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Exploring Antecedents, Performance Outcomes And Psychological Processes Of Multi-Device Use

Chi-Wen Chen

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EXPLORING ANTECEDENTS, PERFORMANCE OUTCOMES AND PSYCHOLOGICAL PROCESSES OF MULTI-DEVICE USE

by

CHI-WEN CHEN

A dissertation submitted to the Graduate Faculty in Business in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2015
This manuscript has been read and accepted for the Graduate Faculty in Business in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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Abstract

EXPLORING ANTECEDENTS, PERFORMANCE OUTCOMES AND PSYCHOLOGICAL PROCESSES OF MULTI-DEVICE USE

By

Chi-Wen Chen

Advisor: Professor Marios Koufaris

Given the widespread use of multiple devices (such as desktop computers, smartphones, and tablets) in performing a task, systematic, theoretic, and empirical studies pertaining to motivations regarding, performance outcomes, and attitudes toward multi-device use have become essential. Despite the increasing importance of multi-device use, research remains scarce regarding this topic.

To comprehensively understand the issues of multi-device use, this dissertation comprises three complementary studies, each of which focuses on a different aspect of multi-device use: Given the availability of multiple devices, what are the motivations behind multi-device use as opposed to the use of only one device to complete a set of related tasks (antecedents; Study 1)? How do people use multiple devices to lead to better performance than when using a single device (performance outcomes; Study 2)? How do users feel about multi-device use when they are free or forced to switch from using one device to another to complete a task (psychological processes; Study 3)?

Drawing on task–technology fit theory and mental workload, this dissertation presents two research models for Study 1 and Study 2, in order to gain deep insight into what happens before (i.e., motivations) and after multi-device use (i.e., task performance). Moreover, on the basis of task–technology fit theory and psychological reactance theory, this dissertation presents a research model for Study 3 to understand the
impact of flexibility of multi-device use on users’ attitudes. A survey, video recording, and experiments were conducted to collect data for Study 1, 2, and 3, respectively. Partial least squares were used to analyze research models of Studies 1, 2, and 3.

Our empirical findings of Study 1 indicate that perceived task fit with multi-device use is a critical factor that forms users’ attitudes toward and expected satisfaction with multi-device use, both of which trigger their intentions to use multiple devices. However, unfamiliarity with multi-device use increases perceived complexity of multi-device use. Such complexity hinders users from perceiving good task fit with multi-device use. The results of Study 2 show that when users can select the right device from their device portfolios to deal with a certain subtask, the task can be completed more quickly and accurately. They also indicate that increasing the number of device switches generates a higher number of application switches and physical movements, both of which add time to task completion. The results of Study 3 indicate the existence of psychological reactance (i.e., as assertive affective and cognitive reactions to a threatened or eliminated freedom) in the context of non-flexibility of multi-device use. This reactance negatively influences affective and cognitive appraisals and in turn affects users’ satisfaction with multi-device use and continued intention toward multi-device use. Furthermore, forcing users to use the devices with the best fit for dealing with a simple task forms positive affective appraisals.

The results of this dissertation have several theoretical contributions and provide important guidelines for device manufacturers, such as Apple, Samsung, and Google, and for companies whose employees use multiple devices at work. I hope that this dissertation will inspire future research on this emerging and critical topic.
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Multi-Device Use

Introduction

Recent years have been marked by the emergence of a diverse array of devices such as desktop and laptop computers, smartphones, and tablets (Levin 2014; Yoo 2010). Increased availability of these devices creates an ecosystem of devices that enable users to use multiple devices in order to complete a single or multiple tasks (Dearman et al. 2008; Kane et al. 2009; Walljas et al. 2010; Yoo 2010). This dissertation calls such device use *multi-device use* and defines it as an individual engaging in an activity during which he or she uses a combination of distinct devices to complete a task.

Multi-device use is still in its early stages, despite the growing awareness and popularity (Dearman et al. 2008; Yoo 2010). One possible reason is that a decade ago, there were no smartphones and tablets in which users had more chances to use different devices. Another possible reason is that cloud computing, which makes multi-device use easy as it facilitates users to share and access files across devices, has become popular only recently (Marshall et al. 2012). As a result, use of multiple devices is just getting started. Also, this is a particularly vital area of research as more organizations are moving toward mobile workforces. Accordingly, this dissertation focuses on multi-device use.

Relevant literature that examines multi-device use can be categorized into either of the following two areas: *device use* includes use patterns (Bales et al. 2011; Dearman et al. 2008; Karlson et al. 2009) and user experience (Walljas et al. 2010), whereas *application design* includes cross-application interface design (Paternò et al. 2012; Pierce et al. 2008) and cross-platform service design (Sohn et al. 2010; Walljas et al. 2010). However, despite the increasing attention paid to multi-device use, the role of individual
psychological characteristics (e.g., motivation) and the impact of multi-device use on factors such as user performance have seldom been researched. Moreover, most studies that focus on multi-device use have adopted qualitative methodologies, such as user interviews, to achieve a preliminary understanding of how users combine multiple devices (e.g., Dearman et al. 2008 and Walljas et al. 2010), further highlighting that an empirical and experimental analysis is warranted.

**Research Questions**

This dissertation seeks to fill the preceding literature gap by presenting three empirical studies that explore the antecedents, performance outcomes, and psychological processes of multi-device use. Specifically, this dissertation addresses the following general research questions:

*Antecedents:* Given the availability of multiple devices, what are the user motivations behind multi-device use as opposed to the use of only one device to complete a set of related tasks (Study 1)?

*Performance Outcomes:* How does multi-device use positively or negatively impact task performance (Study 2)?

*Psychological Processes:* How do users feel about multi-device use when they are free or forced to switch from using one device to another to complete a task (Study 3)?

Therefore, this dissertation comprises three complementary studies, each of which focusing on different aspects of multi-device use: antecedents, performance outcomes and psychological processes of multi-device use.

**Key Elements for This Dissertation**

This dissertation involves three key elements: devices, tasks and users.
Devices

In this dissertation, a device refers to any computing equipment with electronic components capable of running software applications and is designed to perform multiple functions for an individual in a particular activity or for a specific purpose. It possesses the following features: (1) It allows data to be entered using one of various input methods, such as touch, keyboard, voice, or even a gesture; (2) it process data using a set of logic operation programs, and (3) it presents the results of such processing on a display screen that can have a range of sizes. These devices vary in shape, size, and weight. While each device has some unique functions, several functions overlap. Examples of these functions include sending e-mail, watching videos, listening to music, and browsing websites. The devices include, but are not limited to, laptop computers, desktop computers, tablets, and smartphones. These devices have many distinct aspects such as weight, size, and functionality (Dearman et al. 2008).

Task

In this study, tasks consist of information processing and technology-mediated work that has a specific goal, can be fragmented into related subtasks (task decomposability) and performed in specific locations and periods. For example, planning a trip to an unfamiliar place (task) requires different types of information, such as knowing the predicted weather (subtask), calculating the time required for the trip (subtask), and the number of miles required (subtask) to drive to reach the destination.

These subtasks can be accomplished by using different devices. It is important to note that this dissertation focuses on tasks that can be decomposed into related and interdependent subtasks. If tasks are not decomposable, users only need one device. For
example, checking the date on a particular weekend requires only one device; however, replying to an email involves reading and replying, which can be completed by using two devices (e.g., using a smartphone to read and a tablet to reply to an email). Accordingly, this dissertation only focuses on decomposable tasks that consist of a set of related subtasks.

**User**

In this study, a user refers to any person who owns or has access to a range of heterogeneous IT devices, which form his or her own device portfolio, and who can use these devices in the performance of a task. Importantly, the user characteristics vary in terms of personality, habits, familiarity with devices, and motivations for using these devices.

The remainder of this dissertation is organized as follows. The second section details Study 1, “Understanding the Motivations behind Intentions toward Multi-Device Use.” The third and fourth sections detail, respectively, Study 2, “Multiple Device Use and Task Performance,” and Study 3, “The Effects of Flexibility of Multi-Device Use on Users’ Attitudes, Satisfaction, and Continuance Intentions.” Each section provides, for each study, a research background, hypotheses, the research design, analysis results, a discussion, and implications. Finally, the dissertation closes with a general conclusion and discussion of findings, and suggestions for future research for multi-device use.
Study 1: Understanding the Motivations Behind Intention to Multi-Device Use

Introduction

Multi-device use has gradually become a popular pattern of device use in recent years (Levin 2014). In a survey, for example, Google reported that 65% of 1,611 users first used their smartphones to shop online, and then 61% completed the same shopping task on a PC or laptop (i.e., they completed a single task—shopping for a product online—using different devices) (Google 2012). However, despite the growing awareness and popularity of multi-device use, empirical studies pertaining to motivations behind intention to use multiple devices have been limited (Carroll 2008). Therefore, the goal of Study 1 focuses on answering an essential question: given that multiple and heterogeneous devices are available to users, why do users use multiple devices rather than single device to complete a task?

To address the research question, Study 1 draws on task-technology fit (TTF) theory and the concept of mental workload. Specifically, multiple devices give users opportunities to find a good fit between devices and tasks. According to TTF theory, when using the devices based on fit, task performance can be improved (Goodhue et al. 1995). Because TTF theory assumes that a single device is used (Goodhue 1995), as a result, to achieve overall better performance, users may be motivated to switch to other devices when the device they are currently using is not suitable for subtasks on which they are working, so as to maximize device fit with the entire task. However, as per this dissertation’s definition, multi-device use require device switching for the performance of a single task, which requires extra time and effort not encountered with single device use.
(Tungare et al. 2009). When users perceive that they need to spend a lot of time and effort when switching devices, multi-device use becomes perceptually complex, which generates mental workload (Tungare et al. 2009) and influences the willingness of users to use the devices with the best fit for the tasks. As a result, perceived complexity with multi-device use hinders the motivation of multi-device use. Therefore, both TTF theory and the concept of mental workload need to be considered in conjunction to explain motivations behind multi-device use.

In the next section, I review the theories on motivation that underpin multi-device use, develop Study 1’s hypotheses, and propose the research model. I follow with a description of the research design and measurement instrument, provide the data analysis, and end with a conclusion and discussion.

**Theoretical Background**

The questions of individual acceptance of and motivation to use Information Technology (IT) have long been of interest to information systems researchers. One of the most widely used theoretical models for explaining IT usage is the Technology Acceptance Model (TAM). The model suggests that perceived ease of use and usefulness are key antecedents of attitude toward a specific IT device, which influence intention to use the device and subsequently actual device use (Davis 1989). However, in the context of multi-device use, although the TAM variables and the relationships among attitude toward device use, intention, and actual use still exist and are important, they may not completely account for multi-device use. Specifically, TAM is based on the assumption that users only use one device or information system. This assumption is inappropriate in the context of Study 1 because multi-device use is not just a question of a device’s
perceived ease of use and usefulness, but also how it compares with other devices (e.g., which device provides a better fit between devices and tasks than others) and how the combined use of the devices may have an additive effect (e.g., mental workload). To capture this nature in multi-device use, I integrate TTF and the concept of mental workload to provide the main theoretical lenses for Study 1.

**Task–Technology Fit Theory**

Having received widespread acceptance in the IS field for many years, TTF theory has been extensively adopted to explain how, why, and when a technology can or cannot improve user performance and why a user uses a specific device for a certain task (Goodhue 1995; Zigurs et al. 1998). Specifically, TTF theory suggests that a satisfactory fit between a technology and tasks, as well as between a technology and users, may improve the performance of tasks (Goodhue et al. 1995). This concept can be described in Figure 1.1, which shows that using a desktop computer (top of the triangle) provides a good fit for a user (left-hand corner of the triangle) to complete an online shopping task (right-hand corner of the triangle). This fit then improves overall task performance.

![Figure 1.1 Example of Task-Technology Fit Theory](image)

TTF theory has been supported by several studies that focus on a single device or system and have produced consistent results showing that different aspects of TTF theory
have been confirmed relevant to IS in general (Goodhue 1995; Goodhue et al. 2000) as well as to specific technologies, such as knowledge management systems and mobile commerce (Dishaw et al. 1999; Lee et al. 2007; Lin et al. 2008), and for a variety of tasks, such as bidding in online auctions (Hsin 2010). I believe that TTF theory can also be applied in the context of this study because the availability of multiple devices gives users an opportunity to use devices based on the fit between their characteristics and a subtask, improving task performance.

Although TTF theory provides an explicit acknowledgment of the fit between tasks, technology, and users, this concept alone is insufficient for the purposes of this study because the TTF theory assumes that a single device is used (Goodhue 1995), which in the present time may no longer be the most likely scenario; therefore, the conceptualization of technology in this theory needs to be expanded to consider an ecosystem of devices. An important factor in this consideration that needs to be taken into account is device-switching costs that occur when switching between distinct devices. The effect of these costs generated by switching devices can be described as part of a user’s mental workload (Biehl et al. 2006; Tungare et al. 2009).

**Mental Workload**

Mental workload derives from the concept of the limits of working memory capacity introduced by Miller (1956). According to Miller, individuals can recall only five to nine (seven plus or minus two) pieces of information from their working memories, implying their limited capacity for processing information. This finding leads to the major assumption behind mental workload: our level of attentional resources has finite capacity, beyond which further increases in demand degrade performance. This
assumption implies that workload can be accumulated (Colle et al. 1997).

Mental workload has largely been studied with regard to how people operate a device or tool in completing a specific task, such as vehicle driving (Lansdown et al. 2004; Recarte et al. 2003) or flight tasks (Wilson 2002), and how these operations impose workloads on them, which further influences their performance. In recent years, mental workload has been a topic of increasing importance in IS, since modern technologies, such as websites or decision support systems (DSSs), have come to play a major role in our daily lives and using these systems has imposed additional cognitive demands on users (Speier and Morris 2003).

**TTF Theory and Mental Workload**

TTF theory or mental workload alone is not sufficient for the purposes of this study. Rather, TTF theory and mental workload need to be considered and integrated together because each of these theories alone overlook some important elements: TTF theory focuses on the fit between tasks, technology, and users (i.e., the triangle for each task) but neglects to consider the additional workload incurred by device-switching costs in multi-device use. Conversely, mental workload only concerns the demands from tasks, technologies, and users, while disregarding the fit between them. Considering TTF theory and mental workload allow us to better understand multi-device use in that users consider not only fit but also workload when using multiple devices. Accordingly, both TTF and mental workload paradigm are considered in Study 1.

I use the same example in Figure 1.1 to describe how these theories can be integrated together. An online shopping task can be separated into three related subtasks: searching for, comparing, and purchasing an item (see Figure 1.2). When three devices
(e.g., tablet, smartphone, and laptop computer) are available to use, according to TTF theory, a user may base his or her choice of a device on the fit between the user’s characteristics (left-hand corner of the triangle), a task (right-hand corner of the triangle), and device characteristics (top of the triangle) to complete each task (e.g., an individual may use a smartphone to search for items and add them to a wish list; he or she may then use a tablet to compare items and move the ideal item from the wish list into the shopping cart; finally, the user may use a laptop computer to make a payment). In this case, the user’s device-choosing behavior for each subtask can be explained by TTF theory (i.e., the triangle for each task in Figure 1.1) (Goodhue et al. 1995). However, this explanation assumes that each task is independent, without the extra cost incurred in the transition between devices. This assumption is problematic because all tasks and devices are not equally compatible. Prior studies have suggested that extra costs exist and must be considered when switching between devices (Biehl et al. 2006; Tungare et al. 2009) (see the dashed line in Figure 1.2), which is not accounted by TTF theory as this theory only considers single device use (Goodhue et al. 1995). This is where mental workload explains the impact of the extra costs on users when switching between devices. Thus, both TTF and mental workload serve as the theoretical foundations of Study 1.

![Figure 1.2 Example of Multi-Device Use](image-url)
Hypothesis Development and Research Model

The research model underpinning Study 1 is presented in Figure 1.3. The model is based on both TTF theory and the concept of mental workload to understand the motivations behind multi-device use intention. Table 1.1 presents the definitions of the constructs used in this study. The following sections elaborate on the constructs in the model and the proposed relationships among them.

![Research Model of Study 1](image)

Table 1.1 Construct Definitions and Sources of Study 1

<table>
<thead>
<tr>
<th>Construct</th>
<th>Definition</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived task fit with multi-device use</td>
<td>The degree to which multi-device use is perceived as being consistent with the existing values, needs, and past experiences of users.</td>
<td>Adapted from Moore and Benbasat (1991)</td>
</tr>
<tr>
<td>Perceived complexity of multi-device use</td>
<td>The extent to which individuals perceive that using multiple devices to complete a task involves extra effort, time and cognitive processing.</td>
<td>Adapted from Thompson et al., (1991)</td>
</tr>
</tbody>
</table>
### Perceived Task Fit with Multi-Device Use and Attitude toward Multi-Device Use

The availability of multiple devices gives users an opportunity to find the best fit between their own characteristics, a subtask, and a device’s characteristics. According to TTF theory, user performance improves when the fit between a task and a device is good (Goodhue et al. 1995). Since this fit leads to performance improvement, users may form a belief that using the device based on the good fit between a task and a device is a favorable way to complete a task, resulting in positive attitudes toward that device’s use (Dishaw et al. 1999; Liu et al. 2011; Parkes 2013). For example, Dishaw and Strong (1999) proposed a model that integrates constructs from both Technology Acceptance Model (TAM) and TTF. They tested the integrated model using path analysis. The results suggest that when the match between user task needs and the available functionality of the device occurs, users may have a high perceived usefulness of using the device. This perceived usefulness, which is viewed as a positive belief, in turn forms favorable attitude toward the device use.

Study 1 applies this concept to the combined use of multiple devices and call it *perceived task fit with multi-device use*. I believe that TTF theory, which has only been
applied to one device/one task combinations (Goodhue et al. 1995), can be extended to the multi-device use context because Study 1 focuses on decomposable tasks that are composed of interrelated subtasks. Each subtask can have a certain fit with a specific device, as explained by TTF theory. The perceived task fit with multi-device use, in this case, is the aggregation of the levels of fit between the individual devices and the subtasks that form the overall task in question. In other words, the conceptual relationship between a device and a task in TTF theory is still the same (i.e., one device/one task), but Study 1 expands this relationship by considering an ecosystem of devices with interrelated subtasks (i.e., multi-device/multi-subtask). If using more than one device can provide a good fit with a set of interrelated subtasks, users will perceive a high task fit with multi-device use.

Moore and Benbasat’s (1991) original definition of perceived task fit with a device\(^1\) emphasizes the perceived fit of single-device use rather than multi-device use, because, at the time of their study, multi-device fit was not being considered. On the basis of their definition, we define perceived task fit with multi-device use as the degree to which users perceive multi-device use as a good fit to current needs. Prior studies suggest that users who perceive such a fit more greatly will prefer and are more likely to form a belief that multi-device use is the ideal option that provides the performance improvement to them (Dearman et al. 2008; Oulasvirta et al. 2007). This preference and belief show an expression of favor toward multi-device use and thereby is associated with attitude toward multi-device use. Hence, this study posits the following:

\(^1\) In their study, perceived task fit with a device is called compatibility, which the authors define as “the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters” (1991, p. 195).
**H1**: Perceived task fit with multi-device use is positively related to attitudes toward multi-device use.

**Perceived Task Fit with Multi-Device Use and Expected Satisfaction with Multi-Device Use**

The expected satisfaction or anticipated satisfaction is defined as a mental state that people experience with the expectation of positive evaluation of a service or product (Doll et al. 1988; Shiv et al. 2000). On the basis of this definition, expected satisfaction occurs in pre-usage, as opposite to post-usage, and expectation of a positive evaluation is the key antecedent of expected satisfaction (Posselt et al. 2005; Shiv et al. 2000). Indeed, prior research on satisfaction suggests that when people believe that positive evaluations (e.g., perceived performance) are likely to occur (i.e., high expectation) when using an object, such as a product, service, or technology artifact, their expected satisfaction with using that object will increase (Au et al. 2002; Oliver 1980; Tse et al. 1988).

In the context of Study 1, I propose that expected satisfaction is formed by perceptions of the task’s fit with multi-device use. Specifically, according to TTF theory, when using one device that provides a good fit for dealing with a certain subtask, users will have high expectations with positively perceived performance of that subtask (as performance could be improved) (Goodhue 1998; Goodhue et al. 1995). When using multiple devices that provide an overall good fit with all subtasks, the accumulation of the best device selection to perform each subtask will lead to high perceived task fit with multi-device use, increasing their expectations of positive task performance (Oulasvirta et al. 2007). As a result, such expectations of positive evaluation of multi-device use will enhance the expected satisfaction with multi-device use, suggesting the positive
relationship between perceived task fit with multi-device use and expected satisfaction with multi-device use. Thus, this study posits the following hypothesis:

**H2:** Perceived task fit with multi-device use is positively related to expected satisfaction with multi-device use.

**Perceived Task Complexity and Perceived Task Fit with Multi-Device Use**

Perceived task complexity has been studied extensively in decision-making research, where it has been regarded as a factor that changes user behavior, decision outcomes, performance, and mental workload (Speier et al. 2003a; Speier et al. 1999; Speier et al. 2003b). Prior research has operationalized perceived task complexity as the extent to which individuals perceive that a task is difficult and for which cognitive processing is needed to reach a solution (Campbell 1988; Wood 1986).

I believe that high perceived task complexity, in which information processing needs are high (Campbell 1988; Wood 1986), can make using multiple devices more appropriate because users can deploy their devices and different device-use strategies, such as second-screen display (one screen shows the main task while the second screen displays a secondary task) in dealing with a complex task (Google 2012; Levin 2014). In other words, multi-device use is useful and necessary when a certain amount of interrelated information reaches a specific level that allows users to deal with this information by using more than one device (Dearman et al. 2008), creating a better perceived task fit with multi-device use. In contrast, in the low perceived task complexity context, the amount of information needing to be processed is low, making multi-device use unnecessary; that is, using a single device is then sufficient for completing tasks. This can be a reasonable option if the different devices have similar or overlapping functions.
Hence, perceived task fit with multi-device use varies depending on the level of task complexity (i.e., the amount of information and cognitive processing needed). The higher the perceived task complexity, the more opportunities and possibilities there are to assign different devices to specific subtasks, improving perceived task fit with multi-device use over single-device use.

**H3**: Perceived task complexity is positively related to perceived task fit with multi-device use.

**Perceived Complexity of Multi-device Use and Perceived Task Fit with Multi-Device Use**

Prior studies have found that users who contemplate switching among devices may consider the time and effort needed to switch devices (Dearman et al. 2008; Rashid et al. 2012; Walljas et al. 2010). After all, several changes not encountered with single device use may be involved, including screen size changes (i.e., large vs. small), application interface changes (i.e., desktop vs. mobile interfaces), input interface changes (i.e., keyboard vs. touch-screen inputs), and placing method changes (i.e., standing vs. hand-held) (Dearman et al. 2008; Seffah et al. 2004). Hence, multi-device use implies additional actions needed to allocate devices and coordinate between devices and complete the task (Biehl et al. 2006; Dearman et al. 2008; Oulasvirta et al. 2007). For example, using a smartphone to read and a tablet to reply to an e-mail message require additional operational acts (e.g., opening the app on the tablet and searching for the same e-mail) than using only the smartphone. Furthermore, multi-device use requires extra adjustments. This study defines *adjustments* in the context of multi-device use as the
extra effort required to adjust, both physically and mentally, from using one device to using another due to the different characteristics of the distinct devices (Levin 2014). These required actions and adjustments considered together make multi-device use complicated.

The tendency to avoid extra effort and time is inherent in human nature since, according to the concept of mental workload, people have limited cognitive capacity when processing information (Miller 1956; Young et al. 2001). Hence people will typically try to find a way to minimize effort and time or balance effort and outcome when completing a task (Payne et al. 1993). The avoidance of extra effort and time implies the simplification of information processing, which may diminish the quality of outcomes (e.g., decision making), as demonstrated in prior studies that focus on the relationship between effort and accuracy (Johnson et al. 1985; Kuo et al. 2004).

Therefore, owing to the tendency to avoid complications as suggested by the concept of mental workload (Miller 1956; Young et al. 2001), when users have a high perceived complexity of multi-device use, using a single device would be an ideal option. This is reasonable because reducing the number of device switches helps users minimize effort and time expended on switching devices (Tungare et al. 2009). As a result, perceived task fit with multi-device use decreases, suggesting the negative relationship between perceived complexity of multi-device use and perceived task fit with multi-device use. Therefore, when perceived complexity of multi-device use is high, perceived task fit with multi-device use will suffer.

**H4:** Perceived complexity of multi-device use is negatively related to perceived task fit with multi-device use.
Unfamiliarity with Multi-Device Use and Perceived Complexity of Multi-Device Use

Familiarity with a device use refers to the extent to which individuals understand how to use a specific device and the possible results of using it (Komiak et al. 2006). This understanding, often formed through previous interactions while learning about and accumulating experience with a given device, helps individuals mitigate uncertainty when completing a task and reduce extra cognitive effort from learning alternatives (Gefen 2000). Ultimately, users will trust more the device they are currently using and will be more willing to continue using it (Gefen 2000; Gefen et al. 2003; Komiak et al. 2006). Lack of familiarity produces the opposite effect: unfamiliarity with a device use introduces risks in performing a task, increases uncertainty about the possible result of using the device, and requires more cognitive effort in learning how to use the device. Subsequently, users may feel anxiety about using the device, with prior studies calling such computer anxiety (Heinssen Jr et al. 1987). This anxiety is typically conceptualized as a response to perceived threat (Beck et al.) or an emotional strain that may burden a user’s mental workload (Teunissen et al. 2007), prompting the user to report a lower perceived ease of use. As a result, unfamiliarity with a device may result in complicating use of that device (Hackbarth et al. 2003).

