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Essays on Motivations and Motivational Affordances in the Context of Health Information Technology

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ESSAYS ON MOTIVATIONS AND MOTIVATIONAL AFFORDANCES IN THE CONTEXT OF HEALTH INFORMATION TECHNOLOGY

BY

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ACCEPTANCE

This dissertation was prepared under the direction of the Hyoungyong Choi'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

ESSAYS ON MOTIVATIONS AND MOTIVATIONAL AFFORDANCES IN THE CONTEXT OF HEALTH INFORMATION TECHNOLOGY

BY

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Despite the tremendous potential of health information technology (HIT) not only to improve the health and well-being of people but also to solve current problems within the health care system, prior research on HIT has provided only limited insights into the behavioral mechanisms behind why people embrace or reject HIT. Given that the benefits of HITs can only be realized when people use them, the examinations of these mechanisms are critical to promote healthy behaviors and improve health outcomes. Therefore, given the importance of understanding these mechanisms as well as the scarcity of research in this area, this dissertation intends to advance IS knowledge by empirically investigating behavioral mechanisms of how individuals' motivational characteristics influence HIT related behaviors. Specifically, as an overarching behavioral mechanism, this dissertation theorizes that the fit between individuals' motivations and the technological properties of IS that are designed to fulfill these motivations (i.e., motivational affordances) encourages individuals to use HIT.

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CHAPTER 1

Introduction

1.1. Motivation and Objective of Dissertation

While health and well-being are of central importance to individuals, many people in the United States are not as healthy as they should be (Agarwal et al. 2010). While the fraction of GDP spent on healthcare is higher in the U.S. than in any other developed nation, citizens suffer because of the low accessibility and high costs of health care services. Medical errors are also a major problem; over 400,000 Americans died in 2013 as a result of such errors (Makary and Daniel 2016).

Against this background, health information technology (HIT) has a tremendous potential not only to improve the health and well-being of people but also to solve current problems within the health care system (Agarwal et al. 2010; Silva et al. 2015). For example, Computerized Provider Order Entry (CPOE), which is "an order entry application specifically designed to assist practitioners in creating and managing medical orders for patient services and medications" (Information and Society 2017, p.54), provides a solution for medical errors by reducing miscommunication between healthcare professionals (Carli et al. 2018; Niazkhani et al. 2009; Prgomet et al. 2016). Additionally, activity trackers, wearable devices that monitor user-generated physical activity data, allow people to focus on their daily physical activity and practitioners to implement IT-enabled physical activity interventions that deliver more interactive, automated, and personalized interventions to increase people's physical activity (Harrison et al. 2015). However, despite these tremendous potentials of HIT, prior research on HIT has provided only limited insights into the behavioral mechanisms behind why people embrace or reject HIT. Given that the benefits of HITs can only be realized when people use them (Buntin et al. 2011), the examinations of these mechanisms are critical to promote healthy behaviors and improve health outcomes. Therefore, given the importance of understanding these mechanisms as well as the scarcity of research in this area, this dissertation intends to advance IS knowledge by examining these mechanisms.

Specifically, this dissertation theorizes that the fit between individuals' motivations and the technological properties that are designed to fulfill these motivations (i.e., motivational affordances) is central to understanding why people embrace or reject HIT. Motivation is a value-based inner urge that guides human behavior in response to the environment, leading to the intentional fulfillment of desired goals (Moody and Pesut 2006). Because motivations are critical factors directly guiding human behaviors, motivation has been one of the main research topics of social science researchers. Accordingly, previous IS research has examined how intrinsic motivators, such as personal innovativeness, influence IS-related human behaviors. However, despite the increasing importance of HIT, the influence of individuals' motivations on HIT related human behaviors remain understudied. Additionally, few studies have examined how interactions between individuals' motivational characteristics and unique motivational affordances of HITs (Zhang 2007; Zhang 2008) influence human behaviors. Thus, previous research has not provided theoretical explanations or practical insights on critical questions such as how do the properties of a particular HIT differentially appeal to users with different motivational needs?, what are the conditions under which effective engagement with a particular HIT occurs?, and how do the motivational affordances of HITs influence human behaviors? This dissertation seeks to answer these questions. Behavioral mechanisms that will be theoretically explained and empirically validated in this dissertation can contribute to both IS theory and practice by showing how current issues in healthcare can be effectively addressed by HIT and how HIT can be used to promote healthy behaviors.

1.2. Overview of Three Empirical Essays

This dissertation encompasses three empirical research essays. In this section, I present a brief introduction of each essay. Table 1-1 presents an outline for the three essays that comprise this dissertation.

Table 1-1. Outline of Research Essays

Research Essay Title	Methodology	Theoretical Background	Context
Chapter 2 "How Doctors' and Nurses' Motivations Shape Perceptions of System Benefits and Resistance to CPOE"	Longitudinal Survey	Motivation literature/ Motivational Affordance literature	Computerized Provider Order Entry
Chapter 3 "Motivating Use of Smartwatch Health Promotion and Health Prevention Applications: A Regulatory Fit and Locus of Control Perspective"	Lab Experiment	Regulatory Focus Theory	Smartwatch Health App
Chapter 4 "Motivating Increased Physical Activity: An Examination of Social Comparison Mechanism"	Field Experiment	Social Comparison Theory/ Self-Determination Theory	Activity Trackers

1.2.1. Essay One

The first essay (Chapter 2) is a longitudinal survey of healthcare professionals (doctors and nurses) working in a hospital setting. Drawing on the motivational affordance lens, Essay 1 examines how system benefits associated with computerized provider order entry (CPOE) mediate the influence of doctors' and nurses' motivations on resistance to CPOE. Specifically, this essay suggests that healthcare professionals' motivation for healthcare quality and motivation for efficiency in the delivery of healthcare positively influence their perceptions of system benefits (Hoonakker et al. 2012; Kruse and Goetz 2015), which in turn reduces their resistance to CPOE. Further, this study examines how resistance changes over time, as well as role-based differences in resistance between doctors and nurses.

1.2.2. Essay Two

The second essay (Chapter 3) is a web-based experiment conducted via Amazon Mechanical Turk. Drawing on regulatory focus theory, Essay 3 examines how the regulatory fit between smartwatch health apps and individuals motivates the use of such apps and how the effect of this fit is moderated by individuals' motivational strength toward engaging in health behavior (i.e., internal health locus of control). Specifically, this essay suggests that a good fit between individuals' motivational characteristics (i.e., promotion focus, prevention focus) and the properties of smartwatch health apps (i.e., promotion app, prevention app) motivates individuals to use the apps. Also, given that smartwatch health apps rely on self-management, this essay suggests that internal health locus of control strengthens the effect of this fit.

1.2.3. Essay Three

The third essay (Chapter 4) is an 8-week randomized field experiment (one-week baseline, four-week treatment, and three-week follow-up) designed to test an IT-enabled intervention that was developed to help inactive people become more active. Drawing on social comparison theory, Essay 3 examines the effect of IT-enabled social comparison on physical activity and the condition under which effective engagement and behavior change occur through IT-enabled social comparison. Specifically, this essay suggests that intrinsic motivation for using activity tracking software strengthens the effect of IT-enabled social comparison on physical activity. Further, this study examines whether: 1) the influence of IT-enabled social comparison treatment on physical activity is maintained without treatment, and 2) the theorized relationships among constructs hold for both objective and subjective measures of physical activity. Our findings suggest that the use of activity trackers[1] in combination with IT-enabled social comparison can change participants' physically inactive lifestyle into a more active lifestyle.

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[1] Activity trackers are wearable devices that monitor and display user-generated data regarding the user's daily movement such as the number of steps taken and distance covered. In this study, activity trackers (i.e., Fitbit) are used to deliver intervention and measure objective physical activity.

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CHAPTER 2

Research Essay 1

How Doctors' and Nurses' Motivations Shape Perceptions of System Benefits and Resistance to CPOE

2.1. INTRODUCTION

Medical errors, one of the most important quality criteria of healthcare, not only increase healthcare costs and lead to longer hospital stays but also threaten patients' lives, causing over 400,000 deaths in 2013 in the United States (Kohn, Corrigan, & Donaldson, 2000; Makary & Daniel, 2016; Prgomet, Li, Niazkhani, Georgiou, & Westbrook, 2016). Computerized Provider Order Entry (CPOE) is considered to be a solution for medical errors by reducing potential miscommunication between healthcare professionals (Carli, Fahrni, Bonnabry, & Lovis, 2018; Niazkhani, Pirnejad, Berg, & Aarts, 2009; Prgomet et al., 2016). Specifically, in their systematic review studies, Prgomet et al. (2016)) showed that CPOE reduced medical prescribing error rates by 85% in intensive care units and Shamliyan, Duval, Du, and Kane (2008) reported that 80% of CPOE studies found a significant reduction in prescribing errors. Also, the nature of CPOE is to establish a systematic and automated healthcare process; thus, CPOE improves order completeness, reduces the time for processing an order, and improves data accessibility (Baysari, Hardie, Lake, Richardson, McCullagh, Gardo et al., 2018; Bhattacherjee, Davis, Connolly, & Hikmet, 2018; Hoonakker, Carayon, Brown, Cartmill, Wetterneck, & Walker, 2012; Niazkhani et al., 2009). Therefore, CPOE serves as a solution to improve quality and efficiency in the delivery of healthcare (Hoonakker et al., 2012; Kruse & Goetz, 2015). Despite the potential benefits of CPOE, many attempts to implement CPOE in hospitals have been confronted with high levels of resistance from healthcare professionals (Hoonakker et al., 2012). Because healthcare professionals' resistance to CPOE can potentially lead to CPOE implementation failure, understanding the mechanism of resistance to CPOE is critical for establishing effective implementation strategies to reduce healthcare professionals' resistance and ensure CPOE implementation success.

Because user resistance is a critical factor affecting IS implementation (Lapointe & Rivard, 2005; Lin, Huang, & Chiang, 2018), many studies have examined the causes of users resistance (Ali, Zhou, Miller, & Ieromonachou, 2016; Bhattacherjee et al., 2018; Klaus & Blanton, 2010; Laumer, Maier, Eckhardt, & Weitzel, 2016a; Lin et al., 2018; Martinko, Zmud, & Henry, 1996; Selander & Henfridsson, 2012; Xue, Liang, Mbarika, Hauser, Schwager, & Getahun, 2015; Zmud, 1979) as well as the mechanism of resistance (Joshi, 1991; Kim & Kankanhalli, 2009; Lapointe & Rivard, 2005; Markus, 1983). However, to explain resistance, these previous studies focused on the changes triggered by new IS (i.e., in routines, power, autonomy, etc.) and how such changes affect users' perceptions (i.e., inequity, threat, etc.). While valuable, prior work provides little or no insight as to how users' motivations along with the properties of the IS that fulfill users' motivational needs (i.e., motivational affordances) influence resistance to IS. Given that healthcare professionals' resistance to CPOE occurs when CPOE does not fulfill their motivational needs (Bhattacherjee et al., 2018; Hoonakker et al., 2012), it is necessary to examine the mechanism of how the fit between healthcare professionals' motivational needs and the motivational affordances of CPOE affects resistance to CPOE. The examination of this mechanism has critical implications for both IS theory and IS practitioners.

First, individuals' motivations are critical factors that directly guide their behavior (Moody & Pesut, 2006); thus, the role of motivations in the resistance mechanism must be examined to advance our knowledge about resistance to IS. Second, understanding the impacts of motivations on resistance enables IS practitioners to establish effective implementation strategies that reduce users' resistance by fulfilling their motivational needs. Third, even though IS are designed to have motivational affordances, there has been little research concerning the motivational needs of users that should be fulfilled by such affordances. Understanding how motivational affordances influence individuals' behaviors could enable IS practitioners to develop and implement systems that so as to minimize resistance, thereby helping them to achieve organizational goals. Thus, given the importance of understanding the resistance mechanism as well as the scarcity of research in this area, this study intends to advance IS knowledge of this issue.

Drawing on the motivational affordance literature (Zhang, 2007, 2008) that explains how individuals' motivational needs influence their perceptions of technologies, which in turn lead to behavioral intentions, we suggest a new resistance mechanism: healthcare professionals' motivations that are fulfilled by motivational affordances of CPOE influence them to perceive CPOE as beneficial (i.e., perceived system benefit), reducing their resistance to CPOE. Specifically, we argue that healthcare professionals' motivation for healthcare quality and motivation for efficiency in the delivery of healthcare best reflect the essential values that guide their behaviors in healthcare settings and that these two motivations are fulfilled by the motivational affordances of CPOE that is aimed at improving both healthcare quality and efficiency (Hoonakker et al., 2012; Kruse & Goetz, 2015). Therefore, healthcare professionals' high motivation for healthcare quality and efficiency, respectively, may positively influence their perceptions of system benefits associated with CPOE, which in turn may reduce their resistance to CPOE.

To further contribute to IS theory and practice, we examine how the resistance mechanism manifests differently for doctors and nurses as well as how the resistance mechanism changes over time. Despite the fact that a new IS brings changes (e.g., power, autonomy, routine, etc.) (Markus, 1983) and that users' assessments of these changes may differ depending on their roles (Lapointe & Rivard, 2005), few studies have examined role-based patterns of resistance to IS. Given that doctors and nurses have different roles and interact differently with CPOE, that doctors and nurses are satisfied with different aspects of CPOE, and that nurses are more positive about CPOE than doctors (Hoonakker et al., 2012), the patterns of resistance may be different between doctors and nurses. Further, despite the temporal nature of the resistance phenomenon (Lapointe & Rivard, 2005), previous research on resistance to IS has mostly adopted a cross-sectional approach, and thus offers no explanation as to how the resistance mechanism changes over time. By adopting a longitudinal approach, we show the changes in the resistance mechanism that occur over time. Understanding role-based differences in the resistance mechanism and how this plays out over time not only advances IS theory on resistance but also is critical to IS practitioners in establishing effective implementation strategies to reduce resistance. Motivated by this line of thinking, we seek to address the following research questions:

RQ1: How do motivational affordances of CPOE and healthcare professionals' motivation for quality and motivation for efficiency influence resistance to CPOE?

RQ2: How does the resistance mechanism manifest differently for doctors and nurses?

RQ3: How does the mechanism of resistance change over time?

To answer these research questions, we conducted a longitudinal study of a CPOE implementation in which we surveyed both doctors and nurses at three different point in time: pre-implementation (T0), 3-months post-implementation (T1), and 6-months post-implementation (T2).

2.2. THEORETICAL BACKGROUND

This section provides an overview of prior research on resistance to IS and Health Information Systems, CPOE system benefit, and health professionals' motivations and motivational affordance.

2.2.1. Resistance to Information Systems and Health Information Systems

Conceptualized as the opposition to changes triggered by new IS implementation (Kim & Kankanhalli, 2009), user resistance has been considered as a critical factor influencing IS implementation failures (Kim & Lee, 2016; Lapointe & Rivard, 2005; Lin et al., 2018). Prior research has examined resistance from different points of view including the IS itself, the people who use the system, the interaction of the IS and its use context, and the organization (Ali et al., 2016; Markus, 1983). The system-oriented approach considers technology-related factors as the cause of resistance, including poor system design, incompatibility, and complexity (Ali et al., 2016; Klaus & Blanton, 2010; Lin et al., 2018; Markus, 1983). The people-oriented approach posits that the resistance occurs because of factors internal to IS users, including personal dispositions, self-efficacy, preference for routine, and cynicism (Ali et al., 2016; Laumer et al., 2016a; Markus, 1983; Selander & Henfridsson, 2012; Zmud, 1979). The interaction-oriented approach suggests that resistance results from loss of power and autonomy generated by the interaction between information systems and the social context of system use (Ali et al., 2016; Bhattacherjee et al., 2018; Markus, 1983; Xue et al., 2015). Also, organizational factors such as transition support and social influence were found to affect resistance (Klaus & Blanton, 2010; Lin et al., 2018; Martinko et al., 1996).

The most cited models of resistance to IS include the equity-implementation model (Joshi, 1991), the interaction model (Markus, 1983), the multilevel model of resistance (Lapointe & Rivard, 2005), and the status quo bias model (Kim & Kankanhalli, 2009) (Lin et al., 2018). Relying on equity theory, Joshi (1991)) proposed that users resist when they perceive inequity brought about by IS implementation. Markus (1983)) argued that new IS bring changes to the power relationships and social structure of an organization, causing some users to perceive diminished power which leads to resistance. Lapointe and Rivard (2005)) suggested that users assess the interaction between the features of an IS and initial conditions such as their social values or routine and that users' projections about the consequences of IS use lead to resistance if the expected consequences are threatening. Additionally, they argued that the experience of system use modifies initial conditions (e.g., changed routine), recursively triggering the next assessment of interaction. Drawing on status quo bias theory, Kim and Kankanhalli (2009)) proposed a model in which switching costs (i.e., time and effort required to adapt to new IS) directly and indirectly increase user resistance, and switching benefits indirectly decreases user resistance.

In the context of health information systems implementation, user resistance is also seen as a critical factor influencing implementation failures (Bhattacherjee et al., 2018; Bhattacherjee & Hikmet, 2007; Doolin, 2004; Hoonakker et al., 2012; Hsieh, 2015; Hung, Tsai, & Chuang, 2014; Lapointe & Rivard, 2005; Plumb, Hains, Parr, Milliss, Herkes, & Westbrook, 2017; Xue et al., 2015; Yu, Zhang, Gong, & Zhang, 2013) despite the promising benefits of health information technologies in increasing healthcare quality and efficiency (Hung et al., 2014; Venkatesh, Zhang, & Sykes, 2011). One of the major barriers of IS implementation in the healthcare context is the change of work routines that potentially leads to lack of time, intense workload, and unfavorable workflow (Hoonakker et al., 2012; Hsieh, 2015; Østervang, Vestergaard, Dieperink, & Danbjørg, 2019; Plumb et al., 2017; Yu et al., 2013). Laumer, Maier, Eckhardt, and Weitzel (2016b)) found that changes in work routine increased user resistance when the new work routine was not useful. Also, they argued that work routine is a stronger factor on user resistance than technology-related factors (i.e., usefulness and ease of use). The major direct factor influencing resistance to health information systems is perceived threat as suggested by Lapointe and Rivard (2005)) in their multilevel model of resistance, (Bhattacherjee et al., 2018; Doolin, 2004; Hsieh, 2015; Lapointe & Rivard, 2005; Plumb et al., 2017; Xue et al., 2015). However, the mechanisms that lead to the threat perception seem to be much more complex in the context of health information systems implementation than in the non-healthcare setting because the managerial logic (e.g., efficiency) embedded in health information systems affect the traditional healthcare hierarchy. Specifically, doctors have exercised power and autonomy due to their medical knowledge (Plumb et al., 2017) as shown in the healthcare routine that nurses take orders from doctors. However, health information systems such as CPOE require doctors to perform some tasks (e.g., order entry) that have traditionally been performed by nurses or clerks, leading to decreased power and autonomy of doctors. As such, these systems can represent a threat to doctors (Bhattacherjee et al., 2018; Plumb et al., 2017).

In the healthcare setting, the complex mechanisms leading to threat perception are also engendered by the conflict between the nature of health information systems and healthcare professionals' motivational characteristics. For example, when doctors are requested to use health information systems they can perceive this request as a threat because the standardized healthcare engendered by health information systems sometimes conflicts with their role relevant motivation for delivering high quality healthcare (Bhattacherjee et al., 2018; Plumb et al., 2017). More specifically, the nature of health information systems implementation is to establish a systematic healthcare process that is standardized and automated (Hook & Cusack, 2008) to improve healthcare quality; however, doctors may consider that high quality healthcare can only be realized through application of their accumulated tacit knowledge which cannot be standardized within health information systems (Plumb et al., 2017). Therefore, when doctors confront conditions in which they must use health information systems that prevent them from using their best logic of medical care, they may perceive the conditions as threats to their nonnegotiable identity as healthcare providers (Bhattacherjee et al., 2018; Lapointe & Rivard, 2005; Plumb et al., 2017). One interesting point here is that this mechanism that leads to doctors' threat perception may not be applicable to nurses. Even though both doctors and nurses have a motivation to provide quality healthcare to the patient, their respective roles in the delivery of healthcare are quite different, with the doctor being responsible for diagnosis and coming up with a plan of care and the nurse being responsible for helping to implement that plan and providing care to the patient.

While little research has examined the different patterns of resistance associated with role differences, previous research has shown role-based differences in terms of the patterns of attitudes that exist toward health information systems. For example, Hoonakker et al. (2012)) showed that nurses are more satisfied than doctors with the improved readability of orders and efficiency of the ordering processes that result from CPOE.

2.2.2. CPOE System Benefit

CPOE is "an order entry application specifically designed to assist practitioners in creating and managing medical orders for patient services and medications" (Information & Society, 2017, p.54). While paper-based order-management relies on doctors' handwritten orders and in-person communications that can lead to medication errors through possible miscommunications, CPOE requires doctors to directly enter medical orders into hospital computers (or via the web) and enables healthcare professionals to access the order information at any time via computer interface. CPOE also improves clinician-clinician interaction by enabling real time communications between clinicians in different departments and locations (e.g., outside of hospitals) via computer interface, which provides the relevant clinical information they need to communicate effectively; increases consistency of treatment protocols by promoting the use of standard order sets that reflect best practices; increases the completeness of orders by encouraging users to enter complete orders into the systems; and reduces the time for processing an order by electronically transferring orders to the right people (e.g., nurses, radiology technicians, phlebotomists, pharmacists, etc.) in the right medical units (Bates, Teich, Lee, Seger, Kuperman, Ma'Luf et al., 1999; Hoonakker et al., 2012; Kruse & Goetz, 2015; Niazkhani et al., 2009; Romanow, Rai, & Keil, 2018; Romanow, Rai, Keil, & Luxenberg, 2017; Electronic Health Record Incentive Program – Stage 2, Final Rule. 2012). Additionally, CPOE provides clinical decision support in the form of alerts for drug allergies, drug-drug interactions, and duplicate orders (Hoonakker et al., 2012). An often touted benefit of CPOE is that it reduces medical errors (Carli et al., 2018; Hillestad, Bigelow, Bower, Girosi, Meili, Scoville et al., 2005; Electronic Health Record Incentive Program – Stage 2, Final Rule. 2012; Hoonakker et al., 2012; Kruse & Goetz, 2015; Kuperman & Gibson, 2003; Prgomet et al., 2016; Romanow et al., 2018; Romanow et al., 2017). In sum, CPOE can improve quality and efficiency in the delivery of healthcare (Hoonakker et al., 2012; Kruse & Goetz, 2015).

While CPOE is designed to provide benefits, previous research showed that healthcare professionals perceive the CPOE carries both benefits and drawbacks (Baysari et al., 2018; Bhattacherjee et al., 2018; Hoonakker et al., 2012; Niazkhani et al., 2009). As shown in Table 2-1, healthcare professionals' perceptions of the benefits associated with CPOE are mostly consistent with the intended benefits of CPOE (i.e., improvement of healthcare quality and efficiency). On the other hand, perceived drawbacks are mostly related to efficiency issues engendered by new IS implementation. Specifically, in their systematic review, Kruse and Goetz (2015)) showed that the "process change" brought about by CPOE implementation is the most frequently voiced drawback and that the "high level of training required" is the second most frequently mentioned drawback of CPOE. To further understand how these benefits and drawbacks affect resistance, we need to understand the unique motivational characteristics of healthcare professionals.

Table 2-1. Perception for System Benefits and Drawbacks of CPOE

Perceptions	Contents	Criteria		References
		Q[1]	E[2]	
Benefits	Readability ↑	×		Ho[3] (D[4],N[5]), Ba[6] (D,N)
	Medication errors ↓	×		Ho (D,N), Bh (D)[8]
	Order completeness ↑	×		Ho (D,N),
	Duplicate orders ↓	×		Ho (D,N)
	Speeding up process		×	Ho(D,N), Bh(D), Ni(D, N)
	(Remote) data accessibility		×	Ho (D,N), Ba(D,N) Bh(D), Ni[7](D)
	Speeding up data finding		×	Ho (D, N), Bh(D), Ni(D)
	Order sets (eliminate tedium)		×	Ho (D), Bh(D)
Drawbacks	Process change		×	Kr[9], Ba (D,N), Bh(D), Ni (D)
	High level of training		×	Kr, Ba (D)
	System complexity		×	Kr, Ho (D,N), Bh(D), Ni
	Time-consuming		×	Ho(D,N), Ba(D,N), Bh(D), Ni(D)
	Reduced autonomy			Bh(D), Ni (D)
	Reduced power			Bh(D), Ni (D)
	Order sets (low usability)	×		Bh(D)

1. Quality of healthcare
2. Efficiency in healthcare delivery
3. Hoonakker et al. (2012): cross-sectional survey for end-user (doctors and nurses) satisfaction with CPOE
4. Doctors
5. Nurses
6. Baysari et al. (2018): qualitative analysis for the user (doctors and nurses) experience of CPOE
7. Niazkhani et al. (2009): a systematic literature review for the impact of CPOE on inpatient clinical workflow
8. Bhattacherjee et al. (2018): qualitative analysis for the user (doctors) response to CPOE
9. Kruse and Goetz (2015): a systematic literature review for the barriers to adoption of CPOE

2.2.3. Healthcare Professionals' Motivations and Motivational Affordance of CPOE

Motivation is a value-based and "stimulus-driven inner urge that activates and guides human behavior in response to self, other, and environment, supporting intrinsic satisfaction and leading to the intentional fulfillment of human drives, perceived needs, and desired goals" (Moody & Pesut, 2006, p.17). Because healthcare professionals' work motivation affects their intention to perform duties and ultimately influences healthcare system performance, prior research on healthcare professionals' motivation has focused on examining the factors that influence their work motivation, including incentives, competition, education, promotion, recognition from superiors, social interaction, cooperation, self-esteem, and feeling of belonging (Dieleman, Gerretsen, & van der Wilt, 2009; Henderson & Tulloch, 2008; Okello & Gilson, 2015; Willis-Shattuck, Bidwell, Thomas, Wyness, Blaauw, & Ditlopo, 2008). However, most of these studies relied on the general concept of work motivation; that is "the degree to which a person wants to work well in his or her job, in order to achieve intrinsic satisfaction" (Warr, Cook, & Wall, 1979, p.133), and thus failed to address the unique motivational characteristics of healthcare professionals that necessarily reflect their values for delivering high-quality healthcare (Moody & Pesut, 2006; Toode, Routasalo, & Suominen, 2011). Given that delivering high-quality healthcare to the patient is a prime goal of healthcare, we argue that motivation for quality is a more concrete and context-specific construct for examining healthcare professionals' motivation, because it not only reflects an essential value that healthcare professionals often espouse but is also directly associated with one of the key goals of the healthcare sector. Another important motivation that is relevant to healthcare professionals is the motivation for efficiency. Faced with a large number of patients, healthcare professionals have difficulty simultaneously achieving both healthcare quality and efficiency in their work (Farr & Cressey, 2015). However, improving both quality and efficiency in the delivery of healthcare is important for both healthcare professionals and healthcare organizations (Agarwal, Gao, DesRoches, & Jha, 2010; Craig, Thatcher, & Grover, 2019). Thus, both quality and efficiency motivations are likely to guide the behaviors of healthcare professionals. This study defines *motivation for quality* as a healthcare professional's desire to provide a high quality of healthcare to the patient and *motivation for efficiency* as a healthcare professional's desire to do their work efficiently in the delivery of healthcare.

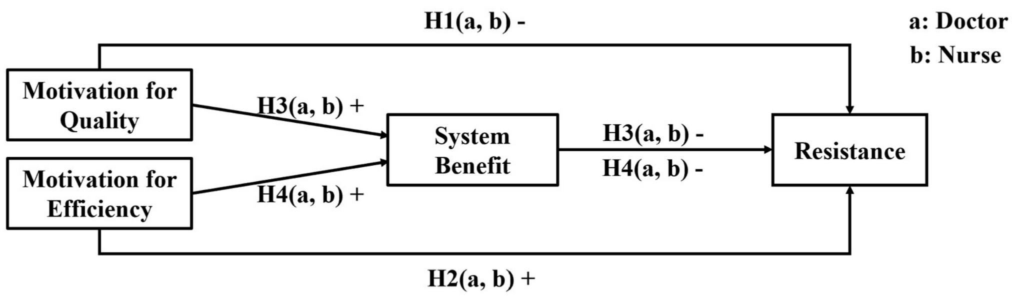
While healthcare professionals experience some tension between quality and efficiency (Farr & Cressey, 2015), CPOE is designed to help them achieve both and to enable healthcare organizations to do the same (Hoonakker et al., 2012; Kruse & Goetz, 2015). As described earlier, the properties of the CPOE system fulfill healthcare professionals' motivational needs for healthcare quality and efficiency in their work. These properties are conceptualized as motivational affordances (Feng, Ye, Yu, Yang, & Cui, 2018; Islam, Mäntymäki, & Benbasat, 2019; Jung, Schneider, & Valacich, 2010; Zhang, 2008). Affordances are actionable possibilities existing in the environment that allow humans to take actions that may fulfill certain needs (Gibson, 1977; Norman, 1988). Zhang (2008) argued that when a technology has motivational affordances, which are the technology's properties that support users' motivational needs, users feel interested in the technology and will use it. Thus, given the theoretical mechanism of motivational affordances, a user may perceive greater benefits of IS when the benefits are aligned with their motivations. However, our review of the literature reveals that the role played by motivational affordances of IS in the resistance mechanism is unclear, leading us to focus our model development and hypotheses to understand this role.

