

ONLINE CONSUMER MOTIVATION: TOWARDS AN UNDERSTANDING OF A
PRIORI MOTIVATIONS IN ECOMMERCE INTERACTIONS

By

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To the Faculty of Washington State University:

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ABSTRACT

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This dissertation is broken into three essays that focus on how *a priori* motivation can play an important role in ecommerce outcomes. The first essay theoretically develops the online consumer motivation construct. Online consumer motivation provides a clearing house for how a user's individual characteristics and the task at hand will influence perceptions of technology presentation. Further, it is proposed that by offering a Web site interface that is congruent with the user's online consumer motivation, Web site utilization and task performance will improve. In addition to the conceptual model, several propositions predict the interplay of key constructs. The paper concludes with a prescriptive protocol for testing the proposed theory as well as for guiding the design of ecommerce Web sites.

The second essay focuses on conceptualizing and developing an instrument for online consumer motivation. Specifically, this essay identifies the important extant literature in both psychology and an information system then can be extended to provide grounds for online consumer motivation. The second essay uses two laboratory experiments to validate the scales used to measure online consumer motivations.

The third and final essay uses Task-Technology Fit theory to posit a temporal view of online consumer motivation (i.e., why a user has chosen to visit a particular Web site at a given time) that can inform Web site design. This includes one laboratory experiment and one survey study to provide: 1) empirical evidence of the existence of online consumer motivation, 2) the effect of online consumer motivation on ecommerce outcomes and 3) a future stream of research.

By first offering a theoretical development of online consumer motivation, followed by the instrument development and then the empirical instantiation, this dissertation hopes to not only inform research but also provide guidance to ecommerce practitioners.

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Dedication

This dissertation is dedicated to my Dad; who has shown me the meaning of perseverance. I love my Dad!

INTRODUCTION

This dissertation is broken into three essays. The focus on this body of work centers on how motivation can play an important role in ecommerce. We will draw from the psychology, information systems and consumer behavior literature to develop the basis for our arguments. In this dissertation we attempt to develop measures that capture the construct of interest. Finally we will use multiple methods in order to empirically test and evaluate our research model.

The first essay theoretically develops the online consumer motivation construct. Online consumer motivation provides a clearing house for how a user's individual characteristics and the task at hand will influence perceptions of technology presentation. Further, it is proposed that by offering a Web site interface that is congruent with the user's online consumer motivation, Web site utilization and task performance will improve. In addition to the conceptual model, several propositions predict the interplay of key constructs. The paper concludes with a prescriptive protocol for testing the proposed theory as well as for guiding the design of ecommerce Web sites.

The second essay focuses on conceptualizing and developing an instrument for online consumer motivation. Specifically, this paper identifies the important extant literature in psychology, consumer behavior and information systems then can be extended to provide grounds for online consumer motivation. The second essay uses two laboratory experiments to validate the scales used to measure online consumer motivations.

The third and final essay uses Task-Technology Fit theory to posit a temporal view of online consumer motivation (i.e., why a user has chosen to visit a particular Web site at a given time) that can inform Web site design. This includes one laboratory experiment and one survey study. They studies provide: 1) empirical evidence if the existence of online consumer

motivation, 2) the affect of online consumer motivation on ecommerce outcomes and 3) a future stream of research.

By offering first a theoretical development, followed by the instrument development and then the empirical instantiation, this dissertation hope to not only inform research but also provide guidance to ecommerce practitioners.

ESSAY ONE: ONLINE CONSUMER MOTIVATION: APPLYING TASK- TECHNOLOGY FIT TO WEB PAGE TAILORING

INTRODUCTION

Web interfaces have often suffered from the inability to satisfy the multiplicity of users' needs. It is therefore a key challenge for organizations operating in the ecommerce arena to design Web sites for the vast range of tasks (e.g., specific purchases, browsing, and so on) being executed by an increasingly heterogeneous user base (e.g., varying degrees of computer and online experience). Since the dawn of the commercial Internet, organizations have experienced moderate-to-high success optimizing Web sites for each user's needs [Schulzrinne, 1996]. Such attempts have primarily examined prior user behavior to predict future needs. While this approach may indeed increase the likelihood that a Web site is meeting a user's needs, it is intuitive that past behavior may not always predict future behavior. As such, there is a need to understand the unique and dynamic needs of each user, each time they visit a Web site, in order to optimize its content and layout. To provide a first step towards better meeting the needs of Web-based customers, the focus of this paper is to provide a theoretical foundation as to why and how task and individual characteristics influence a user's motivation for visiting a Web site. Also, by understanding a user's motivation to visit a Web site an organization could include design elements to better meet the user's needs.

To date, there has been little focus on how different tasks and individual characteristics may influence an online consumer's motivation for interacting with a particular Web site at a particular time. Because online consumer motivation is a user cognitive state which exists *a priori* to a specific e-commerce Web site interaction, understanding this motivation is fundamental for providing guidance regarding customization. Prior research suggests that both the task (e.g., a user needing to get something done) as well as the individual characteristics (e.g., a user's impatience with these types of tasks) will influence an online consumer's motivation prior to interacting with a Web site [Benbasat and Dexter, 1982 ; Benbasat et al., 1986]. Likewise, it is also possible that a user's motivation could shift while interacting with the Web site. As such, the goal of this research is to offer a conceptual model for predicting the interplay of task and individual characteristics on online consumer motivation prior to, and while, interacting with a particular Web site. In particular, this research explores how motivation moderates (i.e., fits) technology characteristics in ecommerce Web sites to improve utilization and task performance. If this conceptual model is supported by empirical testing, it will provide not only a foundation for future research, but will also offer clear guidance for organizations as to how Web sites can be designed to better meet the needs of their customers.

IMPETUS FOR ONLINE CONSUMER MOTIVATION

In the current academic and practitioner literature, a Web site customized to a particular user has been referred interchangeably as "personalized" or "tailored". *Tailorable* technology has been introduced by Germonprez and colleagues [2007 p. 353], as a "technology that is intentionally modified in the context of use." Rayport and Jaworski [2005] define personalization as something the consumer creates and tailoring as something the organization creates. More specifically, in this paper, the customized Web site will be referred to as being *tailored* by

utilizing an individual's characteristics and the task being performed. Thus we offer the following definition for Web site tailoring:

A tailored Web site is customized by an organization for every unique user to optimize the online ecommerce experience.

Although there is a lot of hype surrounding Web site tailoring in the popular press, there is, however, little agreement in the academic literature as to how tailoring Web sites should be undertaken [Ho and Tam, 2005 ; Light et al., 2002] as well as how outcomes should be measured [Alpert et al., 2003 ; Benyon, 1993 ; Blake et al., 2005 ; Tam and Ho, 2006]. In fact, Alpert and colleagues argue that the abundance of recommendations and tailored information causes users to be “unenthusiastic. . . . toward system attempts to infer user needs, goals, or interests and to thereby provide user-specific adaptive content.” [Alpert et al., 2003 p. 373].

Whereas Tam and Ho suggest that, “. . . users are found to be receptive to personalized content and find it useful as a decision aid.” [2006 p. 865]. Further, past research reports that 75% of survey respondents would like to see more products and services that were tailored to their needs, with 70% of these being willing to pay a premium for such offerings [Gardyn, 2001]. Given the possibility for a general desire for tailored ecommerce systems, a clear opportunity exists to develop a richer conceptual and empirical understanding of Web site tailoring. Consequently, our objective is to explore, evaluate, and propose theoretical guidance for researchers and practitioners that will outline the temporal process and protocol for effectively tailoring of an ecommerce experiences to a user's individual characteristics and the task being preformed [Grover et al., 2008].

Current Tailoring Efforts

While there are a variety of different types of Web site tailoring that are being used in practice, all are based on mining data from past Web site interactions, analyzing that data, and making purchase recommendations. Amazon.com, who has been a leader in tailoring efforts, currently uses a process call *collaborative filtering* [Linden et al., 2003]. Collaborative filtering uses an algorithm to evaluate and suggests items based on recommendations of a few customers who have been most similar to the current customer. This approach can be done in real-time. Another current technique is to use *cluster models* to find customers who are similar and divide them into particular segments. The segments then can then be “fitted” with a unique marketing approach or strategy. The market segmentation is typically done off-line. Finally, *search-based methods* are also being employed where the past history of the customers is used to construct a search query to find other popular items by the same author/artist or keyword/subject [Sugiyama et al., 2004]. The search-based method takes place in real-time.