In the context of this study, without prior experience with and understanding of multi-device use, using multiple devices may result in more anxiety and concern (e.g., extra effort and time to learn multi-device use) when switching devices. For example, results of a longitudinal study using diaries and interviews to gather users’ experiences with a cross-platform service suggest that users who have high familiarity with multi-device use can understand the potential and limitation of distinct devices, whereas users who have less familiarity with multi-device use may be confused about how certain
devices can be used and can interact together (Walljas et al. 2010). As a result, multi-device use becomes perceptually complex. Thus, it is likely that unfamiliarity with multi-device use increases perceived complexity of multi-device use.

**H5:** Unfamiliarity with multi-device use is positively related to perceived complexity of multi-device use.

**Expected Satisfaction with Multi-Device Use and Attitude toward Multi-Device Use**

Forming satisfaction expectations requires a series of evaluations of an object such as an IT artifact (Doll et al. 1988; Shiv et al. 2000). These evaluations involve mental-image processing (i.e., the image-related processes that lead people to visualize the possible outcomes after using the object) (Shiv et al. 2000). For example, will the object do what it is supposed to do, and is this good or bad? When these evaluations result in positive outcomes, users may anticipate higher satisfaction with using the object (Shiv et al. 2000), which in turn forms positive attitudes toward that object (Rosenberg et al. 1960). Thus, prior studies have identified the positive relationship between satisfaction with using an object and attitude toward that object (Abdul-Muhmin 2010; Oliver 1980). For example, Oliver (1980), who proposed a cognitive model of the antecedents and consequences of satisfaction decisions, points out that expected satisfaction is the key antecedent to forming attitudes in that the higher the expected satisfaction, the more positive the attitude will be (Oliver 1980).

Therefore, although I have not found prior studies that examine this relationship under the context of multi-device use, I believe that when positive satisfaction with multi-device use is expected (i.e., individuals expect to feel pleased and contented when using multiple devices to deal with tasks), this expectation and its consequent positive evaluations make multi-device use favorable, and thereby users will form a positive
attitude toward multi-device use.

**H6:** Expected satisfaction with multi-device use is positively related to attitude toward multi-device use.

**Attitude toward Multi-Device Use and Multi-Device Use Intention**

Attitude toward a device use has been found to have a positive relationship with intention to use the device. This relationship has been identified as a key determinant of actual behavior in the TAM (Davis 1989; Davis 1993) and theory of planned behavior (TPB) (Ajzen 1991; Madden et al. 1992). Both TAM and TPB suggest that attitude towards a behavior triggers a user’s intention. This intention in turn influences the user’s subsequent behavior such that the greater the intention, the more likely the user’s behavior (Davis 1989). This attitude–intention–behavior relationship has been empirically tested in and applied to studies of the relationships between beliefs, attitudes, behavioral intentions, and behaviors in various fields such as online consumer behavior (Koufaris 2002), service switching (Bansal et al. 2005), and usage of information systems (Davis 1993; Venkatesh et al. 2003; Venkatesh et al. 2011). The results consistently support the positive relationship between attitude and intention to use. I extend this relationship to this study: when users have a positive attitude toward multi-device use, they are more likely to express an intention to use more than one device to carry out a set of interrelated tasks.

**H7:** Positive attitudes toward multi-device use will be positively associated with the intention to use multiple devices.

**Expected Satisfaction and Multi-Device Use Intention**

Prior studies on intention to use an object, such as a product or IT artifact,
indicate that satisfaction is one of factors that forms the intention to use the object. For example, Shiv and Huber (2000) developed a concept called the anticipated-satisfaction-oriented goal, which suggests that expected satisfaction elicits mental-imaging processing. The imagery-related processes lead people to visualize the possible outcomes after using the object, which in turn forms intentions to use that object, suggesting the positive relationship between satisfaction and intention (Shiv et al. 2000). This relationship also has been found in the field of information systems. For instance, the DeLone and McLean IS success model (1992) identified user satisfaction as a key factor that impacts users’ intentions to use a device to perform a task (DeLone et al. 1992). Similarly, Bhattacherjee (2001), based on expectation-confirmation theory, proposes the acceptance model of IS continuance, in which satisfaction determines users’ intentions to use a device.

In the context of Study 1, when multiple devices are available to use, users may create expectations about the possible outcomes that may occur from using the devices. If they realize that one device is insufficient to make them feel satisfied, partly because single-device use cannot achieve a positive outcome, their dissatisfaction with using only one device forms their intentions to search for other devices and to include them in task performance (Dearman et al. 2008; Walljas et al. 2010). For example, a study conducted interviews to understand why people use multiple devices (Dearman et al. 2008). The results show that one reason for multi-device use is because users believe they may feel satisfied by multi-device use because of a lower task completion time. Such satisfaction contributes to users forming intentions to switch to another device.

**H8:** Expected satisfaction with multi-device use is positively related to multi-
device use intention.

**Research Design**

**Subjects**

The subjects were undergraduate business students at a major Northeastern U.S. University and they participated in the experiment for class credit. The subjects were told that they would be taking part in a trip-planning task. Study 1 used students as subjects for two reasons. First, Study1 focuses on users who use their devices to carry out tasks related to daily personal use (i.e., trip-planning) rather than those related to work. Thus, in terms of task type, students are appropriate as subjects for this study. Second, a growing amount of students now own multiple devices (Burger 2013) and many schools also propose a bring-your-own-device (BYOD) initiative to encourage students to use personally owned devices (e.g., laptop or/and tablet) in class. Thus, it is important to understand and explore the motivations behind device use for this population.

**Apparatus**

Study 1 focuses on the context in which three devices, including a desktop computer, tablet, and smartphone, are available to users because these devices are commonly owned and used (Burger 2013; Google 2012), yet the factors motivating users to use a single or multiple devices are not well understood. I selected three devices instead of two or four because three devices is a moderate number of devices; two devices can result in too few combinations of device use, whereas four or more devices can result in too many combinations, making the experiment complicated and uncontrollable.

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2 According to the Bradford Networks’ Impact of BYOD on Education’ global survey, 85 percent of education institutions currently allow some form of Bring-Your-Own-Device (BYOD) on their school networks.
The specifications for each device are listed in Table 1.2. Note that this dissertation used Apple’s iPod touch as a smartphone because its functions are almost identical to that of the iPhone, except for the ability to function as a phone. Moreover, participants were not allowed to make calls to complete the task, making the iPod touch a more appropriate device for this study.

**Table 1.2. Device Specifications**

<table>
<thead>
<tr>
<th>Devices</th>
<th>Desktop Computer</th>
<th>Tablet</th>
<th>Smartphone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand</td>
<td>Dell</td>
<td>Amazon Kindle Fire</td>
<td>Apple iPod Touch</td>
</tr>
<tr>
<td>CPU</td>
<td>166MHz Pentium</td>
<td>1.2 GHz Dual Core</td>
<td>A5</td>
</tr>
<tr>
<td></td>
<td>CPU</td>
<td>ARM Cortex-A9</td>
<td></td>
</tr>
<tr>
<td>Operation System</td>
<td>Windows 7</td>
<td>Android 2.3</td>
<td>iOS 6</td>
</tr>
<tr>
<td>Screen Size</td>
<td>16&quot;</td>
<td>7&quot;</td>
<td>4&quot;</td>
</tr>
<tr>
<td>Resolution</td>
<td>1024 × 768 pixels</td>
<td>1024 × 600 pixels</td>
<td>1036 × 640 pixels</td>
</tr>
</tbody>
</table>

**Task Design**

The subjects were instructed to perform a trip-planning task that involves a series of searches and calculations. The task was developed to ask subjects to select one ideal day out of 10 possible days to take a leisure trip.

To design the task questions, focus groups and a pilot survey were conducted to determine the most preferred device to perform specific sub-tasks. On the basis of the results of the focus group and pilot survey, I designed a set of interrelated task questions that require the subjects to research and provide the information. These questions include the date, weather, total driving time, total miles, gas fee, tolls, attraction admission fee, opening hours, total cost of the trip, and total time (see Appendix A).

To make the trip-planning task more real, this study chose a real destination, which has the official website showing required information for the task. I selected the Yale University Art Gallery as the destination for four main reasons. First, it is not too far
from and not too close to the place where I conducted the experiment (Northeastern U.S.). In other words, it is not too long to drive there and back in one day, making the task more realistic, but subjects still needed to do some calculations to determine fuel costs and toll fees. Second, this is a place with which my subjects are likely not familiar, ruling out the possibility of memory bias. Third, this place has an official website showing opening hours and admission fee. These features fit with this study’s purpose in which subjects can use devices to search for that information. Finally, the opening hours vary depending on the date. On Mondays it is closed while on Thursdays it has the longest opening hours, which provides some additional complexity to the task of the study.

I conducted a pilot test with 100 subjects in order to test and evaluate the relevance of the task for my subject population. Observation and interviews of student subjects were used to understand whether subjects found the task engaging and were motivated to perform well. Minor instrumentation and research design modifications were made based on pilot study results and subject feedback. For example, many subjects asked whether the number they obtained by calculation needed to be rounded up. To achieve consistency in answers, I added a sentence to the task instructions directing that all numbers need to be rounded up to the second decimal.

Procedure

A total of 11 subjects were at each lab session. Upon arrival at the lab, each subject was randomly assigned a seat and provided with a smartphone, tablet, and desktop computer. Upon commencement of the experiment, a training session was held to orient the subjects on the use of each of the three devices. It is important that all the subjects in the training session were aware of the functions of each of the three devices to
complete tasks such as checking the weather, performing simple calculations, and searching destinations using Google Maps.

During the training session, the experimenter ensured that all users understood how to use each device and made sure information that they found by using all three devices was correct. Since all applications (e.g., calendar, weather, maps, and calculator) across all devices involved in the experiment were easy to learn, most subjects learned how to use these devices smoothly without difficulty. If users did not know how to use a specific device after the training\(^3\), they were excluded from the experiment (They still need to complete the task but the data was marked for deletion). After the training session, the experimenter presented and explained the trip-planning task and all task questions to the subjects. In the presentation, subjects could ask questions of clarification regarding the task but they could not use any of the three devices available to them to begin actually doing the task.

Once they had thoroughly understood the task, the subjects were asked to use the desktop computer to visit a website to complete a pre-task questionnaire that was designed to measure the variables related to the research model.

**Measurement**

For all constructs, I used validated scales from prior research, adapted for the specific context of this study. The scale for expected satisfaction with multi-device use was adapted from work by Bhattacherjee (2001) and that for perceived task fit with multiple devices was adapted from research by Moore and Benbasat (1991). The scale for

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\(^3\) I determine whether subjects know how to use devices based on observations and training results. If a subject cannot answer specific training questions using a certain device, the subject’s data will be marked for deletion.
perceived task complexity was based on research by Maynard and Hakel (1997) and that for perceived complexity of multi-device use was adapted from work by Thompson et al. (1991). The scale for attitude toward multi-device use was adapted from research by Madden et al. (1992). To measure the common method bias, Study 1 added perceived information quality that is theoretically unrelated variable, as a marker variable. The scale for this marker was adapted from Wixom and Todd (2005). A seven-point Likert scale was used for all items.

Additionally, intention to use multiple devices was a three-item scale adapted from Bansal et al. (2005). Finally, I measured the number of devices owned by each subject, the extent of use of each owned device, the subject’s age, and their gender (see Appendix B).

**Data Analysis**

A total of 229 subjects took part in the survey. I removed 12 data points that had either significantly incomplete responses or were extreme outliers, resulting in a sample size of 217. The sample demographics were as follows: 42% were male and 53% female, 71% were 22 years old or younger, and 75% owned three devices while only 4% said they own one device (laptop/desktop computer). The full breakdown of the sample can be seen in Table 1.3.
Table 1.3. Subject Demographics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>100 (46%)</td>
</tr>
<tr>
<td>Female</td>
<td>117 (54%)</td>
</tr>
<tr>
<td><strong>Number of device own</strong></td>
<td></td>
</tr>
<tr>
<td>Laptop/Desktop</td>
<td>7 (3%)</td>
</tr>
<tr>
<td>Laptop/Desktop and Smartphone</td>
<td>44 (20%)</td>
</tr>
<tr>
<td>Laptop/Desktop and Tablet</td>
<td>2 (1%)</td>
</tr>
<tr>
<td>Laptop/Desktop, Smartphone and Tablet</td>
<td>164 (76%)</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>13 (6%)</td>
</tr>
<tr>
<td>19-20</td>
<td>78 (36%)</td>
</tr>
<tr>
<td>21-22</td>
<td>62 (29%)</td>
</tr>
<tr>
<td>23-24</td>
<td>20 (9%)</td>
</tr>
<tr>
<td>25-26</td>
<td>12 (5%)</td>
</tr>
<tr>
<td>27-28</td>
<td>17 (8%)</td>
</tr>
<tr>
<td>29 above</td>
<td>15 (7%)</td>
</tr>
</tbody>
</table>

**Measurement Model**

I first conducted a principal components analysis. A direct oblimin rotation was used as I expected the factors to be correlated. Individual item reliability was assessed by examining the loadings of the measurement items on their corresponding construct, where all the item loadings should be significant and exceed 0.60 (Comrey 1973). Although all measurement items were significant at $p < 0.01$, the results eliminated one item from unfamiliarity with multi-device use because of cross loading onto another study variable. After trimming items, all items’ loadings are higher than the recommended value of 0.60 (see Table 1.4) and all of the measurement items loaded heavily on their respective factors, confirming convergent validity.
values are all above 0.70 for all constructs, confirming the constructs’ reliability

Table 1.4. Factor Loadings and Cross Loading for the Measurement Model

<table>
<thead>
<tr>
<th>Component</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Att1</td>
<td>0.841</td>
<td>-0.032</td>
<td>-0.073</td>
<td>-0.057</td>
<td>0.353</td>
<td>-0.312</td>
<td>-0.422</td>
<td>0.031</td>
</tr>
<tr>
<td>Att2</td>
<td>0.807</td>
<td>-0.007</td>
<td>-0.008</td>
<td>-0.05</td>
<td>0.411</td>
<td>-0.313</td>
<td>-0.441</td>
<td>-0.012</td>
</tr>
<tr>
<td>Att3</td>
<td>0.829</td>
<td>-0.059</td>
<td>0.02</td>
<td>-0.065</td>
<td>0.361</td>
<td>-0.387</td>
<td>-0.375</td>
<td>0.007</td>
</tr>
<tr>
<td>Att4</td>
<td>0.808</td>
<td>-0.024</td>
<td>-0.123</td>
<td>0.087</td>
<td>0.446</td>
<td>-0.376</td>
<td>-0.471</td>
<td>0.076</td>
</tr>
<tr>
<td>Att5</td>
<td>0.695</td>
<td>0.028</td>
<td>-0.032</td>
<td>-0.067</td>
<td>0.188</td>
<td>-0.29</td>
<td>-0.458</td>
<td>0.093</td>
</tr>
<tr>
<td>PTaSc1</td>
<td>-0.092</td>
<td>0.794</td>
<td>0.035</td>
<td>0.12</td>
<td>-0.066</td>
<td>0.357</td>
<td>0.065</td>
<td>-0.368</td>
</tr>
<tr>
<td>PTaSc2</td>
<td>0.01</td>
<td>0.83</td>
<td>-0.074</td>
<td>0.144</td>
<td>-0.014</td>
<td>0.161</td>
<td>0.153</td>
<td>-0.306</td>
</tr>
<tr>
<td>PTaSc3</td>
<td>0.044</td>
<td>0.829</td>
<td>-0.035</td>
<td>0.187</td>
<td>-0.005</td>
<td>0.092</td>
<td>0.073</td>
<td>-0.272</td>
</tr>
<tr>
<td>PTaSc4</td>
<td>-0.003</td>
<td>0.835</td>
<td>-0.032</td>
<td>0.05</td>
<td>-0.103</td>
<td>0.301</td>
<td>0.024</td>
<td>-0.341</td>
</tr>
<tr>
<td>ESa1</td>
<td>0.046</td>
<td>0.013</td>
<td>0.941</td>
<td>0.064</td>
<td>0.018</td>
<td>-0.051</td>
<td>-0.135</td>
<td>0.016</td>
</tr>
<tr>
<td>ESa2</td>
<td>0.043</td>
<td>-0.01</td>
<td>0.953</td>
<td>-0.005</td>
<td>0.057</td>
<td>-0.031</td>
<td>-0.125</td>
<td>0.033</td>
</tr>
<tr>
<td>ESa3</td>
<td>0.004</td>
<td>0.092</td>
<td>0.913</td>
<td>-0.002</td>
<td>0.046</td>
<td>-0.026</td>
<td>-0.175</td>
<td>0.028</td>
</tr>
<tr>
<td>ESa4</td>
<td>0.066</td>
<td>0.037</td>
<td>0.937</td>
<td>0.047</td>
<td>-0.011</td>
<td>-0.032</td>
<td>-0.089</td>
<td>-0.016</td>
</tr>
<tr>
<td>PIQ1</td>
<td>-0.028</td>
<td>0.121</td>
<td>-0.067</td>
<td>0.935</td>
<td>-0.052</td>
<td>0.047</td>
<td>-0.004</td>
<td>0.018</td>
</tr>
<tr>
<td>PIQ2</td>
<td>-0.041</td>
<td>0.109</td>
<td>0.001</td>
<td>0.899</td>
<td>-0.103</td>
<td>0.018</td>
<td>0.004</td>
<td>0.03</td>
</tr>
<tr>
<td>PIQ3</td>
<td>-0.033</td>
<td>0.151</td>
<td>-0.013</td>
<td>0.935</td>
<td>-0.118</td>
<td>0.072</td>
<td>-0.029</td>
<td>-0.001</td>
</tr>
<tr>
<td>Intention1</td>
<td>0.477</td>
<td>-0.071</td>
<td>-0.072</td>
<td>-0.116</td>
<td>0.911</td>
<td>-0.294</td>
<td>-0.472</td>
<td>0.078</td>
</tr>
<tr>
<td>Intention2</td>
<td>0.351</td>
<td>-0.059</td>
<td>-0.036</td>
<td>-0.074</td>
<td>0.899</td>
<td>-0.335</td>
<td>-0.453</td>
<td>0.137</td>
</tr>
<tr>
<td>Intention3</td>
<td>0.368</td>
<td>-0.037</td>
<td>0.009</td>
<td>-0.121</td>
<td>0.873</td>
<td>-0.231</td>
<td>-0.318</td>
<td>0.122</td>
</tr>
<tr>
<td>ComplexD1</td>
<td>-0.4</td>
<td>0.095</td>
<td>0.027</td>
<td>0.063</td>
<td>-0.229</td>
<td>0.87</td>
<td>0.21</td>
<td>-0.264</td>
</tr>
<tr>
<td>ComplexD2</td>
<td>-0.14</td>
<td>0.418</td>
<td>0.091</td>
<td>0.151</td>
<td>-0.162</td>
<td>0.615</td>
<td>0.264</td>
<td>-0.54</td>
</tr>
<tr>
<td>ComplexD3</td>
<td>-0.315</td>
<td>0.341</td>
<td>0.046</td>
<td>0.044</td>
<td>-0.312</td>
<td>0.791</td>
<td>0.391</td>
<td>-0.306</td>
</tr>
<tr>
<td>ComplexD4</td>
<td>-0.479</td>
<td>0.205</td>
<td>0.014</td>
<td>0.021</td>
<td>-0.372</td>
<td>0.836</td>
<td>0.436</td>
<td>-0.216</td>
</tr>
<tr>
<td>Fit 1</td>
<td>0.439</td>
<td>-0.1</td>
<td>-0.014</td>
<td>-0.035</td>
<td>0.385</td>
<td>-0.292</td>
<td>-0.808</td>
<td>0.125</td>
</tr>
<tr>
<td>Fit 2</td>
<td>0.451</td>
<td>-0.099</td>
<td>-0.159</td>
<td>0.023</td>
<td>0.309</td>
<td>-0.264</td>
<td>-0.831</td>
<td>0.15</td>
</tr>
<tr>
<td>Fit 3</td>
<td>0.563</td>
<td>-0.03</td>
<td>-0.187</td>
<td>-0.003</td>
<td>0.479</td>
<td>-0.343</td>
<td>-0.893</td>
<td>0.111</td>
</tr>
<tr>
<td>Fit 4</td>
<td>0.478</td>
<td>-0.062</td>
<td>-0.219</td>
<td>0.052</td>
<td>0.464</td>
<td>-0.403</td>
<td>-0.864</td>
<td>0.17</td>
</tr>
<tr>
<td>Unfamiliar2</td>
<td>0.017</td>
<td>0.315</td>
<td>-0.032</td>
<td>-0.057</td>
<td>-0.121</td>
<td>0.223</td>
<td>0.103</td>
<td>0.885</td>
</tr>
<tr>
<td>Unfamiliar3</td>
<td>-0.004</td>
<td>0.312</td>
<td>0.068</td>
<td>-0.03</td>
<td>-0.045</td>
<td>0.288</td>
<td>0.104</td>
<td>0.868</td>
</tr>
</tbody>
</table>

Att: attitude toward multi-device use; PTaSc: perceived task complexity; ESa: expected satisfaction with multi-device use; PIQ: perceived information quality; Intention: intention to use multiple devices; ComplexD: complexity of multi-device use; Fit: perceived task fit with multi-device use; Unfamiliar: unfamiliarity with multi-device use.

Table 1.5 shows each construct’s mean, standard deviation and item reliability (Cronbach’s Alpha). Except for unfamiliarity with multi-device use, Cronbach’s alpha values are all above 0.70 for all constructs, confirming the constructs’ reliability (Fornell
Internal consistency was assessed in a PLS model using composite reliability (CR). CR values for all constructs are above 0.9, suggesting internal consistency (Fornell et al. 1981). In addition, although Cronbach’s alpha and CR values for unfamiliarity with multi-device use have slightly lower than recommended values, I retained them in Study 1 because unfamiliarity with multi-device use is based on previously designed scales and is theoretically sound.

AVE values for all scales exceed 0.5, demonstrating that the latent variable has a high degree of reliability and that the variance captured by the construct was greater than the variance due to measurement error (Fornell et al. 1981).

| Table 1.5. Means, Standard Deviation, AVE and Reliability |
|-------------|-------|-------|----------------|----------------|
|             | Mean  | Std. Dev. | AVE  | Composite Reliability | Cronbach’s Alpha |
| Unfamiliar  | 4.536 | 1.467    | 0.5372 | 0.773               | 0.6578           |
| ComplexityD | 3.431 | 1.239    | 0.6318 | 0.8713              | 0.8054           |
| PTaskC      | 3.006 | 1.202    | 0.6561 | 0.8831              | 0.844            |
| Fit         | 4.917 | 1.285    | 0.7432 | 0.9202              | 0.8839           |
| ESat        | 2.981 | 1.482    | 0.8654 | 0.9625              | 0.954            |
| Att         | 5.137 | 1.098    | 0.6421 | 0.8991              | 0.8597           |
| Intention   | 5.122 | 1.569    | 0.8133 | 0.9288              | 0.8849           |
| PIQ         | 4.871 | 1.026    | 0.8562 | 0.947               | 0.9174           |

Unfamiliar: unfamiliarity with multi-device use; ComplexityD: complexity of multi-device use; Fit: perceived task fit with multi-device use; PTaskC: perceived task complexity; ESat: expected satisfaction; Att: attitude toward multi-device use; Intention: intention to use multiple devices; PIQ: perceived information quality.

Furthermore, I assessed discriminant validity by checking whether the square roots of the AVE values are higher than the off-diagonal elements in the corresponding rows and columns. The results of discriminant validity indicate that all constructs in the proposed model are adequate (see Table 1.6).

**Common Method Bias**

An assessment for common method bias was conducted given that all of the
variables included in the structural regression model were measured through self-reported survey items. To detect common method bias, I used three methods: First, Harman’s single factor test was conducted by running an exploratory factor analysis with all variables included (Podsakoff et al. 2003). A total of 8 factors with eigenvalues greater than 1 were extracted. The results accounted for 74.706% of the total variation, and the first factor accounted for about 25.577% of the total variation; the other factors explained between 2.5% and 11.6% of the variance. Hence, the factor analysis produced neither a single factor nor one general factor that accounted for the majority of the total variance, suggesting that the data did not suffer from common method variance (Podsakoff et al. 2003).

Second, I followed the procedure suggested by Bagozzi (1991) who suggested that if any construct’s correlation is higher than 0.90, it is likely that two constructs are highly correlated and common methods bias would be an issue (Bagozzi et al. 1991). Table 1.6 shows that none of correlation coefficients is higher than 0.612, suggesting that there was minimal evidence of common method bias.