2.3. MODEL DEVELOPMENT AND HYPOTHESES

In this section, we present our research model (Figure 2-1) and the corresponding hypotheses that we posit. In the context of CPOE implementation, healthcare professionals' motivation for quality (i.e., desire for high quality healthcare) and motivation for efficiency (i.e., desire for efficiency in healthcare delivery) are important because these two motivations best reflect healthcare professionals' essential values that guide their behaviors in healthcare settings

(Moody & Pesut, 2006). Given that CPOE is designed to fulfill healthcare professionals motivational needs for quality and efficiency in the delivery of healthcare (Hoonakker et al., 2012; Kruse & Goetz, 2015), healthcare professionals' motivation for quality and motivation for efficiency may influence resistance to CPOE. However, we expect that motivation for quality and motivation for efficiency would have differential effects on resistance to CPOE. Specifically, we suggest that healthcare professionals' motivation for quality will reduce their resistance to CPOE both directly (i.e., direct effect) and indirectly (indirect effect via system benefit); on the other hand, motivation for efficiency will directly increase resistance to CPOE but indirectly reduce resistance via system benefit.

Figure 2-1. Research Model



2.3.1. Direct Effect of Motivation for Quality

Looking at the direct effects of motivation of quality on resistance to CPOE, previous research has shown that the consensus among doctors and nurses is that CPOE improves healthcare quality by reducing medication errors, adverse drug events, etc. (Baysari et al., 2018; Bhattacherjee et al., 2018; Hoonakker et al., 2012; Niazkhani et al., 2009). Therefore, an individual doctor or a nurse who values healthcare quality may have a low intention to resist CPOE, because accepting CPOE fulfills his/her motivational needs for delivering high quality healthcare. In other words, a doctor or a nurse with high motivation for quality may show lower resistance to CPOE than a doctor or a nurse with low motivation for quality. Thus, we hypothesize that:

Hypothesis 1a (H1a): For doctors, motivation for quality will reduce resistance to CPOE.

Hypothesis 1b (H1b): For nurses, motivation for quality will reduce resistance to CPOE.

2.3.2. Direct Effect of Motivation for Efficiency

While many previous studies have shown a consensus among healthcare professionals that CPOE improves work efficiency by providing system benefits such as shortened order processing time and increased (remote) data accessibility, some studies have reported that CPOE decreases work efficiency by changing routines (Baysari et al., 2018; Bhattacherjee et al., 2018; Hoonakker et al., 2012; Kruse & Goetz, 2015; Niazkhani et al., 2009). Therefore, healthcare professionals may perceive two different aspects of CPOE that have opposite effects on their work efficiency. We propose two mechanisms for the effect of motivation for efficiency on resistance to CPOE. One is the mechanism in which motivation for efficiency is reflected in perceived system benefits that lead to reduced resistance (i.e., mediation of system benefit for the effect of motivation for efficiency on resistance). The other is the countervailing mechanism in which motivation for efficiency increases resistance in the absence of the perception of system benefits accruing from CPOE. We now present the hypotheses for this countervailing mechanism that characterizes the relationship between motivation for efficiency and resistance but absent system-benefit perceptions.

Innovation implementation diminishes work efficiency in the short term (Klein & Knight, 2005). likewise, the implementation of new health information systems often lead to efficiency losses, as these systems change healthcare professionals' work routines, which play a critical role in determining the efficiency of healthcare delivery (Goh, Gao, & Agarwal, 2011; Klaus & Blanton, 2010; Laumer et al., 2016b; Merhi & Ahluwalia, 2019). In hospitals, many medical services are carried out through routines, and doctors and nurses can perform their tasks efficiently by becoming familiar with these routines (Feldman, 2000). CPOE implementation breaks these routines by changing work processes (such as order entry) and forcing the creation of new routines. These new routines are frustrating for doctors and nurses because they decrease their work efficiency, thus absorbing time and adding to their workload (at least initially). For this reason, changes in work routines have been consistently reported as the main source of resistance in the context of health information system implementations (Hoonakker et al., 2012; Hsieh, 2015; Østervang et al., 2019; Plumb et al., 2017; Yu et al., 2013).

The inefficiency engendered by CPOE implementation is likely to continue until doctors and nurses become familiar with the new routines (Feldman, 2000). Therefore, when CPOE is implemented in hospitals, doctors or nurses who place a high value on work efficiency may have a high intention to resist to CPOE because doing so will fulfill their motivational needs for efficiency in the delivery of healthcare. In other words, a doctor or a nurse with high motivation for efficiency may show greater resistance to CPOE than a doctor or nurse with low motivation for efficiency. Thus, we hypothesize that:

Hypothesis 2a (H2a): For doctors, motivation for efficiency will increase resistance to CPOE.

Hypothesis 2b (H2b): For nurses, motivation for efficiency will increase resistance to CPOE.

2.3.3. Indirect Effects of Motivations for Efficiency and Quality Via System Benefits

We draw on motivational affordance research (Zhang, 2007, 2008), in which an individual's motivational needs influence his/her perception of a technology, which in turn leads to behavioral intention. We suggest that perceived system benefit is influenced by healthcare professionals' motivation for quality and motivation for efficiency and that this can affect resistance to CPOE.

System benefit refers to healthcare professionals' perceptions of whether CPOE provides benefits in the context of healthcare delivery such as order completeness, treatment protocol consistency, reduced medical errors, and shortened order processing time. Therefore, perceived system benefit reflects the usefulness of CPOE in a manner that is specific to the context of CPOE usage. The usefulness of information technology is a well-known key factor that influences individuals' technology-related intention and behavior. Indeed, previous research studies have consistently demonstrated that usefulness of IS decreases users' resistance to IS in both healthcare organizations (Hsieh, 2015; Xue et al., 2015) and non-healthcare organizations (Kim & Lee, 2016; Kim & Kankanhalli, 2009; Laumer et al., 2016a, 2016b).

Perceived system benefits, which may decrease resistance to CPOE, can be influenced by healthcare professionals' motivation for quality and motivation for efficiency because CPOE has motivational affordances that fulfil their motivational needs for healthcare quality and efficiency in their work. Previous studies have shown a consensus among healthcare professionals that the properties of CPOE improve healthcare quality and efficiency (Baysari et al., 2018; Bhattacherjee et al., 2018; Hoonakker et al., 2012; Niazkhani et al., 2009). In this respect, CPOE has motivational affordances that support healthcare professionals' motivation for quality and motivation for efficiency. Additionally, motivational affordance literature suggests that people with high motivational needs may find motivational affordances more attractive than those with low motivational needs (Zhang, 2007).

Thus, based on the theoretical mechanism of motivational affordance, when CPOE is implemented in hospitals, a doctor or nurse with high motivation for quality may perceive more system benefit from CPOE than a doctor or nurse with low motivation for quality, because a doctor or nurse with high motivation for quality may be more satisfied with CPOE's motivational affordance for healthcare quality improvement. To be clear, our argument is not that the need differences between doctors and nurses lead to their different benefit assessments for CPOE but that healthcare professionals' different motivational levels have differential impacts on the assessments of CPOE system benefit. Furthermore, a doctor's or nurse's perceived system benefit may influence his/her resistance to CPOE. Specifically, we suggest that when a doctor or nurse experiences more system benefit, he/she will exhibit less resistance to CPOE. Thus, we propose the following hypotheses:

Hypothesis 3a (H3a): For doctors, system benefits will mediate the relationship between motivation for quality and resistance to CPOE.

Hypothesis 3b (H3b): For nurses, system benefits will mediate the relationship between motivation for quality and resistance to CPOE.

Likewise, when CPOE is implemented in hospitals, a doctor or a nurse with high motivation for efficiency may perceive more system benefit from CPOE than a nurse or a doctor with low motivation for efficiency, because a nurse or a doctor with high motivation for efficiency may be more satisfied with CPOE's motivational affordance for efficiency improvement in the delivery of healthcare. Furthermore, a doctor's or nurse's perceived system benefit may influence his/her resistance to CPOE. Specifically, we suggest that when a doctor or nurse experiences more system benefit, he/she will exhibit less resistance to CPOE. Thus, we propose the following hypotheses:

Hypothesis 4a (H4a): For doctors, system benefits will mediate the relationship between motivation for efficiency and resistance to CPOE.

Hypothesis 4b (H4b): For nurses, system benefits will mediate the relationship between motivation for efficiency and resistance to CPOE.

2.4. METHOD

2.4.1. Data Collection

Our research model was empirically tested using data collected from a field survey of physicians and nurses at Emory Healthcare, which is the clinical component of the Robert W. Woodruff Health Sciences Center of Emory University and the largest health care system in the state of Georgia with about 9,000 employees, more than 20 health centers in the metro Atlanta-area, and 1,184 licensed patient beds. The data were collected at three time points in the CPOE implementation process: pre-implementation immediately after CPOE training (T0), 3-months post-implementation (T1), and 6-months post-implementation (T2). A reminder was mailed one week after the initial survey. Table 2-2 shows the number of surveys mailed out and returned at T0, T1, and T2 along with the response rates. Table 2-3 shows the number of retained survey for analysis after excluding observations with missing values, along with the average age, years in profession, and gender ratios.

Table 2-2. Survey Response Rate

	T0	T1	T2
Doctor			
Surveys mailed out	1,225	1,178	1,160
Surveys returned	213	251	203
Response rate	17.4%	21.3%	17.5%
Nurse			
Surveys mailed out	1,687	1,708	1,705
Surveys returned	408 (334 nurses)	508 (398 nurses)	429 (361 nurses)
Response rate	24.2%	29.7%	25.2%

Table 2-3. Data Description

	T0	T1	T2	Total
Doctor				
Retained surveys	186	228	172	586
Average age	40.6	40.9	41.1	40.8
Average years in profession	10.5	10.5	11.5	10.8
Gender ratio (Male)	57.0%	64.0%	58.1%	60.1%
Nurse				
Retained surveys	324	384	309	1,017
Average age	43.6	45.1	45.5	44.8
Average years in profession	15.9	16.9	17.4	16.7
Gender ratio (Male)	7.4%	8.9%	6.8%	7.8%

2.4.2. Control Variables

Age, gender, and voluntariness were adopted as control variables for both system benefit and resistance to account for individual differences that potentially influence system benefit and resistance (Laumer et al., 2016a; Venkatesh, Morris, Davis, & Davis, 2003). Additionally, switching costs, social influence, and transition support were included as control variables for resistance to partial out variance attributable to these variables that were verified as correlates of resistance (Kim & Lee, 2016; Kim & Kankanhalli, 2009; Merhi & Ahluwalia, 2019).

2.4.3. Measurement of Constructs

Validated scales to measure *voluntariness, resistance, switching costs, transition support,* and *social influence* were adapted from previous literature. To shorten the survey, we selectively adopted items from original item sets. To select items, we received feedback from doctors and nurses. If doctors or nurses responded that a certain item was not appropriate in the study context, we did not include it. For example, we did not include "monetary switching cost" from the original switching cost items (Jones, Mothersbaugh, & Beatty, 2000) because doctors and nurses said it is inappropriate in the context of CPOE implementation in EMORY healthcare. In this way, two *resistance* items were adapted from the original four items from Kim and Kankanhalli (2009), two *switching costs* items were adapted from the original three items from Jones et al. (2000), two *social influence* items were adapted from the original three *colleague opinion* items from Kim and Kankanhalli (2009), and one *voluntariness* item was adapted from the original four items from Moore and Benbasat (1991).

Given the absence of pre-validated scales, the multiple items for *motivation for quality, motivation for efficiency,* and *system benefit* were self-developed. In every process to select and finalize items, we shared items with stakeholders of the CPOE project (e.g., doctors, nurses, outside consultants) and solicited their feedback on the appropriateness of the content, length, and wording of items to verify the content validity of construct measures. Measurement items are listed in Appendix A. The development of measurement items for *motivation for quality* and *motivation for efficiency* was guided by previous literature that specified essential characteristics of healthcare quality and efficiency. Our *motivation for quality* items reflect the three dimensions of OECD's Health Care Quality Indicator from the standpoint of doctors and nurses. These three dimensions include effectiveness, safety, and patient-centeredness/responsiveness in the delivery of healthcare (Arah, Westert, Hurst, & Klazinga, 2006). In the work settings of doctors and nurses, efficiency is represented by input-output combinations, where the input is labor and the outputs are the number of treated patients and working speed ; thus, our *motivation for efficiency* items reflect these outputs (given the fixed input of labor): volume of work (e.g., patient volume) and working speed. The development of s*ystem benefit* items was guided by both the certification criteria for electric health record technology issued by the U.S. government (Medicare and Medicaid Programs; Electronic Health Record Incentive Program—Stage 2, Final Rule. 2012) and previous literature that specifies essential system benefits of CPOE (Ahmad, Teater, Bentley, Kuehn, Kumar, Thomas et al., 2002; Bates et al., 1999; Carli et al., 2018; Eslami, Abu-Hanna, & De Keizer, 2007; Hillestad et al., 2005; Hoonakker et al., 2012; Kruse & Goetz, 2015; Kuperman & Gibson, 2003; Niazkhani et al., 2009; Prgomet et al., 2016; Romanow et al., 2018; Romanow et al., 2017). Thus, *system benefit* items reflect the following CPOE benefits: treatment protocol consistency, easily handled customized order, reduced medical accidents, shortened order processing time, increased order completeness, improved clinician-clinician interaction, standardized order sets, and an excellent fit with the clinical process of the hospital.

2.5. DATA ANALYSIS AND RESULTS

2.5.1. Measurement Model

To validate the psychometric properties of the scales, we conducted a confirmatory factor analysis (CFA) using AMOS 18.0. The fit indices indicates a good fit of our measurement model with data across T0, T1, and T2 for both doctors (T0: CFI=.949, RMSEA=.059, SRMR=.054; T1: CFI=.957, RMSEA=.055, SRMR=.047; T2: CFI=.981, RMSEA=.037, SRMR=.054) and nurses (T0: CFI=.958, RMSEA=.055, SRMR=.048; T1: CFI=.972, RMSEA=.048, SRMR=.035; T2: CFI=.966, RMSEA=.051, SRMR=.042) (Gefen, Rigdon, & Straub, 2011; Hu & Bentler, 1999), providing support for construct validity.

Next, we assessed the reliability, convergent validity, and discriminant validity of the survey instrument. As shown in Table 2-4, the composite reliability of each variable is greater than 0.7 across T0, T1, and T2 both for doctors and nurses, indicating good reliability (Fornell & Larcker, 1981). Cronbach's α for each variable exceeds 0.70 thresholds except for *resistance* at T1 (0.66 for doctors, 0.67 for nurses) and T2 (0.67 for doctors, 0.69 for nurses) which are close to the threshold. Convergent validity was evaluated by examining the significance of item loadings and the average variance extracted (AVE). All loadings were significant using bias-corrected percentile method and the AVE for each variable exceeds 0.5 across T0, T1, and T2 for both doctors and nurses. These results suggest adequate convergent validity (Fornell & Larcker, 1981). Discriminant validity was evaluated by comparing the inter-variable correlations to the square root of the AVEs for variables (Fornell & Larcker, 1981). As shown in Table 2-5, the square root of the AVE is larger than the inter-variable correlations across T0, T1, and T2 for both doctors and nurses; thus, we concluded that the measurement model has good discriminant validity.

Table 2-4. Result of CFA Measurement Model Analysis (Doctor/ Nurse)

Construct	Scale item	T0				T1				T2			
		Factor Loading	C's α	CR	AVE	Factor Loading	C's α	CR	AVE	Factor Loading	C's α	CR	AVE
Resistance	RTC1	.64**/.55**	.75/.71	.82/.77	.70/.65	.57**/.54**	.66/.67	.72/.74	.58/.60	.54**/.52**	.67/.69	.77/.76	.64/.63
	RTC2	.99**/.99**				.91**/.96**				.99**/.99**			
Motivation for Quality	MQ1	.85**/.90**	.89/.93	.89/.93	.74/.81	.86**/.91**	.89/.95	.89/.95	.74/.86	.84**/.94**	.89/.92	.89/.92	.73/.80
	MQ2	.91**/.90**				.87**/.94**				.83**/.86**			
	MQ3	.82**/.90**				.85**/.93**				.88**/.88**			
Motivation for Efficiency	ME1	.80**/.74**	.89/.85	.89/.87	.82/.77	.60**/.83**	.75/.88	.80/.89	.68/.80	.68**/.74**	.80/.85	.84/.87	.73/.77
	ME2	.99**/.99*				.99**/.95**				.99**/1.0**			
System Benefit	SB1	.67**/.77**	.90/.93	.86/.93	.53/.62	.71**/.80**	.91/.94	.91/.94	.56/.65	.79**/.81**	.91/.93	.91/.94	.57/.64
	SB2	.70**/.81**				.69**/.78**				.72**/.82**			
	SB3	.69**/.69**				.74*/.75**				.72**/.77**			
	SB4	.70**/.73**				.72*/.72**				.67**/.73**			
	SB5	.71**/.86**				.81**/.83**				.80**/.81**			
	SB6	.67**/.72**				.62**/.78**				.67**/.76**			
	SB7	.78**/.84**				.78**/.87**				.78**/.80**			
	SB8	.88**/.87**				.91**/.91**				.90**/.91**			
Social Influence	SI1	.93**/.88**	.82/.77	.83/.78	.72/.64	.92**/.89**	.87/.77	.87/.78	77/.64	.91**/.90**	.86/.76	.87/.77	.76/.64
	SI2	.76**/.72**				.83**/.70**				.84*/.68**			
Switching Costs	SWC1	.63**/.99**	.72/.77	.74/.81	.60/.69	.60**/.72**	.74/.76	.78/.76	.68/.61	.63**/.68*	.77/.77	.81/.78	.69/.65
	SWC2	.89**/.62**				.98**/.84**				.99**/.92**			
Transition Support	TS1	.91**/.91**	.95/.95	.95/.95	.87/.87	.86*/.95**	.94/.97	.96/.97	.85/.91	.92*/.92**	.96/.96	.96/.96	.90/.89
	TS2	.96**/.95**				.98**/.97**				.98**/.96**			
	TS3	.92**/.94**				.95**/.94**				.93**/.94**			

**p < 0.01, *p < 0.05 (bias-corrected percentile method)
CR = composite reliability; C's α= Cronbach's alpha; AVE = average variance extracted
Values on the left of slash (/): doctor; values on the right of slash (/): nurse

Table 2-5. Descriptive Statistics, Inter Construct Correlation, and Square Root of AVE (Doctor/ Nurse)

Construct	Time	C's α	Mean (SD)	Resistance	SB	ME	MQ	TS	SC	SI
Resistance	T0	.75/.71	2.33(1.21)/ 1.77(1.15)	.84/.81						
	T1	.66/.67	2.36(1.36)/ 1.88(1.24)	.76/.78						
	T2	.67/.69	2.28(1.34)/ 1.76(1.04)	.80/.80						
System Benefit	T0	.90/.93	4.33(1.25)/ 5.51(1.10)	-.49**/-.25**	.73/.79					
	T1	.91/.94	4.25(1.36)/ 5.30(1.24)	-.62**/-.23**	.75/.81					
	T2	.91/.93	4.36(1.33)/ 5.27(1.21)	-.58**/-.34**	.76/.80					
Motivation Efficiency	T0	.89/.85	4.86(1.50)/ 5.02(1.49)	-.06/-.03	.18*/.35**	.90/.88				
	T1	.75/.88	5.27(1.22)/ 5.13(1.52)	-.05/-.02	.18**/.29**	.82/.89				
	T2	.80/.85	5.25(1.29)/ 5.11(1.44)	-.13/-.03	.15/.31**	.85/.88				
Motivation Quality	T0	.89/.93	6.21(0.86)/ 6.35(0.89)	-.20**/-.23**	.01/.38**	.27**/.30**	.86/.90			
	T1	.89/.95	6.26(0.85)/ 6.30(0.98)	-.17*/-.15**	.08/.25**	.24**/.28**	.86/.93			
	T2	.89/.92	6.28(0.78)/ 6.29(0.97)	-.18*/-.16**	.08/.18**	.27**/.26**	.85/.89			
Transition Support	T0	.95/.95	4.97(1.48)/ 5.61(1.28)	-.31**/-.20**	.52**/.57**	.19**/.21**	.04/.22**	.93/.93		
	T1	.94/.97	5.10(1.39)/ 5.73(1.23)	-.48**/-.25**	.60**/.60**	.09/.23**	.02/.23**	.92/.96		
	T2	.96/.96	5.16(1.44)/ 5.64(1.24)	-.54**/-.37**	.64**/.67**	.06/.21**	.06/.12*	.95/.94		
Switching Costs	T0	.72/.77	5.68(1.19)/ 5.17(1.37)	.22**/.18**	-.45**/-.20**	-.11/-.01	.02/.02	-.31**/-.18**	.77/.83	
	T1	.74/.76	5.71(1.25)/ 4.98(1.51)	.27**/.12*	-.42**/-.34**	-.06/-.08	.11/.01	-.22**/-.20**	.81/.78	
	T2	.77/.77	5.57(1.35)/ 4.92(1.48)	.23**/.13*	-.34**/-.43**	-.03/-.09	-.04/-.12*	-.23**/-.32**	.83/.81	
Social Influence	T0	.82/.77	4.16(1.40)/ 5.04(1.24)	-.35**/-.11	.57**/.54**	.09/.26**	-.01/.21**	.55**/.58**	-.35**/-.18**	.85/.80
	T1	.87/.77	4.42(1.54)/ 5.34(1.23)	-.57**/-.16**	.63**/.57**	.17*/.20**	.10/.21**	.60**/.59**	-.37**/-.16**	.77/.80
	T2	.86/.76	4.54(1.51)/ 5.30(1.21)	-.52**/-.28**	.67**/.64**	.19*/.26**	.06/.18**	.65**/.67**	-.27**/-.34**	.87/.80
Voluntariness	T0		2.33(1.62)/ 2.23(1.66)	-.00/.23**	.33**/.02	.12/.10	-.03/.03	.29**/.08	-.26**/-.01	.31**/.14*
	T1		2.42(1.62)/ 2.64(1.93)	-.14*/.25**	.30**/.11*	.01/.15**	.01/-.02	.20**/.08	-.27**/-.15**	.20**/.14**
	T2		2.43(1.69)/ 2.59(1.99)	-.03/-.00	.24**/.03	-.02/.07	-.10/-.06	.11/.10	-.18*/-.14*	.15/.17**

**p < 0.01, *p < 0.05

The shaded diagonal is the square root of the AVE; C's α= Cronbach's alpha

Values on the left of slash (/): doctor; values on the right of slash (/): nurse

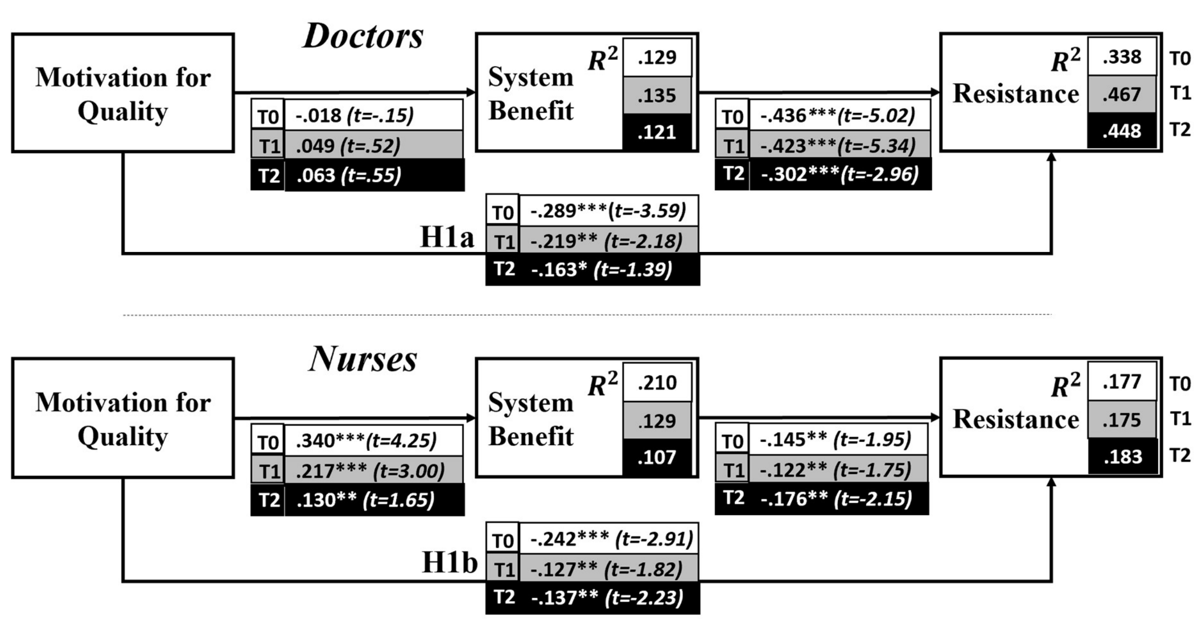
2.5.2. Common Method Bias

We conducted marker variable analyses (Lindell & Whitney, 2001; Malhotra, Kim, & Patil, 2006; Rai, Keil, Hornyak, & WüLlenweber, 2012) to examine common method bias. We identified the lowest correlation marker variable (R_{M1}) and the second lowest correlation marker variable (R_{M2}) for each of doctors and nurses at T0, T1, and T2. After adjusting for R_{M2}, more conservative estimate than R_{M1} (Lindell & Whitney, 2001; Malhotra et al., 2006), the correlations among the substantive variables dropped on average by 0.009 for T0, 0.007 for T1, and 0.006 for T2 and no greater than by 0.013 for T0, 0.011 for T1, and 0.009 for T2 for doctors and, for nurses, by 0.009 for T0, 0.005 for T1, and 0.004 for T2 and no greater than by 0.013 for T0, 0.008 for T1, and 0.006 for T2. All the correlations among the substantive variables remained significant, and the level of significance of any correlation was not changed. Therefore, common method bias should not be of concern in this study. Additionally, we conducted Harmon's single factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Podsakoff & Organ, 1986). As a result of the test, the first extracted factor accounted for less than 38% of the variance in data across T0, T1, and T2 for both doctors (T0: 31.3%, T1: 34.8%, T2: 34.8%) and nurses (T0: 34.2%, T1: 35.1%, T2: 37.3%); thus, common method bias is unlikely to be a significant issue in our data because the first extracted factor did not explain the majority of the variance in our data.

2.5.3. Hypotheses Testing

To test our hypotheses that involve both direct and indirect effects of doctors' and nurses' motivations on resistance to CPOE, we used Hayes' PROCESS macro for SPSS by configuring our model based on Model 4 with 5,000 bootstrap samples (Hayes, 2017). Because our data showed heteroskedasticity based on the Breusch-Pagan Test, we used robust standard errors to test direct effects of motivations on resistance, thus enabling valid statistical inference in the presence of heteroskedasticity (Hayes & Cai, 2007; Wooldridge, 2015)[1]. In the analysis, age, gender, voluntariness, motivation for efficiency/motivation for quality were used as control variables for system benefit (i.e., mediator); age, gender, voluntariness, motivation for efficiency/motivation for quality, switching costs, social influence, and transaction support were used as control variables for resistance (i.e., dependent variable).

Figure 2-2. Path Analysis Results for the Effect of *Motivation for Quality* on *Resistance*



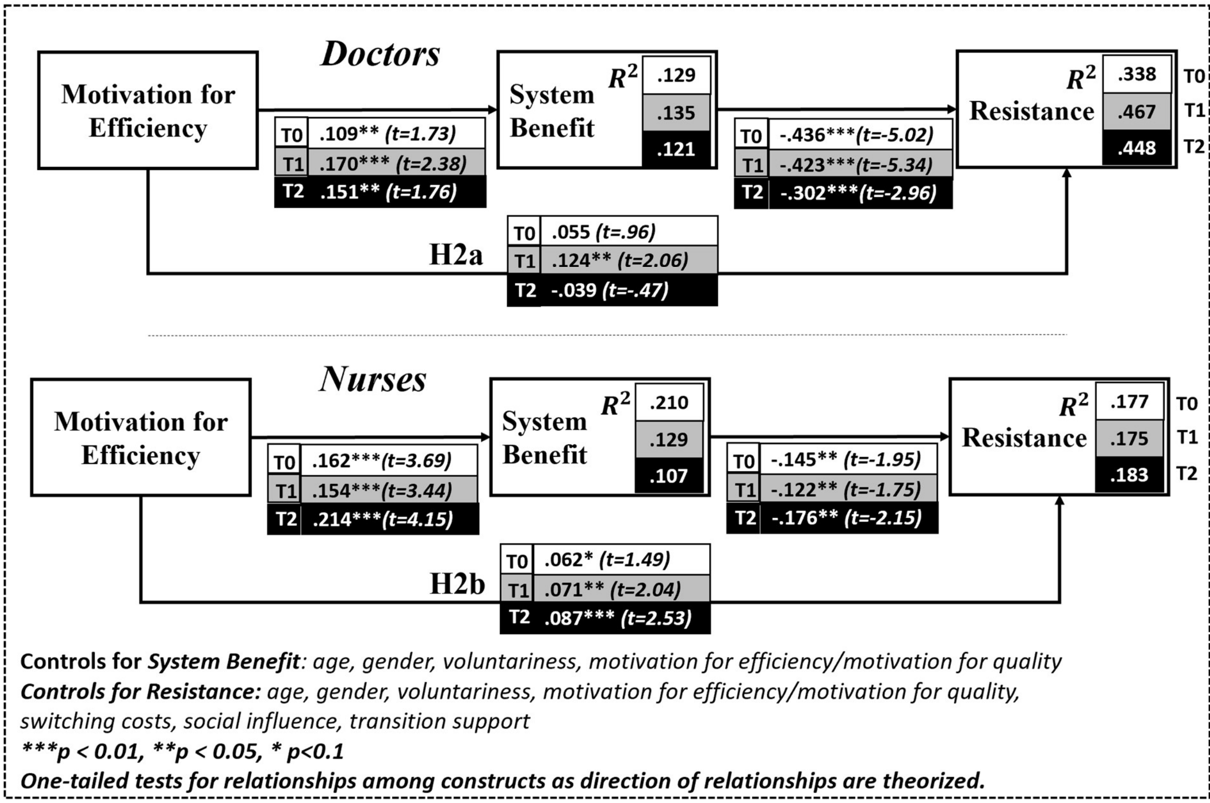
Controls for *System Benefit*: *age, gender, voluntariness, motivation for efficiency/motivation for quality*
Controls for Resistance: *age, gender, voluntariness, motivation for efficiency/motivation for quality, switching costs, social influence, transition support*
******p < 0.01, **p < 0.05, * p<0.1***
One-tailed tests for relationships among constructs as direction of relationships are theorized.