All of the above tailoring techniques are first-generation approaches, but indeed have been extremely successful. In fact, these tailoring approaches are in use today by iTunes’ *Genius* music recommendation engine as well as Amazon’s *Recommended for You* engine. While these approaches demonstrate the ability to tailor items to particular users, they are far from perfect. One limitation of these first-generation approaches is that they are only able to recommend products or services at the item level (based on the past) rather than to tailor the Web site interface to the current situation. For the purposes of this research, the Web mining family of tailoring currently in use will be referred to as Tailoring 1.0. We believe the next major innovation in tailoring, posited here, offers more than a guide to select particular items being offered but to also enhance the experience of the Web site in general for a specific task being

performed by the user. This objective can be achieved by combining data mining techniques while also utilizing a user’s past and current behaviors to predict improvements to the design of the Web site.

As mentioned previously, past research has found that these data mining techniques, although useful for certain shopping situations, are somewhat limited as they assume the customer’s current task is related to past behavior. These techniques also assume that all users searching, browsing and buying traits are similar [Kurniawan et al., 2003]. However, prior conceptual research suggests that online consumers have a “hierarchy of needs” that stimulates a necessity to match the interface characteristic to the specific requirements of a consumer for each particular interaction session with a given Web site [Valacich et al., 2007]. Toward this goal, by integrating past data mining techniques with an understanding of the motivation of users for visiting a particular Web site at a given time, the next generation of Web site tailoring can be achieved. We call this Tailoring 2.0 (see Figure 1 below).

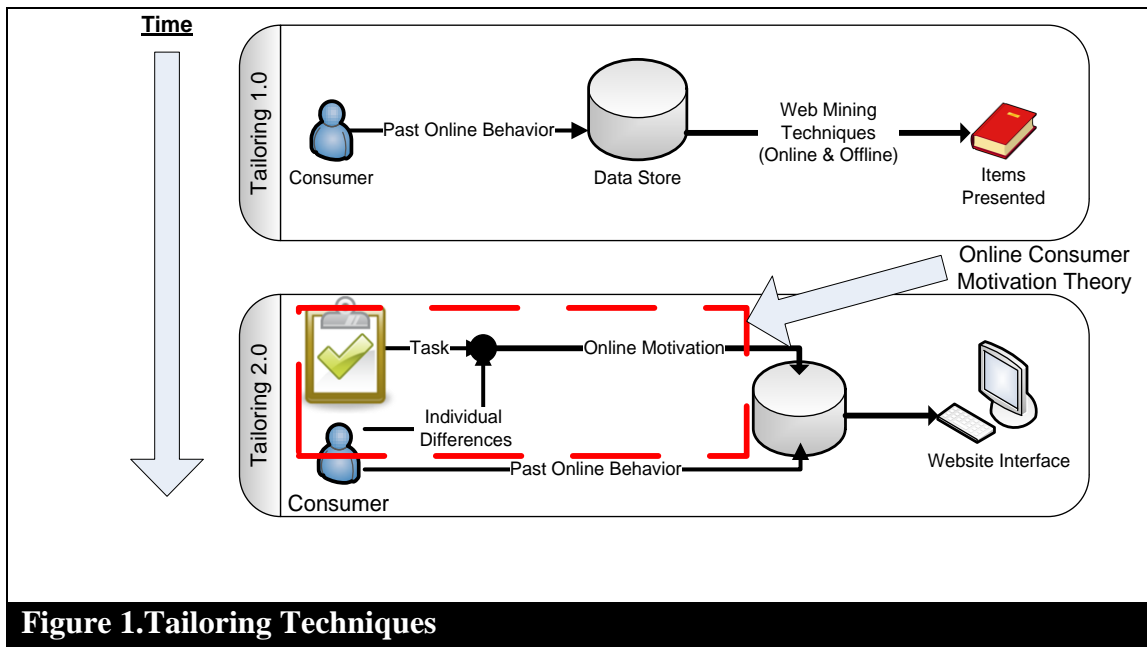


Figure 1. Tailoring Techniques

By understanding the motivation of the user, which is influenced by individual differences and the task at hand, we posit that tailoring becomes a more powerful tool than traditional data mining. Further by understanding the motivational aspects of users, protocols for integrating the current data mining techniques (Tailoring 1.0) with behavioral approaches to tailoring (Tailoring 2.0) can be developed, providing organizations a powerful and comprehensive approach for tailoring Web sites.

In sum, the distinction between Tailoring 1.0 and 2.0 is straightforward. Tailoring 1.0 can only estimate which items should be presented to a user whereas Tailoring 2.0 predicts which type and form of interface should be presented to the consumer. Given that these approaches to tailoring have very distinct objectives, this research will only focus on the unique aspects of Tailoring 2.0. To tailor the complete Web experience (determining the product items offered as well as an optimal interface metaphor) is currently beyond the objectives of this research. Next, prior relevant literature is examined build an overarching conceptual model as well as to predict the interplay of the primary constructs of our model.

REVIEW OF THEORETICAL FOUNDATIONS

There have been two significant research streams guiding the investigations related to tailoring. First, there is a growing body of work by HCI researchers in the area of “adaptive Web interfaces” [Baraglia, 2007 ; Brusilovsky and Maybury, 2002 ; Liu et al., 2003 ; Nyongesa et al., 2003 ; Tam and Ho, 2006]. Like tailoring, adaptive Web interfaces allow Web sites to dynamically change the presentation of content based on previous user interactions, similar to the data mining techniques discussed above. Here, this research has typically taken a design science approach, analyzing click-stream data post hoc in order to predict richer experiences for users in the future.

The second stream of research related to tailoring being conducted by researchers exploring consumer behavior in the MIS domain [Chellappa and Sin, 2005 ; Fogg et al., 2001 ; Klopping and McKinney, 2004 ; Mobasher et al., 2000 ; White and Kelly, 2006 ; Zeithaml et al., 2002]. Here, tailoring research has concentrated on *a priori* theoretical perspectives for creating environments based on individual differences rather than prior behavior. For instance, Benyon [1993] argues that users' individual characteristics differ greatly and that these factors should be taken into account when improving the usability of a system. Extrapolating this logic to an ecommerce context suggests that a tailored online product description that reflects users' expertise and experiences should increase its usability. Likewise, Zudilova-Seinstra [2007] stresses that the abilities of the user must be accounted for in tailored interfaces.

Just as Vessey [Vessey, 1991 ; Vessey and Galletta, 1991] argued that different types of presentation formats may significantly influence cognitive processing and ultimate task performance, we too argue that tailoring an online environment to a user's specific task and individual characteristics will lead to enhanced satisfaction and task performance. Further, individual characteristics have also been examined to determine their influence on users' perceptions [Malhotra et al., 2008 ; Venkatesh, 1999 ; Venkatesh, 2000]. Consequently, our model will incorporate individual user characteristics, task characteristics, and technological characteristics to provide a protocol for tailoring an ecommerce environment. We propose that this prescriptive protocol will produce positive outcomes for both ecommerce users and organizations. Next, Task-Technology Fit and Motivation Theory will be reviewed as they provide an ability to reconcile the respective influences of task and individual characteristics to optimize online consumer interaction through tailoring.

This review of past literature highlights a key issue for understanding how to deliver tailored interfaces. We posit that consumers are influenced by two key factors in an ecommerce setting: task and individual characteristics. For the current research, we will employ both past task research and motivation streams in the development of a conceptual model called the Online Consumer Motivation (OCM).

Task-Technology Fit

Germonprez and colleagues [Germonprez et al., 2007] proposed several core principles in designing tailorable technologies. A key principle in their theory of the Design of Tailorable Technologies is task. Specifically, “Designs that are well aligned with the structure of the task domain and allow for modification of the system in use will succeed in engaging user tailoring. Failure to align with a task domain does not engender user engagement toward tailoring but, instead, engagement associated with workarounds and improvisation” [Germonprez et al., 2007 p. 356]. Prior research in information system innovation has identified the importance of fit between information systems and the tasks [Dennis et al., 2001 ; Goodhue, 1995]. The task-technology fit model (TTF) [Goodhue and Thompson, 1995] offers that the fit between the information system and the task will lead to better performance and increase use intentions. Goodhue applied the TTF framework to understand how the ...

“correspondence between information systems functionality and task requirements leads to positive user evaluations, and positive performance impacts” [Goodhue, 1998 p. 105].

As such, TTF theoretical understanding provides a strong framework for pursuing prescriptive tailoring efforts.

While seminal TTF research has assumed a focus on organizational end-users [Goodhue, 1995 ; Goodhue, 1998 ; Goodhue and Thompson, 1995], it has been applied to various other

domains including ecommerce. Additionally, 'fit' has also been shown to have predicative power for explaining ecommerce interactions between consumer and organization. Nevertheless, the technology characteristics in an ecommerce context are far different from those in an organizational setting. First, and most obvious, is that technology used in an ecommerce setting tends to be a choice, whereas in an organizational setting such use is typically mandatory. TTF has also been used to investigate performance and utilization at an individual level [Goodhue, 1995] and at a group level [Dennis et al., 2001 ; Ziguers and Buckland, 1998]. More recently, TTF has been applied to various non-organizational settings including ecommerce adoption [Jahng et al., 2001] as well as combined with other well known theories including the Technology Acceptance Model (TAM) [Dishaw and Strong, 1999 ; Kloppeing and McKinney, 2004 ; Mathieson and Keil, 1998].

