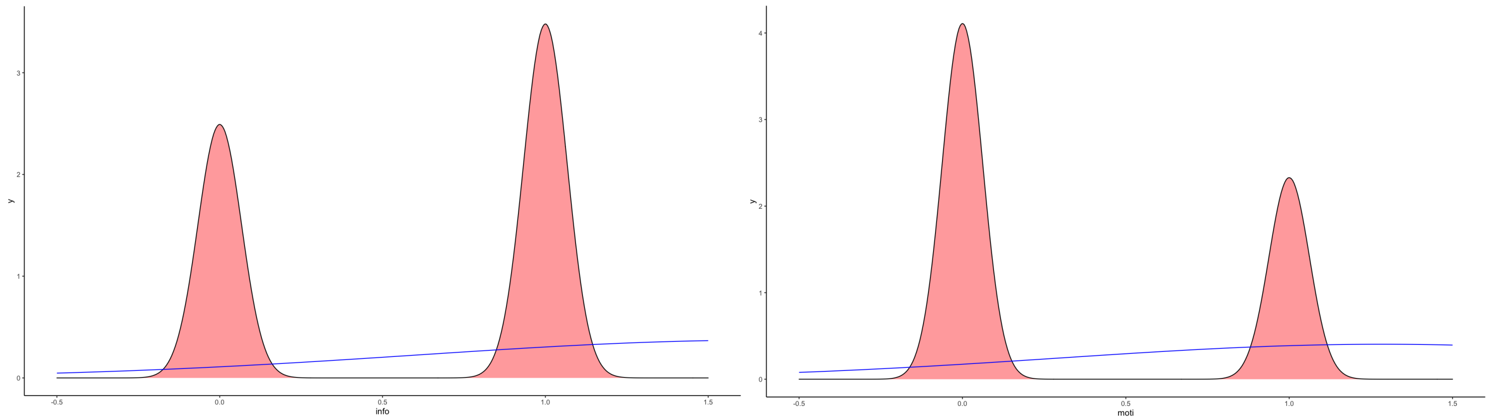
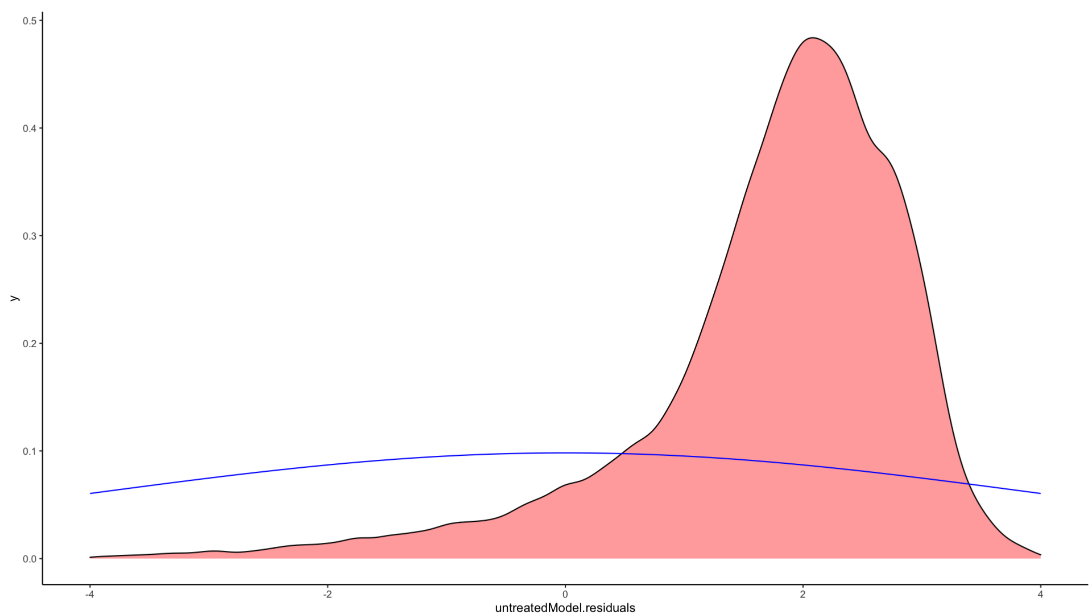