First, the direct effect of *motivation for quality* on *resistance* to CPOE for doctors (H1a) and nurses (H1b) was examined. As Figure 2-2 shows, for doctors, *motivation for quality* significantly decreased *resistance* to CPOE at T0 (β=-.289, t=-3.59, p<.01), T1 (β=-.219, t=-2.18, p<.05), and T2 (β=-.163, t=1.39, p<.1). Thus, H1a was supported at T0, T1, and T2. For nurses, *motivation for quality* significantly decreased *resistance* to CPOE at T0 (β=-.242, t=-2.91, p<.01),

[1] The statistical inferences using robust standard errors and OLS standard errors were consistent, which lends further robustness to our findings.

T1 (β=-.127 t=-1.82, p<.05), and T2 (β=-.137 t=-2.23, p<.05), thus supporting H1b at T0, T1, and T2. The sign of the significant direct effect of *motivation for quality* on *resistance* to CPOE was consistent with our expectation (negative direct effect); that is, doctors'/nurses' motivation for high quality healthcare reduced resistance to CPOE after controlling for the effect of system benefit and other control variables.

Figure 2-3. Path Analysis Results for the Effect of *Motivation for Efficiency* on *Resistance*



Next, the direct effect of *motivation for efficiency* on *resistance* to CPOE for doctors (H2a) and nurses (H2b) was examined. As Figure 2-3 shows, for doctors, *motivation for efficiency* significantly increased *resistance* to CPOE at T1 (β=.124, t=2.06, p<.05); however, the influence of *motivation for efficiency* on *resistance* was not significant at T0 (β=.055, t=.96) and T2 (β=-.039, t=-.47). Thus, H2a was supported at T1, but not supported at T0 and T2. For nurses, *motivation for efficiency* significantly increased *resistance* to CPOE at T0 (β=.062, t=1.49, p<.1), T1 (β=.071, t=2.04, p<.05), and T2 (β=.087, t=2.53, p<.01).Thus, H2b was supported at T0, T1, and T2. The sign of the significant direct effect of *motivation for efficiency* on *resistance* to CPOE was consistent with our expectation (positive direct effect); that is, doctors'/nurses' motivation for efficiency in the delivery of healthcare increased resistance to CPOE after controlling for the effect of system benefit and other control variables.

Table 2-6. Indirect Effects of Motivations on Resistance via System Benefit[2]

Variables	Role	Time	Effect	*SE*	Lower-Level BCCI [a]	Upper-Level BCCI [a]	Hypotheses Testing
Motivation for Quality	Doctors	T0	.008	.053	-.090	.120	H3a: not supported
		T1	-.021	.039	-.097	.061	H3a: not supported
		T2	-.019	.035	-.099	.042	H3a: not supported
	Nurses	T0	-.050	.026	-.112	-.007	H3b: supported
		T1	-.026	.017	-.071	-.001	H3b: supported
		T2	-.023	.016	-.071	-.001	H3b: supported
Motivation for Efficiency	Doctors	T0	-.048	.030	-.105 [b]	-.004 [b]	H4a: supported
		T1	-.072	.032	-.145	-.014	H4a: supported
		T2	-.046	.028	-.115	-.003	H4a: supported
	Nurses	T0	-.024	.014	-.064	-.003	H4b: supported
		T1	-.019	.013	-.052	-.001	H4b, supported
		T2	-.038	.018	-.081	-.008	H4b, supported

Notes: BCCI [a] = bias-corrected 95% confidence interval except for b (90% BCCI)

Having perceived *system benefit* as a mediator for the relationship between motivations and resistance, we proceed to the test of mediation hypotheses (H3a, H3b, H4a, and H4b) using analysis results from Model 4 in PROCESS. Table 2-6 summarizes the indirect effect of *motivation for quality* and *motivation for efficiency* on *resistance* to CPOE. As shown in Table 2-6, for doctors, the indirect effect of *motivation for quality* on *resistance* to CPOE was not significant at T0, T1, and T2 because the upper- and lower-level bias-corrected 95% confidence intervals (BCCIs) included zero. Thus, H3a was not supported at T0, T1, and T2. On the other hand, for nurses, the indirect effect of *motivation for quality* on *resistance* to CPOE was significant at T0, T1, and T2

[2] As stated earlier, system benefit reflects the usefulness of CPOE in a manner that is specific to the context of CPOE usage. To test the generalizability of this study, we also analyzed our model using the perceived usefulness construct. The results using system benefit and perceived usefulness were consistent.

because the BCCIs did not include zero, supporting H3b at T0, T1, and T2. The sign of the indirect effect of *motivation for quality* was consistent with our expectation (i.e., negative indirect effect); that is, *motivation for quality* positively influenced system benefits, which in turn had a negative impact on resistance as shown in Figure 2-2. In other words, nurses' motivation for delivering high-quality healthcare influenced them to perceive more system benefits of CPOE, which in turn decreased resistance to CPOE. However, doctors' motivation for quality healthcare did not influence perceived system benefit of CPOE; thus, *motivation for quality* did not have an indirect effect on *resistance* via *system benefit* despite the significant negative impact of system benefit on resistance to CPOE as shown in Figure 2-2.

Finally, the indirect effect of *motivation for efficiency* on *resistance* to CPOE for doctors (H4a) and nurses (H4b) was examined. As shown in Table 2-6, for both doctors and nurses, the indirect effect of *motivation for efficiency* on *resistance* to CPOE was significant at T0, T1, and T2 because the BCCIs did not include zero (for doctors at T1, bias-corrected 90% confidence interval was applied), supporting H4a and H4b at T0, T1, and T2. The sign of the indirect effect of *motivation for efficiency* was consistent with our expectation (i.e., negative indirect effect); that is, *motivation for efficiency* positively influenced system benefits, which in turn had a negative impact on resistance as shown in Figure 2-3. In other words, doctors'/nurses' motivation for efficiency in the delivery of healthcare influenced them to perceive more system benefits of CPOE, which in turn decreased resistance to CPOE.

Table 2-7. Direct and Indirect Effect of Motivations on Resistance to CPOE

Variables	Role	Time	Direct effect (sign of effect)	Indirect effect (sign of effect)	Criteria
Motivation for Quality	Doctors	T0	Yes (-)	No	Direct only
		T1	Yes (-)	No	Direct only
		T2	Yes (-)	No	Direct only
	Nurses	T0	Yes (-)	Yes (-)	Partial mediation

		T1	Yes (-)	Yes (-)	Partial mediation
		T2	Yes (-)	Yes (-)	Partial mediation
Motivation for Efficiency	Doctors	T0	No	Yes (-)	Full mediation
		T1	Yes (+)	Yes (-)	Partial mediation
		T2	No	Yes (-)	Full mediation
	Nurses	T0	Yes (+)	Yes (-)	Partial mediation
		T1	Yes (+)	Yes (-)	Partial mediation
		T2	Yes (+)	Yes (-)	Partial mediation

2.6. DISCUSSION

Drawing on the theoretical mechanism of motivational affordances, our results demonstrate that healthcare professionals' perceived system benefit mediates the relationship between two kinds of motivations (i.e., motivation for quality, motivation for efficiency) and resistance to CPOE. While system benefit mediates the effect of motivation for efficiency on resistance to CPOE both for doctors and nurses, it mediates the effect of motivation for quality on resistance to CPOE only for nurses. Specifically, our results (see Figure 2-2) showed that doctors' motivation for quality did not influence perceived system benefit. This may be because CPOE represents a move toward standardized healthcare processes (Hook & Cusack, 2008) and doctors may perceive this as a threat to their identity as healthcare providers who intend to deliver personalized high-quality healthcare to each patient. Indeed, doctors tend to believe that healthcare quality can best be realized through the application of their accumulated tacit knowledge that cannot be standardized within CPOE systems (Plumb et al., 2017); thus, for doctors with high motivation for quality, CPOE may not be perceived as beneficial because it prevents or impedes them from using what they may consider to be the best approach for their patients. We examined the mediation effects of system benefit between healthcare professionals' motivations and resistance to CPOE at three-time points in the CPOE implementation process. Given that the results of these mediation effects were consistent at all three-time points, our finding for the mediation effects of system benefit in CPOE implementation appears to be quite robust.

Even though the motivation for quality indirectly reduced resistance to CPOE only for nurses, the negative direct effect (i.e., reducing resistance) of motivation for quality on resistance to CPOE was observed for both doctors and nurses. Interestingly, the negative direct effect (i.e., reducing resistance) of motivation for quality on resistance to CPOE was strongest at the pre-implementation stage both for doctors and nurses and decreased after CPOE implementation. Given that healthcare professionals' perceptions at the pre-implementation stage reflect their expectations for CPOE systems and their perceptions after CPOE implementation reflect their experiences from using CPOE, we can postulate that healthcare professionals might perceive that CPOE is not useful for improving healthcare quality as much as they expected. A similar pattern was also observed for the effect of motivation for quality on perceived system benefit for nurses (from T0 to T2) as shown in Figure 2-2.

While healthcare professionals' motivation for efficiency indirectly (i.e., indirect effect) reduced resistance to CPOE via system benefit for both doctors and nurses at all three time-points (i.e., T0, T1, and T2), the results show that motivation for efficiency directly increases resistance to CPOE except for doctors at T2. This result may indicate that healthcare professionals perceived two different aspects of CPOE that have opposite effects on their work efficiency. Specifically, CPOE is designed to improve the work efficiency of healthcare professionals; thus, healthcare professionals' high motivation for efficiency increases perceived system benefit, which in turn decreases resistance to CPOE. However, CPOE also decreases work efficiency by changing work routines (Baysari et al., 2018; Bhattacherjee et al., 2018; Hoonakker et al., 2012; Kruse & Goetz, 2015); thus, healthcare professionals' high motivation for efficiency increases resistance to CPOE after controlling for the effect of system benefit on resistance to CPOE. One interesting point is that the positive direct effect (i.e., increasing resistance) of motivation for efficiency on resistance to CPOE was strongest at T1 for doctors. Given that T1 (3 months after implementation) was the shakedown phase, in which healthcare professionals were not yet familiar with CPOE, and that CPOE shifts workload from nurses to doctors, doctors might get frustrated at T1 by the major changes to their routine, and this may be what led to the strongest positive effect (i.e., increasing resistance) of motivation for efficiency on resistance to CPOE.

2.6.1. Theoretical Implications

This study makes meaningful contributions to several research streams. First, it contributes to resistance to IS literature by suggesting a new resistance mechanism explaining how users' motivations influence resistance to IS via system benefit of IS. Previous resistance research, which focused on the changes caused by new IS and the users' perceptions affected by those changes, did not model users' motivations and system benefit of IS, and the mechanism of resistance was therefore poorly understood. Individuals' motivations directly guide their behaviors (Moody & Pesut, 2006) and thus play a critical role in their resistance to IS, and generally IS is designed to have system benefits that fulfill users' motivational needs. Using a motivational affordance lens, this study not only provides a theoretical explanation for the new resistance mechanism of how users' motivations and system benefit of IS influence resistance to IS but also empirically demonstrates the validity of this mechanism. Additionally, to the best of our knowledge this is the first empirical study that demonstrates how the resistance mechanism operates differently for individuals with different roles in a process. As previously described, role-based patterns of resistance have not been examined yet. Given that new IS bring changes (Markus, 1983) and that users' assessments for the consequences of these changes can be different depending on their roles (Lapointe & Rivard, 2005), examining role-based differences in resistance is critical to fully understanding the resistance phenomena. Further, this study empirically shows how the mechanism of resistance to IS changes over time. Despite the temporal nature of the resistance phenomenon (Lapointe & Rivard, 2005), most previous studies have investigated resistance through a cross-sectional approach, and thus provide no explanation of how resistance plays out over time. Thus, this study broadens and deepens our understanding of resistance to IS by showing different patterns of resistance at different time points in the IS implementation process.

Second, this study contributes to motivational affordance research by empirically demonstrating how individuals' motivational needs that are supported by motivational affordances of IS influence the perceived benefit of the IS and how motivational affordances of IS affect users' resistance to the IS. Even though IS have motivational affordances that fulfill individuals' motivational needs, few studies have investigated the relationship between specific individuals' motivations and system benefits. The examination of this relationship is critical for understanding what properties of an IS appeal to individuals' different motivational needs.

Third, this study contributes to healthcare literature by suggesting two new constructs (i.e., motivation for quality and motivation for efficiency) that best reflect the values that guide healthcare professionals' behaviors and demonstrating how these two motivations influence individuals' resistance to CPOE. Most previous research on motivations in healthcare settings have relied on the general concept of work motivation and thus fail to address the unique motivational characteristics of healthcare professionals (Moody & Pesut, 2006; Toode et al., 2011). Given that improving both healthcare quality and healthcare efficiency is a goal of both healthcare professionals and healthcare organizations, this research study focusing on healthcare professionals' motivation for quality and motivation for efficiency advances our understanding in this critical area.

2.6.2. Practical Implications

The findings of this study can be translated into practice by providing IS practitioners with insights on how to establish effective CPOE implementation strategy to reduce healthcare professionals' resistance to CPOE. First, IS practitioners need to establish different implementation strategies for doctors and nurses. Specifically, given the results of this study, a strategy that makes doctors with high motivation for quality perceive CPOE as beneficial in increasing healthcare quality is needed. Second, IS practitioners need to implement different strategies at different time points in CPOE implementation period. For example, more support for doctors should be provided at the go-live stage because the positive direct effect (i.e., increasing resistance) of motivation for efficiency on resistance to CPOE is strongest among doctors at this point in the implementation process. Third, given that healthcare professionals' motivation for efficiency directly increases resistance to CPOE, IS practitioners should implement strong transition support for healthcare professionals with high motivation for efficiency to help get them up to speed quickly with the new work routine that will ensue with the implementation of CPOE.

Finally, this study suggests developers of health information systems should think about how to fulfill healthcare professionals' motivations for quality and efficiency in order to reduce their resistance to such systems.

2.6.3. Limitations and Future Research

Even though this study explains how routine changes increase healthcare professionals' resistance to CPOE, we focused on healthcare professionals' benefit perception in the resistance mechanism rather than their threat perception. As previously described in this paper, the managerial logic embedded in CPOE affects the traditional healthcare hierarchy and shifts workload from nurses to doctors. Accordingly, doctors' decreased power and autonomy, as well as increased workload brought about by CPOE, may pose a threat to doctors, thus playing a critical role in generating resistance to these systems. Therefore, we suggest that future research examine the mechanism of how healthcare professionals' threat perceptions are formed and how those perceptions affect their resistance to CPOE.

2.7. CONCLUSION

Despite the important roles of individuals' motivations in guiding their behaviors, previous research studies have not addressed how such motivations influence resistance to IS. This study surfaced how healthcare professionals' motivation for quality and motivation for efficiency influence their resistance to CPOE with consideration of the mediating effect of system benefit, role differences between doctors and nurses in the resistance mechanism, and the temporal nature of IS implementation. We hope that this study leads to additional research on how the relationships between individuals' motivations and motivational affordances of IS influence individuals' behaviors, particularly in contexts involving multiple stakeholders and roles involved in the use of the system.

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APPENDIX A. Measurement Instrument

Construct	Item	Wording	Reference
Resistance	RTC1	I will not comply with the change to the new way of working with CPOE.	Kim and Kankanhalli (2009)
	RTC2	I oppose the change to the new way of working with CPOE.	
Motivation for Quality	MQ1	My behavior as a healthcare provider is motivated by quality of patient care.	Self-developed measure
	MQ2	My behavior as a healthcare provider is motivated by reducing medical accidents.	
	MQ3	My behavior as a healthcare provider is motivated by working effectively with other providers.	
Motivation for Efficiency	ME1	My behavior as a healthcare provider is motivated by volume of work (e.g., patient volume, number of procedures, billing revenue generated, number of cases handled. number of orders processed).	Self-developed measure
	ME2	My behavior as a healthcare provider is motivated by speed with which I complete tasks.	
System Benefit	SB1	CPOE… increases consistency in treatment protocols and use of standards.	Self-developed measure
	SB2	CPOE… handles customized orders easily.	
	SB3	CPOE… reduces medical accidents (e.g., incorrect dosing).	
	SB4	CPOE… reduces the time required to process an order.	
	SB5	CPOE… increases the completeness of orders.	
	SB6	CPOE… improves clinician-clinician Interaction.	
	SB7	CPOE… standardized order sets meet the patients' care needs.	
	SB8	CPOE… is an excellent fit with the clinical process that I follow in the hospital.	
Social Influence	SI1	My peers are supportive of the new CPOE work processes	Kim and Kankanhalli (2009)
	SI2	Most of my co-workers encourage me to change to the CPOE processes.	
Switching Costs	SWC1	It will take a lot of time and effort to switch to the new way of working with CPOE.	Jones et al. (2000)
	SWC2	Switching to the new way of working with the CPOE could result in unexpected hassles.	
Transition Support	TS1	The organization provides enough guidance for me to change to the new way of work.	Kim and Kankanhalli (2009)
	TS2	The administration provides the help and resources required for me to change to the new work processes.	
	TS3	I am given the necessary support and assistance to transition to the new way of work.	
Voluntariness	Vol1	My use of CPOE is voluntary.	Moore and Benbasat (1991)

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CHAPTER 3

Research Essay 2

Motivating Use of Smartwatch Health Promotion and Health Prevention Applications: A Regulatory Fit and Locus of Control Perspective

3.1. INTRODUCTION

In the mobile health application (app) market, smartwatch health apps are gaining in popularity with the advancement of smartwatches (Beukenhorst et al. 2019). A smartwatch is a wrist-worn networked watch with various sensors and a touch screen (Beukenhorst et al. 2019; Lee et al. 2018). Smartwatch apps are unique in that they offer very focused affordances, given the limited screen size and form factor, but also in that they have access to granular sensing capabilities (e.g., motion, heart rate, etc.). In this study, we focus specifically on mobile health apps offered via smartwatches. Mobile health apps offered via smartwatches provide convenient and often personalized health solutions to people for free or very low price for improving their health or preventing them from getting disease. Thus, smartwatch mobile health apps can be one of the solutions for addressing underlying problems within the current health care system such as high cost and low accessibility of health care services by empowering people to manage their health by themselves regardless of time and place (Birkhoff and Smeltzer 2017; Sarkar et al. 2016; Silva et al. 2015).

One benefit of smartwatch health apps is that they provide users better accessibility and convenience (e.g., while engaging in a sit-up) than smartphone health apps because smartwatch health apps are operated on the wrist of users. Additionally, both the breadth and accuracy of what can be measured on a smartwatch keeps improving, enabling real-time monitoring of physiological measures (Reeder and David 2016). The current generation of smartwatches can even include sensing capabilities for ECGs (electrocardiograms) and blood pressure. Thus with the recent advancement of smartwatches, mobile health applications are evolving into user-centered disease prevention tools that allow users to self-monitor and manage their health conditions by themselves in a cost-efficient and resource-efficient manner (Reeder and David 2016; Tison et al. 2018). Accordingly, the number of smartwatch health apps is growing in the application market, and people are using more and more smartwatch health applications for their health and well-being (Aitken et al. 2017).

Despite the increasing popularity of smartwatch health apps, most previous studies on smartwatch health apps focused on the feasibility of the apps for chronic diseases (King and Sarrafzadeh 2018), and few studies have investigated the factors that motivate the use of smartwatch health apps. Even though previous studies on intention to use Information Technologies (IT) (Legris et al. 2003; Venkatesh et al. 2003; Venkatesh et al. 2012) suggest several factors that motivate the use of IT, which encompasses smartwatch health apps, these studies have focused on individuals' general perceptions toward IT (e.g., usefulness of IT) and thus offer a somewhat limited theoretical explanation regarding why individuals with different motivations are differentially motivated to use a particular IT. Individuals have different motivational needs, and smartwatch health apps are designed to fulfill specific needs of individuals such as increasing physical fitness and disease prevention; thus, the degree to which each smartwatch health app appeals to individuals may be different from person to person. Additionally, from the practical standpoint of guiding developers of smartwatch health apps and the marketers of these apps, previous IS models (e.g., UTAUT)(Venkatesh et al. 2003; Venkatesh et al. 2012) do not provide sufficient guidance as to which individuals will prefer to use a specific smartwatch health app, and which properties of the app they will find most appealing. The aim of this study is to provide a theoretical explanation as well as practical insights on how individuals with different motivational characteristics are differentially motivated to use each unique IT. More specifically, given that individuals' motivations guide their behavior (Moody and Pesut 2006) and that technologies have specific properties designed to fulfill specific individuals' motivational needs (Zhang 2007; Zhang 2008), we argue that a good fit between individuals' motivational characteristics and the properties of smartwatch health apps will motivate individuals to use the apps. Also, given that smartwatch health apps rely on self-management, we suggest that individuals' motivational strength toward engagement in self-health-management influences the effect of this fit.

As a first step, we draw on regulatory focus theory which suggests that individuals' can have two distinct motivational orientations relating to the pursuit of a goal: promotion focus and prevention focus (Higgins 1997; Shen 2015). Promotion focus is driven by an individual's need for growth and development, and therefore people with high promotion focus tend to pursue a desired end-state; in comparison, prevention focus is driven by an individual's need for safety and security, and therefore people with high prevention focus tend to pursue avoidance of losses (Higgins 1997; Johnson et al. 2010; Liang et al. 2013; Wang and Lee 2006). Previous studies consistently revealed that regulatory focus affects the choices individuals make through "regulatory fit" and "regulatory relevance" (Arazy and Gellatly 2012; Avnet and Higgins 2006). Specifically, when people experience "regulatory fit," which is a match between their regulatory orientations and goal pursuit strategy, they come to have a positive attitude toward goal-relevant objects (Aaker and Lee 2006; Avnet and Higgins 2006). Additionally, individuals assign higher importance to the same outcomes of choice alternatives when the outcomes are more relevant to their regulatory orientations (i.e., "regulatory relevance") (Aaker and Lee 2001; Avnet and Higgins 2006).

Secondly, to further evaluate fit between the regulatory nature of the app itself and the regulatory focus of the user of the app, we categorize smartwatch health apps as either promotion apps or prevention apps. This regulatory categorization is based on the types of outcomes to be expected from using such apps and the required goal pursuit strategies needed to use the apps. For example, workout apps are categorized as a promotion type app, which helps users gain physical strength (i.e., promotion outcome) by engaging in a workout (i.e., promotion strategy); in comparison, heart monitoring apps are categorized as a prevention type app, which helps users prevent getting heart complications and strokes (i.e., prevention outcome) by monitoring their heart rhythm (i.e., prevention strategy). While we do not claim that these two categories are exhaustive or mutually exclusive, we argue that our categorization has critical implications in practice in that exercise and fitness apps (i.e., promotion app) make up the largest portion of the wellness management category of the digital health app market (Aitken et al. 2017) and disease prevention apps (i.e., prevention app) best reflect the direction of the evolution of smartwatch. Additionally, "health promotion" and "disease prevention" are two main purposes of healthcare management that have been used as a frame in many previous healthcare research studies (Fielding 1984; Hasler 1998; Sallis et al. 2000; Shonkoff et al. 2009; Watt 2005). In this study, we suggest that the influence of regulatory focus on intention to use smartwatch health apps is higher when individuals expect to experience higher regulatory fit and regulatory relevance while using smartwatch health apps.

Third, we argue that individuals' motivational strength toward engagement in self-health-management is represented by their internal health locus of control. Internal health locus of control refers to a person's tendency to attribute health status to their behaviors (Cheng et al. 2016; Snell et al. 1991). Prior studies argue that people with high internal health locus of control invest more in their health than people with low internal health locus of control (Cheng et al. 2016; Cobb-Clark et al. 2014). Thus, internal health locus of control is an indicator of an individual's motivational strength toward engaging in health behavior. In this vein, we propose that internal health locus of control moderates the impacts of regulatory focus on the intention to use mobile health apps. More specifically, we theorize that internal health locus of control moderates the impact of promotion focus on promotion apps and that it also moderates the impact of prevention focus on prevention apps.

In summary, this study suggests that motivation for use of smartwatch health apps starts with a fit between the regulatory focus of the app (promotion or prevention) and the regulatory focus of the user (promotion or prevention) and is further impacted by internal health locus of control. Motivated by this line of thinking, this study seeks to answer the following research questions:

RQ1: How does the fit between smartwatch health apps (promotion and prevention oriented app) and an individual's regulatory focus motivate the intention to use these apps?

RQ2: How does an individual's internal health locus of control affect the relationship between their regulatory focus and their intention to use different types of smartwatch health apps (i.e., promotion and prevention oriented apps)?

To answer these research questions, we conduct a laboratory experiment using a crossover design (Shadish et al. 2002) in which the application type (promotion app/ prevention app) is manipulated. This study measured the subjects' intention to use smartwatch health app as the dependent variable of interest instead of measuring actual usage behavior. Even though investigation into actual behavior has been recommended by some IS researchers (Kim and Malhotra 2005), it is more useful when the investigation focuses on either the causal mechanisms in a non-volitional context or the consequences of IT use (Hsieh et al. 2008). As in the context of this study, when the behavior is volitional and the individual has the information to shape his/her behavioral intention, behavioral intention is a good predictor for the individual's future behavior (Ajzen 1991; Hsieh et al. 2008). In addition, current smartwatch users are early adopters with unique personal characteristics compared to the general public (Choi and Kim 2016). Therefore, at this point in the adoption process when smart watches have not yet been widely adopted, it is appropriate to focus on intention to use rather than actual behavior.

3.2. THEORETICAL BACKGROUND

3.2.1. Smartwatch Health Apps and Motivators for the Use of Such Apps

Unlike smartphones, smartwatches can monitor physiological measures in real time with various sensors, and the accuracy of monitoring is improving with time (Reeder and David 2016). Compared to previous generations of smartwatches that were able to measure calories burned, step counts, and pulse, the current generation of smartwatches can even measure ECG (electrocardiogram) and blood pressure. As smartwatches continue to become more advanced, people may be able to use them to complement or substitute (to some extent) for face-to-face visits with healthcare professionals. Indeed, the technology holds the promise of allowing people to monitor their health conditions in a cost-efficient and resource-efficient manner (Reeder and David 2016; Tison et al. 2018). For example, today's smartwatches can enable people to monitor themselves for cardiac arrhythmias such as Atrial fibrillation (AFib) (Reeder and David 2016). Therefore, with the advancement of smartwatches, smartwatch health apps are evolving into user-centered disease prevention tools, raising questions regarding how individual differences and disease prevention focused characteristics of smartwatch health apps influence intention to use such apps. Additionally, smartwatch health apps provide users better accessibility and ease of use than smartphone health apps because smartwatch health apps are operated on the wrist of the users. For example, when a person does sit-ups while following the guidance of a workout app that visually represents the exercise along with a countdown timer, wrist-worn smartwatches make it easier to follow the displayed exercise and check the timer as compared to using a smartphone (see Figure 3-1).

Figure 3-1. Example of a Smartwatch Workout App

Despite the advantages and increasing popularity of smartwatch health apps, most previous studies on smartwatch health apps have been focused on the feasibility or the effect of smartwatch health apps, and only a few studies have examined the factors that motivate individuals to use them (King and Sarrafzadeh 2018; Reeder and David 2016). While motivators for the use of IT have been extensively studied (Legris et al. 2003) by drawing on well-recognized theories such as the Technology Acceptance Model (TAM) (Davis 1989), the Theory of Planned Behavior (TPB) (Ajzen 1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003; Venkatesh et al. 2012), the focus has been on the general perception of users regarding the target IT (e.g., ease of use, usefulness), environmental factors (e.g., social influences), and facilitating conditions (e.g., self-efficacy) as antecedents of intention to use IT (Nicolaou and McKnight 2006). However, these previous research studies on intention to use IT focusing on the aforementioned theories cannot explain why individuals with different motivations are motivated to use each unique smartwatch health application. Smartwatch health apps are individual-centered and rely on self-management (Sama et al. 2014; Zhou et al. 2017), and smartwatch health apps have their unique characteristics regarding outcomes from using the apps (e.g., disease prevention or physical fitness promotion) and the ways in which the apps are used (e.g., monitoring heart rhythm or engaging in workout). Therefore, people with different individual factors may have different preferences toward each smartwatch health app. Specifically, every smartwatch health app is designed to fulfill specific motivational needs of individuals, and individuals have different motivational needs. Thus, the extent to which individuals are motivated to use a certain app will vary from person to person depending upon the fit between an individual's motivational need and the designed purpose of each app (i.e., fitness app or heart monitoring app). In this study we advance a new model that incorporates the motivational characteristics of individuals as well as the designed characteristics of smartwatch health apps to explain why an individual with specific motivational characteristics is motivated to use certain types of smartwatch health apps.