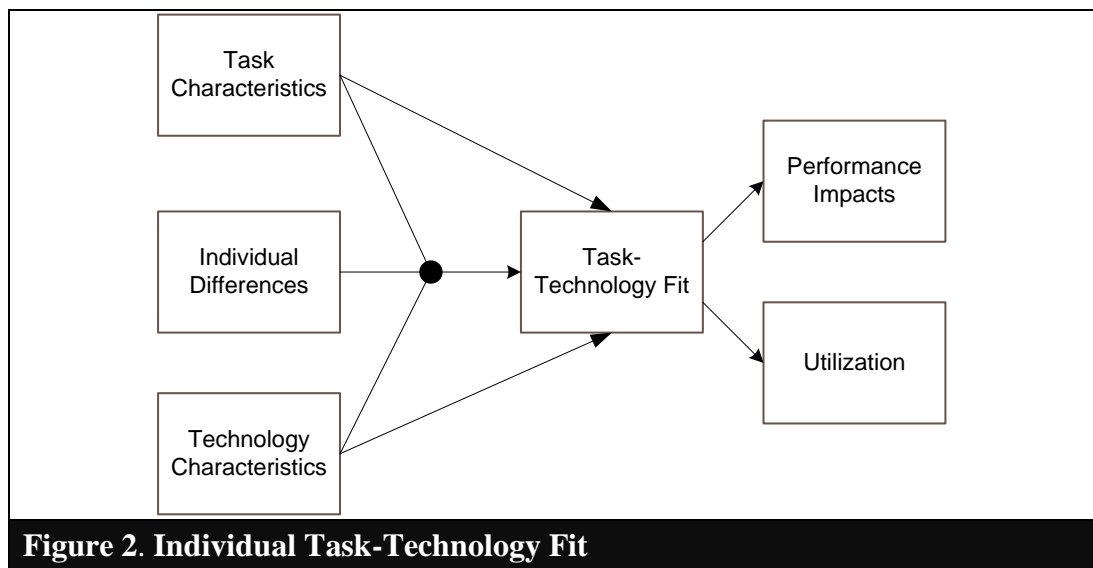
As stated above, TTF has been used extensively to describe and evaluate the outcomes of individual performance when utilizing various IT components [Goodhue and Thompson, 1995]. Outcomes in TTF theory typically include utility and performance; utility is often measured as a subjective perception while performance is frequently measured objectively related to the task being performed by the user. Usability has been extensively explored using models such as Technology Acceptance Model (TAM) [Davis, 1989 ; Davis et al., 1989b], Cognitive Fit [Vessey, 1991 ; Vessey and Galletta, 1991], and Task-Technology Fit [Goodhue, 1995 ; Goodhue, 1998 ; Goodhue and Thompson, 1995]. By evaluating both subjective and objective outcomes we can obtain a clearer picture. The convergence of subjective and objective measurements would suggest that the results minimize common-method bias (a frequent problem in subjective scales) and measurement bias (a general problem in subjective measurement).

Given our desire to measure both the subjective and objective outcomes associated with using a particular Web site, OCM will employ the same two types of outcomes. Further, TTF will be used as the foundation for explaining the interplay of how the user's task and individual characteristics affect user motivation, and ultimately the subjective and objective outcomes of using a particular Web site.

Clearly there is evidence that 'fit' affects performance. Nevertheless, the difficulty in leveraging the TTF paradigm lays within the complexity for researchers and practitioners to operationalize the TTF model within a particular context [Gebauer and Ginsburg, 2009]. As shown in Figure 2, adapted from [Goodhue and Thompson, 1995], the TTF framework is comprised of a three-way interaction, and three main effects. The three-way interaction causes a complexity that makes applying and testing TTF to a particular context (i.e., ecommerce) quite challenging. Additionally, due to the nature of the relationships with its antecedents, the conceptualization of the fit construct is somewhat of a black box, whereas some research tests fit via its own construct [Goodhue, 1998] and others use the variance in outcomes to test proper or relative fit [Junglas et al., 2008 ; Zigurs and Buckland, 1998]. Consequently, in order to operationalize TTF within an ecommerce environment, our research reconciles how motivation reconciles the interaction between task and individual characteristics and, subsequently acts as a clearing house for the decomposition the inherent 3-way interaction in TTF. Specifically, our instantiation of TTF will include a temporal view of how motivation affects 'fit' outcomes and how task and individual characteristics influence motivation.

Given that ecommerce is more a voluntary usage domain, a wider variety of tasks as well as users are emerging which creates the aforementioned hierarchy of needs [Valacich et al., 2007]. In turn, this provides an opportunity to delve into a wide range of motivations that may

influence how consumers interact with ecommerce interface characteristics. Given that motivation plays a central role in our model, we review this literature next.



Motivation

Motivation is an under-utilized theoretical perspective in human behavior research [Zhang, 2008]. The basic tenants of motivation are: what causes certain behavior and second why does behavior vary [Reeves, 2005]. By using motivation within an ecommerce context we have the opportunity to predict online behavior and therefore influence online satisfactions and performance. First an in-depth exploration of the extant motivation literature is needed to extract and utilize this theoretical stream for ecommerce.

Within the psychology literature, motivation refers to “the initiation, direction, intensity and persistence of behavior” [Geen, 1995 p. 213]. Deci [1975] defines motivation as a state that is influenced but is not synonymous with personality and emotion. Deci also identifies two fundamental types of motivation: intrinsic and extrinsic. Intrinsic motivation, common in the educational psychology literature since the 1970s, is based on personal needs (e.g., a student who studies hard to learn for the sake of learning, with no incentive or reward). Extrinsic motivation

is quite the opposite, where people are engaged in activities based on external incentives (e.g., a student who studies hard to earn a high grade in order to be eligible to win an award) [Ryan and Deci, 1985].

In information systems research, several have investigated the dimensions of motivation. For instance, Zhang offers a design perspective where motivational affordance is examined. The term affordance is used to describe the “actionable properties between an object and actor” [Zhang, 2008 p. 145]. Zhang posits that in design of information and communication technologies (ICT) there are several motivation sources and needs. For the purpose of this theory development on online consumer motivation Zhang’s principles inform the emotional affect (e.g., the optimal flow experience) and the psychological need (e.g., customization of applications).

Venkatesh [1999] found that intrinsic motivation was an antecedent for technology acceptance of new technologies. Later, Venkatesh [2000] reported that intrinsic motivation influenced the ease of use in new systems. Davis, Bagozzi and Warshaw [1992] expand the context of motivation by examining certain stimulus in terms of computer use. Specifically, they investigate the dichotomy of extrinsic and intrinsic motivation. Their research in computer usage suggested that perceived usefulness is a proxy for extrinsic motivation when using a system. Also, enjoyment was found to be a proxy for intrinsic motivation. These authors suggest that when systems are improved to include increased output quality and ease of use there will be positive effects on both usefulness and enjoyment. However, the authors caution, “Many systems are rejected by users because, although easy to use and capable of producing high quality output, they do not address tasks that are important to the users’ job.” [Davis et al., 1992 p. 1127]. This

statement by the seminal researcher in technology acceptance highlights our earlier assertion that there is interplay between task and individual characteristics.

Intrinsic motivation has been investigated further in the context of enterprise systems adoption [Hwang, 2005]. Here, field data was used to provide an instantiation of how intrinsic motivation was a significant factor on satisfaction in the use of mandatory systems¹. Likewise, non-mandatory systems such as online consumer-based ecommerce contexts have also provided insights into motivational factors. For instance, researcher have used TAM as a framework for studying whether intrinsic and extrinsic factors can influence online behavior [Shang et al., 2005]. Their findings show that a user's task influences the effects of intrinsic motivation. Also, this research found no significant relationship between extrinsic motivation and task. We speculate measuring motivation as two separate constructs caused nomological problems with how users view intrinsic and extrinsic motivation and therefore confounded this study.

For our purposes, intrinsic and extrinsic motivation can be considered as conceptual anchors along a continuum. For example, a person accessing a Web site to read local news and events for enjoyment, would likely fall closer to the intrinsic end of the motivation continuum. Alternatively, a person motivated to collect information on a competitor's new product offerings in order to impress their colleagues and boss would likely fall closer to the end of extrinsic continuum. It is therefore likely that differing types of motivation will influence an online experience.