Figure B2. Distribution of the residuals of the steps model



Appendix C. Supporting Material for the Main Model

Figure C1. Histograms for Step Count and Logarithmic Transformed Step Count

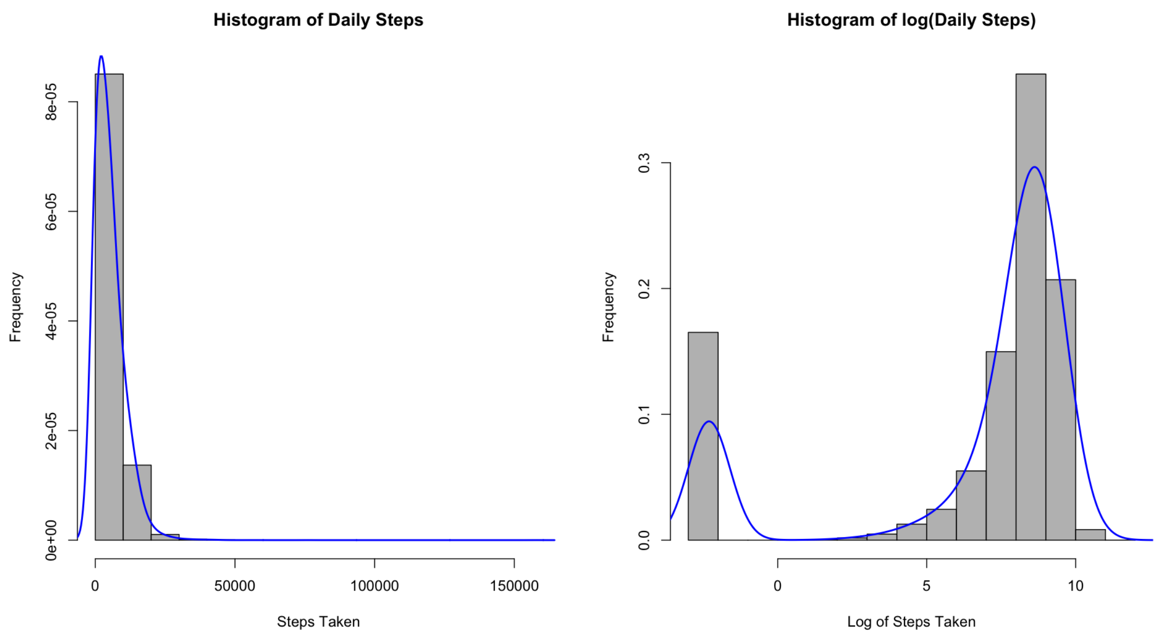
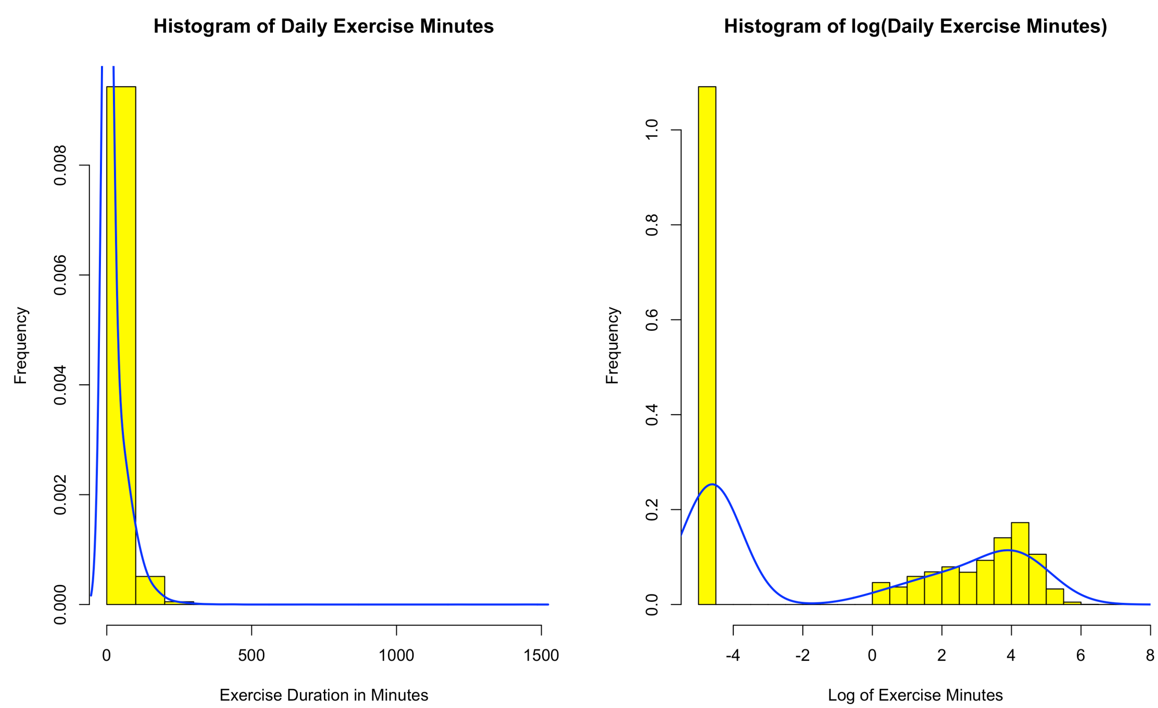