3.2.2. Regulatory Focus

Regulatory focus theory (Higgins 1997) suggests that individuals have two self-regulatory orientations: promotion focus and prevention focus. Promotion focus is driven by the need for growth and development, whereas prevention focus is driven by the need for safety and security (Johnson et al. 2010; Liang et al. 2013). Therefore, promotion focus orientation leads people to realize their aspirations and motivates them to pursue desired end-states (e.g., pursuit of gains), and therefore people with high promotion focus are sensitive to the presence and absence of positive outcomes. In contrast, a prevention focus orientation leads people to fulfill duties and motivates them to avoid undesired end-states (e.g., avoidance of losses), and therefore people with high prevention focus are sensitive to the presence and absence of negative outcomes (Aaker and Lee 2006; Lanaj et al. 2012; Wang and Lee 2006). Previous research studies, in many disciplines, demonstrated that individuals' regulatory orientations influence their perceptions and attitudes, and ultimately their decision-making (Arazy and Gellatly 2012; Higgins 2006; Liang et al. 2013). For example, people perceive health-related information as more valid and easier to process when the information fits their regulatory orientations (Lee and Aaker 2004). It has also been shown that consumers more positively evaluate advertisements when the advertisement fits their regulatory orientations (Werth and

Foerster 2007).

Regulatory focus theory explains that regulatory focus influences individuals' attitudes and behaviors through "regulatory relevance" and "regulatory fit." Prior research has claimed that individuals assign different importance to choice alternatives depending on the "regulatory relevance" of the choice alternatives to their regulatory orientations (Aaker and Lee 2001; Avnet and Higgins 2006). For example, consumers with high promotion focus show more interest in a product's comfort-oriented features, whereas consumers with high prevention focus show more interest in a product's safety-oriented aspects (Werth and Foerster 2007). Similarly, Bettman and Sujan (1987) demonstrated that individuals' preferences for a product with creativity features or a product with reliability features depend on which features are more relevant to their regulatory focus. Additionally, people showed high engagement in health-related behavior such as fruit and vegetable intake when they receive tailored messages relevant to their regulatory focus (Latimer et al. 2008). Another mechanism that explains how regulatory focus influences individuals' attitudes and behaviors is "regulatory fit." Regulatory fit is a match between an individual's regulatory orientations and the manner in which he or she pursues a goal (i.e., goal pursuit strategy); as a consequence of experiencing regulatory fit, people develop a positive attitude and engage more strongly in what they are doing (Aaker and Lee 2006; Avnet and Higgins 2006). Promotion focus, which is driven by the need for growth and leads to the pursuit of gains, fits better with approach strategies striving toward gains; in comparison, prevention focus, which is driven by the need for safety and leads to the avoidance of losses, fits better with avoidance strategies guarding against losses (Wang and Lee 2006). Prior studies showed that people feel positive emotion and are more persuaded and motivated when their goal pursuit strategies fit their regulatory focus (Higgins 2000; Idson et al. 2000; Lockwood et al. 2002). Additionally, Higgins et al. (2003) demonstrated that a fit between regulatory focus and goal pursuit strategies increases the perceived value of objects;

specifically, people assigned a 40% higher price for the same mug and a 24% higher price for the same pen when their regulatory focus (i.e., promotion or prevention) fit with the way in which they made their choice (e.g., making a choice by thinking about what they would gain or lose)

Even though the "regulatory fit" and "regulatory relevance" that individuals experience while using products/services could depend on the characteristics of products/services, the interaction effect of regulatory focus and types of products/services on individuals' choices for products/services has not yet been examined. Given that different products/services have their own promotion or prevention characteristics (Zhang et al. 2018), we categorize smartwatch health apps into promotion app and prevention app based on the outcomes associated with using the apps (i.e., promotion outcome vs. prevention outcome) and the required goal pursuit strategies (i.e., pursuit of gains vs. avoidance of losses) needed to use the apps. Then, we explore how people are differently affected by distinct motivational factors (i.e., regulatory focus) in adopting each type of smartwatch health app. We propose that differences in individuals' regulatory focus orientations give rise to differences in use intentions toward different types of smartwatch health apps depending on the fit between the individual's regulatory focus and the type of app.

3.2.3. Internal Health Locus of Control

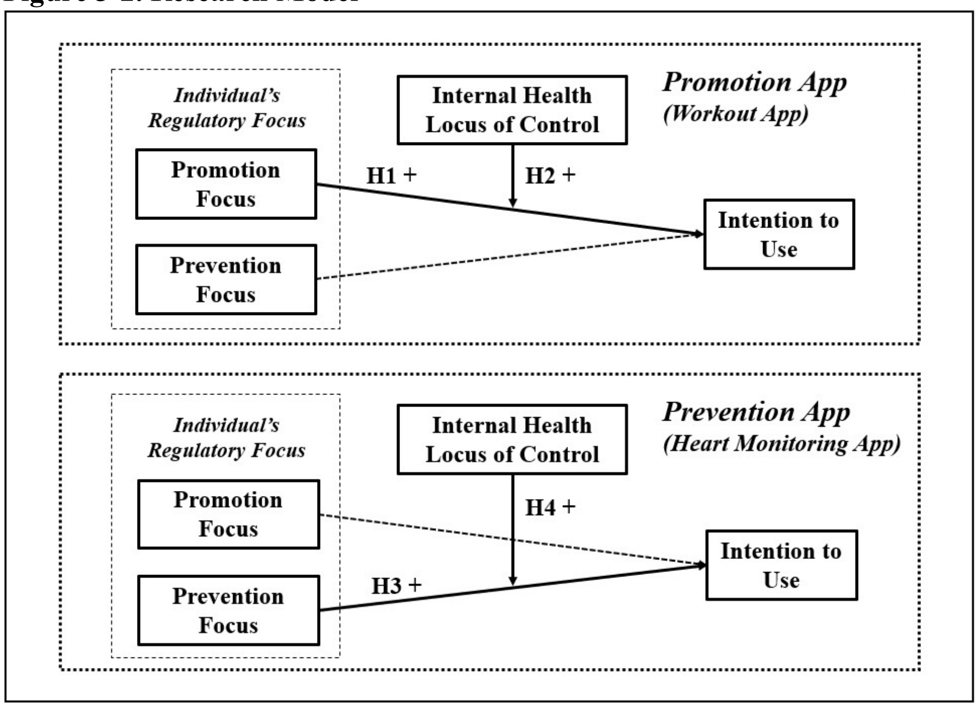
Given that smartwatch health apps rely on self-management (e.g., self-monitoring health condition) (Sama et al. 2014; Zhou et al. 2017), we need to examine how individuals' motivational attitude toward engagement in self-health-management influence intention to use smartwatch health apps. Locus of control is the concept that reflects individual's belief about the degree to which outcomes in life are determined by his/her behavior (Cobb-Clark et al. 2014; Zhou et al. 2017). People who have an internal locus of control believe that the outcomes in life stem mostly from their behavior; in comparison, people who have an external locus of control believe that the outcomes in life stem mostly from external factors that are beyond their control (Cobb-Clark et al. 2014; Gatz and Karel 1993).

Internal health locus of control refers to a person's tendency to attribute their health status to their behaviors (Cheng et al. 2016; Snell et al. 1991). People with high internal health locus of control believe that "they themselves have control over the status of their physical health" (Snell et al. 1991, p.171). Previous research on internal health locus of control has focused on the relationship between this construct and healthy behaviors. For example, Steptoe and Wardle (2001) demonstrated that high internal health locus of control is associated with individuals exhibiting healthier behaviors such as exercise, salt avoidance, and eating fiber. Additionally, Náfrádi et al. (2017) showed that high internal health locus of control promotes medication adherence. Researchers in this area have argued that people with high internal health locus of control invest more in their health because they expect a higher return on investment and get more pleasure and satisfaction out of engaging in healthy behaviors than people with low internal health locus of control (Cheng et al. 2016; Cobb-Clark et al. 2014). Even though many studies found significant relationships between internal health locus of control and healthy behaviors, the significance of these links has been inconsistent across studies, and the strength of these links vary considerably among individuals (Cheng et al. 2016; Strudler Wallston and Wallston 1978; Zhou et al. 2017). In a review study that examined the relationship between internal health locus of control and healthy behaviors, Cheng et al. (2016) demonstrated that the internal health locus of control - diet relationship is stronger for the samples containing more women and argued that this result might be due to women's negative attitude toward foods containing less nutritional value such as snacks. Thus, it is plausible that previous inconsistent results for the relationships between internal health locus of control and healthy behaviors could be explained by individuals' having varying degrees of motivational preference toward healthy behaviors. Therefore, to fully understand the role and influence of internal health locus of control on healthy behavior, we need to examine the interaction effect of internal health locus of control and motivational preference on healthy behavior.

3.3. MODEL DEVELOPMENT AND HYPOTHESES

In this section, we present our research model and hypotheses. Our research model is depicted in Figure 3-2.

Figure 3-2. Research Model



As described earlier promotion apps are those where the outcomes of using apps satisfy the need for growth and require users to engage in an approach strategy (i.e., the pursuit of gains). In comparison, prevention apps are those where that the outcomes of using the apps satisfy the need for safety and the apps require users to engage in avoidance strategies (i.e., avoidance of losses). For this study, we chose to examine a Workout app as being representative of promotion apps in that it can help users gain physical strength (i.e., promotion outcome) by engaging in workout (i.e., approach strategy). We chose a Heart Monitoring app as being representative of prevention apps in that it can help users prevent heart complications and strokes (i.e., prevention outcome) by monitoring their heart rhythm (i.e., avoidance strategy). Table 3-1 presents descriptions for both the promotion app and the prevention app we chose to study.

Table 3-1. Example of Promotion App and Prevention App

Promotion App	Prevention App
Workout App This smartwatch app guides you through each workout like a personal trainer. This app helps you gain strength and endurance. Simply tell the app your body weight and height and it will create customized workout routines for you. The app will tell you how long to rest between sets and will suggest specific exercises for your workout. It's like having your own personal trainer. The feedback and support provided by this app is effective for any level of exercise program.	Heart Monitoring App This smartwatch app monitors your heart - rate to check for irregular heart rhythms. This application will look specifically at an irregular heart rhythm (atrial fibrillation - or afib) which results in more than 130,000 deaths per year in the United States, according to estimates from the Centers for Disease Control and Prevention. Early diagnosis and treatment of irregular heart rhythms may prevent serious heart complications and strokes. If this app detects an irregular heartbeat, it will notify you.

While we do not argue that these two categories are exhaustive or mutually exclusive, we propose that individuals' different regulatory orientations have a differential impact on their use intention toward different types of smartwatch health apps depending on the regulatory fit and regulatory relevance that an individual expects to experience while using smartwatch health apps. Thus, we hypothesize that the promotion focus positively influences intention to use promotion apps, and prevention focus positively influences intention to use prevention apps. According to prior studies, different regulatory orientations (i.e., promotion or prevention) prompt individuals to selectively pay attention to the information that is congruent to their regulatory focus (Aaker and Lee 2006; Lockwood et al. 2002); moreover, when people expect to experience "regulatory fit" and "regulatory relevance" by using products/ services, their attitudes toward a product/ services become more positive and motivation to use it is enhanced (Aaker and Lee 2006; Higgins 2000). This is because people will perceive the products/services as being more useful when they find the outcomes associated with using the products/services and the goal pursuit strategies required to use them to be congruent with their regulatory orientations. Therefore, when a person with a high promotion focus receives information about promotion apps that have promotion outcomes and that require him/her to engage in an approach strategy, he/she may expect to experience high "regulatory relevance" and "regulatory fit", and may therefore show higher intention to use promotion apps than a person with a low promotion focus. Similarly, when a person with a high prevention focus receives information about prevention apps that have prevention outcomes and that require him/her to engage in an avoidance strategy, he/she may expect to experience high "regulatory relevance" and "regulatory fit", and may therefore show higher intention to use prevention apps than a person with a low prevention focus. Thus, we hypothesize that:

Hypothesis 1 (H1): Promotion focus positively influences the intention to use promotion apps.

Hypothesis 2 (H2): Prevention focus positively influences the intention to use prevention apps.

This study further proposes that internal health locus of control strengthens the impacts of regulatory orientations on the intention to use smartwatch health apps. Specifically, internal health locus of control should: (1) positively moderate the impact of promotion focus on promotion apps and (2) positively moderate the impact of prevention focus on prevention apps. As suggested in this study, people's intention to use smartwatch health apps may depend on the degree of fit between their regulatory orientations and the characteristics of smartwatch health apps because the increased fit increases the perceived value of the apps. A previous review article suggested that the positive influence of internal health locus of control on healthy behaviors increases as the individuals' perceived values of healthy behaviors increases (Cheng et al. 2016). Therefore, the positive influence of internal health locus of control on the intention to use smartwatch health apps may increase as the fit between regulatory orientations and the characteristics of smartwatch health apps increases. In other words, the degree of fit between regulatory focus and characteristics of apps interact with internal health locus of control in influencing intention to use smartwatch health apps.

Additionally, people with high internal health locus of control invest more in their health than people with low internal health locus of control because they expect higher return on investment and get more pleasure and satisfaction from engaging in healthy behaviors than people with low internal health locus of control (Cheng et al. 2016; Cobb-Clark et al. 2014). Therefore, the positive influence of the fit between regulatory focus and characteristics of smartwatch health apps on the intention to use apps may be strengthened by internal health locus of control because people with high internal health locus of control invest more in their health than people with low internal health locus of control.

In sum, the positive impact of promotion focus on the intention to use promotion apps may be strengthened by internal health locus of control because people with high internal health locus of control invest more in their health than people with low internal health locus of control, and the positive influence of internal health locus of control on intention to use promotion apps may increase as the fit between promotion focus and promotion apps increases. Similarly, the positive impact of prevention focus on the intention to use prevention apps may be strengthened by internal health locus of control because people with high internal health locus of control invest more in their health than people with low internal health locus of control, and the positive influence of internal health locus of control on intention to use prevention apps may increase as the fit between prevention focus and prevention apps increases. Thus, we hypothesize that:

Hypothesis 3 (H3): Internal health locus of control moderates the effect of promotion focus on the intention to use promotion apps, such that the positive effect of promotion focus on the intention to use promotion apps is stronger when internal health locus of control is high than when internal health locus of control is low.

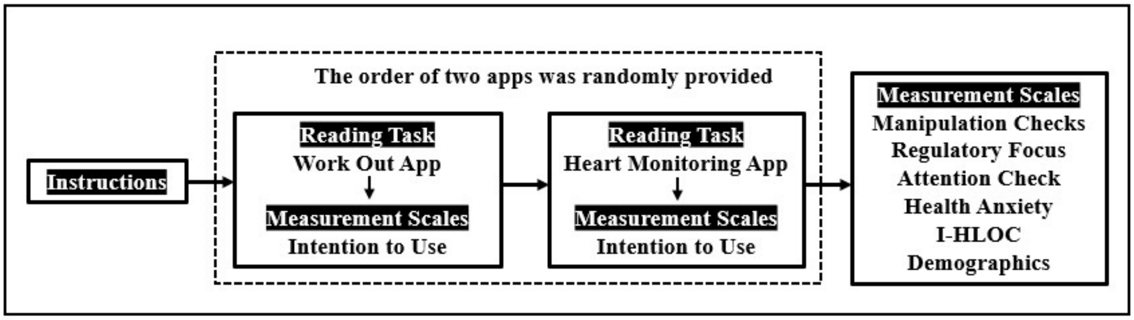
Hypothesis 4 (H4): Internal health locus of control moderates the effect of prevention focus on the intention to use prevention apps, such that the positive effect of prevention focus on the intention to use prevention apps is stronger when internal health locus of control is high than when internal health locus of control is low.

3.4. METHOD

Experimental Design and Participants. In order to test our hypotheses, we conducted an experiment using a crossover design (Shadish et al. 2002) in which the application type (promotion app/ prevention app) was manipulated. Participants were randomly assigned to read either the descriptions of a Workout App (i.e., a promotion app) or a Heart Monitoring App (i.e., a prevention app) and answered a set of measurement items about their intention to use the app, after which participants read the descriptions of the apps they did not previously get and answered questions about their intention to use the app. The experiment was conducted via Amazon Mechanical Turk, a web-based crowdsourcing service. A total of 98 subjects participated in the study, and were compensated 80 cents for doing so. Thirty responses were discarded due to manipulation and attention check failures, which we inferred from the manipulation check and attention check questions embedded in the measurement instrument. The remaining 68 responses were retained for further analysis. The average age of participants was 41.7 years, 53% of the participants were male (n=36), and 47% were female (n=32).

Procedure. The sequence of tasks involved in the experiment is described in Figure 3-3, and the entire protocol for the experiment is presented in Appendix A. First, participants were asked to read some instructions as well as a brief introduction to smartwatch health apps. Participants were asked to assume they already owned a smartwatch, wear this smartwatch at all times, and have full access to all app features on the smartwatch at any time. Next, participants were given information about both the Workout App and the Heart Monitoring App and asked about their intentions to use each of these apps. The order in which participants received information about the two different apps was randomized. Next, participants were asked to answer a set of questions which included a manipulation check, as well as measures for regulatory focus, I-HLOC, and health anxiety (which served as a control variable). Finally, participants were asked to provide demographic information.

Figure 3-3. Flowchart of Experiment



Construct Measure. *Intention to use* items were adapted from Venkatesh et al. (2003) to measure intention to use the Workout App and intention to use the Heart Monitoring App. To measure *regulatory focus*, an eighteen-item measure (i.e., nine for *promotion focus*, nine for *prevention focus*) from Lockwood et al. (2002) was used. Additionally, a five-item measure of *internal health locus of control* and a five-item measure of *health anxiety* were adopted from Snell et al. (1991).

Control Variables. We adopted three control variables: *age, gender,* and *health anxiety*. Age and gender were adopted as control variables because previous research studies demonstrated that age and gender influence mobile health adoption (Hoque and making 2016; Zhang et al. 2014; Zhao et al. 2018). Additionally, we adopted *health anxiety* as a control variable because *health anxiety* is potentially associated with both regulatory focus and intention to use mobile health apps. Previous research study demonstrated that *health anxiety* influences health care utilization such as visiting a doctor (Eastin et al. 2006). Also, *health anxiety* interacts with *promotion focus* and *prevention focus* in influencing individuals' health related attitude (e.g., readiness to engage in cancer detection) and behaviors (e.g., caretaking) (Uskul et al. 2008).

Manipulation Check. To assess the effectiveness of the application type (promotion/ prevention) manipulation, we examined whether participants correctly answered a manipulation check question that prompted them to select two smartwatch apps that they were introduced to from a list of five, including Workout App, Activity Tracking App, Heart Monitoring App, Mental Health App, and Daily Yoga App. Participants who correctly selected both Workout App and Heart Monitoring App were included in subsequent data analysis.

Order Effect. We examined whether the order in which participants received information about the two different apps influences their intention to use Workout App/ Heart Monitoring App. As a result of paired sample t-test, no statistical differences (alpha=0.05) in use intention were found between the two groups of participants who received information about smartwatch health apps in different order.

3.5. DATA ANALYSIS AND RESULTS

3.5.1. Measurement Model

To assess the measurement model of each construct, first we examined correlations between items and conducted factor analysis. Two prevention focus items showed low correlations with other items associated with prevention focus and also exhibited low factor loadings. Further, the factor analysis for prevention focus produced two factors with eigenvalues greater than 1; thus, we dropped these two items out of nine prevention focus items. After dropping the two items, one factor was produced, and all factor loadings for the remaining prevention focus items were greater than 0.5. All of the other constructs showed unidimensionality, and all items of each construct showed high correlations between items and factor loadings that were above 0.7. Next, we conducted exploratory factor analysis, and the result of EFA showed strong support for convergent and discriminant validity (see Appendix B). Convergent validity was also evaluated by examining the significance of item loadings and the average variance extracted (AVE). All loadings were significant at $p<0.01$ except for one item loading of promotion focus that was significant at $p<0.05$ ($p=0.016$). The AVE for each variable exceeds 0.6 (ranging from 0.62 to 0.97). These results suggest adequate convergent validity (Fornell and Larcker 1981). Discriminant validity was further evaluated by comparing the inter-variable correlations to the square root of the AVEs for variables (Fornell and Larcker 1981). As shown in Table 3-2, the square root of the AVE is larger than the inter-variable correlations; thus, we concluded that the measurement model has good discriminant validity.

Table 3-2. Reliabilities, Descriptive Statistics, and Correlations

Construct	α	Mean (SD)	1	2	3	4	5	6
1- Intention to Use Workout App	.99	5.48 (1.67)	.99					
2- Intention to Use Heart Monitoring App	.99	5.45 (1.80)	.31**	.97				
3- Promotion Focus	.95	6.40 (1.87)	.29*	.30*	.86			
4- Prevention Focus	.90	4.30 (1.99)	.10	.22†	-.32**	.79		
5- Internal Health Locus of Control	.93	5.48 (1.01)	.03	.14	.29*	-.14	.87	
6- Health Anxiety	.97	3.54 (1.64)	.23†	.15	-.28*	.67***	-.26*	.88

The shaded diagonal is the square root of the AVE
***p < 0.001, **p < 0.01, *p < 0.05, † P<0.1

3.5.2. Common Method Bias Assessment

To evaluate common method bias, first we conducted Harmon's single factor test (Podsakoff et al. 2003; Podsakoff and Organ 1986). As a result of the test, the six factors with eigenvalues greater than one were produced. The first extracted factor accounted for 29.5% of the variance in the data; thus, the common method bias is unlikely to be a significant issue in our data because the first extracted factor did not explain the majority of the variance in our data. Additionally, following the procedure suggested by Podsakoff et al. (2003), we assessed the measurement model by adding a common method construct. When we did so, we found that the item loadings, correlations, and covariances remained stable between the measurement models with and without common method construct. The average difference of item loadings between the measurement models with and without common method construct was .038, and the values of all correlations and covariances were not changed. Therefore, common method bias should not be of concern in this study.

3.5.3. Testing of Hypotheses

In order to analyze data and test our hypotheses, we used hierarchical OLS regression. Hierarchical regression partitions the variance of the dependent variable based on a set of independent variables which are added incrementally to the regression model. As a result of the Breusch-Pagan Test (see Table 3-3 and Table 3-4), which examines whether the variance of errors from a regression depends on the values of the independent variables, our data showed heteroskedasticity; thus, we used robust standard errors, which enables valid statistical inference in the presence of heteroskedasticity (Wooldridge 2015). Heteroskedasticity does not bias coefficient estimates and does not influence the interpretation of r-squared statistics in OLS regression (Wooldridge 2015). In this study, the statistical inferences using robust standard errors and OLS standard errors were consistent, which lends further robustness to our findings.

First, the effect of promotion focus on the intention to use the Workout App (H1) was examined. As shown in Model 2w in Table 3-3, promotion focus had a significant positive effect on the intention to use the Workout App (β=.297, t=2.56, p<.05), thus supporting H1. In other words, individuals with a higher promotion focus, showed a higher intention to use the Workout App than individuals with a lower promotion focus. In Model 1w, age, gender, health anxiety, and Internal Health Locus of Control (I-HLOC) explain 21.1% of the variance in intention to use Workout App. When promotion focus and prevention focus are added (i.e., Model 2w) to Model 1w, they add 9.8% (ΔR^2= .098, F (2,61) = 4.35, p<.05) to the variance explained. The unique contribution of promotion focus in model 2w is 8.9% (ΔR^2= 0.089, F (1,61) = 7.82, p<.001), which means promotion focus explains 8.9% more variance in intention to use the Workout App over and above the variance explained by age, gender, health anxiety, I-HLOC, and prevention focus.

Table 3-3. OLS Regression Results for Workout App, DV: Intention to Use

Variables	Workout App (N=68)			
	Model 1w	Model 2w	Model 3w	Model 4w
	β (robust s.e.), (95% C.I.)	β (robust s.e.), (95% C.I.)	β (robust s.e.), (95% C.I.)	β (robust s.e.), (95% C.I.)
Age	.030* (.014), (.002,.057)	.028† (.15), (-.001,.058)	.030* (.014), (.002, .059)	.024 (.015), (-.006, .054)
Gender	.975* (.372), (.230, 1.71)	.836* (.372), (.092, 1.58)	.674† (.351), (-.028, 1.38)	.685† (.383), (-.081, 1.45)
Health Anxiety	.308* (.121), (.066, .549)	.407* (.171), (.065, .749)	.448** (.164), (.120, .776)	.406* (.160), (.085, .727)
I-HLOC	.199 (.192), (-.185, .583)	.079 (.192), (-.304, .462)	.208 (.182), (-.155, .571)	.099 (.179), (-.259, .457)
Prevention Focus		-.031 (.132), (-.294, .232)	-.036 (.116), (-.269, .196)	-.009 (.122), (-.253, .235)
Promotion Focus		.297* (.117), (.065, .529)	.325** (.090), (.145, .506)	.317* (.121), (.075, .559)
Promotion × I-HLOC			.211** (.069), (.072, .350)	
Prevention × I-HLOC				-.159*(.066), (-.291, -.03)
R^2	.211	.309	.377	.343
ΔR^2	.084*	.098*	.068**	.034*(1)
Cohen's f^{2}(2)		.142	.109	.052
Power (1-β) (3)		.779	.764	.455
Breusch-Pagan Test, χ^2 Pro > χ^2	11.24 .024	13.3 .039	15.09 0.035	13.9 0.053

Robust s.e.: robust standard errors
C.I.: confidence interval
***p < 0.001, **p < 0.01, *p < 0.05, † P<0.1
(1) ΔR^2 between Model 4w and Model 2w
(2) $f^2 = (R^2_{Y\cdot A, B} - R^2_{Y\cdot A}) / (1- R^2_{Y\cdot A, B})$, where $(R^2_{Y\cdot A, B} - R^2_{Y\cdot A})$ is the proportion of variance explained due to the inclusion of the newly added set of variables (i.e., B) in hierarchical regression, and $(1- R^2_{Y\cdot A, B})$ is the residual variance of the model.
(3) Power of test for the increased variance explained due to the inclusion of variables which are added incrementally to the regression model in hierarchical regression, given α=0.05 and a total sample size of 68.

Table 3-4. OLS Regression Results for Heart Monitoring App, DV: Intention to Use

Variables	Heart Monitoring App (N=68)			
	Model 1h	Model 2h	Model 3h	Model 4h
	β (robust s.e.), (95% C.I.)	β (robust s.e.), (95% C.I.)	β (robust s.e.), (95% C.I.)	β (robust s.e.), (95% C.I.)
Age	.014 (.018), (-.022, .050)	022 (.017), (-.012, .057)	.022 (.018), (-.013, .058)	.025 (.017), (-.008, .058)
Gender	.092 (.434), (-.777, .960)	-.363 (.398), (-1.16, .434)	-.367 (.385), (-1.13, .403)	-.281 (.381), (-1.04, .481)
Health Anxiety	.245 (.148), (-.051, .541)	.083 (.161), (-.240, .405)	.084 (.159), (-.235, .402)	.083 (.160), (-.237, .404)
I-HLOC	.369 (.336), (-.303, 1.04)	.217 (.302), (-.387, .821)	.219 (.280), (-.341, .780)	.206 (.286), (-.366, .778)
Promotion Focus		.408** (.111), (.186, .630)	.409***(.110), (.189, .63)	.397** (.114), (.170, .624)
Prevention Focus		.345* (.129), (.087, .602)	.345* (.129), (.087, .603)	.333* (.136), (.061, .604)
Promotion × I-HLOC			.005 (.116), (-.228, .237)	
Prevention × I-HLOC				.086 (.154), (-.222, .394)
R^2	.068	.240	.242	.251
ΔR^2	.064	.172**	.002	.011(1)
Cohen's f^2		.226	.003	.015
Power (1-β)		.939	.070	.166
Breusch-Pagan Test, χ^2 Pro > χ^2	7.91 0.095	13.67 0.018	15.50 0.03	21.65 0.03

Robust s.e.: robust standard errors
C.I.: confidence interval
***p < 0.001, **p < 0.01, *p < 0.05, † P<0.1
(1) ΔR^2 between Model 4h and Model 2h
(2) $f^2 = (R^2_{Y\cdot A,B} - R^2_{Y\cdot A}) / (1 - R^2_{Y\cdot A,B})$, where $(R^2_{Y\cdot A,B} - R^2_{Y\cdot A})$ is the proportion of variance explained due to the inclusion of the newly added set of variables (i.e., B) in hierarchical regression, and $(1 - R^2_{Y\cdot A,B})$ is the residual variance of the model.
(3) Power of test for the increased variance explained due to the inclusion of variables which are added incrementally to the regression model in hierarchical regression, given α=0.05 and a total sample size of 68.

Next, the effect of prevention focus on the intention to use the Heart Monitoring App (H2) was examined. As shown in Model 2h in Table 3-4, the result indicates that prevention focus had a significant positive effect on the intention to use the Heart Monitoring App (β=.345, t=2.68, p<.05), supporting H2. In other words, individuals with a higher prevention focus, showed a higher intention to use the Heart Monitoring App than people with lower prevention focus. In Model 1h, age, gender, health anxiety, and I-HLOC explain 6.8% of the variance in intention to use the Heart Monitoring App. When promotion focus and prevention focus are added (i.e., Model 2h) to Model 1h, they add 17.2% (ΔR^2= .172, F (2,61) = 10.13, p<0.001) to the variance explained. The unique contribution of prevention focus in Model 2h is 6.6% (ΔR^2= 0.066, F (1,61) = 7.17, p<0.01), which means prevention focus explains 6.6% more variance in intention to use the Heart Monitoring App over and above the variance explained by age, gender, health anxiety, I-HLOC, and promotion focus.