Although much of the past psychological literature has focused on the dichotomy of motivations (e.g., intrinsic and extrinsic), as presented above, recent IS research has provided a

¹ Mandatory systems are defined as the required use of software in an organization.

broad understanding of motivation [Malhotra et al., 2008]. This research based on Deci and Ryan's organismic integration theory (OIT) [Deci and Ryan, 1985] posits a measurement to discern, "if and when behavior results from perceived external influences or from personal volition." [Malhotra et al., 2008 p. 268]. This research recognizes that motivation stems from a "collection" of sources rather than the simple dichotomy of extrinsic and intrinsic factors adopted by prior research. Similar the Malhotra vein, our theoretical orientation leverages a similar users' psychological state in term of *perceived locus of causality* (PLOC) to aid in measuring and defining motivation in an online context. PLOC offers a richer understanding than the intrinsic-extrinsic dichotomy, as PLOC is based on the endogenous view of behaviors. This view of behaviors is able to rectify the conflict between intrinsic beliefs and extrinsic pressures. The endogenous lens used in OIT theory also offers of understanding of how extrinsic and intrinsic factors are internalized. Figure 3 offers several examples of how perceived locus of causality can affect the interplay between intrinsic and extrinsic motivation. Having said this, the examples listed in Figure 3 cannot be generalized as different users will have diverse perspectives on the motivation properties in certain tasks based on their personality. This relationship between individual differences and task will be discussed later in this paper.

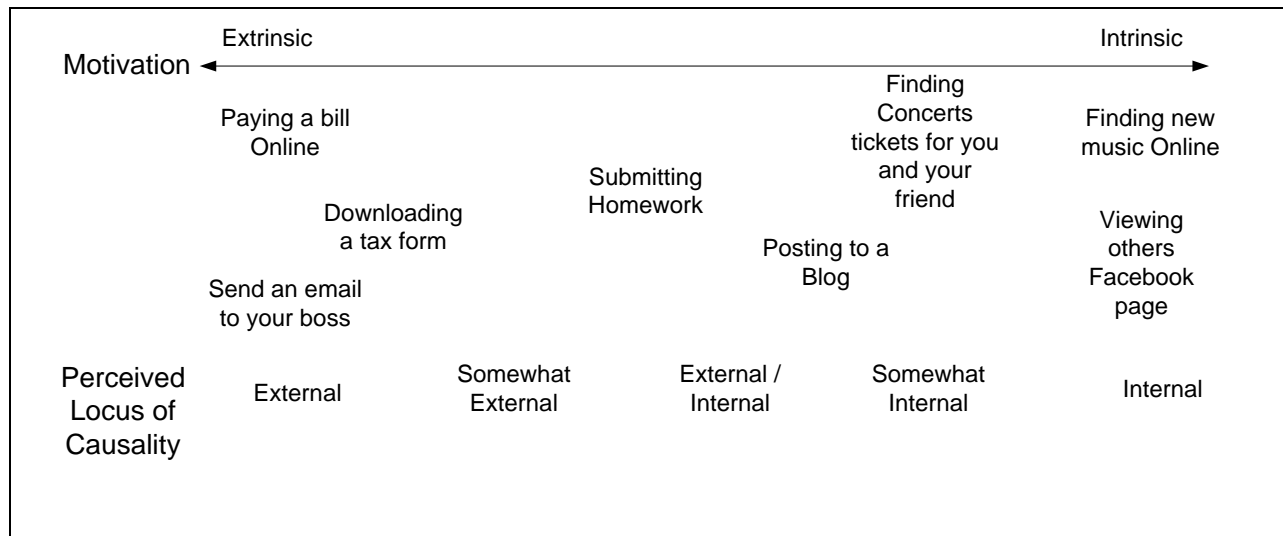


Figure 3. Examples of Intrinsic/Extrinsic Motivations

As we advance our proposed theory, we posit similar to Zhang and Malhotra and colleague [Malhotra et al., 2008 ; Zhang, 2008], that motivation is a combination of factors that are more complex than simple extrinsic and intrinsic forces. Relating this to the concept of task fit, it is intuitive that improved fit can occur when individual motivations, in a PLOC context, are stimulated by the nature of the task. We conceptualize, as does the Malhotra research, that motivation can be measured on the extrinsic and intrinsic continuum but that the antecedents of this state stem from the task (extrinsic forces) and individual difference in Web use (intrinsic forces). These motivating factors have an obvious effect during the online experience. The following section outlines the antecedents and outcomes that are derived from motivational factors in an ecommerce environment.

ONLINE CONSUMER MOTIVATION

Given that we are interested in the interplay between task, individual, and technology (i.e., interface) characteristics, TTF offers a logical theoretical framework for understanding this

phenomenon. Thus, we are proposing a decomposed version of TTF that positions online consumer motivation (OCM) as the focal construct. By positioning OCM as the central construct within a TTF framework, we are able to reconcile the effects of task, individual, and technology characteristics from a unique theoretical perspective.

We propose that OCM is the reason/rationale that a user brings to a specific ecommerce context or encounter. For instance, a consumer may be searching for an effective and efficient execution of a specific shopping goal [Childers et al., 2001 ; Hargittai, 2004]. Conversely, some online consumers look for a broad, unstructured interaction that is not associated with a specific shopping goal [Arnold and Reynolds, 2003 ; Childers et al., 2001 ; Wells et al., 2005]. Marketing research has pointed to this dichotomy of behaviors as search vs. experiential [Arnold and Reynolds, 2003 ; Childers et al., 2001 ; Hargittai, 2004]. More fundamentally, psychology research points to an intrinsic vs. extrinsic motivation continuum [Davis et al., 1992 ; Deci, 1975]. Thus, we posit that online consumer motivation is defined as the specific rationale that a consumer brings to an ecommerce interaction that meets specific intrinsic and/or extrinsic needs. Next, we discuss the antecedents of OCM.

Antecedents of Online Motivation

Although many of the prior task-technology fit ecommerce studies have focused on a particular task context (e.g., search vs. experiential) [Goodhue, 1995 ; Goodhue, 1998 ; Goodhue and Thompson, 1995 ; van der Heijden, 2004 ; van der Heijden et al., 2001], it is likely that fit cannot be mapped to a specific interface characteristic without also understanding individual user characteristics. A basic tenant of TTF is that task characteristics and individual factors will influence the ‘fit’ of with the technology characteristics. Given our assertion that task characteristics and individual characteristics influence the motivation that a consumer brings to a

business-to-consumer interaction, we see an opportunity to better understand the interplay of task, users and interface characteristics within TTF. Consequently, to integrate motivation into the TTF framework, we include both task and individual characteristics as antecedents to online consumer motivation.

Further, Goodhue [Goodhue, 2007] commented that the Technology Acceptance Model (TAM) [Davis, 1989], commonly used for acceptance and adoption of technology, does not best explain how technologies can affect performance in all contexts; (e.g., "... for technology to positively affect performance, it must be utilized and it must be a good fit to the task." [Goodhue, 2007 p. 220]). Goodhue continues by explaining how many current technologies are not a good fit to task. We believe, like Goodhue, that task considerations are critical components for understanding how to optimize the experience for users, specifically in the context of online ecommerce. In order to substantiate this claim we must examine characteristics of online tasks and individual differences.

Online Tasks

Although the use of the Internet has been pervasive for several years, its ubiquity and how people utilize it has evolved significantly over time. For instance, in 2006, 39% of all Internet users have browsed online for information about a place to live; this is up 200% since 2000 [Fallows, 2006b]. Likewise, in 1998, 13% of US adult Internet users (about 10 million) utilized some form of Internet banking; by June 2006, Pew Research reported that 43% of US adult Internet users (63 million) bank online [Fox and Beier, 2006]. This shift in usage has not only been in structured search tasks but also with general browsing. For example, Pew Research also reported that 30% of all Internet users are online, at least once a day [Fallows, 2006a 36],

for fun, to pass time or for no particular reason at all. It is obvious that today's Internet is used by people performing a wide range of tasks.

As such, online tasks can take many forms. Some prior research has created task categories [Hargittai, 2004 ; Kau et al., 2003 ; Rohm and Swaminathan, 2004]. Other researchers have proposed that tasks can be conceptualized along a continuum, but with no clear consensus on what the anchors to this continuum might be. In the Information Systems discipline, most research has centered on the utility of Information Systems, although recent research by van der Heijden and others has investigated hedonic aspects and impacts of Information Systems [Childers et al., 2001 ; van der Heijden, 2004]. Simon and colleagues suggest [1996] that we distinguish between "programmed" and "non-programmed" tasks in an online environment. Where non-programmed tasks are novel and unstructured and programmed tasks are repetitive and routine. Wells and colleagues [2005] go further by identifying the continuum anchors as "goal-directed" and "experiential" by extrapolating from past research (see Table 1 adapted from [Wells et al., 2005]) [Alba et al., 1997 ; Hoffman and Novak, 1996 ; Mathwick et al., 2002 ; Wolfinbarger and Gilly, 2001].