Finally, the marker variable method, recommended by Lindell and Whitney (2001), was conducted to test the effects of common method variance on the study results. To run this method, I needed a theoretically unrelated variable to serve as a marker variable and as a proxy for common method variance (Lindell et al. 2001). This study used perceived information quality as the marker variable. This variable evaluates the degree to which users think that information provided in the task is of high quality (Wixom et al. 2005). To test common method variance using the marker variable method, this study followed Lindell and Whitney’s (2001) suggestion by selecting the lowest
absolute correlation between perceive information quality and other variables \((r = 0.024;\) see Table 1.6). Using equations (4) and (5) of Lindell and Whitney (2001, p. 116), I adjusted all correlations among latent variables by 0.024 and tested the statistical significance of the adjusted correlations. Table 1.6 displays the correlations adjusted for common method variance above the diagonal. The result indicates that none of the correlations among the latent variables is significant or has huge changes after the adjustment for common method bias, suggesting that common method bias is not a major concern in this study (Lindell et al. 2001).

### Table 1.6. Correlations of Constructs

<table>
<thead>
<tr>
<th></th>
<th>Unfamiliar</th>
<th>ComplexD</th>
<th>PTaskC</th>
<th>Fit</th>
<th>ESat</th>
<th>Att</th>
<th>Intention</th>
<th>PIQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unfamiliar</td>
<td><strong>0.733</strong></td>
<td>0.341</td>
<td>0.360</td>
<td>-0.155</td>
<td>-0.038</td>
<td>-0.042</td>
<td>-0.135</td>
<td>-0.084</td>
</tr>
<tr>
<td>ComplexD</td>
<td>0.357**</td>
<td><strong>0.794</strong></td>
<td>0.324</td>
<td>-0.500</td>
<td>-0.076</td>
<td>-0.510</td>
<td>-0.420</td>
<td>0.047</td>
</tr>
<tr>
<td>PTaskC</td>
<td>0.375**</td>
<td>0.340**</td>
<td><strong>0.81</strong></td>
<td>-0.116</td>
<td>0.011</td>
<td>-0.053</td>
<td>-0.093</td>
<td>0.124</td>
</tr>
<tr>
<td>Fit</td>
<td>-0.127</td>
<td>-0.464**</td>
<td>-0.089</td>
<td><strong>0.862</strong></td>
<td>0.159</td>
<td>0.602</td>
<td>0.523</td>
<td>0.000</td>
</tr>
<tr>
<td>ESat</td>
<td>-0.013</td>
<td>-0.05</td>
<td>0.035</td>
<td>0.179**</td>
<td><strong>0.93</strong></td>
<td>0.034</td>
<td>0.016</td>
<td>0.000</td>
</tr>
<tr>
<td>Att</td>
<td>-0.017</td>
<td>-0.474**</td>
<td>-0.028</td>
<td>0.612**</td>
<td>0.057</td>
<td><strong>0.801</strong></td>
<td>0.480</td>
<td>-0.058</td>
</tr>
<tr>
<td>Intention</td>
<td>-0.108</td>
<td>-0.386**</td>
<td>-0.067</td>
<td>0.534**</td>
<td>0.04</td>
<td>0.492**</td>
<td><strong>0.901</strong></td>
<td>-0.147</td>
</tr>
<tr>
<td>PIQ</td>
<td>-0.058</td>
<td>0.07</td>
<td>0.145*</td>
<td>0.024</td>
<td>0.024</td>
<td>-0.033</td>
<td>-0.119</td>
<td><strong>0.925</strong></td>
</tr>
</tbody>
</table>

Note: Diagonal values in the table are the square root of the average variance extracted. For adequate discriminant validity, diagonal elements should be greater than corresponding off-diagonal values. The correlations adjusted for common method variance are shown above the diagonal.

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

**Structural Model**

With an adequate measurement model, the research model was tested by the bootstrapping technique in SmartPLS. The results are shown in Figure 1.4. I used PLS because it is a structural equation modeling technique that simultaneously assesses the reliability and validity of the measures of constructs and estimates the relationships among them (Lohmöller 1989).
All hypotheses were supported, except for hypothesis 3. As hypothesized, perceived task fit with multi-device use was positively associated with attitudes toward multi-device use and expected satisfaction with multi-device use (H1 and H2), with values of 0.495 ($p < 0.01$) and 0.675 ($p < 0.01$), respectively. Surprisingly, perceived task complexity was not significantly related to perceived task fit with multi-device use (H3). This result indicates that users’ perceived task fit with multiple device use may be independent of the different levels of task complexity. Moreover, unfamiliarity with multi-device use was found to positively influence perceived complexity of multi-device use (H4), with a value of 0.367 ($p < 0.01$). Such complexity was negatively associated with perceived task fit with multi-device use (H5), with a value of $-0.501$ ($p < 0.01$).

Furthermore, expected satisfaction with multi-device use was positively related to attitude toward multi-device use (H6), with a value of 0.174 ($p < 0.05$). Finally, as expected, intention to use multiple devices was positively influenced by attitudes toward multi-device use (H7) and by expected satisfaction with multi-device use (H8), with values of 0.339 ($p < 0.01$) and 0.325 ($p < 0.01$), respectively.
Discussion

Despite the ubiquity of devices in our lives and the increasing popularity of multi-device use, research remains scarce regarding why users use more than one device to complete a set of interrelated subtasks. Combining both TTF theory and the concept of mental workload, I developed a research model that attempts to understand the motivations behind multi-device use. I provided three distinct devices (an iPod Touch, Kindle Fire, and desktop computer) to my subjects who were given a set of ten interrelated trip-planning subtasks. A questionnaire that included all constructs of the research model was provided to subjects directly after they were provided with training on how to use all three devices, but before they were able to use them to complete the
tasks. The results of hypothesis testing are summarized in Table 1.7.

<table>
<thead>
<tr>
<th>Table 1.7. Summary of Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypotheses</td>
</tr>
<tr>
<td>H1: Perceived task fit with multi-device use is positively related to attitudes toward multi-device use.</td>
</tr>
<tr>
<td>H2: Perceived task fit with multi-device use is positively related to expected satisfaction with multi-device use.</td>
</tr>
<tr>
<td>H3: Perceived task complexity is positively related to perceived task fit with multi-device use.</td>
</tr>
<tr>
<td>H4: Perceived complexity of multi-device use is negatively related to perceived task fit with multi-device use.</td>
</tr>
<tr>
<td>H5: Unfamiliarity with multi-device use is positively related to perceived complexity of multi-device use.</td>
</tr>
<tr>
<td>H6: Expected satisfaction with multi-device use is positively related to attitude toward multi-device use.</td>
</tr>
<tr>
<td>H7: Positive attitudes toward multi-device use will be positively associated with the intention to use multiple devices.</td>
</tr>
<tr>
<td>H8: Expected satisfaction with multi-device use is positively related to intention to multi-device use.</td>
</tr>
</tbody>
</table>

Study 1 provides empirical evidence that perceived task fit with multi-device use is a critical factor that forms users’ attitudes toward and expected satisfaction with multi-device use. Thus, TTF theory was supported in the context of Study 1. Furthermore, consistent with prior literature that suggests the attitude-intention relationship (Davis 1989), the results of Study 1 indicate that users’ attitudes toward multi-device use trigger their intentions to use multiple devices. In addition, I found that unfamiliarity with multi-device use increases perceived complexity of multi-device use. Such complexity hinders users from perceiving good task fit with multi-device use.

The non-significant result for the impact of perceived task complexity on perceived task fit with multi-device use is surprising. This result implies that perceived task fit with multi-device use varies regardless of the level of task complexity. One possible explanation is that the task was explained to the subjects before they worked on
it, and therefore task complexity was low for all subjects because they already understood the task. To avoid this possibility, rather than presenting and explaining the trip-planning task and all task questions to subjects, further research can provide written task instructions to a set of subjects to see if they can understand the task by themselves. In this case, their perceptions of task complexity could vary more, and there will be a chance of finding a significant relationship. Another possible explanation is that as long as a task can be broken into different subtasks (i.e., task decomposability), the perceived task fit with multi-device use is likely to be independent of the complexity of the task. For example, a simple task, such as replying to an e-mail, may involve only two interrelated subtasks, including reading the e-mail and replying. However, some people may still use multiple devices because they think that a tablet is easier for reading and a computer is faster for typing. Thus, task complexity might not play a significant role here. Given that Study1 did not find such support, which task factors impact perceived task fit with multi-device use remains an open question.

**Contributions to Theory**

The results of Study 1 make essential theoretical contributions to IT usage research. First, although researchers (e.g., Carroll 2008; Yoo 2010) have called for work on multi-device use, few studies have responded to this call, which has severely limited our understanding of multi-device use. Therefore, this study contributes to the IS literature by developing a nomological network of constructs that are related to motivations behind multi-device use. Specifically, Study 1’s research model examines perceived task fit with multi-device use by focusing not only on its antecedents, including a task factor (i.e., perceived task complexity) and a device factor (i.e., perceived complexity of multi-device use), but also on its influences on outcomes – user factors.
(i.e., users’ attitudes toward and expected satisfaction with multi-device use) – that motivate users’ multi-device use. This model, I believe, is an initial endeavor in understanding motivations behind multi-device use.

Second, Study 1 contributes to the literature centered on the concept of TTF theory. Prior research based on TTF theory has broadly developed two major streams. The first stream focuses on TTF theory at the individual level. Research in this stream uses TTF theoretical constructs to assess the value of an IS (Goodhue 1995), to estimate system usage (Dishaw et al. 1999; Pagani 2006), and to evaluate individual performance (Goodhue et al. 2000; Goodhue et al. 1995). Another stream focuses on TTF theory at the group level. Prior studies in this stream have examined how the dimensions of group support systems (GSSs) used in the organization fit with attributes of tasks and how this fit further supports group member interactions (Maruping et al. 2004) and improves overall group performance (Zigurs et al. 1998). Study 1 builds on the first stream but at a higher and broader level: the multi-device use level. Although a wealth of research is based on TTF theory, to the best of my knowledge, this study is the first to use TTF theory to examine multi-device use. This focus is very important because a single device use may not be always the case nowadays and therefore, the conceptualization of technology in this theory needs to be expanded to consider an ecosystem of devices. Therefore, researchers should not take for granted that users only use one device or information system to complete a task (Carroll 2008). The results demonstrate the importance of perceived task fit with multi-device use in a context where multiple distinct devices are available to use, suggesting that TTF theory still has significant explanatory power and plays an important role in explaining intentions to use multiple
Third, by blending theoretical paradigms from TTF theory and the concept of mental workload, I showed that mental workload is related to TTF theory. Specifically, the results suggest that mental workload measured by perceived complexity of multi-device use is an important antecedent of perceived task fit with multi-device use. It is worth noting that the role of mental workload of IT device usage has been relatively ignored in technology adoption research. Accordingly, little was known about the role of perceived mental workload in device use. Thus, one of major theoretical contributions of Study 1 is to introduce the notion of mental workload into the explanation of technology use. The results show that perceived complexity of multi-device use can have a negative effect on users’ perceived task fit with multi-device use.

Another important contribution of Study 1 is its examination of expected satisfaction with multi-device use. Most research on the relationship between end user computing satisfaction and intention to use has focused on satisfaction after using a system or device, measuring if after use their experience exceeds their expectations (Wixom et al. 2005). However, research on satisfaction before using the system or device (i.e., expected satisfaction) is relatively less common. Hence, the results complement end user computing satisfaction research. The inclusion of expected satisfaction is especially important in a context such as this study (multi-device use), where users can flexibly allocate different combinations of device use. Unlike one device for dealing with one task, in which emphasis is on post–device use, the availability of multiple devices allows for a user to evaluate devices and allocate them into an end configuration, making device use more responsive to environmental change (Walljas et al. 2010). Thus, it is interesting
and important to know the process and the user’s anticipation of satisfaction arising from his or her device allocation before actually using multiple devices.

**Implications for Practice**

The findings of Study 1 make unique contributions to IT practice, especially for IT device providers and application designers whose business models are based on multiple hardware and/or software development (e.g., Apple’s iPhone, iPad, and iMac or Google’s Nexus 5, 9 and Google Chromebook), because the results provide preliminary evidence that can inform IT managers and application designers why users intend to use multiple devices, aiding them in designing and developing appropriate multi-product strategies. Specifically, the findings of Study 1 confirm that perceived task fit with multi-device use is a key factor that forms attitudes toward multi-device use and in turn positively influences users’ intention to use multiple devices. To achieve high perceived task fit with multi-device use, the results suggest that multi-device use needs to be simplified. One practical way for IT device providers to simplify multi-device use is to develop a simple and seamless synchronization of data and content between devices and sharing of those devices (Walljas et al. 2010). For example, to share information between devices with the same application, users can simply tap devices together. Also, once users tap one device against another, the application in which users want to share the information will automatically open and be ready to use. This would reduce operational processes (e.g., no need to copy and paste, send information via e-mail, or synchronize information through cloud computing) and minimize extra effort (without needing to rekey or open applications manually) during multi-device use. Additionally, consistency of application interfaces across different devices can reduce the users’ mental
representations of the application interface or layout caused by switching and changing
the way they operate and adjust to applications (Levin 2014; Walljas et al. 2010).
Therefore, IT managers and application designers need to provide similar interfaces or
button icons (e.g., using a floppy disk to represent “save file”) so that adjustment costs
can be reduced, simplifying multi-device use (Levin 2014).

Moreover, Study1’s results show that unfamiliarity with multi-device use is the
antecedent of perceived complexity with multi-device use. To lessen this unfamiliarity,
IT device providers should find a way to help their customers learn how to use multiple
devices together. A practical way for IT device providers and application designers is to
hold an event or workshop to inform their customers of the benefits of using multiple
devices, to educate customers on how to use devices together and/or to help them identify
situations where multiple device use is desirable.

Finally, Study 1’s results suggest that positive attitudes toward multi-device use
play a key role in intention to use multiple devices. Thus, to enhance user attitudes, IT
device providers and application designers need to be aware of each device’s advantages
and disadvantages and to maximize the fit between devices and tasks by strengthening
devices’ unique advantages so that users will want to take advantage of the best fit device
to deal with a certain task. Treating all IT devices as interdependent rather than as
independent and thinking how to combine each device’s advantages while users work on
a task is critical.

Limitations of the Study

Despite the unique contributions to both theory and practice, I acknowledge some
limitations as precautions for interpreting the results and deriving implications. First, the
generalizability of the findings to organizational use of multiple devices may be limited because of the use of undergraduate student subjects. Though these subjects may be representative of the college-educated segment of end users, it would be problematic to extend the results to other end-user segments. However, despite the lack of generalizability, I believe this population is extremely important to understand because an increased number of students own multiple devices (Burger 2013). Furthermore, this study focuses on individual use of devices rather than on business use. After all, the ubiquity of IT devices has blurred the boundary between work and life; as a result, these devices have deeply penetrated our lives beyond work (Yoo 2010). Thus, organizational users are not the target for the purposes of this study. Additional studies with organizational users and environments are needed to strengthen the generalizability of the findings.

Second, given that all the variables included in the model were measured through self-reported survey items, common method variance must be considered (Podsakoff et al. 2003). While this limitation may threaten the validity of the finding, steps were taken in the design of measurement to reduce the likelihood of method bias. For example, randomization of measurement was employed. All the respondents are anonymous. No right or wrong answers and answering questions as honestly as possible were mentioned in the survey. These procedures, suggested by Podsakoff et al. (2003), can reduce evaluation apprehension, social desirability, and method bias. Moreover, the common method variance tests reveal no significant bias. Therefore I believe that the observed relationships in the model are unlikely to be due to common method variance. Further research should adopt study designs that avoid this potential problem.
Third, with a variety of factors that form perceived task fit with multi-device use, this study considers only perceived task complexity and perceived complexity with multi-device use. Although Study 1 is based on appropriate theories (i.e., TTF and mental workload) to identify potential factors, I do recommend that future studies take other factors into account. Examples of factors are personal traits such as personal innovativeness in IT and hedonic factors such as perceived enjoyment. While this limitation may influence the explanation power of multi-device use, the factors used in this study are adequate for an initial endeavor in understanding multi-device use. Hopefully, these factors can pave the way for additional studies to further investigations into multi-device use.

Finally, in Study 1, I controlled the number of devices at three. I believe the availability of three devices is adequate and realistic in the context of the study, and I acknowledge that this number of devices is context dependent. I conjecture that three devices are very common nowadays when people are in the same place such as at home or in an office; however, in some situations, such as walking on the street, they might have more or fewer devices available. Additionally, in practice, users sometimes do not have multiple devices available to them, or users are sometimes forced to switch devices for security reasons. Namely, the effects of device flexibility and those of being forced to switch devices—two common situations in device use—are still unexplored. Therefore, even though the results support most of the hypotheses concerning multi-device use, I do caution readers that the availability of three devices might not always be the case. Further studies can thereby test different numbers of devices and different situations (e.g., force vs. free to use) to see how the number of devices influences users’ intention to multi-
device use.

Conclusion

As a growing number of people now own more than one device, the need to understand the use of multiple devices has become critical. To the best of my knowledge, this is the first study to theoretically articulate and empirically test the underlying drivers of multi-device use. Thus, it serves as a starting point that inspires and opens up a rich and new research avenue for the IS community to move from traditionally single-device use to a model focusing on understanding complex patterns of multi-device use. It is hoped that this study will stimulate others to extend this stream of research further.
Study 2: Multiple Device Use and Task Performance

Introduction

The increasing popularity of owning more than one device (e.g., a smartphone, a tablet, a laptop, and/or a desktop) makes the availability of multiple and heterogeneous devices a common occurrence in people’s lives today. This creates a device ecosystem in which distinct devices not only coexist independently (because each device can run and work alone without the help of other devices) but also sometimes compete with each other (because each device has similar or overlapping functions) and furthermore, are sometimes coordinated interdependently to support a variety of tasks that reach across diverse contextual settings (Levin 2014; Segerståhl 2009; Shih et al. 2004). Therefore, as the availability of multiple devices becomes prevalent in everyday life, issues associated with effectively and efficiently using these devices to deal with a task in a way that improves performance are increasingly critical, particularly for companies that allow their employees to bring their own devices and use multiple devices while working on their tasks.

To study the relationship between multiple device use and task performance, I need to clearly define three elements that are highly related to this research topic: device, application and website, and task. First, in Study 2, a device refers to any computing equipment with electronic components capable to run software programs and is designed to perform multiple functions for an individual in a particular activity or for a specific purpose. Second, an application and website refer to any application and website that consists of a collection of computer programs designed for performance operations for a
specific purpose. Third, a task is an information processing— and technology-mediated action performed by a user that has a specific goal, can be fragmented into related subtasks (task decomposability), and can be performed in specific locations and periods. For example, planning a trip to an unfamiliar place (task) requires various types of information, such as the weather (subtask), time required (subtask), and the number of miles (subtask) to drive to reach the destination. The task decomposability is important in Study 2 because it opens the possibility of using multiple devices.

Task performance is improved when users maximize the overall fit between devices and subtasks while minimizing costs that are incurred when switching devices. Specifically, not all devices are created equal. The technical characteristics of each device offer varying capacities and components in terms of data, functions, input and output methods, and interaction styles (Karlson et al. 2010; Levin 2014). On one hand, the variance of technical characteristics gives users an opportunity to identify a good fit between each device and a certain subtask. On the basis of task-technology fit (TTF) theory, the greater this alignment, the better the task performance (Goodhue et al. 1995).

On the other hand, the variance of technical characteristics adds extra costs on users when switching devices. This dissertation calls these costs device-switching costs, which are defined as any costs that individuals incur when switching devices. Specifically, users accumulate effort and time when switching applications across distinct devices because they need to switch between, operate, and adjust the layouts of different applications across distinct devices (Tungare et al. 2009).

Also, this switching causes additional physical movements, such as shifting the gaze, moving the body, and adjusting the head (e.g., up and down), to check information
across different screens (Cauchard et al. 2011; Shupp et al. 2009; Tungare et al. 2009). If users experience much additional or even unnecessary effort from cross-device switching, on the basis of mental workload, task performance is impaired, as people may involve too many physical movements, adding extra time and causing more errors (Lansdown et al. 2004; Tungare et al. 2009). Therefore, on the basis of TTF and mental workload, this study posits that, when multiple devices are available, overall fit between devices and subtasks as well as device-switching costs need to be both taken into account to determine task performance.

To test this, Study 2 aims to gain insight into the topic of device use by answering the following research question: given that multiple devices are available to users, why, when, and how can multiple device use lead to positive performance outcomes? On the basis of the recommendations of prior research, two relevant dimensions of task performance were measured, completion time and accuracy, noting that for the former, lower is better, and for the latter, higher is better. (Speier et al. 2003a). I develop a research model, considering both the overall fit between devices and subtasks and device-switching costs, which are measured as the number of device switches, application switches and physical movements, to examine the relationship between multiple device use and task performance. I recorded video of how users use the devices in the context of a specific multi-part task, and then coded these recorded videos into objective data to validate the model. The task results produced by each subject were also evaluated.

**Theoretical Background**

Theories are the same as in Study 1.
Literature Review and Hypothesis Development

Characteristics of Devices

Study 2 focuses on devices including laptop computers, desktop computers, tablets, and smartphones. From the human–computer interaction perspective, control methods, input types, placing methods, screen size, and application interface are the primary differences among devices (Levin 2014) (see Table 2.1).

<table>
<thead>
<tr>
<th>Table 2.1. Differences among Devices</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Devices</strong></td>
</tr>
<tr>
<td><strong>Primary control methods</strong></td>
</tr>
<tr>
<td><strong>Primary input types</strong></td>
</tr>
<tr>
<td><strong>Primary placing methods</strong></td>
</tr>
<tr>
<td><strong>Screen size</strong></td>
</tr>
<tr>
<td><strong>Application interface</strong></td>
</tr>
</tbody>
</table>

Note: These devices share many common input and control methods; here we list the primary and typical one. In addition, smartphones can run desktop versions of websites, while tablets, laptops, and desktop computers can run mobile versions of websites; here again we list the primary and typical one.

A variety of screen sizes among devices produce different needs in terms of control methods, input types, placing methods, and application interfaces. Specifically, although devices may share the same input and control methods (e.g., touch feature,
keyboard, dictation, or stylus pen), the touch feature is a typical way for smartphones and tablets to save space, control, and input data (Adipat et al. 2011). Also, smartphones and tablets focus on mobility (Dearman et al. 2008) by requiring no extra peripheral devices such as a keyboard or mouse, they are much lighter and easier to carry, and they differ from the control and inputs of laptops and desktop computers. Furthermore, smartphones are normally handheld and are not necessarily placed on a table to use, thanks to their small screen size and lightweight. On the other hand, tablets can be either handheld or placed on a tabletop (Levin 2014).

Finally, in terms of application functions, there is not as much of a clear distinction because tablets and smartphones can have much of the same functionality as laptops and desktops. However, the application interface and layout must be adjusted to fit the screen size because of the limited display space on smartphones (Levin 2014). For example, although smartphones could run desktop versions of websites, they typically run mobile versions that contain less information with large font sizes and buttons to facilitate browsing for their users (Adipat et al. 2011).

**Overall Fit between Devices and Tasks**

As Table 2.1 shows, each device has its own specific characteristics despite the similarities and overlapping functions among the devices. When users use distinct devices, the characteristics of devices with heterogeneous displays and input methods can be mixed, matched, and configured (e.g., reading an e-mail using a small screen with a touch-operated virtual keyboard and replying to that e-mail using a large screen with a physical keyboard) (Carroll 2008). This allows more flexibility in end configuration and makes device use more responsive to environmental change, thus supporting the different
ways of carrying out an activity (Walljas et al. 2010). According to the TTF theory, if users choose the right device (i.e., using devices based on the fit between the characteristics of devices and tasks), they could improve their task performance by shortening task completion times and achieving more accurate results (Gebauer et al. 2010; Goodhue et al. 1995).

In the context of this study, I focus on a task that consists of several subtasks. Some subtasks might be more compatible with a specific device. In other words, each subtask may exhibit optimal fit with a certain device. This optimal fit is formed due to device characteristics such as screen size and input interfaces (Rashid et al. 2012). Specifically, prior studies have found that compared to large-display devices, small-display devices may negatively impact task performance for two reasons: inherent input restrictions and limited display capabilities (Adipat et al. 2011; Han et al. 1994; Jones et al. 1999). These challenges are particularly evident for tasks such as information seeking (Adipat et al. 2011; Rashid et al. 2012) because, when typing small keys, the users’ finger might occlude the key, resulting in a decreased input rate and increased error rate (Han et al. 1994). Furthermore, although smartphones can display the desktop or full version of a website, text font size will be greatly reduced to below the threshold of legibility. These processes make web browsing and searching tedious and inefficient. Small-display devices, however, have advantages in ease of operation because users can simply hold and operate devices using one hand and browse information simply by tapping and swiping, increasing operation speed and requiring less effort. This advantage is suitable for simple and straightforward function-specific applications with big buttons such as checking the weather or the calendar and setting up a clock alarm (Adipat et al. 2011).
When users use the optimal devices for each subtask, each fit between a device and a subtask contributes to shortening task completion time. The aggregation of contributions from each fit leads to the overall fit between devices and subtasks. Hence according to TTF theory, it is likely that their task completion times will be shorter. Thus we posit the following hypothesis:

**H1a:** Overall fit between devices and subtasks will be negatively related to task completion time.

Furthermore, prior research has shown that, with multi-device use, users have to determine which devices to assign to complete a specific task. Importantly, users may leverage device-specific features, using them complementarily for optimal performance (Oulasvirta et al. 2007). Failure in managing all these devices and/or using devices that do not fit with tasks may result in increased cognitive load (Bergman et al. 2006), causing lower task accuracy. Specifically, using devices based on their fit with certain tasks helps users locate correct answers, partly because the answer displays in a way that is easily processed (Adipat et al. 2011) and partly because the means of searching the information is convenient and easy. For example, when using a small-display device to read information on the full version of a website, users are more likely to find the wrong information because they will need to perform in–out zooming and left–right and up–down scrolling during web browsing and web searching, making them disoriented and unable to properly process content designed for viewing on a large screen (Adipat et al. 2011). Also, using a touch screen for typing and searching for information may result in errors because the screen does not provide tactile feedback to users, making it difficult for users to distinguish the target key from nearby keys (Buxton et al. 1985) and thereby
causing more errors (Kwon et al. 2009), resulting in lower accuracy than in the case when users use the right device. When selections of the best device for each subtask accumulate (i.e., users use the devices that provide an overall good fit for all subtasks), it is likely that the rate of user error will be low. Thus we propose the following hypothesis: **H1b:** Overall fit between devices and subtasks will be positively related to task accuracy.