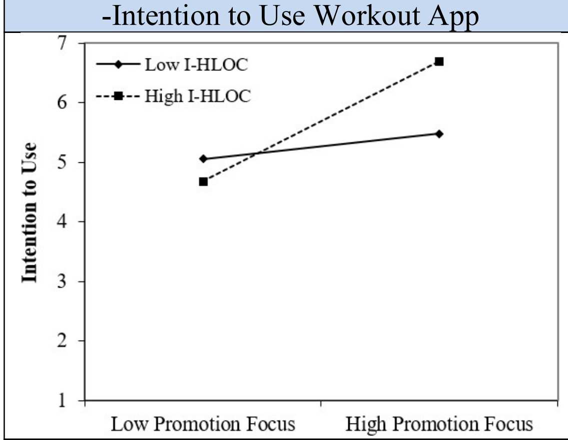
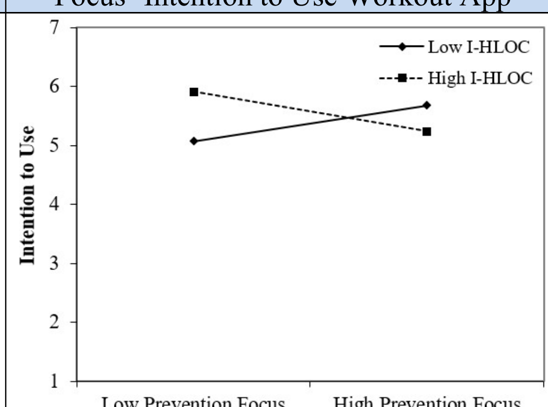
Next, the moderating role of I-HLOC on the effect of promotion focus on the intention to use Workout App (H3) was examined. As shown in Model 3w in Table 3-3, the result indicates that I-HLOC had a significant positive moderating effect on the relationship between promotion focus and intention to use the Workout App (β=.211, t=3.03, p<.01), suggesting that a high I-HLOC strengthened the positive relationship between promotion focus and intention to use the Workout App. Thus, H3 was supported. In the hierarchical regression analysis, the interaction term (i.e., Promotion × I-HLOC) explains an additional 6.8% (ΔR^2= .068, F (1,61) = 9.26, p<.01) of the variance in intention to use the Workout App over and above the variance explained by Model 2w, which includes age, gender, health anxiety, I-HLOC, promotion focus, and prevention focus. Simple slopes and the test for simple slopes are provided in Figure 3-4.

Lastly, the moderating role of I-HLOC on the relationship between prevention focus and the intention to use the Heart Monitoring App (H4) was examined. As shown in Model 4h in Table 3-4, the result indicates that I-HLOC had no moderating effect on the relationship between prevention focus and intention to use the Heart Monitoring App (β=.086, t=0.56). Thus, H4 was not supported.

3.5.4. Post Hoc Analysis

In the post hoc analysis, we examined certain relationships that we were unable to hypothesize based on existing theory, but which could contribute to the extension of theory and extend our understanding of how individual differences influence intention to use smartwatch health apps. First we tested the moderating effect of I-HLOC on the relationship between prevention focus and intention to use the Workout App. As shown in Model 4w in Table 3-3, I-HLOC had a significant negative moderating effect on the relationship between prevention focus and intention to use the Workout App (β=-.159, t=-2.42, p<.05). Specifically, a high I-HLOC weakened the relationship between prevention focus and intention to use the Workout App. In the hierarchical regression analysis, the interaction term (i.e., Prevention × I-HLOC) explains an additional 3.4% (ΔR^2= .034, F (1,61) = 5.84, p<.05) of the variance in intention to use the Workout App over and above the variance explained by Model 2w.

Figure 3-4. Simple Slopes for the Moderating Roles of I-HLOC on the Relationships between Regulatory Focus and Intention to Use Workout App

Moderation of I-HLOC on Promotion Focus -Intention to Use Workout App	Moderation of I-HLOC on Prevention Focus -Intention to Use Workout App
	
Testing Simple Slopes	*Testing Simple Slopes*
Slope (robust s.e.)/ t	Slope (robust s.e.)/ t
High I-HLOC .539*** (.123)/ 4.39	High I-HLOC -.170 (.140)/ -1.21
Low I-HLOC .112 (.105)/ 1.06	Low I-HLOC .152 (.137)/ 1.10

***p < 0.001, **p < 0.01, *p < 0.05, † P<0.1

Figure 3-4 illustrates the interactions between internal health locus of control and promotion focus and the interaction between internal health locus of control and prevention focus that were observed. We conducted a simple slope analysis to test whether the slopes are significantly different from zero. The results demonstrated that promotion focus had a significant positive influence on intention to use the Workout App when internal health locus of control is high (1 standard deviation above mean) (β=.539, t=4.39, p<.001); however, when internal health locus of control is low (1 standard deviation below mean) the influence of promotion focus on intention to use the Workout App was not significant (β=.112, t=1.06). This result implies that the degree of fit between promotion focus and the promotion apps has a higher impact on intention to use promotion apps when people have a higher tendency to attribute health status to their behavior.

Additionally, the results from simple slope analysis indicate that prevention focus did not significantly influence intention to use the Workout App both when internal health locus of control is high (β=-.170, t=-1.21) and when internal health locus of control is low (β=.152, t=1.10). Our findings show, however, that prevention focus can have a differential impact on the intention to use promotion apps depending on the magnitude of internal health locus of control, such that prevention focus has a positive influence on the intention to use a promotion app when internal health locus of control is low and a negative influence when internal health locus of control is high.

Next, we tested the moderating effect of internal health locus of control on the relationship between promotion focus and intention to use the Heart Monitoring App. As shown in Model 3h in Table 3-4, internal health locus of control had no significant moderating effect on the relationship between promotion focus and intention to use the Heart Monitoring App (β=.005, t=0.04).

Lastly, we tested the impact of regulatory orientations that are incongruent with the types of smartwatch health apps on the intention to use smartwatch health apps (i.e., the effect of prevention focus on the intention to use a promotion app, and the effect of promotion focus on the intention to use a prevention app). As shown in Model 2w in Table 3-3, prevention focus did not influence intention to use the Workout App (β=-.03, t=-0.24). However, as shown in Model 2h in Table 3-4, promotion focus had a significant positive effect on intention to use the Heart Monitoring App (β=.408, t=3.67, p<.01).

3.6. DISCUSSION

In our experiment, we demonstrated that the fit between smartwatch health apps (promotion app and prevention app) and an individual's regulatory focus motivates the use of these apps and that the effect of this fit on intention to use a promotion app is strengthened by an individual's motivational strength toward engaging in health behavior (i.e., internal health locus of control). Also, we found that internal health locus of control weakens the effect of prevention focus on intention to use a promotion app.

However, different from our expectation, internal health locus of control did not moderate the relationship between prevention focus and intention to use the Heart Monitoring App. This result may be due to the low effort of using the Heart Monitoring App. Users' intention to use mobile health apps is influenced by the costs and the burdens associated with using such apps (Birkhoff and Smeltzer 2017). Given that internal health locus of control is one of the indicators that represent motivational readiness to engage in healthy behavior (Cobb-Clark et al. 2014) and that motivational readiness is critical when a behavior requires considerable effort (e.g., physical exercise) (Resnicow et al. 2017), internal health locus of control may influence intention to use an app only when the use of the app requires a high amount of effort. When smartwatch health apps don't require users to invest a lot of effort in order to use them (e.g., just wearing the Smartwatch and waiting for the alert from the app), factors such as motivational readiness and internal health locus of control, may not have much influence on intention to use the app (as individuals with both low and high internal health locus of control can overcome whatever small barriers exist to using the app). In other words, there may be an effort threshold that must be overcome before we see much of an effect associated with internal health locus of control and the choice to engage in healthy behavior.

As a post hoc analysis, we examined the impact of promotion focus on intention to use a prevention app, and the impact of prevention focus on intention to use a promotion app. As noted earlier, while prevention focus did not influence intention to use the Workout App (i.e., promotion app), promotion focus had a significant positive impact on intention to use the Heart Monitoring App (i.e., prevention app). These results may be due to the different level of effort associated with using the Workout App and the Heart Monitoring App. Specifically, the Workout App requires users to spend more effort to use the app (i.e., they must engage in a fitness workout) than the Heart Monitoring App, which merely requires users to wear the Smartwatch and wait for a possible alert from the app. Determinants of intention to use products include both the benefits from using it and the cost of using it (Herzenstein et al. 2007). Our post hoc analysis suggests that individuals with high promotion focus might find more promotion type of benefit from Heart Monitoring App (i.e., prevention app) than individuals with a low promotion focus, and their perceived benefit from using the Heart Monitoring app might exceed the low "cost" to use it. However, individuals with high prevention focus might not exhibit higher intention to use the Workout App (i.e., promotion app) than individuals with low prevention focus because the "cost" of using the app is higher than the perceived benefits from using the app (for individuals with both high and low prevention focus).

3.6.1. Theoretical Implications

This study makes meaningful contributions to several research streams. First, this study contributes to regulatory focus literature by examining the relationships between regulatory focus and product/service characteristics. Even though different products/services have promotion or prevention characteristics (Zhang et al. 2018), few previous studies on regulatory focus have examined how these different products/ services differentially appeal to individuals' particular regulatory focus. This study categorizes smartwatch health apps into two categories depending on characteristics (outcomes of using apps and required goal pursuit strategies) that appeals to individuals' different regulatory orientations and empirically shows how people are influenced by their regulatory focus in adopting each type of smartwatch health app.

Second, this study contributes to mobile health literature by demonstrating how individual difference factors, such as regulatory focus and internal health locus of control, influence the adoption of smartwatch health apps. Even though mobile health is more individual-centered and relies on self-management (Sama et al. 2014; Zhou et al. 2017), few previous studies on mobile health have examined how individual difference factors influence the adoption of each mobile health. This study demonstrates two independent constructs (promotion focus and prevention focus) and one moderating construct (internal health locus of control) as individual difference factors that influence the intention to use mobile health.

Third, this study contributes to internal health locus of control literature by examining the interaction effect of internal health locus of control and individuals' motivational factors on the intention to adopt healthy behavior. Previous internal health locus of control research mostly focused on the correlated relationships between internal health locus of control and intention to adopt healthy behaviors; however, the significance of these links were inconsistent across studies and the strength of these links vary considerably among individuals, who might have different attitudes and motivations toward health behaviors (Cheng et al. 2016; Strudler Wallston and Wallston 1978). To the best of our knowledge, this is the first study which examines the interaction effect of internal health locus of control and individuals' motivational factors on the intention to adopt healthy behavior. Specifically, this study empirically shows how internal health locus of control interacts with promotion focus and prevention focus in influencing the intention to use promotion apps.

3.6.2. Practical Implications

The findings of this study can be translated into practice by providing health practitioners with insights on how to design health promotion programs using smartwatch health apps. Health practitioners may be able to consider clients' inherent motivational orientations, such as promotion focus and prevention focus, and the internal health locus of control to provide clients more effective health promotion programs. Also, this study provides marketers of smartwatch health apps with practical implications on how to promote their apps to individuals with different regulatory orientations and health internal locus of control. We suggest that the marketing of promotion type of app should target promotion-oriented individuals but that the marketing of prevention type of app can target both promotion and prevention-oriented individuals for ensuring the effectiveness of the marketing. Additionally, despite the fact that regulatory focus is viewed as a trait, regulatory focus can be manipulated for a short time (Higgins et al. 2003). Therefore marketers of smartwatch health apps may be able to prime (Freitas and Higgins 2002) their potential customers in order to temporarily increase customers' intention to use their apps.

3.6.3. Limitations and Future Research

Even though our operationalizations of promotion apps (i.e., the Workout App) and prevention apps (i.e., the Heart Monitoring App) reflect the apps' characteristics (i.e., outcomes associated with using apps and the required goal pursuit strategies in order to use them) that appeal to individuals' particular regulatory focus, we failed to operationalize the effort that is related to the use of apps in our experiment. Given that both benefits and costs influence the adoption of product/ services (Herzenstein et al. 2007) and that the costs and user burden for using apps negatively affect users' intention to use mobile health apps (Birkhoff and Smeltzer

2017), future research needs to examine how cost-related factors influence the relationships between regulatory focus and the intention to use smartwatch health apps.

As discussed in the previous section, internal health locus of control did not moderate the relationship between prevention focus and intention to use the Heart Monitoring App and this result might be due to the extremely low effort related to the use of Heart Monitoring App. We propose that there is an effort threshold that must be overcome before we see much of an effect of internal health locus of control on the choice to engage in healthy behavior. Future research needs to empirically test whether internal health locus of control influences healthy behaviors only when healthy behaviors require high effort or "cost".

3.7. CONCLUSION

Despite the increasing popularity of smartwatch health apps that rely on self-management (Sama et al. 2014; Zhou et al. 2017), few studies have investigated the influence of individual difference factors on intention to use smartwatch health apps. This study examined how individuals' inherent motivational orientations and internal beliefs regarding their ability to control their health have differential influence on their intention to use a promotion app versus a prevention app. We hope that this study leads to additional research on the impact of fit between individual difference factors and characteristics of mobile health apps on the adoption of mobile health apps.

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Appendix A: Research Protocol and Study Instrument

Instruction

Mobile health applications (apps) can help you manage your health and wellness by promoting a healthy lifestyle and providing access to useful health information and resources.

In this online survey, we would like to introduce you to **two smartwatch applications**. On the next two pages, we will provide descriptions of each of these smartwatch applications.

Please take at least 30 seconds to carefully read the two descriptions of each of these smartwatch apps. After reading each description, you will be asked several questions.

As you are reading these descriptions of the smartwatch applications, please assume that:

- **You already own a smartwatch.**
- **You wear this smartwatch at all times (i.e., 24 hours a day, 7 days a week).**
- **You have full access to all app features on the smartwatch at any time.**

Reading Task: Workout App

Workout App

This smartwatch app guides you through each workout like a personal trainer. This app helps you gain strength and endurance.

Simply tell the app your body weight and height and it will create customized workout routines for you. The app will tell you how long to rest between sets and will suggest specific exercises for your workout. It's like having your own personal trainer.

The feedback and support provided by this app is effective for any level of exercise program.

Measurement: Intention to Use Workout App (Venkatesh et al. 2003)
(1 Strongly disagree…7 Strongly agree)

Based on the information you read about this app (and the assumptions mentioned earlier about having a smartwatch, wearing it all of the time, and having access to the apps at any time), please indicate your level of disagreement or agreement with the following statements.

Ignoring issues of cost for the moment,

1. I intend to use this workout application in the next 3 months.
2. I predict I would use this workout application in the next 3 months.
3. I plan to use this workout application in the next 3 months.

Reading Task: Heart Monitoring App

Heart Monitoring App

This smartwatch app monitors your heart-rate to check for irregular heart rhythms. This application will look specifically at an irregular heart rhythm (atrial fibrillation — or afib) which results in more than 130,000 deaths per year in the United States, according to estimates from the Centers for Disease Control and Prevention. Early diagnosis and treatment of irregular heart rhythms may prevent serious heart complications and strokes.

If this app detects an irregular heartbeat, it will notify you.

Measurement: Intention to Use Heart Monitoring App (Venkatesh et al. 2003)
(1 Strongly disagree…7 Strongly agree)

Based on the information you read about this app (and the assumptions mentioned earlier about having a smartwatch, wearing it all of the time, and having access to the apps at any time), please indicate your level of disagreement or agreement with the following statements.

Ignoring issues of cost for the moment,

1. I intend to use this workout application in the next 3 months.
2. I predict I would use this workout application in the next 3 months.
3. I plan to use this workout application in the next 3 months.

Manipulation Checks

Please select the instruction you received when you started this survey.

1. You don't have to use the smartwatch apps that you are being introduced to
2. Please imagine the characteristics of the smartwatch apps that you are being introduced to
3. Please assume that you wear a smartwatch 24/7
4. You don't have to buy a new smartphone to use the apps you are being introduced to
5. None of the above

Please select the two smartwatch apps that you were introduced to.

1. Workout App
2. Activity Tracking App
3. Heart Monitoring App
4. Mental Health App
5. Daily Yoga App

Measurement: Regulatory Focus (Lockwood et al. 2002)
(1 Not at all true of me… 9 Very true of me)

Please select the appropriate number beside each item.

1. In general, I am focused on preventing negative events in my life.
2. I am anxious that I will fall short of my responsibilities and obligations.
3. I frequently imagine how I will achieve my hopes and aspirations.
4. I often think about the person I am afraid I might become in the future.
5. I often think about the person I would ideally like to be in the future.
6. I typically focus on the success I hope to achieve in the future.
7. I often worry that I will fail to accomplish my goals.
8. I often think about how I will achieve my success.
9. I often imagine myself experiencing bad things that I fear might happen to me.
10. I frequently think about how I can prevent failures in my life.
11. I am more oriented toward preventing losses than I am toward achieving gains.
12. My major goal right now is to achieve my ambitions.
13. My major goal right now is to avoid becoming a failure.
14. I see myself as someone who is primarily striving to reach my "ideal self" to fulfill my hopes, wishes, and aspirations.
15. I see myself as someone who is primarily striving to become the self I "ought" to be to fulfill my duties, responsibilities, and obligations.
16. In general, I am focused on achieving positive outcomes in my life.
17. I often imagine myself experiencing good things that I hope will happen to me.
18. Overall, I am more oriented toward achieving success than preventing failure.

Attention Check

This study will help us understand people's intention to use a mobile health application. Getting meaningful and useful responses from participants in a study depends on a number of important factors. Thus, we are interested in knowing certain things about you. Specifically, we are interested in seeing whether you take the time to read survey directions and questions carefully prior to providing an answer. So, in order to demonstrate that you read these instructions carefully, please select the all of the above answer from the choices listed below. Thank you for your cooperation and participation in this study.

What kind of mobile health application do you think health practitioners "really" use to help sedentary (inactive) individuals?

1. Activity Tracking App
2. Heart Monitoring App
3. Scheduling App
4. Mental Health App
5. Facebook App
6. All of the above

Measurement: Health Anxiety (Snell et al. 1991)
(1 Strongly disagree…7 Strongly agree)

Please indicate the extent to which you disagree or agree with each of the following statements.

1. I feel anxious when I think about my health.

2. I'm worried about how healthy my body is.
3. Thinking about my health leaves me with an uneasy feeling.
4. I usually worry about whether I am in good health.
5. I feel nervous when I think about the status of my physical health.

Measurement: Internal Health Locus of Control (Snell et al. 1991) (1 Strongly disagree…7 Strongly agree)

Please indicate the extent to which you disagree or agree with each of the following statements.

1. I feel like my physical health is something that I myself am in charge of.
2. My health is something that I alone am responsible for.
3. The status of my physical health is determined largely by what I do (and don't do)
4. What happens to my physical health is my own doing.
5. Being in good physical health is a matter of my own ability and effort.

Appendix B: Exploratory Factor Analysis

Table A. Exploratory Factor Analysis: Maximum Likelihood Extraction with Direct Oblimin Rotation(1)

	1 α =.99	2 α =.99	3 α =.90	4 α =.95	5 α =.97	6 α =.93
Intention to Use Workout App 1	-.965	.035	-.038	.005	-.048	.012
Intention to Use Workout App 1	-.961	-.007	.032	.053	-.008	.037
Intention to Use Workout App 1	-.987	.022	-.006	.012	-.018	.057
Intention to Use Heart Monitoring App 1	-.029	.987	-.019	.000	-.060	.033
Intention to Use Heart Monitoring App 2	-.046	.936	.043	.048	-.022	.011
Intention to Use Heart Monitoring App 3	.003	.980	.004	.001	-.047	.050
Prevention Focus 1	-.076	-.097	.536	.048	-.351	.098
Prevention Focus 2	.110	-.089	.735	-.024	-.184	.070
Prevention Focus 3	-.032	-.082	.762	.055	-.228	-.102
Prevention Focus 4	.049	-.032	.765	-.084	-.250	.106
Prevention Focus 5	-.083	.253	.552	.092	.038	-.231
Prevention Focus 6	-.122	.034	.585	-.232	-.034	-.039
Prevention Focus 7	.047	.146	.704	-.098	.060	.048
Promotion Focus 1	-.143	-.078	-.044	.857	.066	-.020
Promotion Focus 2	.133	.037	.023	.735	-.176	.251
Promotion Focus 3	-.003	-.041	.143	.899	.104	.011
Promotion Focus 4	-.010	-.043	.040	.933	.099	-.100
Promotion Focus 5	-.086	-.006	-.041	.819	.028	.028
Promotion Focus 6	-.114	.090	-.113	.666	.042	.178
Promotion Focus 7	-.012	.165	-.257	.745	-.120	.027
Promotion Focus 8	-.049	.067	.072	.806	.083	-.118
Promotion Focus 9	.033	.055	-.164	.769	-.001	-.025
Health Anxiety 1	-.040	.040	.065	-.032	-.845	-.105
Health Anxiety 2	-.135	.027	.085	.021	-.799	-.073
Health Anxiety 3	-.003	.010	.026	-.055	-.903	-.027
Health Anxiety 4	-.017	.116	.152	-.065	-.785	-.036
Health Anxiety 5	.018	.012	.009	-.051	-.938	-.029
Health Internal Control 1	.062	.071	.173	.115	.163	.768
Health Internal Control 2	-.090	-.044	-.070	-.059	.016	.855
Health Internal Control 3	-.092	-.071	-.008	.054	-.064	.892
Health Internal Control 4	.017	.111	.028	-.018	.184	.764
Health Internal Control 5	.032	.065	-.068	.006	-.052	.978

(1) Because our purpose was not dimension reduction and constructs are correlated substantively (as shown in Table 3-2) and theoretically, we used maximum likelihood as an extraction method and direct oblimin as rotation method. In social science research,

EFA for evaluating construct validity should employ oblique rotation method (e.g., direct oblimin), which permits correlations among factors, because almost all phenomena and constructs in social science research are correlated with one another (Fabrigar et al. 1999; Matsunaga 2010). When factors are correlated, "oblique rotation provides much better simple structure, more interpretable results, and more theoretically plausible representations of the data" than orthogonal rotation (Fabrigar et al. 1999, p.291).

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CHAPTER 4

Research Essay 3

Motivating Increased Physical Activity: An Examination of an IT-Enabled Social Comparison Mechanism

4.1. INTRODUCTION

Physical inactivity is one of the biggest threats to an individual's health and considered to be a contributing factor in a variety of illnesses, including cardiovascular disease, cancers, and diabetes mellitus type II (Hermsen et al. 2017). Unfortunately, despite the considerable efforts of the World Health Organization (WHO) and governments through various public campaigns and interventions, many adults in the world still do not meet the recommended physical activity criteria of the WHO [1] (Barreto 2013; Rhodes et al. 2017). To increase people's physical activity, researchers have implemented various interventions; however, the interventions that have been used to date have had small effect sizes and have produced mixed results across studies (Rhodes et al. 2017). Therefore, more innovative interventions are needed to increase people's physical activity (Rhodes et al. 2017).

One promising solution for increasing people's physical activity is to implement information technology (IT) enabled physical activity interventions that use sensors (e.g., GPS and accelerometers) to monitor people's real-time physical activity and deliver more interactive, automated, and personalized interventions based on this information. While previous studies have examined the effects of IT-enabled interventions, such as adaptive goal setting and personalized

[1] ≥ 150 min/week of moderate-intensity physical activity, or ≥ 75 min/week of vigorous-intensity physical activity or an equivalent combination of moderate and vigorous activity accumulated in bouts of more than 10 min.

feedback, on individual activity levels (Adams et al. 2017; Choi et al. 2016; Cowdery et al. 2015; Direito et al. 2014; Franks et al. 2018; Gasser et al. 2006; Gilson et al. 2016; Glynn et al. 2014; Maher et al. 2015; Poirier et al. 2016; Rabbi et al. 2015; Smith et al. 2014; Walsh et al. 2016), the results have been mixed (Schoeppe et al. 2016), and the underlying mechanisms that successfully motivate additional activity have rarely been examined. One mechanism in particular, IT-enabled social comparison, is promising, but has yet to be fully examined. Thus, in this study, we focus on IT-enabled social comparison and examine its effect on physical activity.

Social comparison is the self-evaluation that leads to comparison concern (i.e., the desire to achieve a superior relative position), which causes competitive behavior (Festinger 1954; Garcia et al. 2013). When a social comparison is important to the self and the commensurate counterpart exists, social comparison generates competition and improves performance (Garcia et al. 2006; Garcia et al. 2013; Tesser 1985). IT-enabled social comparison encourages individuals to engage in physical activity by providing real-time information about their physical activity rankings among reference people (i.e., targets that individuals compare with themselves), which may generate competitive behavior. Compared to other IT-enabled physical activity interventions that have been examined, IT-enabled social comparison has received comparatively little attention from researchers and; thus, to the best of our knowledge, the effect of IT-enabled competition on physical activity has yet to be established. One problem has been that previous intervention studies have implemented IT-enabled social comparison together with other interventions such as rewards and have produced mixed results, making it difficult to verify the effect of IT-enabled social comparison on physical activity (Johnson et al. 2016). However, considering the psychological mechanism for the effect of social comparison on human behavior change (Festinger 1954; Garcia et al. 2006; Garcia et al. 2013; Jung et al. 2010; Morschheuser et al. 2018; Tauer and Harackiewicz

2004; Zhang 2008) and the features of IT-enabled social comparison that can generate competitive behavior by allowing people to check their real-time activity rankings at any time, IT-enabled social comparison may have a significant and even better effect on physical activity than non-IT-enabled social comparison. Additionally, previous research has shown that the positive effect of competition on performance is stronger when people can check their progress compared to competitors (Stanne et al. 1999), which is one of the features that IT-enabled social comparison affords. Therefore, IT-enabled social comparison is a potentially promising intervention for increasing people's physical activity that warrants further examination.

This study investigates the conditions under which effective engagement and behavior change occur through IT-enabled social comparison in the context of physical activity. This is an area that is not only understudied, but also critical from a public health perspective. Specifically, we focused on people's motivation as a condition that influences the effect of IT-enabled social comparison on physical activity. Previous research that examined relationships between motivations and physical activity consistently showed the importance of intrinsic motivation in fostering physical activity (Teixeira et al. 2012). However, most of these studies have focused on the intrinsic motivation for the target behavior (i.e., pleasant feeling often associated with physical activity) and on the direct effect of intrinsic motivation on physical activity, and thus offer a somewhat limited explanation regarding the relationship between intrinsic motivation and physical activity. The effectiveness of technology in attracting people depends on users' strength of motivational needs supported by technology (Zhang 2007). Therefore, in order to fully understand the role of intrinsic motivation on physical activity under IT-enabled social comparison, one must consider individuals' motivation for using activity tracking software that provides real-time information about their physical activity and physical activity rankings that may facilitate social comparisons.

Thus, in addition to studying the effect of IT-enabled social comparison on physical activity, this study also examines the moderating role of intrinsic motivation for using activity tracking software on the relationship between IT-enabled social comparison and physical activity as well as the direct effect of intrinsic motivation for using activity tracking software on physical activity. Motivated by these issues, the current study seeks to answer the following research questions:

RQ1: What is the effect of IT-enabled social comparison on physical activity?

RQ2: How does the intrinsic motivation for using activity tracking software influence physical activity in the context of IT-enabled social comparison?

To answer these research questions, we conducted an 8-week field experiment (one-week baseline, four-week treatment, and three-week follow-up) using a randomized experimental design, in which participation in IT-enabled social comparison was the primary treatment. Given that the purpose of our experiment is to help inactive people become more active, the least physically active people were selected as experiment participants among applicants. Physical activity for those in the treatment (IT-enabled social comparison) and control (no IT-enabled social comparison) groups was measured by daily step counts using activity trackers[2] (i.e., objective measure of physical activity) as well as the total MET[3]-min/week[4] (energy expenditure during a week, subjective measure of physical activity) using the International Physical Activity Questionnaire (IPAQ). Intrinsic motivation for using activity tracking software was measured

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[2] Activity trackers are wearable devices that monitor and display user-generated data regarding the user's daily movement such as the number of steps taken and distance covered.

[3] MET (Metabolic Equivalent of Task): the ratio of metabolic rate during physical activity to resting metabolic rate during physical inactivity. Walking = 3.3 METs, Moderate Physical Activity = 4.0 METs, and Vigorous Physical Activity = 8.0 METs

[4] MET-min/week: a combined total physical activity during a week. It can be computed as the sum of Walking + Moderate + Vigorous MET-min/week scores

through longitudinal surveys.

This study contributes to health information technology (HIT) literature as well as physical activity literature by establishing the effect of IT-enabled social comparison mechanism on physical activity and how IT-enabled social comparison influences physical activity. This study also contributes to HIT literature as well as motivation literature by examining the roles of individuals' motivational factors on human behavior change under the context of IT-enabled interventions. The remainder of the paper is organized as follows. First, we review the relevant literature to position the study, integrate the study with extant theories, and provide a theoretical basis for the hypotheses. Next, we present our research model and hypotheses, Then, we describe the research methodology, data analysis, and results. We conclude with implications for theory and practice.

4.2. THEORETICAL BACKGROUND

In this section, we provide theoretical background and previous literature on physical activity, IT-enabled social comparison, and intrinsic motivation.

4.2.1. Physical Activity

Physical activity is "any bodily movement produced by skeletal muscles that results in energy expenditure" (Caspersen et al. 1985, p.126). Physical activity is different from exercise which is defined as "planned, structured, repetitive, and purposive" bodily movement to improve or maintain physical fitness (Caspersen et al. 1985, p.128). Thus, physical activity is a broader concept than exercise and encompasses all activities in our daily life. The most frequently used measures of physical activity in previous studies include daily steps and energy expenditure (e.g., total MET min./week), and these measures have been used to classify the study participants' level of physical activity as sedentary/ inactive, low/ minimally active, or physically active/ health enhancing physically active (Al-Hazzaa 2007; Ryu et al. 2015; Tudor-Locke et al. 2012). Both measures were used in this study, considering that these two measures have advantages and disadvantages[5] for investigating changes in physical activity in relation to IT-based physical activity interventions.