Table 1: Task Characteristics: Experiential vs. Search Directed

Experiential Task Types	Search Task Types	Key Work
Experiential attributes	Search attributes	Alba et al. (1997)
Hedonic	Utilitarian	van der Heijden (2004), Wolfenbarger & Gilly (2001), Hoffman & Novak (1997)
Unstructured Non-directed search Non-linear navigation	Structured Directed search Linear navigation	Hoffman & Novak (1997)
Perceptual attributes	Analytic processing	Mathwick et al. (2002)

In the consumer behavior literature there has been a significant amount of research regarding search and experiential activities in both traditional offline and online settings [Hirschman, 1984 ; Hirschman and Holbrook, 1982 ; Novak et al., 2003a ; van der Heijden, 2004]. Experiential tasks are relatively unstructured using non-linear search and navigation patterns. In the Information Systems discipline, while most related research has centered on the utility of Information Systems, some recent research by van der Heijden and others has investigated the experiential aspects and impacts of Information Systems [Childers et al., 2001 ; van der Heijden, 2004]. Conversely, search tasks are rather structured using linear search and navigation patterns [Novak et al., 2003a ; Wells et al., 2005]. For this theory development paper, experiential and search is used to describe the properties of the task.

Table 2: Examples of Online Tasks	
Search	Experiential
Pay bills	Play a game
Submit homework	Read a blog
Post to a blog	Browse for tech news
Download tax forms	Find new music
Send an email to your boss	View others' myspace/facebook pages

Therefore, it can be argued that Internet users engage in tasks that are relatively experiential (e.g., browsing for fun) or relatively search (e.g., paying bills using online banking), or somewhere in the middle. It can also be argued that tasks can influence not only the online processes and perceptions of users, but also the outcomes of this interaction. Table 2 outlines some examples of search and experiential tasks typical to ecommerce users. Gefen and Straub [2000] identified the IT aspects within the traditional motivation framework:

“Tasks that are intrinsic to the IT are tasks where the IT itself provides the primary ‘end,’ i.e., the product or service for which the IT is ultimately being used. Tasks that are extrinsic to the IT, on the other hand, are those in which the IT is only the ‘means’ to achieving the primary product or service, i.e., where the IT is not the central component of the process but is instrumental in achieving it, such as when the IT is the interface through which one accomplishes a goal.” [Gefen and Straub, 2000 p. 3].

Taken together, we propose:

P1: Task type will influence online consumer motivation.

From the prior literature we can conclude that there is a strong relationship between ecommerce and task outcomes. While task characteristics play an important role in determining a consumer motivation to use technology, it is only part of the dynamic. Next, we will discuss individual differences within a TTF framework.

Individual Differences

Although there are a multitude of individual differences that influence a users motivation in an ecommerce context, we bound our conceptual model to include what we believe is a critical factor to determining OCM. Independent of task, user interactions are influenced by the inherent nature of the user [Goodhue, 1995 ; Goodhue and Thompson, 1995]. For example, in a shopping context consumers can be described as either problem solvers or as fun-seeking that center the shopping experience on arousal, sensory stimulation, and enjoyment [Hirschman and Holbrook, 1982]. Similar to differences in tasks, users can also have intrinsic and/or extrinsic preferences for online experiences. This dichotomy is considered a trait of the user because it influences each shopping experience even if the shopping goal changes [Deci, 1975]. Further, eCommerce researchers have argued that shopping motivations can vary from person-to-person. Specifically, Zhou states “(intrinsic) shoppers always find more enjoyment in interactivity environments than in pure test environments.” [Zhou et al., 2007 p. 43]. On the other hand, extrinsic shoppers are concerned with the shopping experience being efficient and timely [Childers et al., 2001]. Our research draws heavily on Venkatesh’s work on intrinsic motivation which is based on computer playfulness [Venkatesh, 1999 ; Venkatesh, 2000]. We believe, as Venkatesh posits, that motivation can be an extremely significant factor and should be a consideration for designing information systems. As such, computer playfulness is included in the OCM model as

representing individual differences. Examples of individual differences for intrinsic and extrinsic online shopping are summarized in Table 3 below.

Table 3: Examples of Online Individual User Differences	
Extrinsic	Intrinsic
Usually gets in and out	Wants to tinker with the options
Likes a quick and easy option	What to view all aspects
Does not vary from the task at hand	Likes finding new things

Although individual differences in online shopping are influencing factors in determining proper fit, they cannot be studied in a vacuum. TTF, and other theoretical perspectives, strongly link individual differences with task characteristics. Specifically, researchers have posited that aspects of the task will account for more variance in outcomes than individual differences [Simon, 1996]. Because we argue that task and individual differences are antecedents to a user's online motivation state, we further posit that individual motivations not only directly influence consumer motivation, but will also moderate the impact of task characteristics on OCM (See Figure 4). Therefore:

P2a: Individual differences will influence online consumer motivation.

P2b: Individual differences will moderate the effect of task characteristics on online consumer motivation.

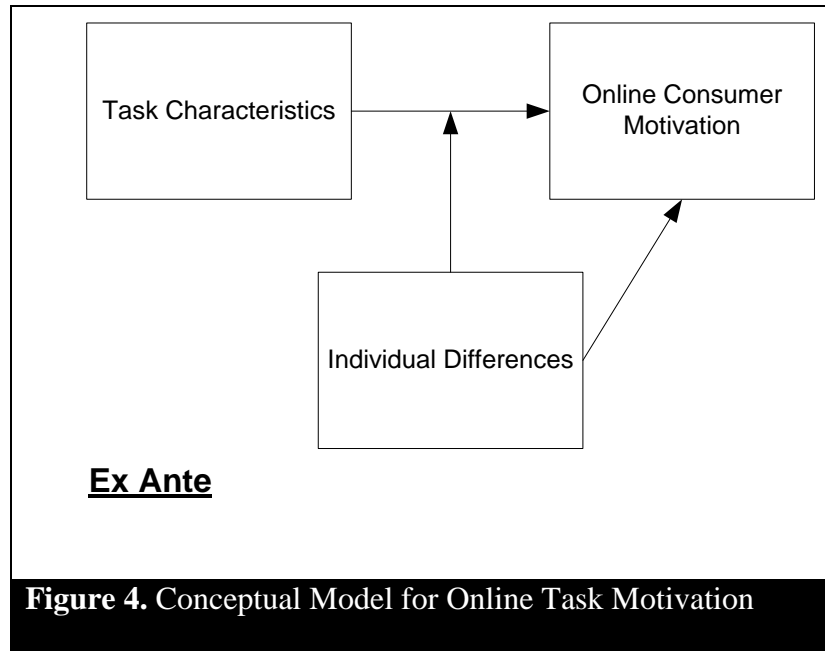
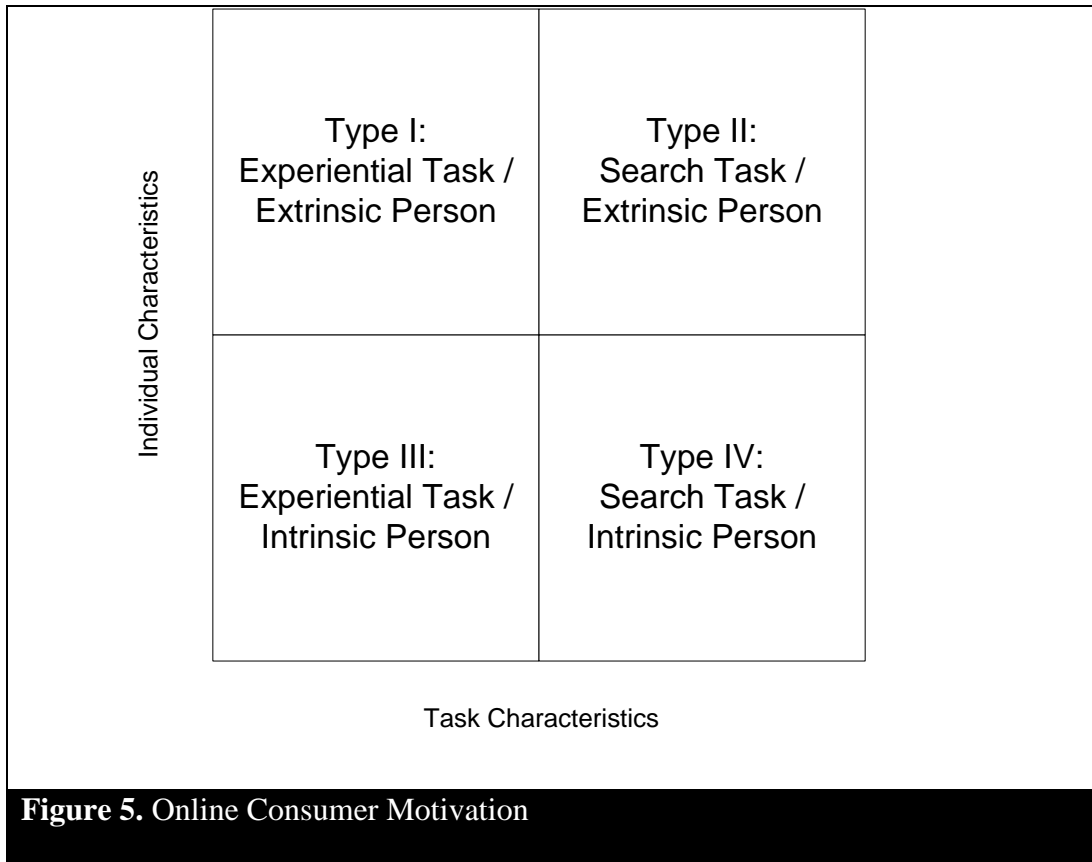