**Device-Switching Costs**

Using devices based on the good fit between each device and a specific task is not always desirable because to use a device based on fit sometimes involves switching devices, which may create device-switching costs (Tungare et al. 2009; Walljas et al. 2010) and in turn influence task performance.

This study considers device-switching costs accumulated at two stages: before and after switching devices. Before switching devices, users must decide whether to switch to another device (Dearman et al. 2008; Rashid et al. 2012; Walljas et al. 2010). Prior studies suggest that making this decision requires additional decision-related effort in allocating among and managing devices because users need to determine which device is more suited to a certain task and how to use devices together (Dearman et al. 2008; Rashid et al. 2012; Walljas et al. 2010). Also, in deciding to switch devices, the user needs to consider learning costs if the device is new to the user and/or users are not familiar with multi-device use (Bales et al. 2011). Learning costs comprise extra efforts made in learning how to use devices together to perform a task. As a result, users in the stage before switching to another device require additional decision-related effort, which becomes salient as the number of device switches increases (i.e., more decision-related effort is required). Therefore, one way to measure device-switching costs in this
study is to count the number of device switches. The higher the number of device switches, the more decision-related effort and more integration costs may accumulate and the higher the device-switching costs would be.

After switching devices, several changes not encountered with single device use may occur, including screen size changes (i.e., large vs. small), application interface changes (i.e., desktop vs. mobile interfaces), input interface changes (i.e., keyboard vs. touch-screen inputs), and placing method changes (i.e., standing vs. hand-held) (Dearman et al. 2008; Seffah et al. 2004). These changes alter the ways in which users physically interact with devices and shift users’ mental representations of the application interface or layout formed by previous device use, which increases mental workload (Tungare et al. 2009). Because these changes involve two elements: the physical body (e.g., input interface changes) and applications (e.g., application interface changes), I measure them by counting the number of application switches and physical movements.

**Number of Device Switches and Number of Application Switches**

The number of device switches may be positively associated with that of application switches because each device is running a particular app and if users want to use it, they need to switch devices (Dearman et al. 2008; Levin 2014). Also, this relationship can be explained by individual preferences about temporal perception, a concept that has been widely used in explaining why people are more likely to engage in multitasking behavior (Benbunan-Fich 2012). Specifically, Hall (1959) has identified two types of individual preferences about temporal perception: monochronicity and polychronicity (Hall 1959). People with monochronic tendencies only attempt to do one task at a time, whereas those with polychronic tendencies prefer to juggle two or more
things at the same time and to hop from one to another because they use time for many purposes at once (Benbunan-Fich 2012; Cotte et al. 1999; Goonetilleke et al. 2010; Hall 1959). In the context of this study, when multiple devices are available to the former group of people, they may use one device for one application. Even when switching devices, they may still use one application on one device at a time and may not switch back and forth between devices or applications. On the contrary, the availability of multiple devices gives the latter group of people an opportunity to use multiple devices that run different applications at once. Importantly, they may switch back and forth between devices and applications because they are comfortable in this way (this is why a prior study calls this group of people “hoppers” (Cotte et al. 1999)). Such polychronic tendencies suggest a multitasking behavior (Benbunan-Fich et al. 2011) in which a high number of device switches and application switches would occur, indicating a positive relationship between them (i.e., users switch devices several times in order to access other applications).

It is important to note that switching between devices does not equate to application switching because there are two possibilities that cause application switching: cross-device switching and within-device switching; that is, users can switch to multiple devices and use multiple applications on different devices or users can switch to another device and use multiple applications only on that device (i.e., low number of device switches but high number of application switches). However, because people with polychronic tendencies enjoy doing multiple things at the same time and jumping from one thing to another (Cotte et al. 1999), switching back and forth between devices that run multiple applications should appeal to them.
**H2:** The number of device switches is positively associated with the number of application switches.

Switching between devices causes visual separation and physical discontinuities (Cauchard et al. 2011; Tan et al. 2003) because, in general, users can only look at one device at a time and because displays do not connect seamlessly: a few inches of metal or plastic separate their surfaces even when monitors are side by side (Grudin 2001). Therefore, to operate different devices or check information on different displays, users need to move their bodies, raise their heads, and/or shift their gazes (Cauchard et al. 2011; Shupp et al. 2009; Tan et al. 2003). For instance, a previous study found that compared to one device display, when distributing information across multiple displays, information is typically separated at much wider visual angles. When distributing information is further separated by depth, more physical movements may occur, resulting in detrimental effects such as lower task performance (Tan et al. 2003). Moreover, prior research showed that switching between different devices requires more physical movement than between the same devices because difference in screen sizes makes users to involve more physical movements (e.g., moving their head further to look for information displayed on a small screen device and/or using their fingers to locate information) (Kern et al. 2010; Rashid et al. 2012). For example, a study focusing on the cost of display switching (measured by task completion time and physical movements) indicated that a hybrid configuration where visual output is distributed across different display sizes (e.g., smartphone and desktop) contributes to increased costs (e.g., physical movements) in searching tasks (Rashid et al. 2012). Therefore, since Study 2 focuses on
switching among distinct devices, it is likely that additional physical movements may occur when the number of device switches increases.

**H3:** The number of device switches is positively associated with the number of physical movements.

**Number of Application Switches and Task Performance**

Application interfaces and layouts vary depending on device characteristics, such as device screen size and input interface (Levin 2014). Specifically, the application interface and layout should be adjusted to fit the screen size because of the limited display space on smartphones. For example, although smartphones can run desktop versions of websites, they typically run mobile versions that contain less information with larger font sizes and buttons to facilitate Internet browsing or application use (Adipat et al. 2011). Furthermore, in a traditional desktop application, the keyboard and mouse are the primary input devices. Changing from a mouse to a touch screen requires different interaction techniques and interface design. Therefore, different versions (e.g., smartphone and tablet applications or smartphone and desktop websites) of applications emerge. As a result, after switching from one application to another (e.g., from a full version website to a smartphone version map), users need to adjust the size and interface of the application and thereby shift their mental representations of the application interface or layout formed by previous application use (Levin 2014). Such a shift adds to users’ adjustment effort and time on the task, which may in turn increase their mental workload (Biehl et al. 2006; Tungare et al. 2009). As the number of application switching
increases, users need to put more effort and time into adjustment and the task, adding unnecessary effort and time.

**H4a:** The number of application switches is positively associated with task completion time.

The extra effort and time generated by application switches may result in low task accuracy because prior studies on information-searching task indicate that extra effort on the task not only adds more time to task completion but also tends to cause more errors (Adipat et al. 2011; Bailey et al. 2001; Speier et al. 2003a). Specifically, switching between objects such as tasks or applications requires cognitive resources (Monsell 2003). The limited cognitive resources demonstrated in studies based on the concept of mental workload (e.g., Miller, 1956) suggest that the increase in switching objects causes a burden on people’s cognitive resources and in turn adds mental workload (Tungare et al. 2009). As a result, performing a task under increased mental workload makes it more difficult to find the correct information or make the right decision (Hart 1986). Thus, error-prone behavior such as heuristic or irrational decision making may occur, decreasing task accuracy (Speier et al. 1999).

**H4b:** The number of application switches is negatively associated with task accuracy.

**Physical Movements and Task Performance**

Physical movements, such as eye, head, and body movements, require time and effort to perform (Rashid et al. 2012; Tan et al. 2003). Therefore, an increase in the number of physical movements, by definition, may result in high task completion time (Cauchard et al. 2011; Shupp et al. 2009). Hence, prior studies on physical movements
typically focus on time and effort as dependent variables (Cauchard et al. 2011; Rashid et al. 2012). Importantly, these studies find that time and effort caused by physical movements increase people’s mental workload (Rashid et al. 2012) and in turn have a negative impact on task performance (Lansdown et al. 2004). For example, a prior study focusing on multiple display environments compared the impact of a flat multi-display and a curved multi-display on task completion time. The results suggested that users completed the task faster when using a curved multi-display than when using a flat multi-display because physical movements (e.g., eye, head, and body movements) were significantly reduced when using a curved multi-display (i.e., the need to shift the gaze or move the head or body decreased) (Shupp et al. 2009). Similarly, Cauchard et al. (2011) found that when multiple displays are in the same field of view, users can check information easily with simple eye movements and little or no head movements. This view saves time for users in completing the task because the need for physical movements is reduced. Thus, on the basis of prior studies’ findings, the more physical movements involved in a task, the more time is required to perform the movements to complete the task (Cauchard et al. 2011; Shupp et al. 2009).

**H5a:** The number of physical movements is positively associated with task completion time.

Prior studies on human-computer interactions and ergonomics suggest that physical movements add to the mental workload of individuals because to perform them requires extra effort (Backs et al. 1992; Recarte et al. 2003; Wilson 2002). Importantly, the increased mental workload caused by physical movements has a deleterious effect on task performance because it places demands on several aspects of people’s cognitive
capabilities (Lansdown et al. 2004; Vitense et al. 2003). For example, a study focusing on the impact of multiple in-vehicle information systems on the driver has found that increasing physical interactions with multiple in-vehicle systems while driving requires more effort and imposes additional mental workload on drivers. The mental workload generated by these physical interactions degrades their driving performance because these drivers are distracted by both the main task (i.e., driving) and other physical interactions (i.e., operating systems) (Lansdown et al. 2004). In the context of this study, switching devices, by definition, requires effort in physical movement (Rashid et al. 2012; Tan et al. 2003). When the number of physical movements increases, users need to put in extra effort and shift their attention to those movements (Rashid et al. 2012). Given the limited cognitive resources, when some have to be used to coordinate physical movements, they are not available for the focal task, possibly resulting in reduced accuracy. Indeed, according to the concept of mental workload, when a person accumulates too much workload, overload may occur, deteriorating his or her capability to perform a task accurately (Lansdown et al. 2004; Recarte et al. 2003; Young et al. 2001).

**H5b:** The number of physical movements is negatively associated with task accuracy.

The hypothesized relationships among the aforementioned factors are shown in Figure 2.1.
Study Design

Subjects

The subjects are undergraduate students in a northeastern university in the United States and are participating in the experiment for class credit. Reasons for choosing students as subjects are the same as for Study 1.

Apparatus, Task Design, Procedure and Research Design

Study 2 uses the same devices, task, procedure and research design as Study 1.

Measure

Performance

Study 2 uses task completion time and task accuracy as the indicators of performance. Task completion time is measured by the time that a subject took to read the subtasks and find answers to them. The starting and ending time is automatically recorded by the task website. Task accuracy is measured by the percentage of correct
answers out of a total of ten, one for each of the ten subtasks.

*Number of Device Switches, Number of Application Switches, and Number of Physical Movements*

The measures for the number of device switches, application switches, and physical movements are as follows:

- **Number of device switches**: the number of times a participant switches among devices to complete a task. The device switch is counted only when a user *physically* operates the device. Viewing and/or moving devices are not counted as device switching.

- **Number of application switches**: the number of times a participant switches among applications to complete a task. Different browser tabs count as separate applications. The application switch is counted only when the application or browser tab is clicked and opened. Viewing without changing applications or clicking on tabs is not counted as an application switch.

- **Number of physical movements**: the number of times a participant moves his or her body or changes his or her head pose between devices. A physical movement may be in order to operate and view different devices but it may also involve just looking around without concentrating on the task.

To accurately collect these data, Study 2 uses video cameras to record subjects while they were working on the task. After the completion of the study, I watched the videos and transcribed all the actions subjects took while they participated, which included the following: (1) which devices and applications they used, (2) how many times they switched among devices and applications, (3) which device(s) and
application(s) they used to answer a certain subtask, and (4) how many times they moved their heads or bodies.

*Overall Fit between Devices and Subtasks*

The calculation of overall fit between devices and subtasks involves four stages. First, subjects are randomly assigned to one of device use groups and they in each group work on 10 subtasks using the assigned device. Second, I calculated the average performance of using each device for each subtask. Third, an ANOVA analysis is conducted to assess which device(s) resulted in statistically better performance than others. Finally, points are assigned to subjects who use the optimal device(s) for each subtask. The sum of points that each subject received is the overall fit between devices and subtasks. These four stages are described in detail in Appendix C.

*Results of Overall Fit between Devices and Subtasks*

A separate group of 120 subjects participated in the pilot study to estimate the average fit between devices and subtasks. Among them, 41 subjects were assigned to the desktop computer group, 39 subjects to the smartphone group, and 40 subjects to the tablet group. The subject demographics and descriptive statistics for the pilot study are shown in Table 2.2 and 2.3, respectively.
The results of the ANOVA analysis on each device’s performance for each subtask are shown in Table 2.4. There are no performance differences between devices for using the calendar to select a date or using the calculator to calculate gas and toll fees. However, using a smartphone resulted in significantly better performance than using other devices when searching weather information and driving time in maps. Utilizing the smartphone or desktop resulted in significantly better performance than using a tablet when searching driving miles using maps. Using the desktop led to significantly better performance than using other devices when searching opening hours and admission fees on a website. Using the tablet led to significantly better performance in calculating total cost. The utilization of the smartphone or tablet resulted in significantly better performance than the desktop when calculating total time.

For the purposes of Study 2, the device(s) that led to significantly better performance in a subtask over others were treated as having a good fit. On the basis of these results, I assigned 1 point to subjects who used the best-performing device to complete a given subtask.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>52 (43)</td>
</tr>
<tr>
<td>Female</td>
<td>68 (57%)</td>
</tr>
<tr>
<td>Age</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>8 (7%)</td>
</tr>
<tr>
<td>19-20</td>
<td>40 (33%)</td>
</tr>
<tr>
<td>21-22</td>
<td>46 (38%)</td>
</tr>
<tr>
<td>23-24</td>
<td>13 (11%)</td>
</tr>
<tr>
<td>25-26</td>
<td>6 (5%)</td>
</tr>
<tr>
<td>27-28</td>
<td>5 (4%)</td>
</tr>
<tr>
<td>29 above</td>
<td>2 (2%)</td>
</tr>
</tbody>
</table>
Table 2.3. Descriptive Statistics of Task Completion Time and Task Accuracy on Each Device

<table>
<thead>
<tr>
<th>Subtasks</th>
<th>Device</th>
<th>Task Completion Time</th>
<th>Task Accuracy</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
</tr>
<tr>
<td>Date</td>
<td>Desktop</td>
<td>8.56</td>
<td>1.03</td>
<td>8.05</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>8.35</td>
<td>1.26</td>
<td>9.23</td>
</tr>
<tr>
<td></td>
<td>Tablet</td>
<td>8.5</td>
<td>1.05</td>
<td>8.5</td>
</tr>
<tr>
<td>Weather</td>
<td>Desktop</td>
<td>7.43</td>
<td>1.3</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>8.56</td>
<td>1.07</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Tablet</td>
<td>7.3</td>
<td>1.24</td>
<td>10</td>
</tr>
<tr>
<td>Driving Time</td>
<td>Desktop</td>
<td>7.28</td>
<td>1.09</td>
<td>8.05</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>7.95</td>
<td>0.7</td>
<td>9.49</td>
</tr>
<tr>
<td></td>
<td>Tablet</td>
<td>7.1</td>
<td>1.01</td>
<td>7.25</td>
</tr>
<tr>
<td>Driving Miles</td>
<td>Desktop</td>
<td>7.54</td>
<td>1.53</td>
<td>8.78</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>7.55</td>
<td>0.94</td>
<td>8.97</td>
</tr>
<tr>
<td></td>
<td>Tablet</td>
<td>7.25</td>
<td>1.28</td>
<td>6.25</td>
</tr>
<tr>
<td>Opening Hour</td>
<td>Desktop</td>
<td>8.27</td>
<td>0.93</td>
<td>8.29</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>7.15</td>
<td>1.42</td>
<td>6.15</td>
</tr>
<tr>
<td></td>
<td>Tablet</td>
<td>7.27</td>
<td>1.74</td>
<td>7.25</td>
</tr>
<tr>
<td>Admission Fee</td>
<td>Desktop</td>
<td>7.85</td>
<td>1.23</td>
<td>8.29</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>6.82</td>
<td>1.61</td>
<td>6.15</td>
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<td></td>
<td>Tablet</td>
<td>7.31</td>
<td>0.93</td>
<td>7.25</td>
</tr>
<tr>
<td>Gas Fee</td>
<td>Desktop</td>
<td>8.01</td>
<td>1.18</td>
<td>6.59</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>8.27</td>
<td>0.8</td>
<td>8.21</td>
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<tr>
<td></td>
<td>Tablet</td>
<td>8.51</td>
<td>1.48</td>
<td>8.75</td>
</tr>
<tr>
<td>Toll Fee</td>
<td>Desktop</td>
<td>8.55</td>
<td>0.94</td>
<td>9.51</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>8.69</td>
<td>0.91</td>
<td>8.97</td>
</tr>
<tr>
<td></td>
<td>Tablet</td>
<td>8.54</td>
<td>1.43</td>
<td>9.25</td>
</tr>
<tr>
<td>Total Cost</td>
<td>Desktop</td>
<td>7.09</td>
<td>1.37</td>
<td>7.59</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>8.32</td>
<td>0.94</td>
<td>7.69</td>
</tr>
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<td></td>
<td>Tablet</td>
<td>8.71</td>
<td>0.74</td>
<td>8</td>
</tr>
<tr>
<td>Total Time</td>
<td>Desktop</td>
<td>6.63</td>
<td>1.24</td>
<td>8.1</td>
</tr>
<tr>
<td></td>
<td>iPod Touch</td>
<td>7.17</td>
<td>0.94</td>
<td>8.21</td>
</tr>
<tr>
<td></td>
<td>Tablet</td>
<td>7.84</td>
<td>0.88</td>
<td>8.5</td>
</tr>
</tbody>
</table>

Note: Accuracy for weather is not included because answers for weather vary in different websites (weather channel, yahoo weather, accurWeather, Google weather) and even in different time (it may change every 30 minutes). Since subjects were free to select weather websites and I recorded the weather information after the experiment, the correct weather information is hard to obtain.
### Table 2.4. The Results of Multiple Comparisons on Performance

<table>
<thead>
<tr>
<th>Subtasks</th>
<th>Devices</th>
<th>Mean Difference</th>
<th>Std. Dev.</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Date</strong></td>
<td>Desktop - iPod Touch</td>
<td>-3.842</td>
<td>.4125</td>
<td>.649</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>-1.599</td>
<td>.4095</td>
<td>.927</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>.2244</td>
<td>.4114</td>
<td>.864</td>
</tr>
<tr>
<td><strong>Weather</strong></td>
<td>Desktop - iPod Touch</td>
<td>-.6910</td>
<td>0.15682</td>
<td>.000***</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>.0808</td>
<td>0.15581</td>
<td>.874</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>.7718</td>
<td>0.15777</td>
<td>.000***</td>
</tr>
<tr>
<td><strong>Driving Time</strong></td>
<td>Desktop - iPod Touch</td>
<td>-1.1524</td>
<td>0.43878</td>
<td>.035**</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>0.4849</td>
<td>0.43596</td>
<td>.541</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>1.6373</td>
<td>0.44145</td>
<td>.001***</td>
</tr>
<tr>
<td><strong>Driving Mile</strong></td>
<td>Desktop - iPod Touch</td>
<td>-0.0181</td>
<td>0.49108</td>
<td>.459</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>1.6512</td>
<td>0.48793</td>
<td>.004**</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>1.6692</td>
<td>0.49407</td>
<td>.004**</td>
</tr>
<tr>
<td><strong>Opening Hour</strong></td>
<td>Desktop - iPod Touch</td>
<td>1.8792</td>
<td>0.53352</td>
<td>.003**</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>1.07</td>
<td>0.53009</td>
<td>.135</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>-0.8093</td>
<td>0.53676</td>
<td>.324</td>
</tr>
<tr>
<td><strong>Admission</strong></td>
<td>Desktop - iPod Touch</td>
<td>1.8688</td>
<td>0.56394</td>
<td>.005**</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>0.8831</td>
<td>0.56032</td>
<td>.293</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>-0.9857</td>
<td>0.56737</td>
<td>.225</td>
</tr>
<tr>
<td><strong>Gas</strong></td>
<td>Desktop - iPod Touch</td>
<td>-0.9892</td>
<td>0.54712</td>
<td>.199</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>-1.3279</td>
<td>0.5436</td>
<td>.054</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>-0.9892</td>
<td>0.54712</td>
<td>.199</td>
</tr>
<tr>
<td><strong>Toll</strong></td>
<td>Desktop - iPod Touch</td>
<td>0.1526</td>
<td>0.2986</td>
<td>.358</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>0.0907</td>
<td>0.29668</td>
<td>.454</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>-0.0619</td>
<td>0.30041</td>
<td>.569</td>
</tr>
<tr>
<td><strong>Total Cost</strong></td>
<td>Desktop - iPod Touch</td>
<td>-1.1957</td>
<td>0.47649</td>
<td>.047</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>-1.5636</td>
<td>0.47343</td>
<td>.005***</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>-0.3679</td>
<td>0.47939</td>
<td>.225</td>
</tr>
<tr>
<td><strong>Total Time</strong></td>
<td>Desktop - iPod Touch</td>
<td>-1.5701</td>
<td>0.53513</td>
<td>.016**</td>
</tr>
<tr>
<td></td>
<td>Desktop - Tablet</td>
<td>-1.7069</td>
<td>0.53169</td>
<td>.007**</td>
</tr>
<tr>
<td></td>
<td>iPod Touch - Tablet</td>
<td>-0.1368</td>
<td>0.53838</td>
<td>.458</td>
</tr>
</tbody>
</table>

**p< .05  ***p< .01

### Analysis

### Subjects

A total of 229 subjects took part in the experiment. I removed 19 data points that had significantly incomplete responses, extreme outliers, or unclear video recording data, resulting in a sample size of 210. The sample demographics were as follows: 47% were
male and 53% female, 71% were 22 years old or younger, and 76% owned three devices, while only 3% said they owned one device (laptop/desktop computer). The full breakdown of the sample can be seen in Table 2.5.

**Table 2.5 Subject Demographics**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>98 (47%)</td>
</tr>
<tr>
<td>Female</td>
<td>112 (53%)</td>
</tr>
<tr>
<td><strong>Number of devices owned</strong></td>
<td></td>
</tr>
<tr>
<td>1 Laptop/Desktop</td>
<td>7 (3%)</td>
</tr>
<tr>
<td>2 Laptop/Desktop and Smartphone</td>
<td>42 (20%)</td>
</tr>
<tr>
<td>2 Laptop/Desktop and Tablet</td>
<td>2 (1%)</td>
</tr>
<tr>
<td>3 Laptop/Desktop, Smartphone and Tablet</td>
<td>159 (76%)</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>13 (6%)</td>
</tr>
<tr>
<td>19-20</td>
<td>75 (36%)</td>
</tr>
<tr>
<td>21-22</td>
<td>61 (29%)</td>
</tr>
<tr>
<td>23-24</td>
<td>18 (9%)</td>
</tr>
<tr>
<td>25-26</td>
<td>12 (6%)</td>
</tr>
<tr>
<td>27-28</td>
<td>17 (8%)</td>
</tr>
<tr>
<td>29 above</td>
<td>14 (7%)</td>
</tr>
</tbody>
</table>

**Number of Devices Use**

The majority of the subjects used either all three devices (43.3%) or two devices (42.4%) to complete the task; 14.3% of subjects used only one device (see Table 2.6).

**Table 2.6. Number of Device Use**

<table>
<thead>
<tr>
<th>Number of Device Use</th>
<th>Frequency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Device Use</td>
<td>30 (14.3%)</td>
</tr>
<tr>
<td>Two Device Use</td>
<td>89 (42.4%)</td>
</tr>
<tr>
<td>Three Device Use</td>
<td>91 (43.3%)</td>
</tr>
</tbody>
</table>

The descriptive statistics for all dependent and independent variables are showed in Table 2.7.
When subjects used only one device to complete the task, the number of device switches was set to zero. The average overall fit between devices and subtasks was 6.72, the average time to complete the task was 565 seconds, and the average task accuracy was 7.14 out of 10.