Physical inactivity is one of the significant causes of mortality, and routine physical activity substantially decreases the risk for mortality; furthermore, regular participation in physical activity reduces the risk for more than 25 chronic diseases such as cardiovascular disease, stroke, and colon cancer (Rhodes et al. 2017). Because of the importance of physical activity on human health, researchers have extensively examined the determinants of physical activity, including emotional factors (e.g., mood disturbance), behavioral attributes and skills (e.g., habit, smoking), social and cultural factors (e.g., social isolation) and physical environment factors (e.g., access to facilities, climate) (Bauman et al. 2002). Also, many intervention strategies have been tested for increasing people's physical activity, including goal setting, feedback, rewards, motivational interviewing and action planning. However, a recent review article on physical activity research reported that many interventions showed small effect sizes for physical activity change and that the results of those interventions were quite inconsistent across studies (Rhodes et al. 2017). Additionally, most previous studies relied on self-reported measures of physical activity which are less accurate than objective measures (e.g., measures using an accelerometer) (Downs et al. 2014; Oyeyemi et al. 2014). Therefore, there is a need for more intervention studies that use objective measures and evaluate specific mechanisms.

[5] Daily step counts using an activity tacker is an objective measure of physical activity that is more accurate than the energy expenditure (total MET min./week) that relies on surveys; however, objective measures cannot be used to examine changes in physical activity influenced by the use of activity trackers because objective daily step counts cannot be measured before people get activity trackers (i.e., there is no objective base from which to compare).

A promising avenue for improving the effectiveness of interventions designed to increase physical activity is to implement IT-enabled interventions that leverage recent technological advancements such as activity trackers and communication technologies (Ferrer and Ellis 2017; McNamee et al. 2016; Michie 2017). IT-enabled physical activity interventions use technical sensors (e.g., GPS, accelerometers, etc.) embedded in wearable devices or a smartphone to monitor subjects' real-time physical activity information such as the number of steps taken, which can then be used to deliver more interactive, automated, and personalized interventions. Since the emergence of wearable devices and smartphones, the effects of IT-enabled physical activity interventions, such as adaptive goal setting, real-time feedback (Choi et al. 2016; Fukuoka et al. 2010; Poirier et al. 2016; Rabbi et al. 2015) and tailored messages (Maher et al. 2015; Wang et al. 2015), have been examined[6]; however, compared to other IT-enabled physical activity interventions, IT-enabled social comparison has received less attention from researchers despite the high potential of IT-enabled social comparison in increasing people's physical activity. Further, most previous studies on IT-enabled physical activity intervention have not incorporated moderators to examine the conditions under which effective engagement and behavior change occur through interventions.

4.2.2. IT-Enabled Social Comparison

According to social comparison theory, people have the tendency to self-evaluate themselves against others and to minimize discrepancies between self and other's performance level (Garcia et al. 2013). Because people have the basic human drive to do better, the self-

[6] IS researchers have not yet paid attention to the effects of information technology on physical activity. While a recent IS study examined the moderating role of social interaction features of fitness technology (i.e., fitness data sharing) on the relationship between intrinsic motivation for exercise and subjective vitality (James et al. 2019), this study didn't adopt physical activity as a dependent variable.

evaluation leads to comparison concern (i.e., the desire to achieve a superior relative position) (Festinger 1954; Garcia et al. 2013). Previous research about social comparison suggested that individual factors, such as the relevance of the performance dimension to the self as well as situational factors such as a decrease in the number of competitors positively influence comparison concern that causes competitive behavior (Garcia et al. 2013). Therefore, when a social comparison is important to the self and the commensurate counterpart (e.g., rivals) to compare against exists, social comparison generates competition and improves performance (Garcia et al. 2006; Garcia et al. 2013; Tesser 1985).

IT-enabled social comparison offers individuals an environment that encourages them to engage in physical activity by providing real-time information about their physical activity rankings among reference people (i.e., targets that individuals compare themselves with). Using sensors (e.g., accelerometer and GPS) and communication technologies (e.g., Bluetooth and internet), wearable devices or smartphones can record daily movements (e.g., the number of steps taken) of compared participants and provide them with real-time physical activity rankings displayed on a smartphone app or webpage (e.g., leaderboard)[7]. Different from non-IT-enabled social comparison, IT-enabled social comparison enables individuals to check their physical activity rankings at any time. Therefore, people under the condition of IT-enabled social comparison may achieve higher performance than those under the condition of non-IT-enabled social comparison because they may have more chances to compare their performance level with others, experience comparison concern, and more actively engage in competition. Additionally, previous research revealed that the positive effect of competition on performance is stronger when people can check their progress relative to competitors (Stanne et al. 1999), which is one of the

[7] A leaderboard is a mechanism for informing a participant how he or she ranks in comparison to others within a social cohort over a limited time period, such as for a weekend or during a week.

features of IT-enabled social comparison and not provided by non-IT-enabled social comparison. Therefore, IT-enabled social comparison may be a more effective intervention than non-IT-enabled social comparison in increasing people's physical activity.

We suggest that IT-enabled social comparison for physical activity has several characteristics in terms of frequency of comparison, type of the comparison, and the reference group, which may influence individuals' performance. First, different from non-IT-enabled social comparison, the frequency of comparison in IT-enabled social comparison can be different from person to person depending on his/her motivation to compare self against others. Also, the frequency of comparison may depend on his/her motivation for using IT devices that deliver social comparison. Second, because IT-enabled social comparison provides individuals real-time information about their physical activity rankings together with their progress relative to competitors, the type of comparison that affects an individual's behavior is not only the final physical activity ranking but also their relative progress to the final outcome. Third, because IT-enabled social comparison for physical activity is implemented in the voluntary context that individuals can choose a comparison group depending on their motivational needs, we suggest that rivals in IT-enabled social comparison are similar, because when rivals in the comparison group are not similar (e.g., too strong rivals) people are demotivated (Liu et al. 2013; Morschheuser et al. 2018). Previous research studies about social comparison suggested that similar rivals (i.e., in terms of ability or performance) in comparison group exhibit greater comparison concern and competitive behavior than less similar rivals (Garcia et al. 2013).

Despite the promising aspect of IT-enabled social comparison that has a high potential in increasing people's physical activity, the effect of IT-enabled social comparison on physical activity has not been fully examined yet (Shameli et al. 2017). As shown in Table 4-1, previous studies that adopted IT-enabled social comparison as an intervention to increase physical activity have implemented IT-enabled social comparison together with rewards, adaptive daily goals, feedback, or social support, making it difficult to isolate the effect of IT-enabled social comparison and determine its effect separate and apart from these other confounding interventions (Johnson et al. 2016). Additionally, these studies showed mixed results as shown in Table 4-1. Thus, additional empirical research using a randomized experiment is needed to examine the effect of IT-enabled social comparison on physical activity.

Table 4-1. Prior Research on IT-Enabled Social Comparison and Physical Activity

Article	Intervention	Compared To[1]	Moderators Examined?	Dependent Variable	Sig.?[2]	Experiment?
Chen and Pu (2014)	IT-enabled social comparison + Rewards	Baseline activity level	No	Step count	No	Yes
Maher et al. (2015)	IT-enabled social comparison + Rewards + Social support[3] + Weekly feedback	Control	No	Moderate-vigorous physical activity[4] (self-report)	Yes	Yes
Zuckerman and Gal-Oz (2014)	IT-enabled social comparison + Rewards + Adaptive daily goal setting[5] + Real-time feedback	1) Rewards + Adaptive daily goal setting + Real-time feedback 2) Adaptive daily goal setting + Real-time feedback	No	Step count	No	Yes
Tu et al. (2018)	IT-enabled social comparison + Social support[6]	Rewards + Level of progression[7]	No	Step count	Yes	Yes
Shameli et al. (2017)[8]	IT-enabled social comparison + Social Interaction	Baseline activity level	No	Step count	Yes	No
Gremaud et al. (2018)	IT-enabled social comparison + Rewards + Adaptive daily goal setting + Daily feedback	Control	No	Step count	Yes	Yes

1. Baseline activity level: within subjects, Control: between subjects

2. Yes: intervention was significant, No: intervention was insignificant
3. Messages from friends
4. Moderate physical activity (e.g., walking briskly): 3.0-6.0 METs, vigorous physical activity (e.g., jogging): >6.0 METs, MET (Metabolic Equivalent of Task): the ratio of metabolic rate during physical activity to resting metabolic rate during physical inactivity
5. When a subject achieved his/her daily goal three days in a row, mobile app automatically suggests 10% increased goal.
6. “Likes” from friends
7. Levels that can be upgraded depending on the number of steps taken.
8. This study used secondary data from Azumio Argus app

4.2.3. Intrinsic Motivation

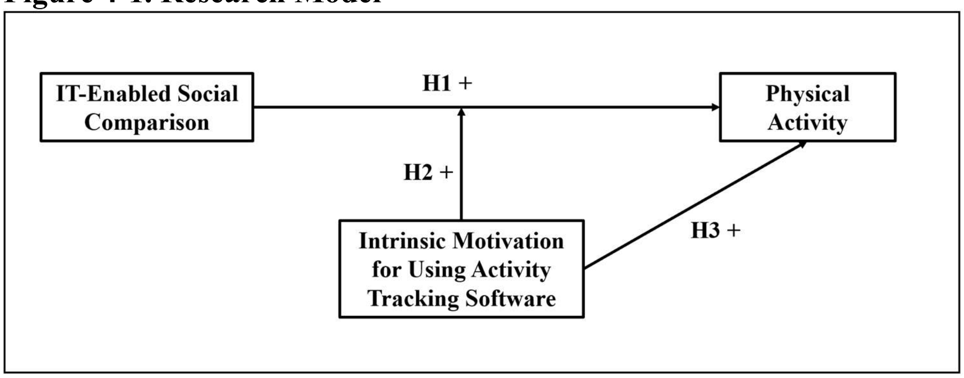
Another aspect that has not been fully researched is the relationship between intrinsic motivation and IT-enabled social comparison. Prior studies have assumed that such motivations are homogenous between participants. Yet, we also know that use of IT-based activity trackers tends to exhibit highly variable patterns, such as frequent use early on with declining use over time. One construct that could help explain variability within and between users is intrinsic motivation, but this construct has not received much attention in this literature. Thus, given that the effectiveness of IT-enabled social comparison may depend on the strength of participants' motivational needs supported by the properties of IT-enabled social comparison (Zhang 2007; Zhang 2008), it is also important to examine the moderating effect of an individual's motivations on the relationship between IT-enabled social comparison and physical activity. According to self-determination theory, individuals have different motivations in engaging in activities, and these motivations can be categorized into intrinsic and extrinsic motivation (Deci and Ryan 2002). Intrinsic motivation is an autonomous motivation, which is shown by an individual who performs out of his/her own volition (Rockmann and Ballinger 2017). Intrinsic motivation is associated with behavior that individuals pursue due to an interest in the activity, or pleasure/satisfaction that is derived from it (Ryan and Patrick 2009; Wu and Lu 2013). In contrast, extrinsic motivation is associated with behavior that individuals pursue for external reasons (Ryan and Patrick 2009; Wu and Lu 2013), such as rewards, praise, and monetary incentives. Previous studies that examined the relationship between motivations and physical activity have consistently demonstrated that intrinsic motivation is more critical than extrinsic motivation in promoting physical activity, and that intrinsic motivation is a good predictor of exercise participation and long-term physical activity adherence (Teixeira et al. 2012). Specifically, most of these are non- intervention studies that have focused on intrinsic motivation for physical activity (e.g., pleasant feeling inherent in physical activity) and have only examined the direct association between intrinsic motivation and physical activity. However, given that studies that aim to increase people's physical activity are intervention studies and that previous physical activity intervention studies have produced mixed results across studies (Rhodes et al. 2017), studies that examine individuals' motivation that encourages additional activity under physical activity interventions are critical. Prior research, therefore, offers a somewhat limited explanation regarding the relationship between intrinsic motivations and physical activity. This study aims to address that limitation by examining the motivational conditions under which effective engagement in physical activity occurs through an IT-enabled intervention.

Given the unique intervention context (i.e., use of fitness technologies and IT-enabled social comparison to promote increased physical activity), a new type of intrinsic motivation may be relevant: intrinsic motivation with respect to the use of activity tracking software (i.e., Fitbit app) which constitutes the platform upon which the intervention is implemented. We suggest that intrinsic motivation for using activity tracking software strengthens the positive influence of IT-enabled social comparison on physical activity. As suggested in recent studies in the Information Systems (IS) discipline that examine the association between users' exercise motivations and fitness technology feature set selection, individuals with different motivational characteristics use fitness technologies differently (James et al. 2019; James et al. 2019). Therefore, the influence of intrinsic motivation for using activity tracking software on physical activity is worth investigating. Further, while recent IS research has demonstrated that the social interaction features of fitness technology (e.g., fitness data sharing, competitions, comparison) positively moderates the effect of intrinsic motivation for exercise on subjective vitality (James et al. 2019), the moderating effect of intrinsic motivation on the relationship between IT-enabled social comparison and physical activity has not been previously investigated.

4.3. MODEL DEVELOPMENT AND HYPOTHESES

In this section, we present the research model (Figure 4-1) and three hypotheses that we seek to test.

Figure 4-1. Research Model



4.3.1. Impact of IT-Enabled Social Comparison on Physical Activity

According to social comparison theory, people have the tendency to evaluate themselves by comparing themselves to others, and to minimize discrepancies between their performance levels and others'(Garcia et al. 2013). Because people have a unidirectional drive to do better, the self-evaluation leads to the comparison concern (i.e., the desire to achieve a superior relative position) that causes competitive behavior (i.e., the action to protect one's superiority) (Festinger 1954; Garcia et al. 2006; Garcia et al. 2013; Tesser 1985). Therefore, competitive behavior that leads to improved performance is one of the phenomena manifested in the social comparison process (Garcia et al. 2013).

IT-enabled social comparison provides people with real-time physical activity rankings and enables them to check their rankings at any time. Therefore, people under the condition of IT-enabled social comparison may achieve higher performance than those who are not involved in IT-enabled social comparison because they have more chances to compare their performance level with others, experience comparison concern more often, and thus more actively engage in competitive behavior than people who are not involved in IT-enabled social comparison. In this respect, IT-enabled social comparison provides individuals a strong and appropriate environmental condition for encouraging them to engage in physical activity. Despite the high potential of IT-enabled social comparison in increasing people's physical activity, the effect of IT-enabled social comparison on physical activity has yet to be established. Therefore, we hypothesize that:

Hypothesis 1 (H1): IT-enabled social comparison positively influences physical activity.

4.3.2. Moderating Effect of Intrinsic Motivation for Using Activity Tracking Software on the Relationship between IT-Enabled Social Comparison and Physical Activity

Intrinsic motivation for using activity tracking software refers to using activity tracking software for the internal rewards such as satisfaction experienced while using activity tracking software. Activity tracking software displays user-generated data regarding the user’s daily movement such as the number of steps taken and distance covered. Using activity tracking software, IT-enabled social comparison provides individuals real-time physical activity ranking together with their progress relative to competitors. Previous research revealed that the positive effect of competition on engagement and performance is stronger when individuals can check their progress relative to competitors (Stanne et al. 1999). Thus, in IT-enabled social comparison, intrinsic motivation for using activity tracking software may play an important role in increasing participants’ physical activity because a person with high intrinsic motivation for using activity tracking software may more frequently check their real-time physical activity rankings and progress, and therefore may have more chances to be encouraged to engage in physical activity. However, in the absence of IT-enabled social comparison, even though a person with high intrinsic motivation for using activity tracking software can frequently check his/her real-time physical activity achievement (i.e., daily step counts), he/she may not be encouraged to engage in physical activity as much. Therefore, people with high intrinsic motivation for using activity tracking software may achieve higher performance with IT-enabled social comparison than without IT-enabled social comparison. Thus, we hypothesize that:

Hypothesis 2 (H2): Intrinsic motivation for using activity tracking software moderates the effect of IT-enabled social comparison on physical activity, such that the positive effect of IT-enabled social comparison on physical activity is stronger when intrinsic motivation for using activity tracking software is high than when intrinsic motivation for using activity tracking software is low.

4.3.3. Direct Effect of Intrinsic Motivation for Using Activity Tracking Software on Physical Activity

As mentioned earlier, activity tracking software displays user-generated data about a user's daily movements such as steps taken and distance covered, so activity tracker users can track progress towards achieving their physical activity goals or standards (e.g., 10,000 steps per day). When people can track their progress, they can adjust their level of effort or strategy to effectively achieve their goals (Locke and Latham 2002). Therefore, people who frequently check real-time physical activity data have more chances to meet their physical activity goals or standards. In addition, the positive feelings they can get by self-monitoring their progress toward achieving physical activity goals can enhance the feelings of competence, which is a source of motivation for physical activity (Ryan and Patrick 2009). Therefore, in the context of activity tracker use, in which the IT-enabled social comparison is implemented, a person with high intrinsic motivation for using activity tracking software may achieve higher physical activity performance than a person with low intrinsic motivation for using activity tracker. This is because a person with high intrinsic motivation for using activity tracking software may have more chances to meet their physical activity goals and motivate themselves to engage in physical activity. Thus, we hypothesize that:

Hypothesis 3 (H3): Intrinsic motivation for using activity tracking software positively influences physical activity.

4.4. METHOD

Experimental Design. To test our hypotheses, we conducted a field experiment for eight weeks with a basic randomized design comparing the treatment (IT-enabled social comparison) to control (no IT-enabled comparison). Among applicants to our experiment, those who were the least physically active were selected as study participants because the goal of our experiment was to help inactive people become more active. Physical activity was measured using both an objective measure (daily step counts using Fitbit, activity tracker) and a subjective measure (International Physical Activity Questionnaire – Short Form). Intrinsic motivation for using activity tracking software was measured through a repeated (weekly) survey.

Treatment Design. To implement IT-enabled social comparison (treatment) and to measure physical activity, we used Fitbits and the associated Fitbit mobile application (i.e., the Fitbit app). All subjects were requested to wear a Fitbit activity tracker at all times while awake and were allowed to access the Fitbit app at any time to monitor their real-time daily step count (i.e., self-monitoring). Subjects were randomly assigned either to a control group or to one of several social comparison groups, each consisting of eight participants and one researcher. Those in the IT-enabled social comparison treatment groups received a physical activity challenge sent by the researcher and were requested to accept the challenge every Monday (work week[8] challenge

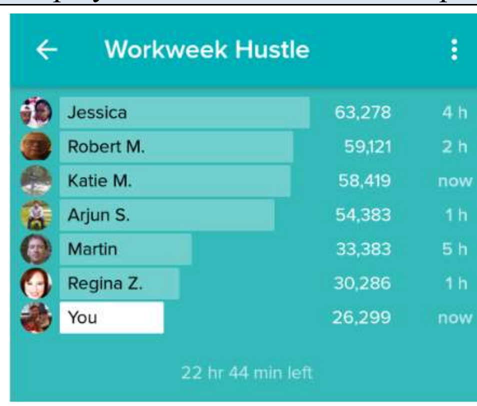
[8] Work weeks are from Monday to Friday in this study.

for five days) and Saturday (weekend challenge for two days). A researcher checked whether subjects in the social comparison treatment groups accepted each physical activity challenge. Membership in a social comparison group was not changed during the treatment period. Only the subjects involved in a social comparison group were able to access the leaderboard that displays their real-time ranking information together with their progress relative to competitors within their group. The information that displays in the Fitbit app is presented in Figure 4-2. The leaderboard provides a mechanism for informing a participant how he or she ranks in comparison to others within a social cohort over a limited time period, such as for a weekend or during a week.

Figure 4-2. Information that Displays in Fitbit App

Display for self-monitoring

Display for IT-enabled social comparison



Participants. Study participants were undergraduate students in a public research university located in metro Atlanta, Georgia, USA. To recruit participants, we sent 6,675 undergraduate students an advertising email explaining the purpose and procedure of the experiment. To participate in the experiment, email recipients were asked to answer the International Physical Activity Questionnaire (IPAQ)[9] to be evaluated for whether they are physically inactive. Among the 885 students who completed IPAQ, we selected 87 of the least

[9] IPAQ is one of the most widely used measures of physical activity(Hagströmer et al. 2006). IPAQ was developed for measuring people's physical activity and inactivity and have acceptable measurement properties (Craig et al. 2003; Hagströmer et al. 2006).

physically active, based on the physical activity assessment method (i.e., MET[10]-min/week[11]: energy expenditure during a week) using the IPAQ instrument (Al-Hazzaa 2007; Lee et al. 2011). The eighty-seven participants were randomly assigned either to a treatment group (N=48) or a control group (N=39). The average age of participants was 20.1 years, 19.6% of the participants were male (n=17), and 79.4% were female (n=70). The details of the IPAQ questionnaire and physical activity assessment method are presented in Appendix B. In accordance with IRB recommendations, pregnant women, and those with heart disease, asthma, hypertension, or diabetes were excluded from the participating because of the potential harm of increased physical activity. Table 4-2 shows the number of participants in each week after excluding those lost to attrition.

Table 4-2. Number of Participants

	1st week		2nd week		3rd week		4th week		5th week		6th week		7th week		8th week	
	WK	WW	WK	WW	WK	WW	WK	WW	WK	WW	WK	WW	WK	WW	WK	WW
Treatment	48	48	45	48	45	48	42	45	42	46	41	46	41	40	33	38
Control	37	38	34	39	37	37	35	37	31	36	28	33	28	29	25	31

WK: weekend, WW: work week

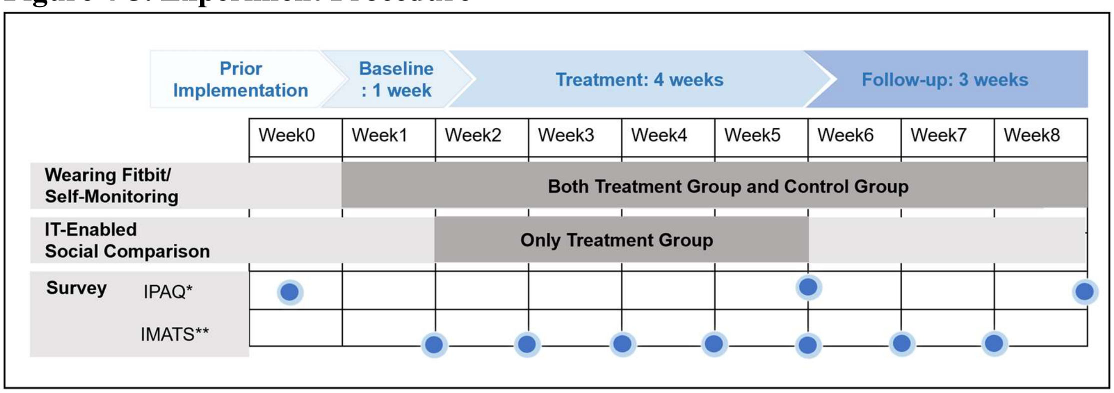
Experiment Procedure and Implementation. Before the start of the experiment, all study participants visited a researcher to receive a Fitbit device, download the Fitbit app, create a Fitbit account, connect the Fitbit device to the Fitbit app, and receive an explanation about the experiment procedure. Study participants provided the research team with their Fitbit IDs and passwords so that the research team could access their physical activity information on the Fitbit app. A new Fitbit device was given to each participant as an incentive to participate in the

[10] MET (Metabolic Equivalent of Task): the ratio of metabolic rate during physical activity to resting metabolic rate during physical inactivity. Walking = 3.3 METs, Moderate Physical Activity = 4.0 METs, and Vigorous Physical Activity = 8.0 METs

[11] MET-min/week: a combined total physical activity during a week. It can be computed as the sum of Walking + Moderate + Vigorous MET-min/week scores

experiment. The experiment was implemented for eight weeks for both the treatment and control groups. For the first one week, subjects in both the treatment and control groups did not receive any treatment, and the daily step counts of subjects during this period was used as baseline physical activity for the objective measure. For the next four weeks, subjects in the treatment groups received the IT-enabled social comparison, and subjects in the control groups did not receive any treatment. For the last three weeks, subjects in both conditions did not receive any treatment. During the experiment period (i.e., eight weeks), all subjects were asked to answer a weekly survey that measured intrinsic motivation for using activity tracking software. Also, they were asked to answer the IPAQ (i.e., subjective physical activity measure) at the end of the treatment period (5th week) and at the end of the follow-up period (8th week). Figure 4-3 provides an overview of the experiment procedure.

Figure 4-3. Experiment Procedure



*IPAQ: International physical activity questionnaire, **IMATS: Intrinsic motivation for using activity tracking software

Measurement of Constructs. *Intrinsic motivation for using activity tracking software* items was adapted from McAuley et al. (1989). The measurement items are presented in Appendix A.

4.5. DATA ANALYSIS AND RESULTS

4.5.1. Measurement Model

To assess the measurement model of intrinsic motivation for using activity tracking software, first we examined correlations between items and conducted a factor analysis. Separate factor analyses were conducted for each week of experimental data. In each factor analysis, a single factor was produced for *intrinsic motivation for using activity tracking software*. However, one reverse coded item exhibited low factor loadings (i.e., less than 0.5). Thus, we dropped this item, while retaining the other four items for *intrinsic motivation for using activity tracking software*. All factor loadings for the remaining items were greater than 0.7.

Next, we assessed the reliability and convergent validity of the survey instrument. As shown in Table 4-3, the composite reliability (CR) and Cronbach's α of *intrinsic motivation for using activity tracking software* are both greater than 0.9 across week 1, week 2, week 3, week 4, week 5, week 6, week 7, and week 8, indicating good reliability (Fornell and Larcker 1981). Convergent validity was evaluated by examining the significance of item loadings and the average variance extracted (AVE). All loadings were significant, and the AVE for *intrinsic motivation for using activity tracking software* exceeds 0.7 (ranging from 0.73 to 0.85) across week 1, week 2, week 3, week 4, week 5, week 6, week 7, and week 8. These results suggest adequate convergent validity (Fornell and Larcker 1981).

Table 4-3. Result of CFA Measurement Model Analysis and Descriptive Statistics: Intrinsic Motivation for Activity Tracking Software

Construct	Scale item	Start of Week 2					Start of Week 3				
		Factor Loading	Mean (SD)	C's α	CR	AVE	Factor Loading	Mean (SD)	C's α	CR	AVE
Intrinsic Motivation for Using Activity Tracking Software	IMATS1	.93***	3.59 (.13)	.91	.91	.73	.93***	3.52 (.13)	.94	.94	.79
	IMATS2	.94***					.94***				
	IMATS3	.81***					.90***				
	IMATS4	.71***					.78***				
Construct	Scale Item	Start of Week 4					Start of Week 5				
		Factor Loading	Mean (SD)	C's α	CR	AVE	Factor Loading	Mean (SD)	C's α	CR	AVE
Intrinsic Motivation for Using Activity Tracking Software	IMATS1	.94***	3.46 (.14)	.95	.94	.80	.92***	3.35 (.14)	.95	.95	.82
	IMATS2	.95***					.93***				
	IMATS3	.88***					.94***				
	IMATS4	.81***					.82***				
Construct	Scale Item	Start of Week 6					Start of Week 7				
		Factor Loading	Mean (SD)	C's α	CR	AVE	Factor Loading	Mean (SD)	C's α	CR	AVE
Intrinsic Motivation for Using Activity Tracking Software	IMATS1	.92***	3.04 (.14)	.96	.95	.84	.97***	3.12 (.15)	.96	.96	.85
	IMATS2	.95***					.98***				
	IMATS3	.94***					91***				
	IMATS4	.85***					.82***				
Construct	Scale Item	Start of Week 8									
		Factor Loading	Mean (SD)	C's α	CR	AVE					
Intrinsic Motivation for Using Activity Tracking Software	IMATS1	.92***	2.99 (.15)	.95	.95	.82					
	IMATS2	.96***									
	IMATS3	.94***									
	IMATS4	.80***									

***p < 0.001, **p < 0.01, *p < 0.05

CR = composite reliability; C's α= Cronbach's alpha; AVE = average variance extracted

4.5.2. Hypotheses Testing

In order to test our hypotheses, we used the average daily steps of study participants. Two sample t-tests were used for testing H1, and OLS regression was used for testing H2 and H3. Hypotheses were tested at five percent significance level for subjects' physical activity every weekend and work week of the treatment period. Also, we examined whether the theorized relationships among constructs were significant without treatment during the follow-up period. Before testing hypotheses, we compared the average step per day of the control groups to that of treatment groups during the baseline period and found no statistical difference (using one-way ANOVA) between the treatment group and the control group for both weekends (p = .96) and work weeks (p = .83). First, the effect of IT-enabled social comparison on physical activity (H1) was examined using two sample t-tests. As shown in Table 4-4, IT-enabled social comparison (i.e., treatment) had a significant positive effect on the physical activity (i.e., average steps per day) at 2nd weekend (p = .039, d = .40), 2nd work week (p = .039, d = .38), 3rd weekend (p = .027, d = .43), 3rd work week (p = .015, d = .49), 5th weekend (p = .013, d = .50), and 5th work week (p = .014, d = .50), thus supporting H1 during treatment period except for 4th weekend and 4th work week. Specifically, subjects involved in the treatment group walked a daily average of 1,228 more steps during 2nd weekend, 1,056 more steps during 2nd work week, 1,527 more steps during 3rd weekend, 1,379 more steps during 3rd work week, 944 more steps during 4th weekend, 17 more steps during 4th work week, 1,598 more steps during 5th weekend, and 1,076 more steps during 5th work week than the subjects involved in the control group. Thus, IT-enabled social comparison positively influenced the subjects' physical activity during most of the treatment period. However, as shown in Table 4-4, the effect of IT-enabled social comparison on physical activity was not significant during the follow-up period except for the 8th work week. In other words, the positive effect of the IT-enabled social comparison on physical activity did not persist after the end of treatment. We return to this finding in the Discussion.