Figure 4. Conceptual Model for Online Task Motivation

This process of forming OCM is ex-ante to the introduction of the technology and therefore has yet to affect the ‘fit’ component of the interface. For example, if a user was to go online to pay a bill (search task), and was generally very experiential in their use of the Internet, then the overall OCM would be able to reconcile any discrepancies between individual and task characteristics. OCM would classify a user by both the task characteristics (search/experiential) and the individual motivational factors (intrinsic/extrinsic) (see Figure 5). When the Web site interface is presented to the user, the user has a preconceived motivation based on the task and their individual differences. This motivation can be classified as one of four types of OCM. By estimating the dimensions of OCM, technology now can be tailored to the user. Next the importance of technology characteristics and the interplay with OCM will be discussed and integrated into the conceptual model.



Technology Characteristics

A core concept in TTF is finding the best suited technology characteristics for the task at hand that will enhance utility and ultimately optimize performance. For instance, the consumer behavior literature has focused on how information presentation can affect utilization.

Specifically, information presentation has been observed to improve utilization, which in this instance was measured by improving one's ability to process and store information [Pitkow and Kehoe, 1996]. Further, studies have also shown that different information presentation characteristics can optimize user performance [Vessey, 1991 ; Vessey and Galletta, 1991].

P3a: Technology characteristics will influence a user's utilization of a Web site.

Information presentation has also been studied in ecommerce in terms of interface metaphors and how they map to tasks [Wells et al., 2005]. The Wells et al. (2005) investigation

highlights the importance of mapping the task to the interface characteristics. A manipulation of the interface experience was used to provide evidence that the interaction between different interface characteristics (experiential or search) and the task (experiential) would influence performance. Specifically, when an experiential/intrinsic interface was matched to a experiential task, retention and recall was significantly improved. Conversely, when a search interface was matched with a experiential task, retention and recall significantly decreased. Performance can be measured in several ways, this includes retention/recall as in the Wells et al. [2005] study or from a task perspective, the ability to easily and quickly accomplish a task [Campbell and Wright, 2008]. Further, Web site performance will be viewed as the ability to perform the task at hand whether it is a search task or an experiential task [Wells et al., 2005]. Consequently, it is intuitive that technology characteristics can either inhibit or enhance performance. Therefore we propose that:

P3b: Technology characteristics will influence a user's performance on the Web site.

Ultimately, the prior TTF literature points to a fit component between technology characteristics and two key factors: task and individual characteristics. Yet, as stated earlier, the three-way interaction that is inherent in TTF makes it extremely difficult to isolate and distinguish the respective roles that task and individual characteristics play in this fit component. Thus, how does the interaction between individual differences and task characteristics influence utilization and performance? Our theoretical development addresses this gap by providing a mapping of how OCM and its inherent antecedents (individual differences and task characteristics), when matched with the proper technology characteristics, can positively influence utilization and, ultimately, performance. Figure 5 demonstrates the four different

classifications of OCM. This interaction will provide guidance on the proper fit to inform the technology characteristics of a tailored Web site environment.

ONLINE CONSUMER MOTIVATION FIT

A core contribution of the proposed extension to TTF is the incorporation of OCM to guide the design of interface characteristics in an ecommerce context. It is proposed that OCM will influence the strength of the fit between OCM and the technology. Extending TTF, we provide a dichotomy of technology characteristics that assume three possible interface designs: experiential/intrinsic, search/extrinsic, and hybrid².

First, we can have a purely experiential interface design where one's ability to freely browse is the primary focus. A current real-world example of such site is the news aggregation site called Swarm by Digg.com. In this example, bubbles are used to represent news stories, with the relative size of the bubble being how popular the news story is. Using Swarm you can watch other users browse stories real time by watching small fly like objects attract themselves to stories. If a user moves to another story you can watch the fly like objects move to that bubble. This approach encourages hedonic behavior. Alternatively, Digg.com also has a very linear site whereby articles are listed in order of popularity. This interface would therefore be classified as a more search-oriented interface since it has fewer options and is laid out in a very structured fashion.

Finally, of course, one could represent the interface in a hybrid manner where characteristics of both the pure search and pure experiential sites are used. This type of tailoring

² We assume that most interface designs do incorporate both hedonic and goal-directed, which is deemed hybrid. This research posits when it would be more appropriate to display a more hedonic or more goal-oriented interface.

is used extensively by companies such as eBay and Amazon.com even though the organizations are unsure as to the purpose of the user's visit. What we propose is that the Web site can be tailored based on the OCM context as described above and therefore the catchall hybrid model will only be given to those users who fit a particular profile. By using OCM we can then measure the moderating factors on the technology characteristics ex post the ecommerce interaction (see Figure 6 below). Therefore:

P4a: Online Consumer Motivation will interact with the technology characteristics to influence a user's performance on the Web site.

P4b: Online Consumer Motivation will interact with the technology to influence a user's Web site utilization.

Performance and utilization are often the ultimate goal for a number of technology initiatives, including that of ecommerce research [Fogg et al., 2001 ; Ho and Tam, 2005 ; White and Kelly, 2006]. Although there is several definitions and measures for IS success, the DeLone and McLean model is still considered very prominent in the IS literature [DeLone and McLean, 1992 ; DeLone and McLean, 2006]. For this reason, we also use performance and utilization as the ultimate outcomes for our conceptual model. What is unclear is how performance and utilization should be measured. We believe that both of these variables are contextual. For this reason, it is appropriate that in an ecommerce context that the performance and utilization metrics be instantiated by the organizations. For example, if someone was browsing for tickets for a football game, then the performance metric could be the ability to convert the user to premium seating, whereas if the context is browsing for a car, the performance metric would be the frequency to which the Web site collects a user's contact information.

Utilization has been linked as a contributing antecedent, as measured by satisfaction of the ecommerce system, in many studies [Campbell and Wright, 2008 ; Ho and Tam, 2005]. Further, TTF points to a relationship between the utilization and the performance of using the system to perform a particular task. Goodhue's original Technology-to-Performance Chain exemplifies how utilization is central to the outcomes measurements of a given system [Goodhue and Thompson, 1995].

Therefore:

P5: Utilization of the Web site will influence the overall user performance on the Web site.