**Research Model**

To test the research mode, Partial Least Squares was used with SmartPLS (Ringle et al. 2014). I used PLS because it is a structural equation modeling technique that estimates the relationships among them (Lohmöller 1989). Furthermore, since PLS does not require a large sample size, it is more suitable for this research (Barclay et al. 1995; Fornell and Bookstein 1982). The results are shown in Figure 2.2.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall fit between devices and subtasks</td>
<td>3</td>
<td>10</td>
<td>6.72</td>
<td>1.798</td>
</tr>
<tr>
<td>Number of Device Switches</td>
<td>0</td>
<td>82</td>
<td>25.31</td>
<td>20.453</td>
</tr>
<tr>
<td>Number of Application Use</td>
<td>20</td>
<td>116</td>
<td>45.63</td>
<td>15.283</td>
</tr>
<tr>
<td>Number of Physical Movements</td>
<td>0</td>
<td>88</td>
<td>27.03</td>
<td>15.855</td>
</tr>
<tr>
<td>Task Completion Time</td>
<td>212</td>
<td>1264</td>
<td>565.00</td>
<td>197.506</td>
</tr>
<tr>
<td>Task Accuracy</td>
<td>2</td>
<td>10</td>
<td>7.14</td>
<td>2.396</td>
</tr>
</tbody>
</table>
Figure 2.2 Results of Analysis

Note: *p< .05 **p< .01 ***p<.001

All hypotheses were supported, except for hypothesis 4b, in which I hypothesize that the number of application switches is negatively associated with task accuracy; here I instead found a positive association. Overall fit between devices and subtasks was a significant predictor of task completion time and accuracy, with values of −0.287 (p < .001) and 0.257 (p < .001), respectively. Furthermore, as hypothesized, the number of device switches was positively associated with the number of application switches and number of physical movements, with values of 0.153 (p < .001) and 0.509 (p < .001), respectively. In addition, the number of application switches was significantly related to task completion time, with the value of 0.418 (p < .001); however, contrary to my prediction, the number of application switches was positively associated with task accuracy. Moreover, the number of physical movements was positively and negatively associated with task completion time and task accuracy, respectively.
Discussion

The results of hypothesis testing are summarized in Table 2.8.

<table>
<thead>
<tr>
<th>Table 2.8 Summary of Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypotheses</td>
</tr>
<tr>
<td>H1a: Overall fit between devices and subtasks will be negatively related to task completion time.</td>
</tr>
<tr>
<td>H1b: Overall fit between devices and subtasks will be positively related to task accuracy.</td>
</tr>
<tr>
<td>H2: The number of device switches is positively associated with the number of application switches.</td>
</tr>
<tr>
<td>H3: The number of device switches is positively associated with the number of physical movements.</td>
</tr>
<tr>
<td>H4a: The number of application switches is positively associated with task completion time.</td>
</tr>
<tr>
<td>H4b: The number of application switches is negatively associated with task accuracy.</td>
</tr>
<tr>
<td>H5a: The number of physical movements is positively associated with task completion time.</td>
</tr>
<tr>
<td>H5b: The number of physical movements is negatively associated with task accuracy.</td>
</tr>
</tbody>
</table>

The significance of the overall fit between device and subtask shows that when users can select the right device from their IT device portfolios to deal with a certain subtask, the task can be completed more quickly and accurately. I also found that increasing the number of device switches generates a higher number of application switches and physical movements, both of which add time to task completion. However, while the number of physical movements significantly decreases task accuracy, which is consistent with previous studies’ findings (Rashid et al. 2012), I did not find evidence that the number of application switches decreases it. Though this result is slightly counterintuitive, there are two possible reasons for this surprising finding. First, to increase the task accuracy, subjects may want to switch back and forth between applications to make sure they get the right answer. For example, in Study 2, calculating
total fees for the trip requires the subjects not only to use the calculator but also to check total miles from maps. To calculate total fees correctly, they may switch back and forth between the calculator and the map. Second, using more applications for the same task could be indicative of subjects double-checking the information, thereby increasing their task accuracy. For example, if users want to check the weather predicted for the date on which they want to take a trip, they can go to different websites (applications), such as the Weather Channel, Yahoo! Weather, and/or AccuWeather to confirm the weather information, increasing the possibility of getting the right answer.

**Contributions to Theory**

Study 2 provides several important contributions to theory. First, previous research based on the TTF theory has found that using a device that provides good fit with a task improves user performance (Gebauer et al. 2010; Goodhue et al. 1995; Parkes 2013); however, these studies only consider single information system use or device use. Consequently, the question of whether the TTF theory can be applied to multi-device use needs to be tested because this theory in single and multi-device use differs in terms of granularity. Specifically, TTF theory in single device use considers an overall and general fit between a device and a task (e.g., desktop computer vs. trip-planning task); however, in multi-device use it focuses on the granular fit between devices and subtasks (e.g., smartphone and desktop computers vs. checking weather and maps and calculations), considering each device and each subtask rather than one device and the entire task. Therefore, I could not use TTF theory in single device use to directly explain the granular fit in multi-device use. Thus, Study 2 makes an important contribution by demonstrating its robustness in the context of a multi-device environment. Study 2’s results show that
when users use devices that fit better with their subtasks, the tasks can be completed faster and more accurately.

Moreover, Study 2 also contributes to the literature centered on the concept of mental workload. The concept of mental workload posits that our level of attentional resources has finite capacity, beyond which further increases in demand degrade performance (Hong et al. 2004; Vitense et al. 2003; Young et al. 2001; Young et al. 2002). This concept has been a topic of increasing importance in Information Systems, since modern technologies, such as websites or DSSs, have come to play a major role in our daily lives and using these systems has imposed a cognitive demand on users (Hong et al. 2004; Speier et al. 2003a). For example, Speier and Morris (2003) examined what types of query interfaces (including visual and text-based interfaces) in a DSS may generate more mental workload for decision makers. Their results show that when using a visual-based interface, decision makers’ subjective workloads were lower than when they used a text-based interface indicating that text-based interfaces of DSSs require more cognitive workload than visual-based interfaces. Study 2 contributes to the concept of mental workload in Information Systems as I empirically examine the impact of three device use actions, i.e., the number of device switches, application switches, and physical movements, as opposed to websites or decision support system (DSS) interfaces (Speier and Morris, 2003 and Hong et al., 2004). Focusing on user device actions adds new insights to the prior literature on mental workload. Study 2 found a negative impact of device use actions on increasing mental workload, which in turn negatively influences performance. Therefore, I believe that it is important, from a theoretical viewpoint, to
acknowledge the potentially detrimental workload effect generated not only from system features but also from device use.

Furthermore, Study 2’s results provide unique insight to both TTF and mental workload. This study found that both TTF theory and concept of mental workload should be considered together while multiple devices are available to use. Specifically, although they both consider tasks, technology, and users, each ignores some important elements: TTF theory focuses on the fit between tasks, technology, and users but neglects to consider the additional workload incurred by device-switching costs. Conversely, mental workload only concerns the aggregation of demands from tasks and technologies, while disregarding the fit between them. Indeed, my data indicates that device-switching cost is another important factor that has a detrimental effect on task performance but is not considered in the theory of TTF. Hence, combining TTF theory and mental workload in the same model allows us to better understand the relationship between device use and task performance under the context of the availability of multiple devices.

In addition, in most IT usage studies, actual IT usage is typically collected through users’ subjective experience; these studies use a questionnaire to enquire about subjects’ prior experience of IT usage or their intention to use IT (Ye and Portter, 2011), resulting in the lack of objective methods to measure actual usage. I do not deny the importance of understanding users’ subjective experience and intention; however, users’ subjective experience or intention may not be an absolute indicator of actual user behavior. Prior studies have found intention-behavior discrepancy, suggesting that users’ subjective experience and intention may not necessarily lead to their actual behavior (Sheeran 2002; Wong et al. 1985). Hence, an objective method is required in IT usage
studies. Study 2 contributes to IT usage studies by providing a method to obtain objective data from actual user activity, i.e., video recording. Specifically, I collect the data by video recording how users use device(s), and then code them into data to validate the model. This method allows us to directly observe and objectively understand about how subjects actually use device(s), such as the number of device switches, which provides useful insights for future research on measuring actual IT usage.

Finally, while there is a significant amount of research on physical movements among technology users in the field of ergonomics and human-computer interaction (Backs et al., 1992 and Myrtek et al., 1994), it has been largely ignored in IT usage studies in the field of information systems. Ignoring physical movements is problematic and requires the attention of Information System researchers. After all, multi-device use becomes increasingly common (Google 2012; Yoo 2010) and such a use requires switching between devices and involves physical movements (Rashid et al. 2012). Therefore, what role does physical movements play in multi-device use is critical to know. Study 2 has confirmed the importance of physical movements in IT usage, i.e., physical movements negatively impact task performance, and it is hoped that this finding will inspire further research considering this essential and negative factor in IT usage and uncovering deeper insights.

**Implications for Practice**

The practical implications of Study 2’s results are noteworthy for companies that allow their employees to use multiple devices, partly their own devices, in the office. The findings suggest that, when multiple devices are available to use, to improve task performance, users have to use the right device and at the same time use the device right,
in order to complete a task. Using the right device means that users need to determine the best fit between devices and subtasks. Using the devices right means that users need to consider the number of device switches, physical movements, and application switches. Specifically, when managers have concerns regarding task completion time, maximizing the fit between devices and subtasks and minimizing the number of application switches and physical movements are important to improve task completion time. However, in regards to task accuracy, maximizing the fit between devices and subtasks, encouraging application switches, and reducing physical movements are critical. On the basis of these results, managers need to focus on three things when providing multi-device use training to their employees for improving performance. First, managers need to find out which devices are suitable for dealing with certain tasks in their companies beforehand and then inform them about which device(s) is the optimal for specific tasks and encourage them to use the optimal device(s), if available. Second, managers need to tell their employees that the number of device switches is a double-edged sword. On one hand, the number of device switches increases the number of application switches, which is beneficial to task accuracy. On the other hand, its increase may generate a higher number of physical movements, which may increase task completion time and decrease task accuracy. Third, they need to advise their employees regarding the trade-off between task accuracy and task completion time. On the basis of the findings, when a project needs to be completed as quickly as possible, managers can educate their employees to control the number of device switches. However, when the project needs to be completed with minimum number of errors, number of application switches is encouraged but number of physical movements is not.
Finally, Study 2’s results have shown that the number of physical movements is a factor that negatively impact performance. Therefore, managers need to find a way to reduce its effect and provide the solution to their employees. One way to do so would be to avoid physical movements when switching devices by placing devices as close as possible or letting device screens display in the same field of view so that the impact of physical movements on task performance may not be significant.

Limitations

Some limitations should be acknowledged when readers interpret the results. First, to precisely control the variables of interest and to test Study 2’s hypotheses by eliminating extraneous influences and confounding factors, I did not allow participants to use their own devices but rather to use the devices that I assigned to them. Therefore, some subjects may have never used a specific device (e.g., Kindle Fire) before. Although I provided the training sessions and many subjects used all three devices (see Table 2.6), a caution needs to be taken when generalizing the results to the contexts in which people use the devices that they are familiar with.

Furthermore, Study 2’s participants were drawn from the student population at a major urban college in the U.S. Northeast. As a result, the generalizability of the findings to organizational use of devices may be limited. Further studies with different organizational users and environments are encouraged to strengthen the generalizability of the findings.

Third, with a variety of factors that influence task performance, I consider only overall fit between devices and subtasks, the number of device switches, application switches and physical movements. I recommend that future studies take other factors into
account. Examples of factors are IT efficacy, task familiarity and/or capability with multi-device use. While this limitation may influence the explanation power, the factors used in this study are adequate for an initial endeavor in understanding multi-device use. Hopefully, these factors can pave the way for additional studies to further investigate into multi-device use.

Finally, different tasks need to be tested. Study 2 used a trip-planning task because I focus on individual users rather than on organization users. Further studies are encouraged to examine other tasks, such as work-related tasks and shopping-related tasks, and to compare and validate the results of this study.

**Conclusion**

Multiple devices provide an IT portfolio with different resources for the user to utilize strategies in dealing with a variety of tasks. The ideal goal of device use from the IT portfolio is to create better performance. However, the problem is how to achieve this goal. To the best of my knowledge, Study 2 is the first empirical study to examine task performance when multiple devices are available but not required. Thus, this study is a stepping-stone on which further research can build an effective and efficient understanding of task performance using device(s). Importantly, because of its novelty, this study bridges a gap in the IS literature by, on the basis of TTF and mental workload, developing a research model of the relationship between device use and task performance in the context of the availability of multiple devices. The findings provide valuable theoretical and practical insights. I hope that Study 2 will inspire future research to focus on the relationship between device use and task performance.
Study 3: The Effects of Flexibility of Multi-Device Use on Users’ Attitudes, Satisfaction and Continuance Intention

Introduction

An increasing number of people own more than one device (i.e., laptops, tablets, and smartphones) (Google 2012). These multiple devices create a device portfolio for users, which allows users to allocate certain devices to certain tasks and to freely switch between devices to perform a variety of tasks (Carroll 2008). This degree of freedom, with which users can choose devices from their device portfolio to carry out a task or set of tasks, can vary depending on the users’ environment or context. For the purposes of Study 3, I call this degree of freedom the flexibility of multi-device use.

For example, at home, users can employ any devices they want. In contrast, in an office or classroom, this is not always the case as users may have non-flexibility of multi-device use, in that they are restricted to using only certain devices for a specific task, due to security and privacy issues (Harris et al. 2013) or classroom management (Hockly 2012). As a result, users’ original expectations of choice from the device portfolio are constrained, which decreases flexibility of multi-device use and may have unintended, and negative, consequences. As suggested by the psychological reactance theory (Brehm 1966), if people believe that choices A and B are available to them, but they are restricted only to choice A, a reaction called psychological reactance, defined as assertive affective and cognitive reactions to a threatened or eliminated freedom (Brehm 1966; Brehm et al. 1981), may lead to dissatisfaction and lower expectations of performance outcomes (Lessne et al. 1989; Murray et al. 2011).
However, whether psychological reactance is also triggered among users with non-flexibility of multi-device use is currently unknown, as it has not been studied yet. The answer to this question may not be obvious, primarily for two reasons. First, devices such as laptops, tablets, and smartphones usually have similar or overlapping functions (e.g., they can all be used to send e-mail, check the weather, and search for information on a website), meaning that loss of freedom of device choice may not necessarily result in losing a specific function (Levin 2014). Thus, although psychological reactance theory can be applied under the condition of non-flexibility of multi-device use because of users’ loss of freedom of device choice to complete a task, this reactance may not take place or could be lower under multi-device use conditions than under other situations.

Second, although users may be constrained in using specific devices in certain places (e.g., the office), they may be restricted in using a device that is optimal for the task but may not be their preferred device. According to task-technology fit (TTF) theory, such device use may lead to better task performance and satisfaction (Goodhue 1995; Parkes 2013), and resulting in continuance intention of device use (Dishaw et al. 1999). Therefore, the possible negative impact caused by the inflexibility of multi-device use may be lessened.

Additionally, task complexity may play an important moderating role in flexibility of multi-device use. Specifically, as task complexity increases, users need to process more information and complete more actions (Campbell 1988; Speier et al. 2003b). Under these conditions, if the choice among devices has been limited, it could further increase the degree of perceived task complexity. This may not be the case for simple tasks where the actual device used is less important. Thus, the effects of flexibility
of multi-device use could be more salient for complex tasks than for simple tasks.

Drawing on psychological reactance theory and TTF theory, Study 3 focuses on the flexibility of multi-device use as the construct of interest and attempts to understand its impact on users and how we can reduce that impact. Specifically, Study 3 addresses three research questions:

1. Will inflexibility of multi-device use negatively impact users’ attitudes toward, satisfaction with, and continuance intention of multi-device use?

2. If so, can this impact be reduced by assigning the devices with the best fit for the tasks?

3. How does this impact vary with task complexity?

I conducted two studies (Study 3.1 and 3.2) to answer the research questions. The purpose of Study 3.1 is to confirm whether the non-flexibility of multi-device use does cause a negative impact on users’ attitudes toward multi-device use (measured by affective and cognitive appraisals). To test this, I manipulated the presence or absence of flexibility of multi-device use (no vs. yes) and different levels of task complexity (low vs. high). I focused on the extreme case of non-flexibility of multi-device use with bad task-device fit. In the non-flexibility condition, I forced users to use the devices with the worst fit for their tasks. If I could not find a significantly negative impact on users’ attitudes toward multi-device use in such a case of non-flexibility of multi-device use, it would be strong evidence that flexibility of multi-device use has no effect on user attitudes. As I will discuss in this paper, I did find such a negative impact. Therefore, I conducted a second study (Study 3.2) to address the second research question. In the second study, I assigned users the devices with the best fit for the tasks. By comparing the results of
worst fit Study 3.1 with those of best fit Study 3.2, I was able find whether maximizing fit between devices and tasks is a solution to counteracting the impact caused by the non-flexibility of multi-device use, in those cases were non-flexibility is necessary (e.g., for security purposes).

**Theoretical Background**

**Attitudes**

Attitudes have been extensively studied in the field of psychology, marketing, and human resources (Kempf 1999; Trafimow et al. 1998; Trafimow et al. 2004). These studies have suggested that attitudes comprise two distinct elements, affective appraisals and cognitive appraisals, both of which contribute to predicting individuals’ further behavior (Kempf 1999; Trafimow et al. 1998; Trafimow et al. 2004). Affective appraisals reflect the hedonic aspect of attitudes and refer to emotional, experience-based evaluations of an object (Breckler 1984; Van der Heijden 2004), whereas cognitive appraisals reflect the utilitarian aspect of attitudes and refer to cognitive, needs-based, value-focused, and goal-orientated evaluations of the object (Kempf 1999). In the field of information systems, most previous studies have mainly focused on cognitive appraisals (Beaudry et al. 2010). These studies have posited that attitude toward IT use is evaluated based on instrumental beliefs (i.e., cognitive appraisals) such as usefulness and ease of use (Van der Heijden 2004). In recent years, attention has shifted toward affective appraisals (Beaudry et al. 2010; Van der Heijden 2004) and has argued that considering both affective and cognitive appraisals together can lead to better understanding of users’ attitudes toward IT (Van der Heijden 2004). In other words, users’ attitudes toward IT is not solely determined by either cognitive or affective appraisals, but both of them should
be considered together in determining the formation of attitudes toward IT.

**Psychological Reactance Theory**

Psychological reactance theory has been the subject of study for many years in the field of psychology, both in the laboratory and in the field (Murray et al. 2011; Schwarz 1984). This theory explains how people react to the situation in which their freedom of choice has been threatened. Specifically, people may form an expectation of freedom of choice because they are accustomed to it (Brehm et al. 1981; Lessne et al. 1989). For example, individuals become accustomed to having the freedom to choose among menu items at a restaurant. Similarly, they are free to choose among different clothing options at the clothing store. A loss of freedom of choice goes counter to their expectations. Such unexpectedly limited freedom creates a negative force in their motivational state, called *reactance*, which decreases the perceived attractiveness of the object they were given and increases the attractiveness of the object they cannot have (Clee et al. 1980; Murray et al. 2011). Thus, psychological reactance theory posits that people may react negatively toward a freedom-threatening situation when their expected freedom has been threatened or eliminated (Brehm 1966; Brehm et al. 1981).

Prior research has suggested that loss of freedom of choice may result in several reactions. First, when people are constrained to one alternative, that alternative becomes less attractive to them than it would have been had it been freely chosen. As a result, negative affective attitudes (e.g., anxious or angry) toward the alternative are formed (Murray et al. 2011). Second, reactance to constraints on people’s freedom of choice may negatively affect their satisfaction with the decision process. Kalda et al. (2003), for example, found that a free choice of physicians resulted in patients who were more
satisfied with their medical care (Kalda et al. 2003). Another study in the same setting indicated that when patients are not able to choose their physicians, they may have lower levels of trust (Kao et al. 1998). Third, freedom of choice can increase people’s confidence levels, which can lead to higher perceived performance. Constrained choice, however, leads to a lack of control and decreased confidence, impairing people’s perceived performance (Chen et al. 2014; Tafarodi et al. 1999).

**Task–Technology Fit Theory**

TTF theory, which has received widespread acceptance in the Information Systems field for many years, suggests that the matching of the functions of the device to the demands of the task improves the overall performance of tasks (Goodhue 1998; Goodhue et al. 1995). This theory has been examined in different contexts by several studies that focus on one specific system or device such as knowledge management systems and mobile commerce (Dishaw et al. 1999; Lee et al. 2007; Lin et al. 2008), and for a variety of tasks, such as bidding in online auctions (Hsin 2010) and maintenance projects (Dishaw et al. 1999). The results of these studies consistently show that a satisfactory fit between a device and tasks, as well as between a technology and users can lead to improvement in the performance of tasks (Goodhue et al. 1995).

Prior research based on TTF theory has shown that, in addition to task performance improvement, when a good fit between a device and a task occurs, this fit may also form positive attitudes toward use of the device (Dishaw et al. 1999; Staples et al. 2004). For example, Staples et al. (2004) developed a model that focuses on the impact of task-technology fit on performance, attitude, and expected consequence of use. Their results suggest a significantly positive relationship between task-technology fit,
attitude toward use, and performance (Staples et al. 2004).

**Attitudes, Psychological Reactance Theory and Task-Technology Fit Theory**

Prior studies based on psychological reactance theory or TTF theory used attitudes as outcome variables to understand individuals’ reactions. However, the formation of attitudes in these studies focuses on the opposite direction. Psychological reactance theory asserts that when the reactance effect occurs, individuals form negative attitudes toward the option that individuals are forced to choose (Brehm et al. 1981). Nevertheless, TTF theory posits that when using the device with the best fit for a certain task, individuals generate positive attitudes toward the device they are using (Dishaw et al. 1999). Although these two theories were applied under two different conditions (i.e., psychological reactance theory focuses on the context of freedom of choice, whereas TTF theory applies to the context of using a device with the best fit for a certain task), these conditions are likely to take place at the same time. That is, when individuals are in a situation in which they are forced to use a specific device (i.e., loss of freedom of device choice) that has the best fit for a specific task. As a result, it is likely that a mix of positive and negative attitudes toward the device use would be formed, leading to a counteracting effect. In other words, using the device with the best fit for the task, results in a potential reduction of the detrimental effects of psychological reactance. In Study 3, I conducted experiment to examine the possible existence of this counteracting effect in the context of multi-device use.

**Literature Review and Hypothesis Development**

**Flexibility of Multi-Device Use and Attitudes toward Multi-Device Use**
Flexibility of multi-device use is the degree of freedom of choice for users to freely allocate their devices towards completing a task. This freedom may have a positive impact on user attitudes (both affective and cognitive appraisals) and a negative impact when it is not provided. According to psychological reactance theory, when individuals are aware of their choices yet are forced to accept a certain choice, or when they realize that certain choices are eliminated, reactance is aroused (Brehm et al. 1981; Lessne et al. 1989). Thus, in the context of Study 3, I propose that non-flexibility of multi-device use may cause reactance because users are already aware of all devices but are forced to use a specific one. Prior research has shown that an unwillingness to accept the limited choice that threatens free behavior can generate negative emotions, including frustration and an increasing resistance to current circumstances (Iyengar et al. 2000; Kalda et al. 2003; Murray et al. 2011). Meanwhile, the reverse effect may occur with an increasing level of choice. With more choices available, individuals are able to accept the one they make, which reduces threat and anxiety, increases credibility (Kukde et al. 1994; Rokke et al. 1991) and pleasure (Hui et al. 1991). However, it is important to note that prior studies have suggested that when a user has too many choices, threat and anxiety may increase, resulting in lower satisfaction (Scheibehenne et al. 2010). In Study 3, users make a choice among only three distinct devices (i.e., a smartphone, tablet, and desktop computer) so the effect of too many choices should be negligible. Hence, I propose that when users are able to flexibly allocate devices towards completing a certain task, they may have more positive affective attitudes than people who were given less or no choice.

**H1:** Positive affective appraisal of multi-device use will be higher for users with flexibility of multi-device use than for users with non-flexibility.

Additionally, freedom of choice has been recognized as a factor influencing
cognitive appraisal. Specifically, active thinking and interaction facilitated by freedom of choice makes individuals more engaged in an activity. This engagement process increases the individual’s motivation toward completing the task (Perlmuter et al. 1977) and enhances his or her sense of control over the outcome of the task (Dunn et al. 1990; Langer 1975). This positive motivation and enhanced sense of control may lead to higher self-confidence, or even overconfidence, about outcomes (e.g., success of completing the task), resulting in higher cognitive appraisal (i.e., higher perceived performance) (Chen et al. 2014; Dunn et al. 1990; Langer 1975). For example, Langer (1975) found that people who are allowed to choose their own numbers in a lottery game are more confident of winning than people who are randomly given numbers, because the former are less likely to trade their tickets, even for one in a game with better odds (Langer 1975). Likewise, Dunn and Wilson (1990) found that freedom of choice of a target number makes participants bet more because they become more confident in their ability to produce the outcome of a roll of a die than without freedom of choice. The results of these two studies indicate that freedom of choice enhances people’s perceived control and their confidence in performing a task, even for tasks in which outcomes are determined by chance, resulting in higher cognitive appraisal.