Figure C2. Histograms for Exercise Minutes and Logarithmic Transformed Exercise Minutes



Appendix D. Monte Carlo Markov Chain Plots

Figure D1. Trace and Density Plots of Pareto/GGG Model

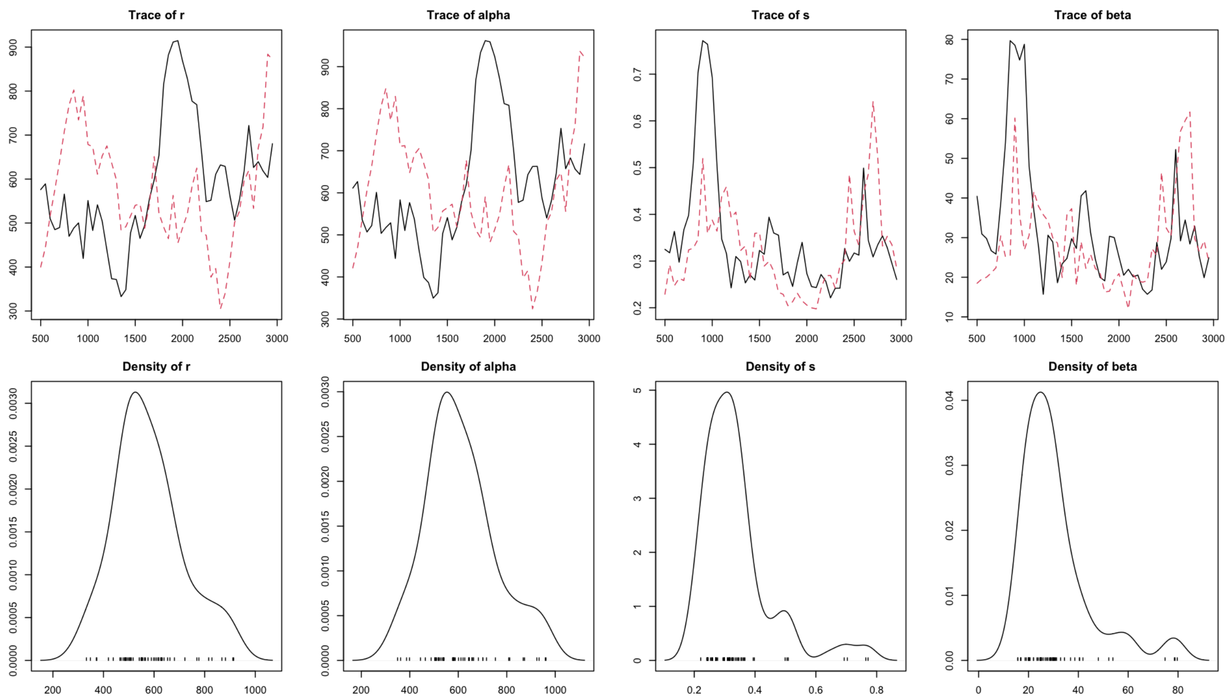


Figure D2. Model Fit for Pareto/GGG