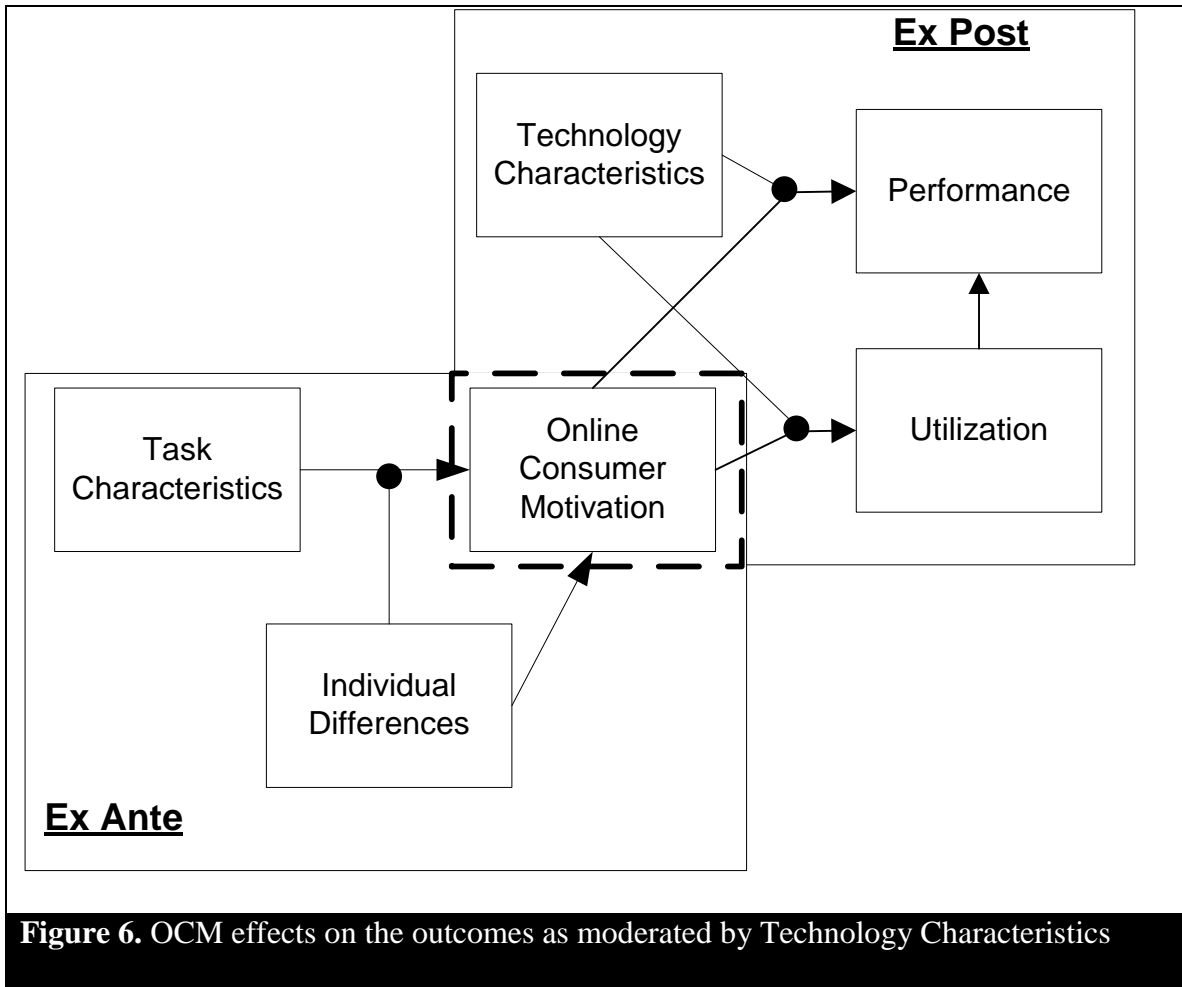


Figure 6. OCM effects on the outcomes as moderated by Technology Characteristics

PROGRAM OF RESEARCH

Of particular interest to practitioners and academics alike in conceptual model building is the ability to empirically test the theoretical assumptions. For OCM, the next logical step is providing a path to this empirical evaluation and to follow a prescriptive framework on to how to instantiate this conceptual model into practice. For this reason, a program of research will be outlined that will include 1) initial measurement of the model guidelines, 2) generalizable metrics, and 3) a design science initiative.

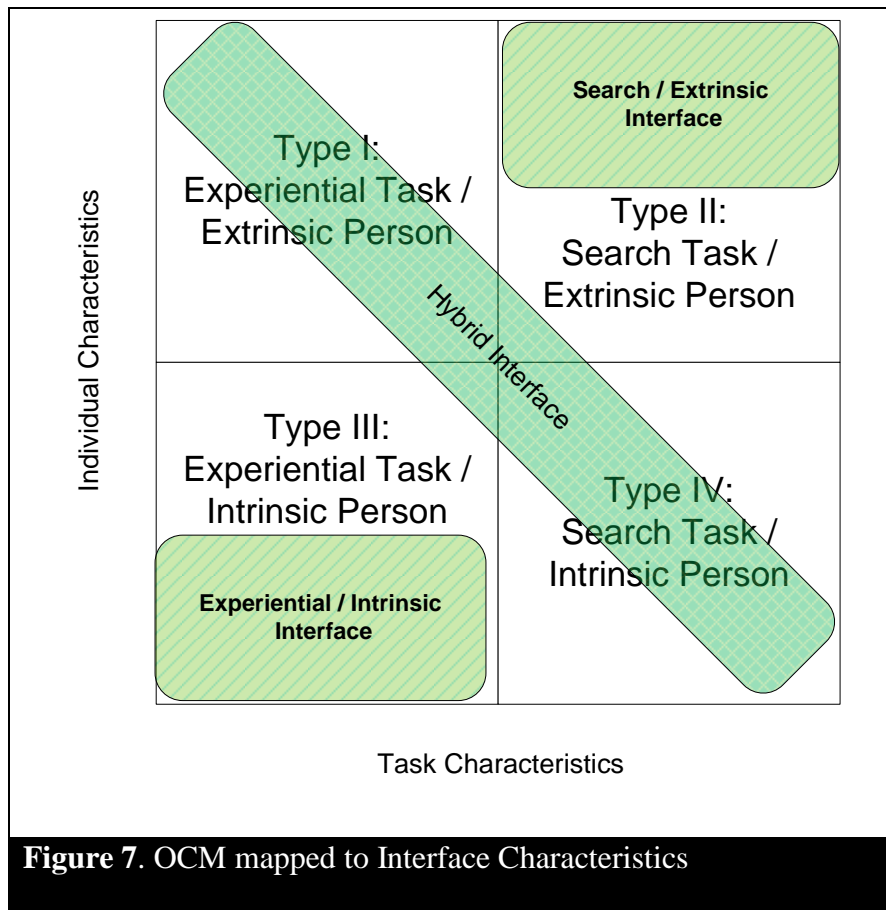
First, the goal for the initial empirics will be to establish a psychometrically sound instrument to measure task characteristics, individual differences and OCM. The theory

developed in this paper introduces the new construct of OCM that must be initially tested in a laboratory environment in order to establish reliability and validity. Appendix A outlines possible items that can be evaluated to create a scale for OCM. The goal of this step is to confirm the antecedents of OCM, individual differences and task characteristics, examine these relationships and provide evidence that OCM is a distinct construct.

The second step involved in the empirical examination process is a confirmatory sample for instrument validation as well as to test the research model using structural equation modeling using both survey methodology and laboratory analysis. The laboratory setting is ideal to test the model as it allows the researcher a high degree of control and precision [Dennis and Valacich, 2001 ; McGrath, 1982]. A 2X2 full factorial design is encouraged whereby the shopping task will be manipulated (experiential task and search task) and the interface will be manipulated (experiential Web site and a search Web site). This will allow the research team to create variance in the sample. Ecommerce Web sites have been designed to aid in the execution of this proposed experiment (See Appendix B). In this example, the task would be based on buying football tickets to the upcoming game. The search Web site has a list like structure whereas the experiential site has an environment where users could look at the seat and “experience” their views. The third data collection should include a non-student sample that would be administered using a survey format.

Finally, if the theoretical model has been supported, a design science approach would be the next appropriate step. The design science approach allows researchers to produce prototypes of ecommerce Web sites that would include an algorithm which would tailor the Web site environment based on OCM as suggested in Figure 7. For example, if a user has been

categorized as a Type II user by the OCM algorithm (extrinsically motivated person / search task) the Web site structure will automatically change to fit the requirements of the user.



Further, the next step in the design science approach would be based on a precise measurement of OCM. By categorizing the consumers in a fine grain approach it is possible to have several or “n” interfaces that can be tailored to many different types of OCM users. (See Figure 8).

We believe that using today’s sophisticated Web analytics; it is possible to measure OCM at this fine grain level. First, task type can be determined by using current real time data mining techniques [Kalczynski et al., 2006 ; Mobasher et al., 2000]. Second, individual differences can be measured quite simply during the registration process by asking a few questions about the consumer’s computer playfulness. The combination of the two can provide an accurate OCM in

a real-time ecommerce environment. The next section will outline the practical importance of this research while also evaluating the impact of this theoretical extension to TTF.