In the context of Study 3, the freedom of choice among devices gives users opportunities to select and create the ideal combination of devices, as they perceive it. Users can work on the task based on the perceived fit between the devices they chose and the task, which creates a belief that they can control the task and complete it more efficiently (Oulasvirta et al. 2007), leading to higher confidence in their ability to carry out tasks and enhancing their cognitive appraisal of multi-device use. Conversely, when users know that they own multiple devices but are restricted to using a specific one for dealing with a certain task, their actions are limited, according to psychological reactance theory, resulting in diminishing confidence in accomplishing tasks.
**H2:** Positive cognitive appraisal of multi-device use will be higher for users with flexibility of multi-device use than for users with non-flexibility.

---

**The Impacts of Task Complexity in Flexibility of Multi-Device Use on Users’ Attitudes**

According to psychological reactance theory, individuals react positively toward freedom of choice but negatively toward limited choice (Brehm 1966; Brehm et al. 1981). This relationship remains the same in different task complexity conditions but its intensity may vary. For simple tasks, freedom of choice may not impact users’ feelings as strongly as it would for complex tasks (Clee et al. 1980). In the context of Study 3, I believe that for simple tasks, the need to freely use devices is not strong because one device can be sufficient to perform the task. This can be a reasonable option if the different devices have similar or overlapping functions, which is the case with the devices used in Study 3 (Dearman et al. 2008). As a result, non-flexibility of multi-device use may only slightly influence users’ attitudes toward device use. Conversely, complex tasks typically contain more informational cues and processes than simple tasks (Campbell 1988; Speier et al. 2003b; Wood 1986). Hence, when processing complex tasks, people may prefer to use more devices to deal with difficult and interrelated subtasks (Dearman et al. 2008). As a result, freedom of choice among devices matters because, in performing the complex task, it can give users the capability to freely allocate the appropriate devices based on their perceived fit between device and task, and increases users’ sense of control and confidence in dealing with complex tasks (Tafarodi et al. 1999). This can lead to higher affective and cognitive appraisals towards multi-device use (Goodhue 1995). Under this condition, if users are forced to choose specific alternatives, high levels of
reactance would be generated (Clee et al. 1980). Therefore, task complexity is a factor that strengthens the relationship between flexibility of multi-device use and attitudes toward multi-device use.

**H3:** Task complexity positively moderates the positive relationship between the flexibility of multi-device use and positive affective appraisal with device use.

**H4:** Task complexity positively moderates the positive relationship between the flexibility of multi-device use and positive cognitive appraisal with device use.

**Attitudes and Satisfaction with Multi-Device Use**

Both affective and cognitive appraisals toward an object have been recognized by prior studies as the antecedents in forming satisfaction and continuance intentions for using IT devices (Bhattacherjee et al. 2004; Lee et al. 2009b). In the field of information systems, *satisfaction* refers to users’ positive evaluations of an IT service or product (Bhattacherjee et al. 2004; Wixom et al. 2005). These positive evaluations include affective and cognitive appraisals of the IT product or service (Lee et al. 2009b). When users have positive affective appraisals (e.g., pleasure and enjoyment) and positive cognitive appraisals (e.g., productivity and helpfulness) after using the IT product or service, both appraisals contribute to the users’ subsequent satisfaction (Bhattacherjee 2001b; Bhattacherjee et al. 2004; DeLone et al. 1992; Lee et al. 2009b).

Therefore, although I have not found prior studies that examine this relationship under the context of multi-device use, I believe that when users’ affective and cognitive appraisals with regard to multi-device use improve (i.e., individuals feel that multi-device use is enjoyable and helpful), they will have positive experiences with multi-device use. According to prior research, these experiences will in turn lead to satisfaction with multi-
device use.

**H5:** The more favorable the users’ affective appraisal, the higher their satisfaction with multi-device use.

**H6:** The more favorable the users’ cognitive appraisal, the higher their satisfaction with multi-device use.

**Attitudes and Continuance Intention of Multi-Device Use**

The attitude-intention chain has been well established in prior studies. These studies are based on Ajzen and Fishbein’s (1975) theory of reasoned action and Ajzen’s (1985) extended model of the theory of planned behavior, both of which suggest that a positive attitude toward an object will lead to the continuance intention to use it. In the field of information systems, prior studies based on these theories have found that perceived usefulness and perceived enjoyment are two of the key determinants of attitudes that lead to IT continuance intentions (for perceived usefulness, see Bhattacherjee (2001), and for perceived enjoyment, see Kim (2010)). In other words, when users believe that using a specific device can enhance their productivity (i.e., positive cognitive appraisal) and/or increase their enjoyment (i.e., positive affective appraisal), their positive attitudes toward device use are formed and make them want to continue to use the device (Bhattacherjee 2001b; Bhattacherjee et al. 2004; DeLone et al. 1992; Lee et al. 2009b).

In the context of Study 3, I define continuance intentions of multi-device use as the intentions of users to use the same devices to perform similar tasks in the future given that the same number of devices is available to them. On the basis of the attitude-intention chain, I believe that if users have an attitude that using certain device(s) can
lead to better performance and/or make task completion more interesting and fun (i.e., affective and cognitive appraisals), such a positive attitude will lead them to continue using the same device(s) in the future.

**H7:** The more favorable the users’ affective appraisal, the higher their continuance intention of multi-device use.

**H8:** The more favorable the users’ cognitive appraisal, the higher their continuance intention of multi-device use.

**Satisfaction and Continuance Intentions of Multi-Device Use**

A considerable body of research has found the positive influence of satisfaction on usage continuance intentions in different contexts, including e-commerce (Bhattacherjee 2001a; Bhattacherjee 2001b), online learning (Lee 2010), and mobile services (Thong et al. 2006). These studies are based on the post-acceptance model of IS continuance proposed by Bhattacherjee (2001) and have consistently indicated that the more positively one evaluates a technology-related experience (satisfaction), the greater one's intentions will be to engage in future exchanges with the technology (usage continuance intention). Indeed, satisfaction leads to positive evaluations of an IT product or service. These positive evaluations make users experience the benefits of the IT service or product, which motivates them to use it again. Since the positive influence of satisfaction on usage continuance intentions has been supported by many studies in different contexts, I apply this finding to the context of Study 3. When users are satisfied with device use, their positive experiences may result in triggering their intention to continue using the same device(s) in the future.

**H9:** Satisfaction with multi-device use will be positively related to continuance intention of multi-device use
The overall research model of Study 3 is shown in Figure 3.1.

![Research Model of Study 3](image)

**Figure 3.1 Research Model of Study 3**

**Method**

As mentioned in the introduction, I conducted two studies (Study 3.1 and Study 3.2) to answer Study 3’s research questions. The purpose of worse fit Study 3.1 is to confirm whether the lack of flexibility of multi-device use causes a negative impact on users’ attitudes toward multi-device use. The purpose of best fit Study 3.2 is to examine whether the best fit between devices and tasks is a solution to counteracting the impact caused by the lack of flexibility of multi-device use.
Study 3.1: The Impact of Flexibility of Multi-Device Use on Users’ Attitudes toward Multi-Device Use

Experimental Design

Study 3.1 employed a $2 \times 2$ full factorial design with the following factors: yes vs. no flexibility of multi-device use, high vs. low task complexity. Subjects were randomly assigned to each condition to eliminate any possible extraneous effects in Study 3’s experiment, (see Table 3.1).

<table>
<thead>
<tr>
<th>Table 3.1 Study 3.1 Experimental Design</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Flexibility of multi-device use</strong></td>
</tr>
<tr>
<td>1 (50)</td>
</tr>
<tr>
<td>2 (51)</td>
</tr>
<tr>
<td><strong>Non-flexibility of multi-device use</strong></td>
</tr>
<tr>
<td>3 (50)</td>
</tr>
<tr>
<td>4 (49)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Note: The table provides the condition number, with the number of subjects in parentheses.</td>
</tr>
</tbody>
</table>

Subjects

The subjects were undergraduate students in a northeastern university in the United States and were participating in the experiment for class credit. Reasons for choosing students as subjects are the same as for Study 1.

Apparatus

Study 3 uses the same devices as Study 1.

Task Design

The subjects were instructed to perform a trip-planning task that involves a series of searches and calculations. The task was manipulated so as to have both a simple and a complex version (see Appendix D). The simple task is the same as Study 1. The complex task used the equivalent questions as the simple task but I increased the degree of complexity by following Campbell’s (1988) four primary characteristics that can increase...
task complexity:

(1) Multiple paths: Task complexity increases when there are multiple ways to obtain the same result, but only one or few of them result in the ideal outcome.

(2) Multiple outcomes: Task complexity increases when there are multiple outcomes that require more information processing involved in the task.

(3) Conflicting interdependence: Task complexity increases when achieving one outcome conflicts with achieving another.

(4) Uncertain or probabilistic linkages: Task complexity increases when there is uncertainty of selecting links from a large pool of potential paths to reach a desirable outcome.

Specifically, for the complex task, subjects had two requirements that the simple task does not have: total budget for the trip was $80 and total time for the trip could only be a maximum of 7 hours and 30 minutes. Furthermore, when working on the task, subjects needed to select one of two cars to take the trip and decide which one is the best for the trip. These two cars were different in terms of speed and fuel efficiency. The first car could complete the trip in 80% of the time reported by the mapping application used by the subjects (e.g., if driving to the destination normally requires one hour, then this car would require only 48 minutes of driving time). However, the first car required 120% more gas (in terms of cost) than the average car (e.g., if normal cost of gas is 10 dollars for the trip, then this car requires 12 dollars). The second car can complete the trip in 120% of the time reported by the mapping application but requires only 80% of the gas (in terms of cost) than the average car.

Driving each of the two cars could lead to different results but only the second car
could get the desirable outcome (i.e., spend less than $80 budget and 7 hours and 30 minutes for the trip). The result of calculation is shown in Appendix E. Subjects in the complex task needed to find the right car for the trip. Additionally, in the complex task, subjects needed to find a restaurant that gets a 4.5 review score and had more than 120 reviewers, which added some extra effort to the task.

It is important to note that I conducted pilot studies to adjust the manipulations based on their results to arrive at a correct and appropriate task complexity design. Observation and interviews of student subjects were used to understand whether subjects found the task engaging and were motivated to perform well. The goal of these pilot studies was to ensure that the simple and complex tasks were equivalent, but with differences only in their levels of complexity.

**Flexibility Manipulation**

Hammock and Brehm (1966) suggested that to create reactance, subjects should first be shown a number of alternatives and then have their freedom of choice constrained by making some of these alternatives unavailable to them. Following their suggestion, the subjects in this study were first shown all devices (i.e., an iPod touch, a Kindle Fire, and a desktop computer) on a table and participated in a 15-minute training session to familiarize themselves with all three devices. In the high flexibility of multi-device use condition, they were told that they could freely access any of these devices for completing any part of the task. In the non-flexibility of multi-device use condition, they could see these three devices on the table but they were forced to use the specific devices I had chosen for them to complete each part of the task.

Study 3 used the results from Study 2 regarding which device(s) had the best fit
with each subtask (pp. 62). I used these results in the non-flexibility of multi-device use condition to force subjects to use device(s) that were not optimal for completing each part of the task.

**Experimental Procedure**

Written consent of each participant was sought upon arrival at the lab. Each participant was randomly assigned to each condition. In all conditions, an iPod Touch, Kindle Fire and desktop computer were placed on a table where subjects could easily access them.

Upon commencement of the experiment, a 15-minute training session was held to orient the participants on how to use the three devices in all conditions. The training was the same as that of Study 1. After the training session, they were asked to use the desktop to visit a website on which they were told to work on a trip-planning task.

Subjects in the flexibility of multi-device use condition (i.e., condition 1 and 2) were told to freely allocate the devices in front of them to any part of the task. Subjects in the non-flexibility of multi-device use condition (i.e., condition 3 and 4) were told to use the specific devices that the task website instructed them to use. Video recording of each subject was used to ensure that subjects used the correct devices. In the event that a subject did not follow the instructions (i.e., used the wrong device), the data was discarded. The subjects were also randomly assigned to either the simple or complex task condition. The different conditions were conducted separately in different sessions to avoid possible contaminant effects. In other words, subjects in the condition where they were forced to use specific devices could not see other subjects who were free to use devices as they wished. An online post-task questionnaire was provided immediately
after the completion of the task.

Measurement

The questionnaire was designed to measure a wide range of demographic factors, affective appraisal, cognitive appraisal, satisfaction with multi-device use and continuance intention of multi-device use. In addition, it recorded the number of devices owned by each subject, and the frequency of use for each owned device.

The scale for satisfaction with multi-device use was adapted from work by Bhattacherjee’s (2001) and the scales for affective and cognitive appraisals were adapted from by Van der Heijden (2004) and Lee et al., (2012), respectively The scale for continuance intention of multi-device use was adapted from Bhattacherjee’s (2001). To conduct a manipulation check for Study 3’s manipulated variables (i.e., flexibility of multi-device use and task complexity), I measured flexibility of multi-device use and task complexity. The scale for flexibility of multi-device use was adapted from Goodhue (1998) and that for perceived task complexity was adapted from Maynard and Hakel (1997) (see Appendix F).

Data Analysis

A total of 204 subjects took part in the experiment. I removed 4 data points that had either significantly incomplete responses or were extreme outliers, resulting in a sample size of 200. The sample demographics were as follows: 56.5% were male and 43.5% female. 68% were 22 years old or younger.

Measurement Model

A principal components analysis using oblimin rotation was conducted to test individual item reliability as I expected the factors to be correlated. The results show that all items’ loadings are higher than the recommended value of 0.70 (Comrey 1973) and all
of the measurement items loaded heavily on their respective factors, confirming convergent validity (see Table 3.2).

### Table 3.2 Study 3.1: Factor Analysis for the Measurement Model

<table>
<thead>
<tr>
<th>Component</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cogn_App1</td>
<td>0.797</td>
<td>-0.365</td>
<td>0.11</td>
<td>-0.332</td>
<td>0.367</td>
<td>-0.473</td>
</tr>
<tr>
<td>Cogn_App2</td>
<td>0.877</td>
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<td>0.172</td>
<td>-0.367</td>
<td>0.312</td>
<td>-0.437</td>
</tr>
<tr>
<td>Cogn_App3</td>
<td>0.874</td>
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<td>0.114</td>
<td>-0.285</td>
<td>0.307</td>
<td>-0.42</td>
</tr>
<tr>
<td>Cogn_App4</td>
<td>0.83</td>
<td>-0.377</td>
<td>0.066</td>
<td>-0.246</td>
<td>0.451</td>
<td>-0.272</td>
</tr>
<tr>
<td>Affect_App1</td>
<td>0.003</td>
<td>0.893</td>
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<td>-0.021</td>
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<tr>
<td>Affect_App2</td>
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<td>-0.298</td>
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<tr>
<td>Affect_App3</td>
<td>0.22</td>
<td>0.901</td>
<td>0.056</td>
<td>-0.137</td>
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<tr>
<td>Satisfaction1</td>
<td>0.396</td>
<td>-0.327</td>
<td>0.923</td>
<td>-0.066</td>
<td>0.274</td>
<td>-0.218</td>
</tr>
<tr>
<td>Satisfaction2</td>
<td>0.348</td>
<td>-0.32</td>
<td>0.911</td>
<td>-0.107</td>
<td>0.201</td>
<td>-0.245</td>
</tr>
<tr>
<td>Satisfaction3</td>
<td>0.377</td>
<td>-0.391</td>
<td>0.912</td>
<td>-0.129</td>
<td>0.232</td>
<td>-0.246</td>
</tr>
<tr>
<td>Intention1</td>
<td>0.396</td>
<td>-0.017</td>
<td>0.252</td>
<td>-0.882</td>
<td>0.267</td>
<td>-0.178</td>
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<tr>
<td>Intention2</td>
<td>0.383</td>
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<td>-0.911</td>
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<td>-0.195</td>
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<tr>
<td>Intention3</td>
<td>0.446</td>
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<td>Flexibility1</td>
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<td>0.078</td>
<td>-0.127</td>
<td>-0.164</td>
<td>0.864</td>
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</tr>
<tr>
<td>Flexibility2</td>
<td>-0.39</td>
<td>0.07</td>
<td>-0.106</td>
<td>-0.098</td>
<td>0.885</td>
<td>0.216</td>
</tr>
<tr>
<td>Flexibility3</td>
<td>-0.208</td>
<td>0.244</td>
<td>-0.076</td>
<td>-0.046</td>
<td>0.839</td>
<td>0.107</td>
</tr>
<tr>
<td>TComplex1</td>
<td>-0.198</td>
<td>-0.05</td>
<td>0.151</td>
<td>0.132</td>
<td>-0.289</td>
<td>0.875</td>
</tr>
<tr>
<td>TComplex2</td>
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<td>0.138</td>
<td>-0.021</td>
<td>0.178</td>
<td>-0.472</td>
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<tr>
<td>TComplex3</td>
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<td>0.203</td>
<td>-0.403</td>
<td>0.842</td>
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<tr>
<td>TComplex4</td>
<td>-0.313</td>
<td>0.059</td>
<td>0.064</td>
<td>0.082</td>
<td>-0.27</td>
<td>0.894</td>
</tr>
</tbody>
</table>

Cronbach’s alpha values are above 0.70 for all scales, which confirmed their reliability (Fornell et al. 1981). Internal consistency was assessed in a PLS model using composite reliability (CR). CR value for each construct is above 0.9, suggesting internal consistency (Fornell et al. 1981), and AVE values exceed 0.5, demonstrating that the latent variable has a high degree of reliability and that the variance captured by the construct was greater than the variance due to measurement error (Fornell et al. 1981).
Table 3.3 Means, Standard Deviation, AVE and Reliability

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>AVE</th>
<th>Composite Reliability</th>
<th>Cronbach’s Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cogn_App</td>
<td>5.365</td>
<td>1.316</td>
<td>0.7211</td>
<td>0.9117</td>
<td>0.8719</td>
</tr>
<tr>
<td>Affect_App</td>
<td>4.8033</td>
<td>1.176</td>
<td>0.7875</td>
<td>0.9173</td>
<td>0.8745</td>
</tr>
<tr>
<td>Satisfaction</td>
<td>5.983</td>
<td>1.339</td>
<td>0.8453</td>
<td>0.9425</td>
<td>0.9085</td>
</tr>
<tr>
<td>Intention</td>
<td>5.480</td>
<td>1.287</td>
<td>0.8062</td>
<td>0.9258</td>
<td>0.88</td>
</tr>
<tr>
<td>Flexibility</td>
<td>3.358</td>
<td>1.814</td>
<td>0.7351</td>
<td>0.8919</td>
<td>0.8297</td>
</tr>
<tr>
<td>TComplexity</td>
<td>3.187</td>
<td>1.404</td>
<td>0.6674</td>
<td>0.8874</td>
<td>0.8844</td>
</tr>
</tbody>
</table>

Furthermore, I assessed discriminant validity by checking whether the square roots of the AVE values are higher than the off-diagonal elements in the corresponding rows and columns. The results of discriminant validity indicate that all constructs in the proposed model are adequate (see Table 3.4).

Table 3.4 Study 3.1: AVE and Correlations of Constructs

<table>
<thead>
<tr>
<th></th>
<th>Cogn_App</th>
<th>Affect_App</th>
<th>Satisfaction</th>
<th>Intention</th>
<th>Flexibility</th>
<th>TComplexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cogn_App</td>
<td>0.849</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affect_App</td>
<td>.155*</td>
<td>0.887</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satisfaction</td>
<td>.437**</td>
<td>.274**</td>
<td></td>
<td>0.919</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intention</td>
<td>.491**</td>
<td>.252**</td>
<td>.273**</td>
<td>0.897</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flexibility</td>
<td>-0.394**</td>
<td>-0.132</td>
<td>-0.13</td>
<td>-0.242**</td>
<td>0.857</td>
<td></td>
</tr>
<tr>
<td>TComplexity</td>
<td>-0.423**</td>
<td>0.076</td>
<td>-0.427**</td>
<td>-0.092</td>
<td>0.180*</td>
<td>0.816</td>
</tr>
</tbody>
</table>

Note 1: Diagonal values in the table are the square root of the average variance extracted. For adequate discriminant validity, diagonal elements should be greater than corresponding off-diagonal values.
Note 2: ***p<0.01  **p<0.05  *<0.1

Common Method Bias

Two methods were used to assess for common method bias given that variables (attitudes toward, satisfaction with, and continuing intention toward multi-device use) included in the research model were measured using self-reported items. First, Harman’s single factor test was conducted. I loaded all the items into an exploratory factor analysis with the unrotated solution. The results show that no a single factor accounted for more than 50% of the total variance, suggesting that common method bias was not high (Podsakoff et al. 2003). Second, unmeasured latent factor methods suggested by
Podsakoff et al. (2003) and Williams et al. (2003) were conducted. Following Liang et al.’s (2007) procedure for using partial least squares (PLS) to assess common method bias (Liang et al. 2007), I converted each indicator of interest into a single-indicator construct and added a latent method factor to the structural model. The test results indicated that the significance of all relationships in the nomological network was unchanged, suggesting that common method bias was not present.

**Manipulation Check**

A manipulation check for flexibility of multi-device use and task complexity was conducted. The results show that the manipulations of the flexibility of multi-device use and task complexity were effective. Participants perceived the non-flexibility of multi-device use as more restricted (M = 4.65) than the flexibility condition (M = 2.01; F(1, 197) = 73.244, p < 0.01), and they perceived the simple task as easier (M = 2.701) than the complex task (M = 3.72; F(1, 197) = 7.331, p < 0.01).

**Structural Model**

To test the significance of experimental manipulations, I conducted PLS analysis using smartPLS (Ringle et al. 2014) with the bootstrapping resampling procedure (Chin 2000). I tested the moderating effect of task complexity by creating an interaction term between task complexity and flexibility of multi-device use and testing its relationship with affective appraisal and cognitive appraisal in smartPLS. I chose the PLS structural equation as the main statistical technique as it is a preferred method for testing theory in its early stages and requires a small sample size (Fornell et al. 1981).

I created two dummy variables (D1 and D2) for flexibility of multi-device use and task complexity, respectively. Specifically, D1 = 0 refers to flexibility of multi-device
use, whereas $D1 = 1$ refers to non-flexibility; $D2 = 0$ refers to a simple task, whereas $D2 = 1$ refers to a complex task. I then tested the coefficients for the relationships of $D1$ and $D2$ with cognitive and affective appraisals.

The results are shown in Figure 3.2. The coefficient between the flexibility of multi-device use and affective appraisal is positive and significant ($\beta = 0.148, p < 0.01$), as is the coefficient between the flexibility of multi-device use and cognitive appraisal ($\beta = 0.299, p < 0.001$), indicating support for H1 and H2. However, task complexity did not significantly moderate the relationship between flexibility of multi-device use and affective appraisal (H3) and cognitive appraisal (H4).

Affective and cognitive appraisals positively influence satisfaction with multi-device use, with values of 0.273 ($p < 0.01$) and 0.369 ($p < 0.01$), respectively. Finally, the nonsignificant coefficient of the relationship between satisfaction with multi-device use and continuing intention toward multi-device use indicates that satisfaction with multi-device use is not an antecedent of continuing intention toward multi-device use.

Figure 3.2 Results of PLS Analysis of Study 3.1
Testing Unobserved Heterogeneity in the Structural Model

Prior studies suggest that unobserved heterogeneity in the samples causes a validity thread for the structural model and the measurement model. Therefore, testing unobserved heterogeneity to identify validity threats is needed (Becker et al. 2013; Wedel et al. 2002). Unobserved heterogeneity is likely to exist in the samples when aggregating them at group level (i.e., combining the data of all conditions) (Wedel et al. 2002), leading to serious biases, such as spurious or suppressor effects (Becker et al. 2013), and generally to misinterpretation if there are significant differences in path coefficients across conditions. To address this issue, I tested whether there is a significant difference between coefficients across different conditions using PLS multigroup analysis (PLS-MGA), an analysis for comparing PLS model estimates across groups of data (Keil et al. 2000). Significant differences between coefficients across different conditions mean the existence of unobserved heterogeneity.

The results show that almost all (26 out of 30) path coefficients across conditions had insignificant differences, suggesting that the problem of heterogeneity should be minor (see Table 3.5). However, path coefficients on the relationship between affective appraisal and continuing intention toward multi-device use across condition 2 versus condition 4 and across condition 1 versus condition 2 indicated significant differences, with values of 0.043 ($p < 0.05$) and 0.014 ($p < 0.05$), respectively. Also, path coefficients on the relationship between cognitive appraisal and continuing intention toward multi-device use across condition 3 versus condition 4 and across condition 1 versus condition 3 indicated significant differences, with values of 0.015 ($p < 0.05$) and 0.02 ($p < 0.05$). Therefore, while both affective and cognitive appraisals positively influence continuing
intention toward multi-device use (i.e., H3 and H4), these relationships contain unobserved heterogeneity. Thus, these relationships were partially supported.