Table 4-4. Two Sample T-Test Results[12] for the Effect of IT-Enabled Social Comparison on Physical Activity: Testing H1

Period		Average step per day: Control	Average step per day: Treatment	t-test	Cohen's d	H1
Baseline	1st WK	5,295 (n=37)	5,260 (n=48)	F=.00, p= .96		
	1st WW	7,769 (n=38)	7,646 (n=48)	F=.05, p= .83		
Treatment	2nd WK	4,722 (n=34)	5,950 (n=45)	t=1.78, p= .039*	.40	Supported
	2nd WW	7,622 (n=39)	8,678 (n=48)	t=1.78, p= .039*	.38	Supported
	3rd WK	5,200 (n=37)	6,727 (n=45)	t=1.96, p= .027*	.43	Supported
	3rd WW	7,171 (n=37)	8,550 (n=48)	t=2.22, p= .015*	.49	Supported
	4th WK	5,751 (n=35)	6,695 (n=42)	t=1.26, p= .106	.29	Not supported
	4th WW	7,242 (n=37)	7,259 (n=45)	t=.031, p= .488	.01	Not supported
	5th WK	4,378 (n=31)	5,976 (n=42)	t=2.26, p= .013*	.50	Supported
	5th WW	6,613 (n=36)	7,689 (n=46)	t=2.25, p= .014*	.50	Supported
Follow-up (without treatment)	6th WK	4,164 (n=28)	5,449 (n=41)	t=1.38, p= .085†	.34	
	6th WW	6,916 (n=33)	6,853 (n=46)	t=-.010, p= .540	-.02	
	7th WK	4,278 (n=28)	5,287 (n=41)	t=1.42, p= .080†	.35	
	7th WW	5,223 (n=29)	4,666 (n=40)	t=-.82, p= .793	.20	
	8th WK	5,035 (n=25)	5,120 (n=33)	t=.082, p= .467	.023	
	8th WW	6,391 (n=31)	7,619 (n=38)	t=1.99, p= .025**	.48	

** p<0.01 *p<0.5 †p<0.1, WK: weekend, WW: work week, one-tailed tests for relationships among constructs as direction of relationships are theorized

Next, the moderating role of intrinsic motivation for using activity tracking software on the effect of IT-enabled social comparison on physical activity (H2) was examined using OLS regression by testing the interaction effect of IT-enabled social comparison and intrinsic motivation for using activity tracking software on physical activity. As shown in Table 4-5, intrinsic motivation for using activity tracking software did not moderate the effect of IT-enabled social comparison on physical activity except for the 2nd weekend (β= 1,400.7, t= 2.05, p=.044) and the 7th weekend (β= 1820.7, t= 2.86, p= .003); thus, H2 was not supported in most of the treatment or in the follow-up period. However, during the treatment period, the sign of the moderating effect of intrinsic motivation for using activity tracking software on the effect of IT-enabled social comparison on physical activity was consistent with the direction of the

[12] Because the variances between the groups were not equal in 5th WK and 8th WK (five percent significance level), we used Welch's t-test for these weekends. When the assumption of homogeneity of variance for t-test is not met, Welch's t-test should be used (Delacre et al. 2017). For each weekend and work week during experiment period, inferences using Student's t-test and Welch's t-test were consistent, which lends further robustness to our findings.

theorized relationship among constructs except for 3rd work week and 5th work week.

Table 4-5. OLS Regression Results for the Moderation of IMATS on the Effect of IT-Enabled Social Comparison on Physical Activity: Testing H2 (controls: age, gender)

Period		Moderation of IMATS (IT-enabled social comparison × IMATS)	H2
Treatment	2nd WK	β= 1,400.7, t= 2.05, p=.022**	Supported
	2nd WW	β= 394.8, t= .71, p=.240	Not supported
	3rd WK	β= 307.4, t= .44, p= .330	Not supported
	3rd WW	β= -29.0, t= -.05, p= .521	Not supported
	4th WK	β= 138.7, t= .20, p= .420	Not supported
	4th WW	β= 288.4, t= .62, p= .269	Not supported
	5th WK	β= 337.1, t= .52, p= .304	Not supported
	5th WW	β= -114.8, t= -.28, p= .611	Not supported
Follow-up (without treatment)	6th WK	β= -34.1, t= -.04, p= .484	
	6th WW	β= -214.5, t= -.39, p= .650	
	7th WK	β= 1820.7, t= 2.86, p= .003***	
	7th WW	β= 291.4, t= .45, p= .327	
	8th WK	β= -297.2, t= -.31, p= .622	
	8th WW	β= -664.5, t= -1.29, p= .900	

**p<0.01 *p<0.5 †p<0.1, one-tailed tests for relationships among constructs as direction of relationships are theorized

Next, the effect of intrinsic motivation for using activity tracking software on physical activity (H3) was examined using OLS regression. As shown in Table 4-6, intrinsic motivation for using activity tracking software did not significantly influence physical activity; thus, H3 was not supported. However, as shown in Table 4-6, the sign of the effect of intrinsic motivation for using activity tracking software on physical activity was consistent with the direction of the theorized relationship (i.e., the positive influence of intrinsic motivation for using activity tracking software on physical activity) except for the 8th weekend.

Table 4-6. OLS Regression Results for the Effect of Intrinsic Motivation for Using Activity Tracking Software on Physical Activity: Testing H3 (controls: age, gender, IT-enabled social comparison (for follow-up period))

Period		Effect of IMATS	H3
Treatment	2nd WK	β= 318.5, t= .96, p=.172	Not supported
	2nd WD	β= 288.4, t= 1.04, p=.150	Not supported
	3rd WK	β= 514.2, t= 1.49, p= .070†	Not supported
	3rd WD	β= 333.6, t= 1.26, p=.107	Not supported
	4th WK	β= 89.8, t= .26, p=.397	Not supported
	4th WD	β= 153.5, t= .66, p=.256	Not supported
	5th WK	β= 505.5, t= 1.56, p=.062†	Not supported
	5th WD	β= 39.6, t= .19, p=.424	Not supported

Follow-up (without treatment)	6^{th} WK	β= 177.2, t= .43, p=.335	
	6^{th} WD	β= 374.2, t= 1.39, p=.085†	
	7^{th} WK	β= 138.9, t= .43, p=.334	
	7^{th} WD	β= 57.9, t= .19, p=.426	
	8^{th} WK	β= -45.1, t= -.11, p=.544	
	8^{th} WD	β= 21.6, t= .09, p=.464	

** p<0.01 * p<0.5 † p<0.1, one-tailed tests for relationships between constructs as direction of relationships are theorized

4.5.3. Robustness Checks

In this section, we examine whether theorized relationships among constructs are significant (at five percent significance level) when we use other physical activity measures to fully understand and verify the effect of IT-enabled social comparison on physical activity. These measures for the additional analyses include: 1) the subjective measure of physical activity, which is the surveyed total MET min./week (energy expenditure during a week), 2) the objective physical activity (i.e., average steps per day) difference scores, which indicate physical activity changes after baseline (i.e., 1^{st} week), and 3) the subjective physical activity difference scores, which indicate a perceived physical activity change after the use of activity tracker (0^{st} week).

4.5.3.1. Hypotheses Testing Using a Subjective Physical Activity Measure.

We tested hypotheses using a subjective measure of physical activity (i.e., total MET min./week: energy expenditure during a week) that was calculated using IPAQ which was administered before the treatment began (0^{th} week), the final week of the treatment period (5^{th} week), and final week of the follow-up period (8^{th} week). In order to test our hypotheses, two sample t-tests were used for testing H1, and OLS regression was used for testing H2 and H3. Before testing hypotheses, we compared the total MET min./week of the control groups to that of the treatment groups before the treatment began and found no statistical difference (ANOVA result: F=1.33, p=0.252) between the treatment group (MET min./week: 988) and the control group (MET min./week: 1,168). First, the effect of IT-enabled social comparison on physical activity (H1) was examined. As shown in Table 4-7, IT-enabled social comparison had a significant positive effect on physical activity (total MET min./ week) at the 5th week (*p*=.011, *d*=.52), thus supporting H1 at the final week of the treatment period. Also, the effect of IT-enabled social comparison on physical activity was significant at the 8th week (*p*=.024, *d*=.57). Specifically, subjects involved in the treatment group showed 1,990 more total MET min./week for 5th week and 1,720 more total MET min./week for 8th week than the subjects involved in the control group. In other words, IT-enabled social comparison positively influences the subjects' perceived physical activity at the final week of the treatment period, and this influence persisted without treatment at the final week of the follow-up period.

Table 4-7. Hypotheses Testing[13] Using Subjective Physical Activity Measure: Total MET min./week

Variables	5th week[1]		8th week[2]	
	Total MET min./week	Test Statistics	Total MET min./week	Test Statistics
H1: IT-enabled SC[3] → PA[4]	T[6]: 4,147(N=39) C[7]: 2,157(N=31)	*t*=2.36, *d*= .52, *p*=.011*	T: 3,692(N=26) C: 1,972(N=24)	*t*=2.05, *d*= .57, *p*=.024*
H2: IT-enabled SC × IMATS[5]→ PA		*β*= 1,992, *t*= 2.65, *p*=.005**		*β*= -23.2, *t*= -.03, *p*=.51
H3: IMATS → PA		*β*= 962, *t*= 2.51, *p*=.007**		*β*= 114.2, *t*= .32, *p*=.38

** p<0.01 * p<0.5 † p<0.1, one-tailed tests for relationships between constructs as direction of relationships are theorized
Two sample t-tests are used for testing H1, and OLS regression is used for testing H2 (controls: age, gender) and H3 (controls: age, gender, IT-enabled social comparison)
1: final week of the treatment period, 2: final week of the follow-up period
3: IT-enabled social comparison, 4: physical activity, 5: intrinsic motivation for using activity tracking software
6: treatment, 7: control

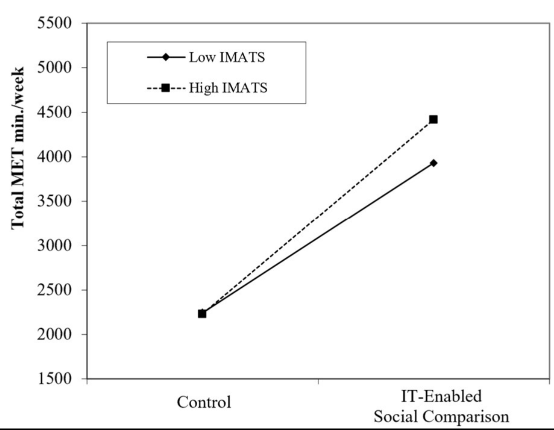
Next, the moderating role of intrinsic motivation for using activity tracking software on the effect of IT-enabled social comparison on physical activity (H2) was examined. As shown

[13] Because the variances between the groups were not equal for both 5th week and 8th week (five percent significance level), we used Welch's t-test for these weeks. When the assumption of homogeneity of variance for t-test is not met, Welch's t-test should be used (Delacre et al. 2017). For both 5th week and 8th week, inferences using Student's t-test and Welch's t-test were consistent, which lends further robustness to our findings.

in Table 4-7, intrinsic motivation for using activity tracking software strengthens the positive effect of IT-enabled social comparison on physical activity at the 5th week (β= 1,992, t= 2.65, p=.005). However, intrinsic motivation for using activity tracking software did not moderate the effect of IT-enabled social comparison on physical activity at the 8th week (β= -23.2, t= -.03, p=.51).

Figure 4-4 illustrates the interaction between intrinsic motivation for using activity tracking software and IT-enabled social comparison treatment for the 5th week. The simple slopes demonstrate that the positive effect of IT-enabled social comparison on physical activity is stronger when subjects' intrinsic motivation for using activity tracking software is high than when their intrinsic motivation for using activity tracking software is low. In addition, the results from a simple slope analysis indicate that IT-enabled social comparison positively influences physical activity when intrinsic motivation for using activity tracking software is high (β=2,188, t=2.49, p=.016). When intrinsic motivation for using activity tracking software is low, IT-enabled social comparison has a marginal influence on physical activity (β=1,689, t=1.93, p=.058).

Figure 4-4. Simple Slopes for the Moderating Role of IMATS on the Effect of IT-Enabled Social Comparison on Physical Activity (Using Subjective Measure)



Testing Simple Slopes

	Slope (β)/ t-value/ p-value
High IMATS	2,189*/ 2.49/ .016
Low IMATS	1,689†/ 1.93/ .058

**p < 0.01, *p < 0.05, † P<0.1

Next, the effect of intrinsic motivation for using activity tracking software on physical activity (H3) was examined. As shown in Table 4-7, intrinsic motivation for using activity tracking software positively influences physical activity at the 5th week (β= 962, t= 2.51, p=.007). However, intrinsic motivation for using activity tracking software did not influence physical activity at the 8th week (β= 111.4, t= .32, p=.38).

4.5.3.2. Hypotheses Testing Using Objective Physical Activity Difference Scores

We tested hypotheses using objective physical activity (average daily steps) difference scores[14, 15], which indicate physical activity changes from baseline. Given that the purpose of this study is to examine how to enable inactive people to become more active, it is necessary to examine whether IT-enabled social comparison increases subjects' physical activity and how changes in physical activity are affected by subjects' intrinsic motivation. Two sample t-tests were used for testing H1, and OLS regression was used for testing H2 and H3. First, the effect of IT-enabled social comparison on physical activity change (H1) was examined. As shown in Table 4-8, IT-enabled social comparison had a significant positive effect on physical activity change (from baseline) at both the 5th weekend (p=.034, d=.45) and the 5th work week (p=0.006, d=.58), thus supporting H1 at the final week of the treatment period. However, for the 8th week, the effect of IT-enabled social comparison on physical activity change (from baseline) was significant only for the work week (p=.004, d=.67). Specifically, subjects involved in the treatment groups walked a daily average of 567.4 more steps during the 5th weekend, 114.5 more steps during the 5th work week, 18.4 more steps during the 8th weekend, and 125 more steps during 8th work week than their average daily steps during the baseline period. However,

[14] When a difference score is created by two conceptually different constructs, the use of difference score is often criticized for issues such as low reliability and ambiguity in interpretation (Edwards 2001; Klein et al. 2009). However, this study creates difference score using same construct (i.e., physical activity) in a pre-test/ post-test experimental design.

[15] Physical activity (PA) difference between 5th week and 1st week = average daily steps of 5th week - average daily steps of 1st week,
PA difference between 8th week and 1st week = average daily steps of 8th week - average daily steps of 1st week

subjects involved in the control groups walked a daily average of 1,347 fewer steps during the 5th weekend, 1,271 fewer steps during the 5th work week, 857 fewer steps during the 8th weekend, and 1,653 fewer steps during 8th work week than their average daily steps during the baseline period.

Table 4-8. Hypotheses Testing Using Objective Physical Activity (average daily steps) Difference Scores

Weekend	PA difference between 5th weekend[1] and 1st weekend[2]		PA difference between 8th weekend[3] and 1st weekend	
	Difference of average daily steps	Test Statistics	Difference of average daily steps	Test Statistics
H1: IT-enabled SC[4] → PA (change)[5]	T[7]: 567.4(N=41) C[8]: -1,347(N=29)	t=1.85, d=.45, p=.034*	T: 18.4(N=32) C: -857(N=25)	t=.90, d=.24, p=.186
H2: IT-enabled SC × IMATS[6]→ PA (change)		β=-30.6, t=-.03, p=.513		β=-211.2, t=-.23, p=.590
H3: IMATS → PA (change)		β=832.2, t=1.89, p=.032*		β=13.1, t=.03, p=.487
Work week	PA difference between 5th work week and 1st work week		PA difference between 8th work week and 1st work week	
	Difference of average daily steps	Test Statistics	Difference of average daily steps	Test Statistics
H1: IT-enabled SC → PA (change)	T: 114.5(N=46) C: -1,271 (N=35)	t=2.60, d=.58, p=.006**	T: 125 (N=38) C: -1,653(N=30)	t=2.75, d=.67, p=.004**
H2: IT-enabled SC × IMATS→ PA (change)		β=131.5, t=.28, p=.389		β=-301.9, t=-.53, p=.699
H3: IMATS → PA (change)		β=19.0, t=.08, p=.47		β=-251.7, t=-.96, p=.830

**p<0.01 *p<0.5 †p<0.1 one-tailed tests for relationships between constructs as direction of relationships are theorized
Two sample t-tests are used for testing H1, and OLS regression is used for testing H2 (controls: age, gender) and H3 (controls: age, gender, IT-enabled social comparison)
1: final week of the treatment period, 2: baseline, 3: final week of the follow-up period
4: IT-enabled social comparison, 5: physical activity (average daily steps) change from the baseline, 6: intrinsic motivation for using activity tracking software
7: treatment, 8: control

Next, the moderating role of intrinsic motivation for using activity tracking software on the effect of IT-enabled social comparison on the physical activity change (H2) was examined.

As shown in Table 4-8, intrinsic motivation for using activity tracking software did not moderate the effect of IT-enabled social comparison on physical activity change (from baseline) for the 5th weekend, the 5th work week, the 8th weekend, or the 8th work week.

Next, the effect of intrinsic motivation for using activity tracking software on physical activity change (H3) was examined. As shown in Table 4-8, IT-enabled social comparison did not significantly influence physical activity change (from baseline) except for the 5th weekend (β=832.2, t=1.89, p=.032).

4.5.3.3. Hypotheses Testing Using Subjective Physical Activity Difference Scores

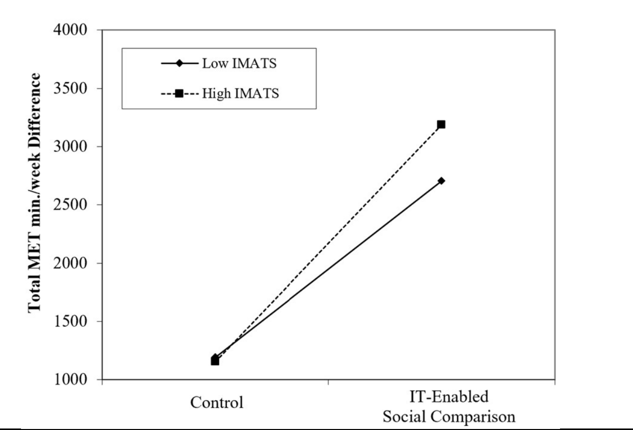
We tested hypotheses using subjective physical activity (total MET min./week: energy expenditure during a week) difference scores[16], which indicate physical activity changes from 0th week (before experiment implementation). Therefore, subjective physical activity difference scores represent the perceived physical activity changes after the use of activity trackers. Two sample t-tests were used for testing H1, and OLS regression was used for testing H2 and H3. First, the effect of IT-enabled social comparison on physical activity change (H1) was examined. As shown in Table 4-9, IT-enabled social comparison had a significant positive effect on physical activity change at the 5th week (p=.019, d=.47), thus supporting H1. Also, the effect of IT-enabled social comparison on physical activity change was significant at the 8th week (p=.028, d=.54). Specifically, subjects involved in the treatment group showed 2,936 more total MET min./week for 5th week and 2,540 more total MET min./week for 8th week than their total MET min./week for 0th week (before experiment implementation). However, subjects involved in the control group showed only 1,141 more total MET min./week for 5th week and 912 more total MET min./week for 8th week than their total MET min./ week for 0th

[16] PA difference between 5th week and 0th week = total MET min./week of 5th week - total MET min./week of 0th week,
PA difference between 8th week and 0th week = total MET min./week of 8th week - total MET min./week of 0th week

week.

Next, the moderating role of intrinsic motivation for using activity tracking software on the effect of IT-enabled social comparison on the physical activity change (H2) was examined. As shown in Table 4-9, intrinsic motivation for using activity tracking software strengthens the positive effect of IT-enabled social comparison on physical activity change at the 5th week (β=2,001, t=2.76, p=.004), thus supporting H2. However, intrinsic motivation for using activity tracking software did not moderate the effect of IT-enabled social comparison on physical activity change at 8th week (β= 162.9, t= .020, p=.422).

Figure 4-5. Simple Slopes for the Moderating Role of IMATS on the Effect of IT-Enabled Social Comparison on Physical Activity (Using Subjective Physical Activity Difference Scores)



Testing Simple Slopes

	Slope (β)/ t-value/ p-value
High IMATS	2,032./ 2.31/ .022*
Low IMATS	1,512./ 1.73/ .086†

**p < 0.01, *p < 0.05, † P<0.1

Figure 4-5 illustrates the interactions between intrinsic motivation for using activity tracking software and IT-enabled social comparison treatment for the 5th week. The simple slopes demonstrate that the positive effect of IT-enabled social comparison on physical activity change is stronger when subjects' intrinsic motivation for using activity tracking software is high than when their intrinsic motivation for using activity tracking software is low. In addition, the results from a simple slope analysis indicate that IT enabled social comparison positively influences physical activity when intrinsic motivation for using activity tracking software is high (β=2,032, t=2.31, p=.022). When intrinsic motivation for using activity tracking software is low, IT-enabled social comparison has a marginal influence on physical activity (β=1,512, t=1.73, p=.086).

Next, the effect of intrinsic motivation for using activity tracking software on physical activity change (H3) was examined. As shown in Table 4-9, intrinsic motivation for using activity tracking software significantly influenced the physical activity change at the 5th week (β=915, t=2.38, p=.010). However, intrinsic motivation for using activity tracking software did not influence physical activity change at the 8th week (β=5.8, t=.02, p=.494).

Table 4-9. Hypotheses Testing [17] Using Subjective Physical Activity (Total MET min./week) Difference Scores

Weekend	PA difference between 5th week[1] and 0th week[2]		PA difference between 8th week[3] and 0th week	
	MET min./week Difference	Test Statistics	MET min./week Difference	Test Statistics
H1: IT-enabled SC[4] → PA (change)[5]	T[7]: 2,936(N=39) C[8]: 1,141(N=31)	t=2.14, d=.47, p=.019*	T: 2,540 (N=26) C: 912(N=24)	t=1.97, d=.54, p=.028*
H2: IT-enabled SC × IMATS[6]→ PA (change)		β=2,001, t=2.76, p=.004**		β=162.9, t=0.20, p=.422
H3: IMATS → PA (change)		β=915, t=2.38, p=.010*		β=5.8, t=.02, p=.494

** p<0.01 *p<0.5 †p<0.1 One-tailed tests for relationships between constructs as direction of relationships are theorized.
Two sample t-tests are used for testing H1, and OLS regression is used for testing H2 (controls: age, gender) and H3 (controls: age, gender, IT-enabled social comparison)
1: final week of the treatment period, 2: before experiment implementation, 3: final week of the follow-up period
4: IT-enabled social comparison, 5: physical activity (total MET min/week) change from 0th week (i.e., physical activity change after the use of activity tracker), 6: intrinsic motivation for using activity tracking software
7: treatment, 8: control

[17] Because the variances between the groups were not equal for both 5th week and 8th week (five percent significance level), we used Welch's t-test. When the assumption of homogeneity of variance for t-test is not met, Welch's t-test should be used (Delacre et al. 2017). For both 5th week and 8th week, inferences using Student's t-test and Welch's t-test were consistent, which lends further robustness to our findings.

Table 4-10. Summary of Robustness Checks (Hypotheses Testing Using Various Measures)

	Objective PA measure: average step/ day				Subjective PA measure: total MET min./week			
Variables	Absolute[1]		Relative[2]		Absolute[3]		Relative[4]	
	W5	W8	W5-W1	W8-W1	W5	W8	W5-W0	W8-W0
IT-enabled SC[5] → PA[6]	*(WK[8]) *(WW[9])	† (WW)	† (WK) *(WW)	** (WW)	*	†	†	†
IT-enabled SC × IMATS[7] → PA					**		**	
IMATS → PA	† (WK)		*(WK)		**		*	

** p<0.01 *p<0.5 †p<0.1

1: Average daily steps at 5th week (W5: final week of treatment period) and 8th week (W8: final week of follow-up period)

2: Average daily steps difference between 5th week and 1st week (W5-W1) and between 8th week and 1st week (W8-W1)

3: Total MET min./week at 5th week (W5) and 8th week (W8).

4: Total MET min./week difference between 5th week and 0th week (W5-W0) and between 8th week and 0th week (W8-W0)

5: IT-enabled social comparison, 6: physical activity, 7: intrinsic motivation for using activity tracking software, 8: weekend, 9: work week

4.5.4. Post Hoc Analysis

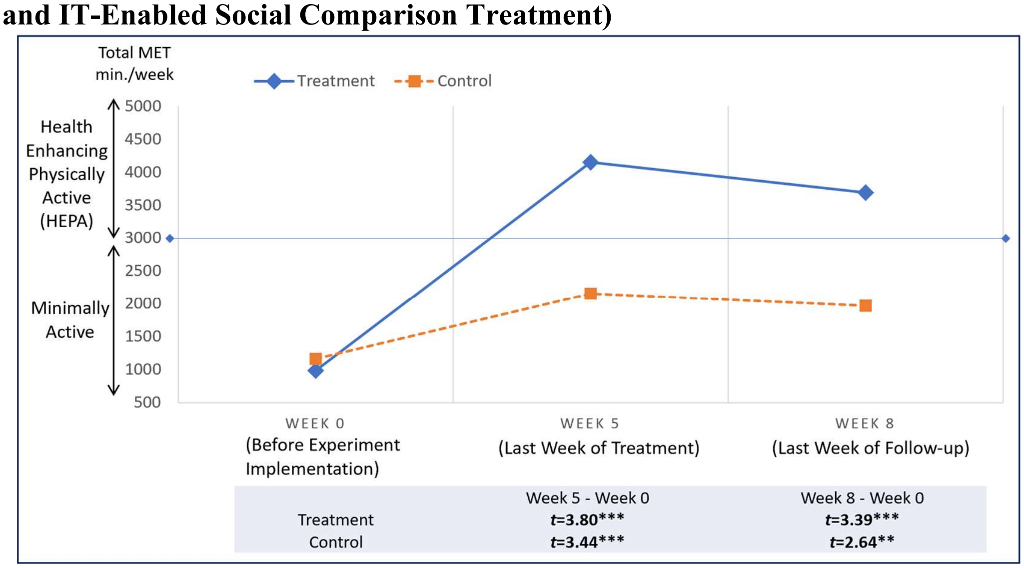
In the post hoc analysis, we examined participants' transition to a physically active lifestyle after using an activity tracker and after being involved in IT-enabled social comparison treatment.

First, we examined how much the participants' physically inactive lifestyle changed to an active lifestyle using a subjective measure of physical activity (total MET min./week: energy expenditure during a week). As noted earlier, experiment participants were the least physically active 87 people (based on IPAQ scores) among a sample of 885 undergraduate applicants, based on physical activity assessment (i.e., total MET min./week). Before the experiment implementation (i.e., before the use of activity trackers), the average total MET min./week of the treatment groups was 998, and that of the control groups was 1,168, both of which can be characterized as minimally active[18] based on the scoring system for IPAQ (see Appendix B)

[18] According to the scoring system provided by IPAQ, physical activity levels are classified into three categories: inactive (e.g., total MET min./week <600), minimally active (e.g., 600 ≤ total MET min./week ≤ 3,000),

(Al-Hazzaa 2007; Ryu et al. 2015). After the experiment implementation, the average total MET min./week of the treatment groups increased to 4,147, and that of the control groups increased to 2,157 at the 5th week (final week of treatment period). The total MET min./week difference between 5th week and 0th week was statistically significant[19] both for the treatment group (t=3.80, p=0.0005) and the control group (t=3.44, p=0.0017). As shown in Figure 4-6, physical activity level classification of treatment group, based on average total MET min./week, changed from minimally active category in 0th week (before experiment implementation) to health-enhancing physically active (HEPA) category in 5th week. Specifically, as shown in Table 4-11, the proportion of inactive people in the treatment group decreased from 33% (0th week) to 15.4% (5th week), while the percentage of HEPA people increased from 0% (0th week) to 46.2% (5th week). While the physical activity level classification of average weekly energy expenditure of the control groups at the 5th week was not changed from the 0th week, the proportion of inactive people in the control group decreased from 38% (0th week) to 12.9% (5th week) and the proportion of HEPA people increased from 0% (0th week) to 22.6% (5th week).

Figure 4-6. Total MET min./week Change from 0th Week (Before Activity Tracker Use and IT-Enabled Social Comparison Treatment)



*** p<0.01 **p<0.5 *p<0.1, The two-tailed t-test between total MET. min/week of nth week (e.g., 5th week) and total MET min./week of 0th week

and health enhancing physically active (HEPA) (e.g., 3,000 ≤ total MET min./week).