Table 3.5 Study 3.1: Results of PLS-MGA

<table>
<thead>
<tr>
<th>Relationship</th>
<th>Comparison (Conditions)</th>
<th>Coefficient Difference</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Affective Appraisals → Expected Satisfaction</strong></td>
<td>1 vs. 2</td>
<td>$0.073 - 0.318$</td>
<td>0.245</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>3 vs. 1</td>
<td>$0.334 - 0.073$</td>
<td>0.261</td>
<td>1.35</td>
</tr>
<tr>
<td></td>
<td>3 vs. 2</td>
<td>$0.334 - 0.318$</td>
<td>0.016</td>
<td>0.102</td>
</tr>
<tr>
<td></td>
<td>3 vs. 4</td>
<td>$0.334 - 0.244$</td>
<td>0.090</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>4 vs. 1</td>
<td>$0.235 - 0.085$</td>
<td>0.150</td>
<td>0.725</td>
</tr>
<tr>
<td></td>
<td>4 vs. 2</td>
<td>$0.235 - 0.318$</td>
<td>0.083</td>
<td>0.414</td>
</tr>
<tr>
<td><strong>Affective Appraisals → Continuance intention of Multi-Device Use</strong></td>
<td>1 vs. 2</td>
<td>$0.379 - (-0.103)$</td>
<td>0.482</td>
<td>2.495</td>
</tr>
<tr>
<td></td>
<td>3 vs. 1</td>
<td>$0.188 - 0.379$</td>
<td>0.191</td>
<td>1.038</td>
</tr>
<tr>
<td></td>
<td>3 vs. 2</td>
<td>$0.188 - (-0.103)$</td>
<td>0.291</td>
<td>1.322</td>
</tr>
<tr>
<td></td>
<td>3 vs. 4</td>
<td>$0.188 - 0.331$</td>
<td>0.143</td>
<td>0.718</td>
</tr>
<tr>
<td></td>
<td>4 vs. 1</td>
<td>$0.335 - 0.390$</td>
<td>0.054</td>
<td>0.315</td>
</tr>
<tr>
<td></td>
<td>4 vs. 2</td>
<td>$0.335 - (-0.103)$</td>
<td>0.438</td>
<td>2.047</td>
</tr>
<tr>
<td><strong>Cognitive Appraisals → Expected Satisfaction</strong></td>
<td>1 vs. 2</td>
<td>$0.435 - 0.307$</td>
<td>0.128</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>3 vs. 1</td>
<td>$0.539 - 0.435$</td>
<td>0.104</td>
<td>0.655</td>
</tr>
<tr>
<td></td>
<td>3 vs. 2</td>
<td>$0.539 - 0.307$</td>
<td>0.232</td>
<td>1.197</td>
</tr>
<tr>
<td></td>
<td>3 vs. 4</td>
<td>$0.539 - 0.465$</td>
<td>0.073</td>
<td>0.475</td>
</tr>
<tr>
<td></td>
<td>4 vs. 1</td>
<td>$0.473 - 0.447$</td>
<td>0.025</td>
<td>0.145</td>
</tr>
<tr>
<td></td>
<td>4 vs. 2</td>
<td>$0.473 - 0.307$</td>
<td>0.166</td>
<td>0.798</td>
</tr>
<tr>
<td><strong>Cognitive Appraisals → Continuance intention of Multi-Device Use</strong></td>
<td>1 vs. 2</td>
<td>$0.188 - 0.501$</td>
<td>0.313</td>
<td>1.127</td>
</tr>
<tr>
<td></td>
<td>3 vs. 1</td>
<td>$0.743 - 0.188$</td>
<td>0.555</td>
<td>2.356</td>
</tr>
<tr>
<td></td>
<td>3 vs. 2</td>
<td>$0.743 - 0.501$</td>
<td>0.242</td>
<td>1.182</td>
</tr>
<tr>
<td></td>
<td>3 vs. 4</td>
<td>$0.743 - 0.372$</td>
<td>0.371</td>
<td>2.486</td>
</tr>
<tr>
<td></td>
<td>4 vs. 1</td>
<td>$0.372 - 0.233$</td>
<td>0.140</td>
<td>0.567</td>
</tr>
<tr>
<td></td>
<td>4 vs. 2</td>
<td>$0.372 - 0.501$</td>
<td>0.129</td>
<td>0.612</td>
</tr>
<tr>
<td><strong>Expected Satisfaction → Continuance intention of Multi-Device Use</strong></td>
<td>1 vs. 2</td>
<td>$0.146 - 0.006$</td>
<td>0.140</td>
<td>0.491</td>
</tr>
<tr>
<td></td>
<td>3 vs. 1</td>
<td>$-0.186 - 0.146$</td>
<td>0.332</td>
<td>1.356</td>
</tr>
<tr>
<td></td>
<td>3 vs. 2</td>
<td>$-0.186 - 0.006$</td>
<td>0.192</td>
<td>0.681</td>
</tr>
<tr>
<td></td>
<td>3 vs. 4</td>
<td>$-0.186 - 0.041$</td>
<td>0.227</td>
<td>0.969</td>
</tr>
<tr>
<td></td>
<td>4 vs. 1</td>
<td>$0.036 - 0.123$</td>
<td>0.087</td>
<td>0.381</td>
</tr>
<tr>
<td></td>
<td>4 vs. 2</td>
<td>$0.036 - 0.006$</td>
<td>0.030</td>
<td>0.11</td>
</tr>
</tbody>
</table>

Note 1: please check Table 1 for corresponding conditions.
Note 2: ***p<0.01 **p<0.05 *p<0.1
**Study 3.2 Reducing the Impact of the Non-Flexibility of Multi-device Use on Users’ Attitudes toward Multi-Device Use**

On the basis of the significant findings from Study 3.1 showing a strong effect of the non-flexibility of multi-device use in negatively influencing affective and cognitive appraisals regardless of the level of task complexity, I attempt to investigate a way to alleviate its impact. This is important because, in some situations, the non-flexibility of multi-device use is unavoidable (e.g., due to a company’s policy for privacy and security reasons). Thus, the issue of how users can use assigned devices and at the same time not develop negative attitudes toward using them is critical.

From the perspective of TTF theory, I propose that when users lose freedom of choice in device use, the negative impact of the non-flexibility of multi-device use on users’ attitude toward multi-device use can be reduced by making them use devices with the best fit for the tasks. After all, using devices with the best fit for the task will result in positive attitudes toward device use (Dishaw et al. 1999; Staples et al. 2004). However, this positive impact cannot be assumed, because psychological reactance generates negative attitudes toward multi-device use, whereas using the devices with the best fit for the tasks generates positive attitudes toward multi-device use, resulting in a counteracting effect on attitudes. Therefore, I conducted Study 3.2 without hypothesizing about its results and compared the findings from Study 3.2 to those from Study 3.1.

Experimental design, task design, and experimental procedures for Study 3.2 are identical to those for Study 3.1. The only difference is that I manipulated the non-flexibility of multi-device use by assigning the devices with the best fit for the subtasks. The experimental design for Study 3.2 is shown below.
Table 3.6 Study 3.2: Experimental Design

<table>
<thead>
<tr>
<th></th>
<th>Simple Task</th>
<th>Complex Task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flexibility of multi-device use</td>
<td>1 (49)</td>
<td>2 (50)</td>
</tr>
<tr>
<td>Non-flexibility of multi-device use</td>
<td>3 (50)</td>
<td>4 (49)</td>
</tr>
</tbody>
</table>
with the best fit for the subtasks

Note: The table provides the condition number, with the number of subjects in parentheses.

Data Analysis

A total of 201 subjects took part in the experiment. This sample is different from the one used in study 3.1. I removed 3 data points that had significantly incomplete responses, resulting in a sample size of 198. The sample demographics were as follows: 52.1% were male and 47.9% female. 71% were 22 years old or younger.

Measurement Model

I followed the same procedure as in Study 3.1 to conduct factor analysis. The results show that all items’ loadings are higher than the recommended value of 0.70 (Comrey 1973) and that all of the measurement items loaded heavily on their respective factors, confirming convergent validity (see Table 3.7).

Following the same procedure as in Study 3.1, I assessed the construct reliability, convergent validity, and discriminant validity. The results show that the Cronbach’s alphas of all constructs, which were all greater than or equal to 0.848, indicated the high reliability of the items used for each construct. Each construct had an AVE greater than 0.6, exceeding the minimum threshold of 0.5 (Fornell and Larcker 1981). All measurement items loaded significantly on the designated construct ($p < 0.001$). All correlations between constructs were less than 0.7 and less than the square root value of the AVE, which is also in support of discriminant validity.
### Table 3.7 Study 3.2: Factor Analysis for the Measurement Model

<table>
<thead>
<tr>
<th>Component</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cogn_App1</td>
<td>0.723</td>
<td>-0.128</td>
<td>-0.002</td>
<td>-0.082</td>
<td>-0.028</td>
<td>0.091</td>
</tr>
<tr>
<td>Cogn_App2</td>
<td>0.875</td>
<td>0.069</td>
<td>0.068</td>
<td>-0.051</td>
<td>-0.01</td>
<td>0.023</td>
</tr>
<tr>
<td>Cogn_App3</td>
<td>0.838</td>
<td>-0.012</td>
<td>-0.005</td>
<td>0.035</td>
<td>-0.063</td>
<td>0.128</td>
</tr>
<tr>
<td>Cogn_App4</td>
<td>0.856</td>
<td>-0.043</td>
<td>-0.005</td>
<td>0.016</td>
<td>0.119</td>
<td>-0.102</td>
</tr>
<tr>
<td>Affect_App1</td>
<td>-0.027</td>
<td>0.943</td>
<td>0.002</td>
<td>0.072</td>
<td>-0.036</td>
<td>-0.015</td>
</tr>
<tr>
<td>Affect_App2</td>
<td>-0.026</td>
<td>0.87</td>
<td>-0.016</td>
<td>-0.045</td>
<td>0.004</td>
<td>0.08</td>
</tr>
<tr>
<td>Affect_App3</td>
<td>0.127</td>
<td>0.812</td>
<td>0.031</td>
<td>-0.059</td>
<td>0.131</td>
<td>-0.024</td>
</tr>
<tr>
<td>Satisfaction1</td>
<td>-0.01</td>
<td>-0.062</td>
<td>0.866</td>
<td>0.01</td>
<td>0.127</td>
<td>-0.01</td>
</tr>
<tr>
<td>Satisfaction2</td>
<td>0.024</td>
<td>0.028</td>
<td>0.919</td>
<td>-0.006</td>
<td>-0.122</td>
<td>0.067</td>
</tr>
<tr>
<td>Satisfaction3</td>
<td>0.011</td>
<td>-0.06</td>
<td>0.846</td>
<td>-0.037</td>
<td>0.132</td>
<td>0.008</td>
</tr>
<tr>
<td>Intention1</td>
<td>-0.004</td>
<td>-0.014</td>
<td>0.036</td>
<td>0.879</td>
<td>0.071</td>
<td>-0.026</td>
</tr>
<tr>
<td>Intention2</td>
<td>-0.024</td>
<td>-0.032</td>
<td>-0.014</td>
<td>0.937</td>
<td>0.051</td>
<td>0.042</td>
</tr>
<tr>
<td>Intention3</td>
<td>0.103</td>
<td>0.042</td>
<td>0.02</td>
<td>0.851</td>
<td>-0.067</td>
<td>-0.058</td>
</tr>
<tr>
<td>Flexibility1</td>
<td>-0.065</td>
<td>-0.029</td>
<td>0.029</td>
<td>-0.054</td>
<td>0.832</td>
<td>-0.039</td>
</tr>
<tr>
<td>Flexibility2</td>
<td>-0.05</td>
<td>-0.073</td>
<td>0.038</td>
<td>-0.05</td>
<td>0.908</td>
<td>0.034</td>
</tr>
<tr>
<td>Flexibility3</td>
<td>0.088</td>
<td>0.122</td>
<td>-0.068</td>
<td>0.087</td>
<td>0.862</td>
<td>-0.023</td>
</tr>
<tr>
<td>TComplex1</td>
<td>0.071</td>
<td>0.079</td>
<td>0.011</td>
<td>0.05</td>
<td>-0.072</td>
<td>0.868</td>
</tr>
<tr>
<td>TComplex2</td>
<td>-0.189</td>
<td>0.041</td>
<td>-0.035</td>
<td>0.008</td>
<td>-0.014</td>
<td>0.766</td>
</tr>
<tr>
<td>TComplex3</td>
<td>-0.032</td>
<td>-0.039</td>
<td>0.085</td>
<td>-0.01</td>
<td>-0.109</td>
<td>0.827</td>
</tr>
<tr>
<td>TComplex4</td>
<td>0.025</td>
<td>-0.091</td>
<td>-0.047</td>
<td>-0.011</td>
<td>0.101</td>
<td>0.877</td>
</tr>
</tbody>
</table>

### Table 3.8 Study 3.2: Means, Standard Deviation, AVE and Reliability

<table>
<thead>
<tr>
<th>Component</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>AVE</th>
<th>Composite Reliability</th>
<th>Cronbach’s Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cogn_App</td>
<td>5.516</td>
<td>1.260</td>
<td>0.7372</td>
<td>0.918</td>
<td>0.8814</td>
</tr>
<tr>
<td>Affect_App</td>
<td>5.026</td>
<td>1.208</td>
<td>0.7978</td>
<td>0.922</td>
<td>0.8756</td>
</tr>
<tr>
<td>Satisfaction</td>
<td>5.843</td>
<td>1.366</td>
<td>0.835</td>
<td>0.9382</td>
<td>0.901</td>
</tr>
<tr>
<td>Intention</td>
<td>5.494</td>
<td>1.365</td>
<td>0.8359</td>
<td>0.9386</td>
<td>0.9021</td>
</tr>
<tr>
<td>Flexibility</td>
<td>3.170</td>
<td>1.726</td>
<td>0.767</td>
<td>0.908</td>
<td>0.8487</td>
</tr>
<tr>
<td>TComplexity</td>
<td>3.359</td>
<td>1.360</td>
<td>0.7269</td>
<td>0.9141</td>
<td>0.8792</td>
</tr>
</tbody>
</table>
Table 3.9 Study 3.2: AVE and Correlations of Constructs

<table>
<thead>
<tr>
<th></th>
<th>Cogn_App</th>
<th>Affect_App</th>
<th>Satisfaction</th>
<th>Intention</th>
<th>Flexibility</th>
<th>TComplexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cogn_App</td>
<td>0.893</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affect_App</td>
<td>0.320**</td>
<td>0.859</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satisfaction</td>
<td>0.387**</td>
<td>0.392**</td>
<td>0.914</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intention</td>
<td>0.318**</td>
<td>0.553**</td>
<td>0.234**</td>
<td>0.914</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flexibility</td>
<td>-0.189**</td>
<td>-0.402**</td>
<td>-0.242**</td>
<td>-0.331**</td>
<td>0.876</td>
<td></td>
</tr>
<tr>
<td>TComplexity a</td>
<td>-0.148*</td>
<td>-0.383**</td>
<td>-0.398**</td>
<td>-0.224**</td>
<td>0.294**</td>
<td>0.853</td>
</tr>
</tbody>
</table>

Note 1: Diagonal values in the table are the square root of the average variance extracted. For adequate discriminant validity, diagonal elements should be greater than corresponding off-diagonal values.

Note 2: ***p<0.01  **p<0.05  *p<0.1

**Manipulation Check**

The results of the manipulation check show that the manipulations of the flexibility of multi-device use and task complexity were successful. Participants perceived the non-flexibility of multi-device condition as more restricted (M = 4.32) than the high flexibility condition (M = 2.05; F(1, 195) = 52.942, p < 0.01), and they perceived the simple task as easier (M = 2.81) than the complex task (M = 3.85; F(1, 195) = 11.940, p < 0.01).

**Structural Model**

PLS was conducted to test the research model. The results are shown in Figure 3.3. Most of these results are the same as for Study 3.1 (see Tablet 3.11): hypotheses 2, 5, 6, 7, and 8 were either supported or partially supported (due to significant differences in the unobserved heterogeneity tests) in both studies. Specifically, the flexibility of multi-device use significantly and positively impacts cognitive appraisal (H2), with the value of 0.158 (p < 0.01). Moreover, affective appraisals positively influence satisfaction with multi-device use (H5) and continuance intention of multi-device use (H6), with values of 0.305 (p<0.01) and 0.170 (p<0.01), respectively. On the other hands, cognitive appraisals positively influence both satisfaction with multi-device use (H7) and continuance
intention of multi-device use (H8), with values of 0.296 (p<0.01) and 0.579 (p<0.01). Additionally, consistent with Study 3.1’s findings, satisfaction with multi-device use was not significantly associated with continuance intention of multi-device use.

However, the findings of Study 3.2 have some dissimilarities. First, hypothesis 1 was not supported. The nonsignificant coefficient of the relationships between flexibility of multi-device use and affective appraisals indicates that different levels of flexibility of multi-device use did not impact affective appraisals (H1). Second, unlike Study 3.1 findings, task complexity in Study 3.2 positively moderates the relationships between flexibility of multi-device use and affective appraisals (H3), and the relationships between flexibility of multi-device use and cognitive appraisals (H4), with the values of 0.146 (p < 0.05) and 0.126 (p < 0.05).

![Figure 3.3 Results of PLS Analysis of Study 3.2](image)

**Testing Unobserved Heterogeneity in the Structural Model**

The results show that most path coefficients across conditions had insignificant
differences (see Table 3.10). However, path coefficients on relationship between affective appraisal and expected satisfaction across condition 1 versus condition 3 indicated significant differences, with values of 0.0048 (p<0.01). Also, path coefficients on relationship between affective appraisal and continuance intention of multi-device use across condition 1 versus condition 2 indicated significant differences, with values of 0.014 (p<0.05). Therefore, hypotheses 5 and 8 were partially supported due to the existence of unobserved heterogeneity.

<table>
<thead>
<tr>
<th>Relationship</th>
<th>Comparison (Conditions)</th>
<th>Coefficient Difference</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affective Appraisals → Satisfaction with Multi-Device Use</td>
<td>1 vs. 2</td>
<td>0.073 – 0.318 = 0.245</td>
<td>0.61</td>
<td>0.543</td>
</tr>
<tr>
<td>Affective Appraisals → Continuance intention of Multi-Device Use</td>
<td>1 vs. 2</td>
<td>0.379 – (-0.103) = 0.482</td>
<td>2.495</td>
<td>0.014*</td>
</tr>
<tr>
<td>Cognitive Appraisals → Expected Satisfaction</td>
<td>1 vs. 2</td>
<td>0.435 – 0.307 = 0.128</td>
<td>0.61</td>
<td>0.543</td>
</tr>
<tr>
<td>Cognitive Appraisals → Continuance intention of Multi-Device Use</td>
<td>1 vs. 2</td>
<td>0.188 – 0.501 = 0.313</td>
<td>1.127</td>
<td>0.262</td>
</tr>
</tbody>
</table>
I summarize the results of Study 3.1 and 3.2 below.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Study 3.1</th>
<th>Study 3.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Positive cognitive appraisal of multi-device use will be higher for users with flexibility of multi-device use than for users with non-flexibility.</td>
<td>Supported</td>
<td>Not Supported</td>
</tr>
<tr>
<td>H2: Positive cognitive appraisal of multi-device use will be higher for users with flexibility of multi-device use than for users with non-flexibility.</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H3: Task complexity positively moderates the positive relationship between the flexibility of multi-device use and positive affective appraisal with device use.</td>
<td>Not Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H4: Task complexity positively moderates the positive relationship between the flexibility of multi-device use and positive cognitive appraisal with device use.</td>
<td>Not Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H5: The more favorable the affective appraisal, the higher the satisfaction with multi-device use.</td>
<td>Supported</td>
<td>Partially Supported</td>
</tr>
<tr>
<td>H6: The more favorable the cognitive appraisal, the higher the satisfaction with multi-device use.</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H7: The more favorable the affective appraisal, the higher the continuance intention of multi-device use.</td>
<td>Partially Supported</td>
<td>Partially Supported</td>
</tr>
<tr>
<td>H8: The more favorable the cognitive appraisal, the higher the continuance intention of multi-device use.</td>
<td>Partially Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H9: Satisfaction with multi-device use will be positively related to continuance intention of multi-device use</td>
<td>Not Supported</td>
<td>Not Supported</td>
</tr>
</tbody>
</table>

Discussion

Building on psychological reactance theory and TTF theory, I extend the investigation into how the flexibility of multi-device use interact with task complexity to influence users’ attitudes toward multi-device use, including affective and cognitive appraisals, which in turn affect users’ satisfaction with multi-device use and continued
intention toward multi-device use. Two experimental studies (Study 3.1 and 3.2) were conducted, and the results of the studies have both theoretical and practical implications.

**Contributions to Theory**

Study 3’s two-part study makes several important contributions to theory. First, although many previous studies have analyzed and modeled the relationships between user choice and technology/system use (Kwon et al. 2010; Lee et al. 2009a; Murray et al. 2011), research on users’ choice between multiple devices used to complete a single task is sparse. Also, prior empirical investigations on the attitude–intention link have tended to focus on single-device use (Bhattacharjee et al. 2004; Davis 1989), leaving the attitude–intention link with multi-device use unexplored. Addressing this gap, Study 3 is among the first in IS research to explore the effects of flexibility of multi-device use on users’ attitudes and intentions toward device use. Utilizing controlled experiments, I demonstrate that the flexibility of multi-device use positively influences affective and cognitive appraisals, both of which in turn affect users’ satisfaction with multi-device use and continued intentions toward multi-device use.

Second, Study 3 confirms the existence of psychological reactance in the context of flexibility of multi-device use. It is a topic that I believe deserves additional attention, because devices (i.e., laptops, tablets, and smartphones) have many similar or overlapping functions, meaning that loss of freedom of choice may not necessarily mean that the user loses a specific function (Levin 2014). Given that the functions are still available to users, psychological reactance caused by loss of freedom of choice could be non-existent or minor in multi-device use conditions. However, the results of Study 3.1 and 3.2 reveal that psychological reactance still exists and that it negatively influences
cognitive and affective appraisals when users’ freedom of choice among devices has been threatened or eliminated, particularly when tasks are complex, supporting and showing the robustness of this theory in the context of Study 3.

Third, Study 3 contributes to the literature stream centered on TTF theory, which posits that when users use devices based on the fit between the characteristics or functions of the devices and the tasks at hand, they may have higher perceived cognitive appraisals owing to a possible improvement in overall task performance (Goodhue 1998; Goodhue et al. 1995). Although this relationship has proven to be very robust across multiple studies (Dishaw et al. 1999; Hsin 2010; Lee et al. 2007; Lin et al. 2008), Study 3 shows that this is not always the case. Specifically, Study 3’s findings suggest that if users’ freedom of choice among devices has been limited, even when using the device with the best fit for the task, they still have low perceived cognitive appraisals. In other words, the degree of freedom of choice plays a key role in determining this relationship; that is, being free to use the device with the best fit for a task raises users’ cognitive appraisal, whereas being assigned to use the device with the best fit for the task does not. Therefore, using the device with the best fit for the task alone may not necessarily form positive cognitive appraisals. The degree of freedom of choice needs to be taken into account. However, I understand that the results are specific to the context of multi-device use and I welcome new research that examines this phenomenon in other contexts.

Fourth, Study 3’s results on the role of satisfaction with multi-device use were less conclusive as satisfaction did not positively influence continued intention toward multi-device use in both Studies 3.1 and 3.2. This result is surprising given that prior literature had found a strong relationship between them (Bhattacherjee 2001a;
Bhattacherjee 2001b). One possible reason for this result is that there are different combinations of multi-device use. Although users were satisfied with one combination of device use, they may not continue to use the same combination next time because they might think that other combinations may lead to better satisfaction. The second possible reason is that the three devices provided in the experiments are not participants’ devices. Owing to their lack of ownership, the participants’ continuance intentions might be influenced. Another possible reason is that though users are satisfied with multi-device use, it does not mean that they are dissatisfied with single device use. If they have to deal with the same task, they can use a single device instead, with no need to continue to use multiple devices. Given that these are just speculations, the reason for the insignificant relationship between satisfaction with multi-device use and continued intention toward multi-device use remains an open question and requires further investigation.

Furthermore, prior research based on psychological reactance theory has generally focused on the consequences of loss of freedom of choice (Burke 2002; Peterson et al. 1997; Suh and Lee 2005). For example, Murray and Häubl (2011) discovered that when users are constrained to using a single website interface to complete a task, their preference for it decreases, suggesting that freedom of choice is a critical determinant of interface preference. However, there has been less attention paid to how to counteract the negative impact of psychological reactance on users’ attitudes. Study 3 goes a step beyond previous research by focusing on this gap and by considering both psychological reactance theory and TTF theory together. This consideration is important as it helps us explain how to reduce the negative consequences caused by psychological reactance. Specifically, the findings provide new insights into both psychological reactance theory
and TTF theory by demonstrating the occurrence of the counteracting effect under a certain condition—forcing users to use the devices with the best fit for dealing with a simple task forms positive affective appraisals, resulting in a reduction in the detrimental effects of psychological reactance. Nevertheless, it is important to note that I do not find the existence of counteracting effects under complex task conditions. Also, assigning the devices with the best fit for tasks cannot lessen negative cognitive appraisals caused by psychological reactance.

Moreover, Study 3 contributes to the literature stream centered on task complexity. There is a wealth of research in IS on the role of task complexity in user–computer/system interaction (e.g., Speier et al., 2003; Adipat et al., 2011; Jiang et al., 2007). Typically, these studies used task complexity as a moderator that influenced different outcomes, such as decision-making performance (Speier et al. 2003a), device use performance (Adipat et al. 2011) or user perceptions (Adipat et al. 2011; Jiang et al. 2007). However, attitudes in this stream have received relatively little attention. Study 3 fills this research gap. More importantly, this research goes one step further and enriches our understanding of task complexity by revealing not only whether task complexity can influence users’ attitudes toward multi-device use but also when. Specifically, the results of Study 3 reveal that task complexity significantly influences users’ attitudes toward multi-device use when users are forced to use the device with the best fit. However, task complexity does not significantly impact users’ attitudes toward multi-device use when users are forced to use the device with the worse fit. In other words, forcing users to use devices with the best or worse fit determines when the impacts of task complexity on users’ attitudes toward multi-device use become salient.
Finally, there is a significant research stream on the importance of perceived control (or perceived behavior control) in motivating people to use a system or a device. (Ajzen et al. 1986; Hsieh et al. 2008; Pavlou et al. 2006). Those studies have typically used the theory of planned behavior and have suggested that if people can decide at will to utilize a system or device, they will have high perceived control, which would result in the people forming positive attitudes toward the system or device use and increase their intentions to use it (Ajzen et al. 1986). Study 3 contributes to this research stream as flexibility of multi-device use in Study 3 includes both high flexibility (i.e., high perceived control) and non-flexibility (i.e., no perceived control). The results show that, consistent with prior studies’ findings, high perceived control (i.e., high flexibility of multi-device use) leads to positive attitudes toward multi-device use and in turn increases intention to use multiple devices. However, interestingly, inconsistent with prior studies’ findings, the results of Study 3.2 indicate that even when users do not have perceived control (i.e., under the non-flexibility condition), they still have high positive affective appraisals with multi-device use if they have been assigned to the devices with the best fit. In other words, contrary to our understanding, the negative impact of no perceived control on people’s affective appraisals may not necessarily exist. This finding is critical because prior research has revealed that high perceived control may lead to negative consequences such as illusion of control, overconfidence, and risky behavior (Chen and Koufaris, 2014; Langer, 1975). In other words, sometimes reducing the perceived control is needed to avoid these negative consequences. The result therefore has taken a step in the direction of how to maintain positive affective appraisals even when users have no perceived control.
Implications for Practice

From a practical viewpoint, Study 3 highlights some important issues that should be of concern to institutions, such as governments, companies, hospitals, and universities, that allow their employees or students to bring their devices to the workplace or classroom and use those devices to perform a variety of tasks (Shim et al. 2013). Specifically, when individuals can bring multiple devices to the workplace or classroom, flexibility in multi-device use takes place. Under this situation, administrators in institutions should let their employees or students use any device they want because, as Study 3’s results have shown, high flexibility of multi-device use increases their affective and cognitive appraisals, particularly when tasks are complex.

However, if administrators need to constrain their employees or students to use certain devices for a specific task (i.e., non-flexibility), probably because of security and privacy issues (Shim et al. 2013; Singh 2012), or classroom management (Hockly 2012), on the basis of Study 3’s results, I would advise institutions to be careful of the potential negative impact of non-flexibility of multi-device use on affective and cognitive appraisals and also to find a way to reduce this impact. One way to improve affective appraisals under conditions of non-flexibility of multi-device use, as Study 3’s results have shown, is to make sure that users are assigned to use the devices with the best fit for the tasks at hand. Hence, institutions need to determine the potential good fit between devices and subtasks beforehand to assign the optimal devices. The way to improve cognitive appraisals may be to educate employees or students how to use multiple devices effectively and efficiently so that they believe that multi-device use is useful even when they are forced to use devices.
Finally, Study 3’s findings indicate that satisfaction with multi-device use is not associated with continued intention toward multi-device use. On the basis of these findings, I would advise institutions to be aware that focusing on satisfaction with multi-device use may not necessarily trigger users’ continued intention toward multi-device use. Therefore, if their goal is to achieve continued intention toward multi-device use, increasing cognitive and affective appraisals is key.

**Limitations**

The results of this study have to be interpreted within the context of some limitations. First, the participants in this study were students who may not precisely represent the population of other users. However, since an increasing number of student not only owns multiple devices and but also bring them to school to deal with different tasks (Afreen 2014), the use of students as subjects should be for an initial endeavor in understanding the effects of flexibility of multi-device use on users’ attitudes. I encourage further research to focus on different settings such as hospitals and compare the findings with Study 3’s.

Second, experimental studies, by their very nature, are subject to several threats to external validity. Though this study tried to make the task realistic (e.g., using the official website providing opening hours and admission fees of the destination), I controlled many factors, which may scarify the external validity because the environment and the procedure are not the same as under real-world conditions. For example, subjects cannot use their own and familiar devices to complete the task. While I provided the training and made sure that users do know how to use provided devices, users might behave differently when using their own devices. Additionally, they also need to complete the
task in the same place within a short period of time, which is somehow different from a real setting. Therefore, although this study has an advantage of greater internal validity, further research can conduct the model in a field to enhance the external validity of the findings.

Finally, different tasks need to be tested. I used a trip-planning task because I focus on individual users rather than on organization users. Further studies are encouraged to examine other tasks, such as work-related tasks and shopping-related tasks, and to compare and validate the results of this study. While this limitation exists, the task used in this study is adequate for an initial endeavor in understanding of the impact of flexibility of multi-device use on users’ attitudes toward multi-device use. Hopefully, Study 3’s findings can pave the way for additional studies to further investigate into multi-device use.
Dissertation Conclusion

Given the widespread use of multiple devices in performing tasks and our limited knowledge of multi-device use, the present work addresses a theoretically and practically important gap in our understanding of this phenomenon. This dissertation focuses on antecedents (Study 1), performance outcomes (Study 2) and psychological processes (Study 3) of multi-device use. Drawing on TTF theory and the concept of mental workload, and with a focus on what happens both before and after multi-device use, the first and the second studies presented in this dissertation provide a systematic approach to examining the motivations behind multi-device use and the impact of multi-device use on task performance. The results of Study 1 suggest that perceived task fit with multi-device use is a critical factor that triggers users’ intentions to use multiple devices. However, unfamiliarity with multi-device use increases the perceived complexity of multi-device use. Such complexity hinders users from perceiving good task fit with multi-device use. As for task performance, the results of Study 2 reveal that using the right devices (i.e., maximizing overall fit between devices and subtasks) and using the devices correctly (i.e., minimizing device-switching costs) are key to improving task performance. Furthermore, on the basis of TTF theory and psychological reactance theory, and utilizing controlled experiments, Study 3 demonstrates the existence of psychological reactance in the context of non-flexibility of multi-device use. However, forcing users to use the device with the best fit for dealing with a simple task forms positive affective appraisals, resulting in a reduction in the detrimental effects of psychological reactance.

The findings of the three complementary studies contribute several theoretical and
practical insights into multi-device use. In terms of theoretical contributions, this
dissertation builds a theoretical foundation for understanding what takes place before
multi-device use as well as after multi-device use. Specifically, Studies 1 and 2 consider
TTF theory and the concept of mental workload that together provide complementary
explanations of multi-device use. Thus, this consideration is theoretically meaningful,
helping us understand why people use multiple devices and explaining when multi-device
use can lead to better performance than single-device use. Study 3 takes both TTF theory
and psychological reactance theory into account. These two theories provide the
theoretical understanding of the counteracting effect on attitudes toward multi-device use
under different degrees of flexibility.

In terms of practical contributions, the findings provide a direction for those
companies that manufacture devices (e.g., Apple, Google, and Amazon) in designing
their multiple device strategies. For example, the results of Study 1 show that the
simplification of multi-device use (i.e., low perceived complexity of multi-device use) is
one reason why users want to use multiple devices. This finding suggests that companies
that manufacture these devices should design them in such a way so to let users easily use
multiple devices together so that they may choose to purchase and use these devices. The
findings of this dissertation also offer guidelines for those companies whose employees
regularly use multiple devices at work. For example, the findings of Study 2 suggest that
the concept of “using the right devices and using the devices correctly” is the key to
improving task performance with multi-device use. Thus, these companies need to
identify the best fit between a specific device and a certain task and then provide training
to enable their employees to understand this concept.
The results of this dissertation also inspire some ideas for future research. One research direction could be to focus on the use of more than three devices because it is likely that users will have more distinct devices in the near future than they have now. An interesting issue here is device overload, which refers to the difficulty an individual may have in understanding and handling a task due to the presence of too many similar but distinct devices available for use. Another issue for future research is that of the illusion of productivity. In this phenomenon, multi-device use may create an illusion in which users subjectively believe that their productivity increases as they have many devices to deal with different things, but in reality their productivity objectively decreases. The last issue on which further research can focus, is the synergistic use of multiple devices, which is based on the premise that the joint value of devices is greater than the sum of their individual values. Specifically, when users use their devices, all functionalities from these devices can be grouped together as modular in the sense that functionalities can be mixed and matched and configured, which allows more flexibility in their end configuration and makes device use more responsive to environmental changes. This can provide support for different ways of performing an activity and, more importantly, increase performance overall.

In summary, the topic of multi-device use contains several intriguing issues. I hope that this dissertation inspires future research on this emerging and important topic.
Appendix

Appendix A. Task

Suppose that your 10-day vacation begins tomorrow. You will be asked to select one out of the next 10 days to take a leisure trip. There is one destination that you wish to go to: The Yale Art Gallery. The questions below are designed to help you plan your trip. You must choose either a sunny or a cloudy day for your trip. You may not choose a rainy day unless the next 10 days are all rainy days. You will be free to use one or more of the three devices (iPod Touch, tablet, laptop) in front of you to answer these questions at this point.

For now, please, read these questions carefully. Once you read these questions, continue to answer the survey below the questions.

<table>
<thead>
<tr>
<th>The destination: the Yale University Art Gallery</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. <strong>Date:</strong> On which date would you take the leisure trip? (The date must fall within the next 10 days, starting tomorrow.)</td>
</tr>
<tr>
<td>2. <strong>Weather:</strong> What will the weather be at the destination on the date that you chose? (The date chosen must not be a rainy day unless the next 10 days are rainy.)</td>
</tr>
<tr>
<td>3. <strong>Driving Time (roundtrip):</strong> How much time would you take to drive by car from Baruch College to the destination and back?</td>
</tr>
<tr>
<td>4. <strong>Total miles (roundtrip):</strong> How many miles would you drive by car from Baruch College to the destination and back?</td>
</tr>
<tr>
<td>5. <strong>Cost of gas:</strong> Assuming that $5 worth of fuel can sustain 30 miles of driving, how much gas will you need (in dollars) for the total trip?</td>
</tr>
<tr>
<td>6. <strong>Toll fees:</strong> Assuming that average toll fees are $3 for every 20 miles, what would be the total toll fees for the total trip?</td>
</tr>
<tr>
<td>7. <strong>Attraction admission fees for one person:</strong> How much is the admission fee of the Yale Art Gallery on the date chosen?</td>
</tr>
<tr>
<td>8. <strong>Opening hours:</strong> What are the opening hours of the Yale Art Gallery on the date chosen?</td>
</tr>
<tr>
<td>9. <strong>Total cost for trip:</strong> Assuming that you will spend $29 on food, what would be the total cost for the trip? (Sum of gas, tolls, food, and admission fees.)</td>
</tr>
<tr>
<td>10. <strong>Total time for driving and staying at the destination:</strong> Assuming that you will stay at the Yale Art Gallery for 2.5 hours and a restaurant for 1 hour, what would be the total time that you will spend on the trip? (Total the time taken for the trip including driving hours and time spent at the Yale Art Gallery and the restaurant).</td>
</tr>
</tbody>
</table>
Appendix B. Study 1 Measures

All scales are measured with 7-point Likert scales from Strongly Disagree to Strongly Agree.

**Perceived Complexity of Multi-Device Use** (Thompson et al. 1991)

1. Using multiple devices (desktop, smartphone, tablet) takes too much time from my normal duties.
2. Working with multiple devices (desktop, smartphone, tablet) is so complicated, it is difficult to understand what is going on.
3. Using multiple devices (desktop, smartphone, tablet) involves too much time doing mechanical operations.
4. It takes too long to learn how to use multiple devices (desktop, smartphone, tablet) to make it worth the effort.

**Perceived Task Fit with Multi-Device Use** (Moore et al. 1991)

Using multiple devices, such as a desktop, a smartphone, and a tablet to complete this task...

1. … is compatible with all aspects of the task.
2. … is completely compatible with my current situation.
3. … fits well with the way I like to work.
4. … fits into my work style.

**Satisfaction with Multi-Device Use** (Bhattacherjee 2001b)

Please select a score for each pair of words that describe what you expect your experience will be if there are the desktop, the smartphone and the tablet available to you to complete the task, as opposed to only the desktop available to you:

1. Very dissatisfied ... Very satisfied.
2. Very displeased ... Very pleased.
3. Very frustrated ... Very contented.
4. Absolutely terrible ... Absolutely delighted.

**Perceived Task Complexity** (Maynard et al. 1997)

1. I find this task to be a complex task.
2. This task is mentally demanding.
3. This task requires a lot of thought and problem solving.
4. I find this task to be a challenging task.
**Attitude toward Multi-Device Use** (Bansal et al. 2005)

1. Using multiple IT devices (smartphone, tablet and/or desktop) to complete a task would be beneficial.
2. Using multiple IT devices (smartphone, tablet and/or desktop) to complete a task would be useful.
3. Using multiple IT devices (smartphone, tablet and/or desktop) to complete a task would be a good idea.
4. Using multiple IT devices (smartphone, tablet and/or desktop) to complete a task would be wise.
5. Using multiple IT devices (smartphone, tablet and/or desktop) to complete a task would be desirable.

**Intention to Multi-Device Use** (Bansal et al. 2005)

Please rate the probability that you will use multiple personal IT devices (desktop, smartphone, tablet) to accomplish the task:

1. Very Unlikely ... Very Likely
2. Improbable ... Probable
3. No Chance ... Certain

Please check one or more checkboxes to indicate which personal IT device(s) you will likely use to accomplish the task:

- [ ] Desktop Computer
- [ ] Smartphone
- [ ] Tablet

**Perceived Information Quality** (Wixom and Todd (2005))

1. I would give the information provided by iPod Touch, Kindle Fire and Desktop computer high marks.

2. I would give the information provided by iPod Touch, Kindle Fire and Desktop computer

3. In general, the iPod Touch, Kindle Fire and Desktop computer provides me with high-quality information.
Appendix C. Flowchart of Calculating Overall Fit between Devices and Subtasks

Step 1: Estimating task accuracy and task completion time for each device

- Creating three device use groups: iPod Touch, Kindle Fire and Desktop

Step 2: Performance Calculation

- Subjects are randomly assigned to one of device use groups

- Training

- Subjects in each group work on 10 subtasks using the assigned device

- Recording time and calculating accuracy once each subtask is

- Standardizing time and accuracy for each subtask

- Calculating the average performance of using each device for each subtask

- Using ANOVA analysis to assess which device(s) resulted in statistically better performance than others

Step 3: Optimal Device Determination

- Assigning points to subjects who use the optimal device(s) for each subtask

Step 4: The overall fit between devices and subtasks used by subjects

- Calculating the overall fit between devices and subtasks used by subjects
Stage 1: Estimating task accuracy and task completion time for each device

I conducted a pilot study in order to obtain a set of benchmarks on the fit between each device and each subtask. I separated subjects into three groups in terms of devices: smartphone, tablet, and desktop computer. The subjects in each group were able to use only one device assigned to them to perform the complete task (all ten subtasks). To avoid potential contamination effects, the pilot study for each group was conducted in a different session. In other words, subjects in the smartphone group were in the same room with only other subjects using smartphones. They were not able to see others using different devices and no other devices were made available to them.

The procedure of the training session is identical to that mentioned in Study 1 (pp.24). After the training session, subjects in all three groups were asked to go to a website using a desktop computer where they were shown each subtask separately (instead of all the subtasks shown on the same page). I do not show all subtasks on the same page because it is difficult to ascertain the time taken by each subject to answer each subtask while working on these subtasks together. Specifically, when showing all subtasks on the same page, it is likely that the subjects may read all or part of subtasks first and then decide to deal with each subtask. The problem is that reading the subtask is also the part of task completion time. As a result, if some subjects read three subtasks and other subjects read five subtasks and so on, it is not possible to know how much time each subject takes to reads and deal with the specific subtask. Thus, I decide to ask subtasks separately so that the task completion time including reading and answering a specific subtask can be correctly and accurately recorded. For each subtask, they used the
device assigned to them to answer it. Once they answered the subtask, they then clicked the “Next” button and the second subtask was shown to them. After each subtask was answered, their answer and the time that subjects took to complete the subtask were recorded.

**Stage 2: Calculating the average performance of using each device for each subtask**

To calculate the performance based on both time and accuracy, I first standardized time and accuracy, which I obtained from stage 1, by transforming them into 10 points for each subtask. This was necessary due to the different units of measure for time and accuracy (i.e., the unit of time was seconds, while the unit of accuracy was a percentage)

For completion time, in pilot tests conducted prior to this study, none of the subjects spent more than 5 minutes (300 seconds) using a device to answer a specific subtask. Therefore, in this study, I transformed completion time into points, using intervals of 30 seconds. Responses found in 0 second earned 10 points, those found in 1 to 30 seconds earned 9.0 to 9.9 points, those found in 31 to 60 seconds earned 8.0 to 8.9 points, and so on. For instance, if a user spent 45 seconds to complete a question, he or she was assigned 8.5 points. If a subject spent more than 300 seconds on a specific subtask, he or she was not assigned any points. As for accuracy, 10 points was assigned for 100% accuracy; 9 points for 90% accuracy; 8 points for 80% accuracy, and so forth.

Once the points for time and accuracy for each subtask were assigned, I calculated performance as the Euclidean distance in a two-dimensional space where task accuracy and task completion time are the two dimensions.

**Stage 3: Determining the optimal device(s) for each subtask**
After calculating the performance of each device for each subtask, I used ANOVA to assess which device resulted in statistically better performance than others. To be considered the optimal device for responding to a specific question, a device needed to perform significantly better than others on that subtask. If two devices performed similarly (i.e., no statistically significant difference), but were significantly better than a third device, those two devices were considered the best devices for responding to that subtask. If there was no significant difference between all devices, then all of those devices were considered equally suitable for responding to that subtask.

Stage 4: Calculating the overall fit between devices and subtasks used by subjects in the study.

The overall fit between the devices and subtasks used by the subjects in our study was then calculated by assigning one point for use of the optimal device(s) for a specific subtask and zero point otherwise. If they used the two or more devices that are all optimal devices to complete a certain task, they also can get one point. The more points each subject was given, the better the overall fit between devices and subtasks for that subject.

Appendix D. Complex Task

Suppose that your 10-day vacation begins tomorrow. You will be asked to select one out of the next 10 days to take a leisure trip. There is one destination that you wish to go to: The Yale Art Gallery. The questions below are designed to help you plan your trip. You must choose either a sunny or a cloudy day for your trip. You may not choose a rainy day unless the next 10 days are all rainy days. Additionally, there are two restrictions in your trip: (1) Your Budget is $120 (2) Your total time for the trip is 450 minutes.

There are two different cars below. There are different in terms of speed and fuel efficiency. There is one of the best car that can fulfill the restriction.
<table>
<thead>
<tr>
<th></th>
<th>Car 1</th>
<th>Car 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>Saving 0.8 time total driving time</td>
<td>Adding 1.2 times total driving time.</td>
</tr>
<tr>
<td>Fuel efficiency</td>
<td>Adding 1.2 times more total cost of gas.</td>
<td>Saving 0.8 times cost of gas.</td>
</tr>
</tbody>
</table>

You will be free to use one or more of the three devices (iPod Touch, tablet, laptop) in front of you to answer these questions at this point.

The destination: the Yale University Art Gallery

1. Date: On which date would you take the leisure trip? (The date must fall within the next 10 days, starting tomorrow.)
2. Weather: What will the weather be at the destination on the date that you chose? (The date chosen must not be a rainy day unless the next 10 days are rainy.)
3. Driving Time (roundtrip): How much time would you take to drive by car from Baruch College to the destination and back?
4. Total miles (roundtrip): How many miles would you drive by car from Baruch College to the destination and back?
5. Cost of gas: Assuming that $5 worth of fuel can sustain 30 miles of driving, how much gas will you need (in dollars) for the total trip?
6. Toll fees: Assuming that average toll fees are $3 for every 20 miles, what would be the total toll fees for the total trip?
7. Opening hours: What is the opening hour of the Yale Art Gallery on the date chosen?
8. Attraction admission fees for one person: How much is the admission fee (single and student) of the Yale Art Gallery on the date chosen?
9. Total cost for trip: Assuming that you will spend $29 on food, what would be the total cost for the trip? (Sum of gas, tolls, food, and admission fees.)
10. Total time for driving and staying at the destination: Assuming that you will stay at the Yale Art Gallery for 2.5 hours and the restaurant for 1 hour, what would be the total time that you will spend on the trip? (Total the time taken for the trip including driving hours and time spent at the Yale Art Gallery and the restaurant.)
Appendix E. The Calculation and Results of Study 3’s Complex Task

Driving Time (roundtrip): How much time would you take to drive by car from Baruch College to the destination and back?

The result is 2 hour and 59 minutes (round trip).
Thus, we can calculate the time that each car takes:

Car 1: 2 hour 59 minutes * 0.8 = 143.2
Car 2: 2 hour 50 minutes * 1.2 = 214.8

Cost of gas: Assuming that $5 worth of fuel can sustain 30 miles of driving, how much gas will you need (in dollars) for the total trip?

The total mile for the trip is 156 miles.
Thus, we can calculate the total cost for each car takes:

Car 1: (156/30)* 5 = 26 * 1.2= 31.2
Car 2: (156/30)* 5 = 26 * 0.8 = 20.8

Toll fees: Assuming that average toll fees are $3 for every 20 miles, what would be the total toll fees for the total trip?

The result is:
(156/20)*3 = 23.4

On the basis of above calculations, we can find the results of total costs and total time for the trip below:

<table>
<thead>
<tr>
<th>Total cost for the trip:</th>
<th>Car 1</th>
<th>Car 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost of gas</td>
<td>31.2</td>
<td>20.8</td>
</tr>
<tr>
<td>Toll fees</td>
<td>23.4</td>
<td>23.4</td>
</tr>
<tr>
<td>Food</td>
<td>29</td>
<td>29</td>
</tr>
<tr>
<td>Total</td>
<td>83.6</td>
<td>73.2</td>
</tr>
</tbody>
</table>
Total driving time:

<table>
<thead>
<tr>
<th></th>
<th>Car 1</th>
<th>Car 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Driving hours</td>
<td>2 hours and 23 minutes</td>
<td>3 hours and 34 minutes</td>
</tr>
<tr>
<td>Time at the Yale Art</td>
<td>2 hours and 30 minutes</td>
<td>2 hours and 30 minutes</td>
</tr>
<tr>
<td>Gallery</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Food</td>
<td>1 hour</td>
<td>1 hour</td>
</tr>
<tr>
<td>Total</td>
<td>5 hours and 46 minutes</td>
<td>7 hours and 04 minutes</td>
</tr>
</tbody>
</table>

Total costs for driving car 2 are lower than $80. Total driving times for car 1 and 2 are lower than 7 hours and 30 minutes. On the basis of these results, only car 2 can be used for the trip. Thus, car 2 is the correct answer.

**Appendix F. Study 3 Measures**

Have you ever been to the Yale Art Gallery? If so, when?

**Manipulation Check**

You just used the [name of devices] to complete the trip-planning task. Now, please indicate the level of your agreement with the following statement.

**Flexibility**

1. I lost the freedom of choice in device use to complete the task.
2. I cannot use the device that I want to complete the task.
3. I had limited control over the device selection.

**Task Complexity**

1. The task is a complex task.
2. The task is mentally demanding.
3. This task requires a lot of thoughts.
4. This task is a challenging task.

All scales above are seven-item scale.

**Affective Appraisals** (Van der Heijden, 2004)

Please select a score for each pair of words that describe your experience about using the [name of devices] provided to complete this task:

Dull. . .Exciting
Unpleasant . . . Pleasant
Unenjoyable… Enjoyable.

**Cognitive Appraisals** (Lee et al., 2012)

1. Using the [name of devices] provided was effective in achieving the task goal.
2. Using the [name of devices] provided was convenient in attaining the task goal.
3. I felt comfortable using the [name of devices] provided to achieve the task goal.
4. Using the [name of devices] provided was helpful in achieving the task goal.

All scales above are seven-item scale

**Satisfaction with multi-device use** (Bhattacherjee, 2001b)

Please select a score for each pair of words that describe your experience about using the [name of devices] provided to complete this task:

- Very dissatisfied ... Very satisfied.
- Very displeased ... Very pleased.
- Very frustrated ... Very contented.
- Very terrible ... Very delighted.

All scales above are seven-item scale

**Continuance Intention of multi-device Use** (Bhattacherjee, 2001b)

1. Given the devices (i.e., iPod touch, tablet and desktop) are available to use, I intend to continue using the [name of devices] that I used to perform the task rather than discontinue using it (them).
2. Given the devices (i.e., iPod touch, tablet and desktop) are available to use, my intentions are to continue using the [name of devices] that I used to perform the task than using alternative means.
3. Given the devices (i.e., iPod touch, tablet and desktop) are available to use, if I could, I would like to continue using the [name of devices] that I used to perform the task in the future.

All scales above are seven-item scale
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