[19] Two-tailed test

Table 4-11. Physical Activity Levels of Subjects at Key Time Points[1]

	Treatment				Control			
	Inactive	Minimally Active	HEPA	N	Inactive	Minimally Active	HEPA	N
W0	33%	66.7%	0%	48	38%	62%	0%	39
W5	15.4%	38.5%	46.2%	39	12.9%	64.5%	22.6%	31
W8	19.2%	46.2%	34.6%	26	33.3%	41.7%	25.0%	24

1: Classification is based on total MET min./week
W0 (0th week): before experiment implementation, W5 (5th week): final week of treatment period, W8 (8th week): final week of the follow-up period

These significant increases of weekly energy expenditure both in the treatment group and control group persisted at the 8th week, which was the final week of the follow-up period (i.e., the period without IT-enabled social comparison treatment). At the 8th week, the average total MET min./week of treatment groups had increased to 3,692 (from 998 at 0th week), and that of the control groups had increased to 1,972 (from 1,168 at 0th week). The total MET min./week difference between the 8th week and the 0th week was statistically significant[20] both for the treatment group (t=3.39, p=0.0023) and the control group (t=2.64, p=0.014). As shown in Figure 4-6, physical activity level classification of treatment group, based on average total MET min./week, changed from minimally active category in 0th week (before experiment implementation) to HEPA category in 8th week. Specifically, as shown in Table 4-11, the proportion of inactive people in the treatment group decreased from 33% (0th week) to 19.2% (8th week), while the percentage of HEPA people increased from 0% (0th week) to 34.6% (8th week). Even though physical activity level classification of average weekly energy expenditure of control groups at the 8th week was not changed from the 0th week, the proportion of inactive people in the control group decreased from 38% (0th week) to 33.3% (8th week), while the proportion of HEPA people increased from 0% (0th week) to 25% (8th week).

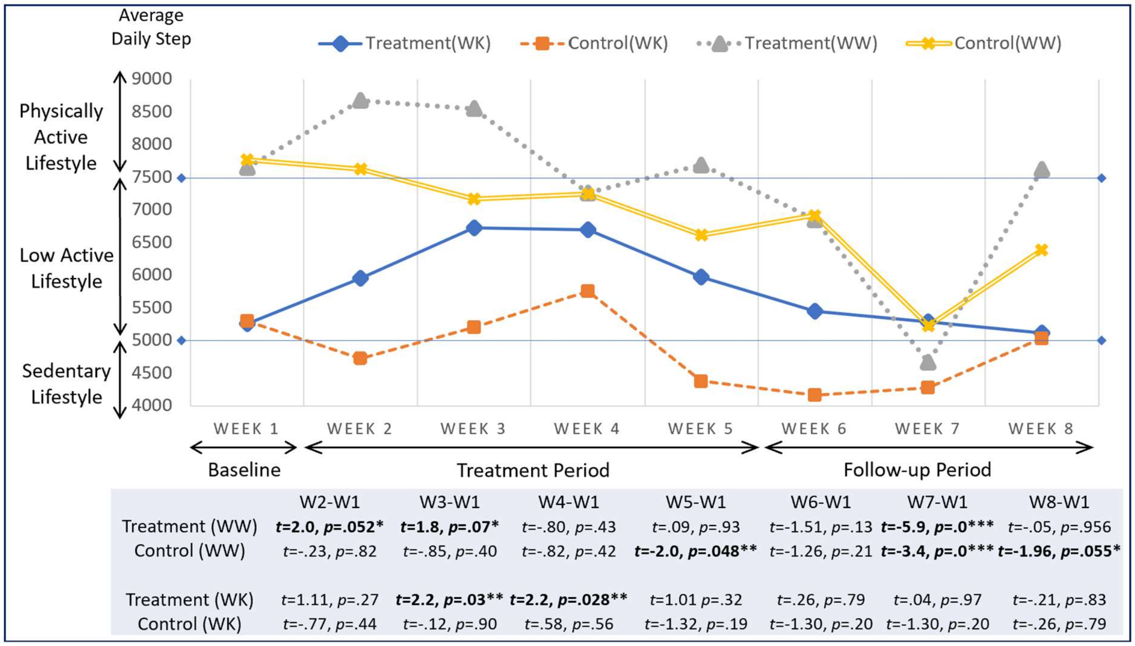
Next, we examined how much the participants' physically inactive lifestyle changed to an active lifestyle after participating in IT-enabled social comparison treatment in each

[20] Two-tailed test

treatment and follow-up period using an objective measure of physical activity (i.e., average daily steps recorded by activity trackers). At the baseline (i.e., after activity tracker use and before IT-enabled social comparison treatment implementation), the average daily steps for the treatment groups were 5,260 on weekends and 7,646 on work weeks, and those of control groups were 5,295 on weekends and 7,769 on work weeks. Based on a step-defined sedentary lifestyle index[21] (Tudor-Locke et al. 2012), the averages of both treatment groups and control groups were classified into the low active lifestyle for weekend and into the physically active lifestyle for work week. After participating in IT-enabled social comparison treatment, as shown in Figure 4-7, the average daily steps of the treatment groups increased during treatment period except for the 4th work week. Even though physical activity level classifications of treatment group didn't change during most of the treatment period, the average daily steps significantly increased (from the 1st week) at the 2nd work week (t=1.97, p=0.052), the 3rd work week (t=1.82, p=0.070), the 3rd weekend (t=2.16, p=0.033), and the 4th weekend (t=2.23, p=0.028). Interestingly, the changes of physical activity level classifications during the treatment period were observed in the control group. Specifically, physical activity levels of the control group decreased from the physically active lifestyle to the low active lifestyle for work weeks except for the 2nd work week. As shown in Figure 4-7, this decreased physical activity level of the control groups was maintained during the follow-up period for work weeks.

[21] Sedentary Lifestyle <5,000 steps/day,
5,000 ≤ Low Active Lifestyle < 7,500.
7,500 ≤ Physically Active Lifestyle

Figure 4-7. Average Daily Steps Change from 1st Week (After Activity Tracker Use and Before IT-Enabled Social Comparison Treatment)



*** $p<0.01$ ** $p<0.5$ * $p<0.1$, WK: weekend, WW: work week

Two-tailed t-test between average daily steps on n^{th} week (e.g., 2^{nd} week) and average daily steps on 1^{st} week.

Table 4-12. Proportion of Subjects' Physical Activity Levels[1]

	Treatment (WK)				Control (WK)				Treatment (WD)				Control (WD)			
	Sed	Low	Act	N	Sed	Low	Act	N	Sed	Low	Act	N	Sed	Low	Act	N
W1	49%	34%	17%	47	46%	24%	30%	37	10%	40%	50%	48	13%	32%	55%	38
W2	49%	22%	29%	45	65%	18%	18%	34	8%	29%	63%	48	15%	31%	54%	39
W3	38%	29%	33%	45	54%	19%	27%	37	2%	35%	63%	48	22%	38%	41%	37
W4	43%	24%	33%	42	46%	26%	29%	35	16%	42%	42%	45	24%	32%	43%	37
W5	48%	24%	29%	42	68%	23%	10%	31	9%	46%	46%	46	28%	39%	33%	36
W6	61%	12%	27%	41	71%	14%	14%	28	26%	35%	39%	46	24%	33%	42%	33
W7	46%	32%	22%	41	68%	18%	14%	28	65%	23%	13%	40	59%	31%	10%	29
W8	55%	21%	24%	33	60%	28%	12%	25	8%	39%	53%	38	39%	32%	29%	31

1: Classification is based on a step-defined sedentary lifestyle index (Tudor-Locke et al. 2012)
Sed: sedentary lifestyle, Low: low active lifestyle, Act: physically active lifestyle

4.6. DISCUSSION

Consistent with the aim of our study which was to develop and test an intervention that helps inactive people become more active, we were able to demonstrate that IT-enabled social comparison positively influences physical activity and that this holds for both objective[22] and

[22] During the four-week treatment period, IT-enabled social comparison did not significantly influence physical activity for the 4th week. The 4th week might be the period when study participants (undergraduate students) focused on other activities such as exams. When subjects are busy, the effect of IT-enabled social comparison on physical activity may be reduced because subjects may prioritize other activities (e.g., test preparation) over

subjective measures of physical activity. Also, we demonstrated how intrinsic motivation for using activity tracking software influences physical activity in the context of IT-enabled social comparison. Specifically, intrinsic motivation for using activity tracking software not only strengthens the influence of IT-enabled social comparison on physical activity but also directly influences physical activity in the context of activity tracker use. Even though these influences of intrinsic motivation for using activity tracking software were not consistently significant when using an objective measure of physical activity, the signs of the moderation effect and the direct effect of intrinsic motivation for using activity tracking software were mostly consistent (see table 4-5 and 4-7) with the direction of the theorized relationship among constructs when using an objective measure, and these effects were significant when using a subjective measure and subjective physical activity difference scores. Therefore, there might be a marginal influence of intrinsic motivation for using activity tracking software on the relationship between IT-enabled social comparison on physical activity as well as a marginal influence of intrinsic motivation for using activity tracking software on physical activity.

As a post hoc analysis, we demonstrated that IT-enabled social comparison implemented in conjunction with the use of activity tracker successfully increases participants' physical activity and possibly changes people's physically inactive lifestyle to a physically active lifestyle.

4.6.1. Theoretical Implications

This study makes meaningful contributions to several research streams. First, this study contributes to health information technology (HIT) as well as physical activity literature by establishing the effect of an IT-enabled social comparison mechanism on physical activity and providing insights into how IT-enabled social comparison influences physical activity. To the best of our knowledge, this is the first study that thoroughly investigates the effect of IT-

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physical activity.

enabled social comparison on physical activity by employing a randomized experiment and both objective and subjective measures of physical activity. Despite the high potential of IT-enabled social comparison in increasing people's physical activity, previous studies failed to examine the effect of IT-enabled social comparison in isolation, as this treatment was confounded with other interventions such as rewards, adaptive daily goals, feedback, or social support (Johnson et al. 2016).

Second, this study contributes to the HIT literature by examining how an individual's motivation influences the impact of IT-enabled health interventions on human behavior change. While advances in technology have enabled researchers to implement IT-enabled health interventions, which are interactive, automated and personalized, using technical sensors or user input data (McNamee et al. 2016), moderators on the relationships between IT-enabled interventions and health-related behavior have received little attention (Rhodes et al. 2017; Wilson and Dishman 2015). In addition, while recent IS studies demonstrated that individuals with different motivational characteristics use fitness technologies differently (James et al. 2019; James et al. 2019), the moderating effect of intrinsic motivation on the relationship between IT-enabled health interventions and human behavior change has not been previously investigated. Given that IT-enabled interventions are more individual-centered and rely on self-management, the understanding of individuals' motivational factors that interact with IT-enabled interventions will help us to understand the conditions under which effective engagement and behavior change occur through IT-enabled interventions. This study suggests that individuals' motivation for using information technology that delivers IT-enabled interventions can play an important role in changing human behavior in the context of IT-enabled interventions.

Third, this study contributes to motivation literature and physical activity literature by investigating the roles of intrinsic motivation for using activity tracking software on physical activity. Most previous research that has examined the relationship between intrinsic motivation and physical activity focused on intrinsic motivation for physical activity, and thus offered a somewhat limited explanation for the relationship between intrinsic motivation and physical activity. Given that the effectiveness of technology in attracting people depends on the user's strength of motivational needs supported by technology (Zhang 2007), in order to fully understand the role of intrinsic motivation on physical activity under IT-enabled interventions, we need to consider an individual's motivation for using IT. By demonstrating the influence of intrinsic motivation for using activity tracking software on physical activity, this study broadens our understanding.

Fourth, this study contributes to physical activity literature by providing an empirical test of the effect of IT-enabled social comparison using an objective measure. Even though physical activity is critical to human health, the results from previous research have shown small effect sizes and inconsistent results across studies (Rhodes et al. 2017). Additionally, most previous studies have employed self-report measures that are less accurate than objective measures (Downs et al. 2014; Oyeyemi et al. 2014). Thus, the verification of the effect of IT-enabled social comparison on physical activity using an objective measure represents a contribution to the field.

Fifth, this study contributes to the physical activity literature by providing full empirical results on the impact of IT-enabled social comparison on physical activity. To be specific, this study shows that IT-enabled social comparison had a positive impact on physical activity during the treatment period, but this impact did not persist after the end of treatment. Given that little is known about the duration of the effect produced by IT-enabled interventions, the empirical results we provide are meaningful. Additionally, this study demonstrates that the strength of the theorized relationships among constructs depends on the use of different physical activity measures. Specifically, the influences of intrinsic motivation for using activity tracking software on physical activity (i.e., moderating effect and direct effect) were stronger when using subjective physical activity measures than when using objective measures. Thus, we can postulate that subjects with high intrinsic motivation for using activity tracking software might overestimate their level of physical activity (e.g., they think they did more physical activity than they actually did) than subjects with low intrinsic motivation for using activity tracking software when they participate in IT-enabled social comparison as well as when they use activity tracker. Previous physical activity studies have suggested that subjective measures of physical activity may represent overestimates in comparison to objective measures (Downs et al. 2014; Oyeyemi et al. 2014); however, to the best of our knowledge, this is the first study that demonstrates the empirical differences between the use of objective measures and the subjective measures. Finally, this study shows how IT-enabled social comparison and the use of activity trackers can change participants' physically inactive lifestyle into a more active lifestyle. Given that our aim was to demonstrate and test how an IT enabled social comparison intervention can help inactive people become more active, the empirical results we provide are meaningful.

4.6.2. Practical Implications

Given the importance of physical activity on human health, the results of this study will have practical implications for practitioners in developing intervention strategies to increase the physical activity of individuals who do not meet the WHO recommendations. Especially, this study helps practitioners to understand how intrinsic motivation for using activity tracking software can influence the effect of IT-enabled social comparison on physical activity. Also, based on the empirical results provided in this study, practitioners may be able to consider a more specific and effective intervention strategy to increase people's physical activity. For example, this study showed that there were differences in participants' physical activity between weekends and work weeks (see Table 4-4 and Figure 4-4)[23]. Therefore, in practice it may be necessary to implement different types intervention strategies on weekends and work weeks.

4.6.3. Limitations and Directions for Future Research

Even though this study demonstrated the significant effect of IT-enabled social comparison on physical activity using both objective and subjective measures of physical activity, we focused on establishing the treatment effect rather than the difference in the effect observed when using objective vs subjective measures and sources of this difference. Given that previous studies suggested that self-reported measures of physical activity can be overestimated relative to objective measures (Downs et al. 2014; Oyeyemi et al. 2014) and that many studies still adopt a subjective measure of physical activity, we suggest that future research examine the factors affecting overestimation of a subjective measure of physical activity.

As demonstrated in the previous section, the moderation effect and direct effect of intrinsic motivation for using activity tracking software in our research model were stronger when using a subjective measure of physical activity than when using an objective measure. We propose that people with high intrinsic motivation for using activity tracking software may overestimate their level of physical activity relative to people with low intrinsic motivation for using activity tracking software when they participate in IT-enabled social comparison as well as when they use an activity tracker. Future research needs to empirically test the influence of intrinsic motivation for using activity tracking software on the overestimation of physical activity.

While this study successfully showed the influence of IT-enabled social comparison on

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[23] When we did t-test, the differences in physical activity between work week and weekend were statistically significant ($p<0.01$) throughout experiment period except for 7th week.

physical activity by conducting a randomized field experiment, we did not incorporate individual factors associated with social comparison theory, such as relevance of performance dimension, similarity (e.g., the existence of rivals), and relationship closeness that potentially influence the effect of IT-enabled social comparison (Garcia et al. 2013). To establish more effective implementation strategies using IT-enabled social comparison in applied settings, we need to examine how these individual factors may influence IT-enabled social comparison. Therefore, we suggest that future research incorporate individual factors of social comparison theory into the research design.

Though all subjects who participated in our experiment were requested to wear a Fitbit activity tracker at all times while awake, we cannot be one hundred percent sure that the study participants followed this request throughout the experiment period. To minimize the influence of participants' non-compliance on the study results, we excluded any instances (daily step count) with less than 100 daily step counts from the data set. After removing these, 2,215 instances (i.e., 89.7%) out of 2,469[24] are included in the data analysis for the treatment group, and 1,717 instances (i.e., 90.4%) out of 1,910[25] are included in the data analysis for the control group. We suggest that future research examine whether study participants are compliant throughout the experiment period.

4.7. Conclusion

Despite the importance of physical activity on human health and the potential of IT-enabled social comparison to increase people's physical activity, the effect of IT-enabled social comparison on physical activity has not been established. This study demonstrated the effect of IT-enabled social comparison on physical activity and how the intrinsic motivation for using

[24] Total instances of treatment group: $\sum_{n=1}^{8}(\text{number of subjects in the treatment group in weekend } \boldsymbol{n} \times 2) + (\text{number of subjects in the treatment group in work week } \boldsymbol{n} \times 5)$

[25] Total instances of control group: $\sum_{n=1}^{8}(\text{number of subjects in the control group in weekend } \boldsymbol{n} \times 2) + (\text{number of subjects in the control group in work week } \boldsymbol{n} \times 5)$

activity tracking software influences physical activity in this context. Also, this study examined the extent to which people with a physically inactive lifestyle can be moved to adopt an active lifestyle after using an activity tracker and after participating in IT-enabled social comparison. We hope that this study leads to additional research on the impact of IT-enabled interventions on physical activity.

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APPENDIX A: Measurement Items

Intrinsic Motivation for Using Activity Tracking Software (McAuley et al. 1989)
(1 Strongly disagree…7 Strongly agree)

For each of the following statements, please indicate how true it is for you

1. I enjoyed using Fitbit app very much.
2. Using Fitbit app was fun.
3. I would describe using Fitbit app as very interesting.
4. While using Fitbit app, I was thinking about how much I enjoyed it.

APPENDIX B: IPAQ and Evaluation Method for Screening Participants

International Physical Activity Questionnaire

We are interested in finding out about the kinds of physical activities that people do as part of their everyday lives. The questions will ask you about the time you spent being physically active in the **last 7 days**. Please answer each question even if you do not consider yourself to be an active person. Please think about the activities you do at work, as part of your house and yard work, to get from place to place, and in your spare time for recreation, exercise or sport.
Think about all the **vigorous** activities that you did in the **last 7 days**. **Vigorous** physical activities refer to activities that take hard physical effort and make you breathe much harder than normal. Think *only* about those physical activities that you did for at least 10 minutes at a time.

1. During the **last 7 days**, on how many days did you do **vigorous** physical activities like heavy lifting, digging, aerobics, or fast bicycling?
_____ days per week
□ No vigorous physical activities

2. How much time did you usually spend doing **vigorous** physical activities on one of those days?
_____ hours per day
______minutes per day
□ Don't know/Not sure

Think about all the **moderate** activities that you did in the **last 7 days**. **Moderate** activities refer to activities that take moderate physical effort and make you breathe somewhat harder than normal. Think only about those physical activities that you did for at least 10 minutes at a time.

3. During the **last 7 days**, on how many days did you do **moderate** physical activities like carrying light loads, bicycling at a regular pace, or doubles tennis? Do not include walking.
_____ days per week

□ No moderate physical activities

4. How much time did you usually spend doing **moderate** physical activities on one of those days?
_____ hours per day
_____ minutes per day
□ Don't know/Not sure

Think about the time you spent **walking** in the **last 7 days**. This includes at work and at home, walking to travel from place to place, and any other walking that you have done solely for recreation, sport, exercise, or leisure.

5. During the **last 7 days**, on how many days did you **walk** for at least 10 minutes at a time?
_____ days per week
□ No walking

6. How much time did you usually spend **walking** on one of those days?
_____ hours per day
_____ minutes per day
□ Don't know/Not sure

The last question is about the time you spent **sitting** on weekdays during the **last 7 days**. Include time spent at work, at home, while doing course work and during leisure time. This may include time spent sitting at a desk, visiting friends, reading, or sitting or lying down to watch television.

7. During the **last 7 days**, how much time did you spend **sitting** on a **weekday**?
_____ hours per day
_____ minutes per day
□ Don't know/Not sure

Physical Activity Evaluation Method

MET[26] Values and Formula for Computation of MET-minutes
Walking MET-minutes/week = 3.3 * walking minutes * walking days.
Moderate MET-minutes/week = 4.0 * moderate-intensity activity minutes * moderate days
Vigorous MET-minutes/week = 8.0 * vigorous-intensity activity minutes * vigorous-intensity days

A combined total physical activity MET-min/week can be computed as the sum of Walking + Moderate + Vigorous MET-min/week scores.

[26] MET (Metabolic Equivalent of Task): the ratio of metabolic rate during physical activity to resting metabolic rate during physical inactivity. Walking = 3.3 METs, Moderate Physical Activity = 4.0 METs, and Vigorous Physical Activity = 8.0 METs

Three levels of Physical Activity Proposed by IPAQ

1. *Inactive*
• No activity is reported **OR**
• Some activity is reported but not enough to meet Categories 2 or 3.

2. Minimally Active
Any one of the following 3 criteria
• 3 or more days of vigorous activity of at least 20 minutes per day **OR**
• 5 or more days of moderate-intensity activity or walking of at least 30 minutes per day
OR
• 5 or more days of any combination of walking, moderate-intensity or vigorous intensity activities achieving a minimum of at least 600 MET-min/week.

3. HEPA active
Any one of the following 2 criteria
• Vigorous-intensity activity on at least 3 days and accumulating at least 1500 MET-min/week **OR**
• 7 or more days of any combination of walking, moderate-intensity or vigorous intensity activities achieving a minimum of at least 3000 MET-minutes/week

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CHAPTER 5

Conclusion

Health information technology (HIT) has a huge potential not only to improve the health and well-being of people but also to solve the underlying problems within the current health care system (Agarwal et al. 2010; Silva et al. 2015). Given that the benefits of HITs can only be realized when people use them, the examinations about the behavioral mechanisms behind why people embrace or reject HIT are critical to promote health behaviors and healthy outcomes, but these mechanisms remain understudied. Therefore, my dissertation addresses this gap by empirically investigating behavioral mechanisms of how individuals' motivational characteristics influence HIT related behaviors. Specifically, in Essay 1, I investigate how healthcare professionals' motivations influence resistance to Computerized Provider Order Entry (CPOE). In Essay 2, I investigate how individuals' inherent motivational orientations (i.e., regulatory focus) and motivational strength toward engaging in health behavior (i.e., internal health locus of control) influence their intention to use different types of smartwatch health apps (i.e., promotion app, prevention app). In Essay 3, I investigate the effect of IT-enabled social comparison on physical activity and how intrinsic motivation for using activity tracking software influences physical activity in the context of IT-enabled social comparison. Table 5-1 provides a summary of the key findings in Essay 1, Essay 2, and Essay 3.

Table 5-1. Summary of Key Findings

Essay Title	Key Findings
Essay 1 "How Doctors' and Nurses' Motivations Shape Perceptions of System Benefits and Resistance to CPOE"	• System benefit mediates the effect of motivation for efficiency on resistance to CPOE both for doctors and nurses, but it mediates the effect of motivation for quality on resistance to CPOE only for nurses • Countervailing mechanisms exist for the effect of motivation for efficiency on resistance to CPOE (i.e., positive direct effect and negative indirect effect via system benefit).

	• The identified resistance mechanism manifests differently over time.
Essay 2 "Motivating Use of Smartwatch Health Promotion and Health Prevention Applications: A Regulatory Fit and Locus of Control Perspective"	• The fit between smartwatch health apps (promotion app and prevention app) and an individual's regulatory focus (promotion focus and prevention focus) motivates the use of these apps. • The effect of this fit on the intention to use a promotion app is strengthened by an individual's motivational strength toward engaging in health behavior (i.e., internal health locus of control). • Internal health locus of control weakens the effect of prevention focus on the intention to use a promotion app.
Essay 3 "Motivating Increased Physical Activity: An Examination of IT-Enabled Social Comparison Mechanism"	• IT-enabled social comparison positively influences physical activity, and this holds for both objective and subjective measures of physical activity. • Intrinsic motivation for using activity tracking software not only strengthens the influence of IT-enabled social comparison on physical activity but also directly influences physical activity in the context of activity tracker use. • IT-enabled social comparison implemented in conjunction with the use of activity tracker successfully increases participants' physical activity and can help change people's physically inactive lifestyle to a physically active lifestyle.

The overarching behavioral mechanism this dissertation demonstrates is that the fit between individuals' motivations and the technological properties of IS that are designed to fulfill these motivations (i.e., motivational affordances) encourages individuals to use HIT. Given that the benefits of HITs can be realized when people use them (Buntin et al. 2011) and that one of the main directions of HIT evolution is the personalization (e.g., personalized care, personalized usability, etc.) enabled by technological advances such as interoperability and advanced analytics, the suggested behavioral mechanism has several implications for HIT literature, IS professionals, and health practitioners. First, this mechanism provides a theoretical explanation on critical questions about why individuals with different motivations are differentially motivated to use a particular HIT and how do properties of a specific HIT differentially appeal to users with different motivational needs. Previous HIT literature that focused on individuals' general perceptions toward HIT (e.g., ease of use) as factors that motivate the use of HITs did not answer these critical questions. Second, given that recent technological advances allow IS professionals to develop more personalized HIT, the newly suggested mechanism provides IS professionals practical insights into developing HITs that are more personalized to individuals with different motivations.

Finally, the overarching mechanism explored in this dissertation provides guidance that can help increase the use of HITs both among health practitioners and their clients.

5.1. Contributions to Research and Practice

The major contribution of this dissertation is that it demonstrates how individuals' motivational characteristics influence HIT related behaviors.

Essay 1 makes a theoretical contribution by identifying a new resistance mechanism of how users' motivation influence resistance to IS via system benefit of IS, and by demonstrating how this mechanism manifests differently for individuals with different roles. Previous resistance research, which focused on the changes caused by new IS and the users' perceptions affected by those changes, did not model users' motivations and system benefit of IS, and the mechanism of resistance was therefore poorly understood. Essay 1 provides IS practitioners with insights on how to establish an effective CPOE implementation strategy to reduce healthcare professionals' resistance to CPOE depending on their roles and the time point in the CPOE implementation process.

Essay 2 contributes to the literature by demonstrating that the fit between individuals' inherent motivational orientations (i.e., regulatory focus) and properties of smartwatch health apps (i.e., promotion apps and prevention apps) motivates individuals to use such apps. Further, this study demonstrates how individuals' motivational strength toward engagement in self-health-management (i.e., internal health locus of control) strengthens the effect of this fit. Even though mobile health is more individual-centered and relies on self-management (Sama et al. 2014; Zhou et al. 2017), few previous studies on mobile health have examined how individual difference factors influence the adoption of each type of mobile app. Essay 2 represents the first empirical investigation into how individuals with different motivational orientations are inspired to use different types of mobile health. Essay 2 provides health practitioners and makers of smartwatch health apps with insights on how to design health promotion programs using smartwatch health apps and how to promote these apps to individuals with different regulatory orientations and health internal locus of control.

Essay 3 contributes to the literature by establishing the effect of IT-enabled social comparison on physical activity. Despite the high potential of IT-enabled social comparison in increasing people's physical activity, previous studies failed to examine the effect of IT-enabled social comparison in isolation, as this treatment was confounded with other interventions such as rewards and daily goals (Johnson et al. 2016). Further, Essay 3 demonstrates the roles of intrinsic motivation for using activity tracking software on physical activity in the context of IT-enabled social comparison. Previous research on motivations and physical activity has focused on the direct association between physical activity and intrinsic motivation for physical activity; thus, the motivational conditions under which effective engagement in physical activity occurs through IT-enabled intervention remain understudied. Given that previous IT-enabled intervention studies that aim to increase people's physical activity have produced mixed results across studies (Schoeppe et al. 2016), the examination of these conditions are critical. Therefore, Essay 3 addresses the limitation of previous research by demonstrating that the positive influence of IT-enabled social comparison on physical activity is strengthened by intrinsic motivation for using activity tracking software. Essay 3 provides health practitioners with insights on how to implement effective intervention strategies using IT-enabled social comparison to increase people's physical activity. Especially, this study helps practitioners to understand how intrinsic motivation for using activity tracking software can influence the effect of IT-enabled social comparison.

5.2. Limitations and Directions for Future Research

Like other studies, this dissertation has its limitations. First, Essay 1 and Essay 2 focus only on users' perceptions of the benefits of IT and do not examine their perception of the costs. Specifically, Essay 1 focuses on healthcare professionals' benefit perception in the resistance mechanism rather than their threat perception. However, as described earlier in Essay 1, the changes engendered by CPOE implementation (e.g., decreased autonomy and increased workload) may pose a threat to doctors, and the perceived threat may play a critical role in generating resistance to CPOE system. Therefore, I suggest that future research examine the mechanism of how healthcare professionals' threat perceptions are formed and how those perceptions affect their resistance to CPOE. Likewise, Essay 2 failed to operationalize the effort that is related to the use of smartwatch apps. Given that both benefits and costs influence customers' adoption decision (Herzenstein et al. 2007) and that the cost and user burden for using apps negatively affect users' intention to use mobile health apps (Birkhoff and Smeltzer 2017), I suggest that future research is needed to examine how cost-related factors influence the identified relationships between regulatory focus and the intention to use smartwatch health apps.

Second, while Essay 3 successfully shows the effect of IT-enabled social comparison on physical activity, this essay did not incorporate individual factors (e.g., relationship closeness) associated with social comparison theory that potentially influence the effect of IT-enabled social comparison (Garcia et al. 2013). Therefore, to establish a more effective implementation strategy to increase people's physical activity in applied settings, I suggest that future research needs to examine how these individual factors influence IT-enabled social comparison.

5.3. Conclusion

Motivated by the importance of understanding the behavioral mechanisms behind why people embrace or reject HIT as well as by the scarcity of research in this area, this dissertation investigated behavioral mechanisms of how individuals' motivational characteristics influence HIT related behaviors. Three empirical studies were conducted to investigate how healthcare professionals' motivations influence resistance to CPOE (Essay 1), how individuals' inherent motivational orientations and motivational strength toward engaging in health behavior influence their intention to use smartwatch health apps (Essay 2), and the effect of IT-enabled social comparison on physical activity and how intrinsic motivation for using activity tracking software influences physical activity in the context of IT-enabled social comparison (Essay 3). I hope that this dissertation leads to additional research on how the relationships between individuals' motivations and motivational affordances of IS influence HIT related behaviors.

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