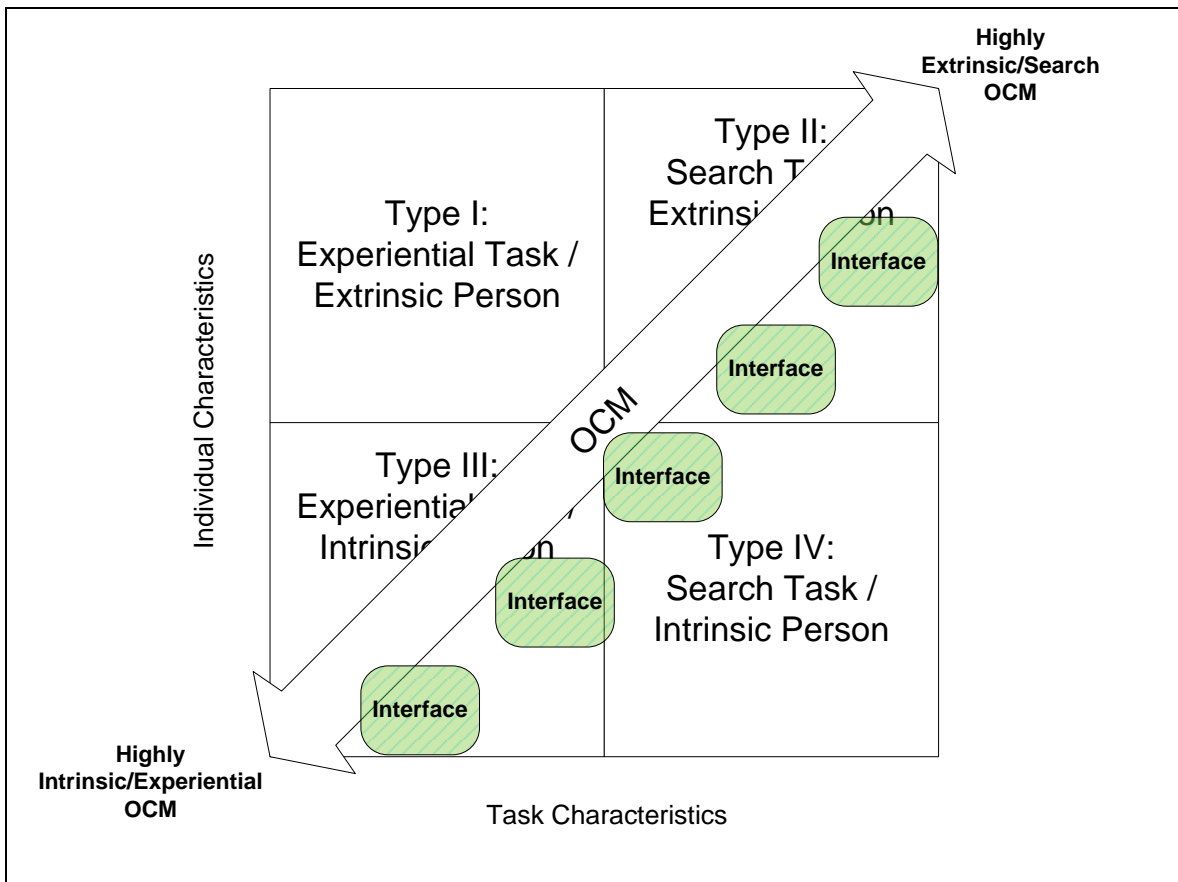


Figure 8. OCM mapped to Interface Characteristics

TOPIC IMPORTANCE AND CONCLUSIONS

The practical implication for this research focuses on providing a prescriptive approach for Web design to tailor interfaces. If successful, this research stream develops a clear protocol for guiding designers and developers on how to affect behavior and cognitive processes by presenting certain technology characteristics based on task type and individual differences. More specifically, if the Web site knows some individual traits (e.g., computer playfulness) about the user *ex ante* and click-stream data can forecast the user's current task, then an accurate tailored Web site can be presented which will positively affect satisfaction and performance. There are

several ways in which in which modern system could provide the real-time click-stream analysis to detect task include complex decision trees, cluster analysis, and so on. The most promising analytic technique for our prescriptive research is the use of neural networks. Neural networks has been used extensively in business analytics and data mining [Swingler, 1996 ; Witten and Frank, 2005].

Similarly, individual differences (e.g., computer playfulness) can be diagnosed in several different ways. This includes cluster modeling, where organizations can track complete Web site interactions and then infer certain individual differences by grouping behaviors. The easily method for understanding a user's playfulness is be using a scale during a registration process. By combining possible task analytics and utilizing computer playfulness scales during registration this can create a unique consumer profile. For example, if a user is engaged in a search task, say paying bills, the Web site could be tailored to best enable the completion of the task based on someone's computer playfulness. Alternatively, if the task is experiential, such as surfing for a Christmas gift, the Web site could be tailored to provide multiple options that will better engage the user. Lastly, if the user is switching from an experiential activity to a search activity (e.g., browsing the iTunes site for new music and then deciding to purchase a particular CD), the site would need to rapidly shift its orientation to meet the changing task needs of the user.

There are also several potential research implications of this work. First, theoretic contributions include an empirical test of a seminal information systems theory, Task-Technology Fit. Conceptually, TTF is an elegant model, but has been difficult to investigate empirically due to the 3-way interaction. This research will expand TTF so that the interactions will be presented temporally, rather than as a single instance. By developing an extension to TTF

this research contributes to both the information systems discipline as well as reference disciplines that are likely to use TTF. Second, the successful application of TTF also has implications for HCI research. Specifically given that much of the prior research concerning the tailoring of interfaces has been somewhat atheoretical in nature, providing a method for applying this parsimonious theory will aid in future empirical studies within the HCI and broader Information Systems community.

The proposed research focuses on extending TTF to include a temporal component that predicts how motivation plays an important role when tailoring a Web site. By being able to distinctly measure online consumer motivation should not only inform future HCI research but also guide the design of organizational Web sites. As a first step, task and individual characteristics are the antecedents to motivation. It is likely that other factors will influence motivation and ultimately the optimal Web site design. This research provides a foundation for pursuing these parallel objectives. Clearly, much work remains.

ESSAY TWO: ASSESSING AND MEASURING ONLINE CONSUMER MOTIVATION USING CROSS-SECTIONAL DATA FROM TWO INDEPENDENT EXPERIMENTS

INTRODUCTION

The design of ecommerce Web sites has offered many challenges and opportunities for organizations throughout the world. There has been a rich stream in the information systems research on the antecedents of good Web design. For instance, this has included ideas of how the size of the Web site affects users perceptions (e.g., the download delay) [Galletta et al., 2006] or even how interactive components affect consumer behavior [Campbell and Wright, 2008 ; Palmer, 2002]. In this paper, we will go a step beyond examining which components of a Web site affect consumer behavior and evaluate the possibility that there are psychological needs that can inform ecommerce Web design. Specifically, Self-Determination Theory (SDT) [Ryan and Deci, 2000] will be presented as a framework for understanding how psychological needs can inform Web design elements in an ecommerce context.

At the center of SDT is motivation [Deci, 1975 ; Deci and Ryan, 1985 ; Ryan and Deci, 2000]. Motivation, “concerns energy, direction, persistence and equifinality – all aspects of activation and intention.” [Ryan and Deci, 2000 p. 69]. Motivation in ecommerce can be highly valued as it offers insight into the consequences of behavior (e.g., consumer behavior). In other words, by understanding one’s motivation in certain contexts, we can determine the design factors that affect their behavior.

This paper provides insight into the critical psychological factors that affect online consumer behavior. Further, this paper develops and validates an instrument to measure the factors that are attributed to online consumer motivation in an ecommerce context. The development of an online consumer motivation instrument is useful as it will allow researchers and practitioners alike to be able to measure and therefore predict which Web site components will but suit the consumer.

The contributions of this paper are two-fold. First a conceptual model of the factors influencing online consumer motivation is presented. This model draws on SDT as well as the current practices used in Web design. The model adapts concepts from SDT [Deci, 1975 ; Deci and Ryan, 1985 ; Ryan and Deci, 2000], and references several components of use of motivation in design [Fang and Salvendy, 2000 ; Galletta et al., 2006 ; Palmer, 2002 ; Zhang, 2008]. Second, this paper presents an instrument that has been validated in both laboratory and field tests.

The structure of the paper is as follows: Section 2 will include a background on the research domain (e.g. ecommerce design) and the consumer motivation literature. Section 3 will provide the theoretical underpinnings for this research and also present the research model. Section 4 highlights the development of the instrument to measure online consumer motivation. The research methodology and study execution is presented in Section 5. The results are presented and discussed in detail in Section 6. Finally the discussion and conclusion are presented in Section 7.

PAST RESEARCH

Research domain

Most ecommerce systems have unique objectives, features and structures that are based on certain organizational goals. Although there are many different types of systems, Web designer have argued that consumers expect certain features in certain locations and therefore standard design must be used in ecommerce Web sites [Lynch and Horton, 2009 ; Zeldman, 2003].

Unfortunately, the extant literature on the use of standards by organizations in their ecommerce Web site has suggested that the design of ecommerce Web sites has not exactly been consistent (e.g., consistent layout, consistent shopping experiences, and so on). Prior research has offered a broad classification of ecommerce Web sites as well as the key attributes and features of online stores [Novak et al., 2003b ; Spiller and Lohse, 1998]. Although there was some overlap in the recommended categories there was no standard way of presenting an ecommerce Web site. Others have suggested that there are four distinct eras in ecommerce Web design standards, and no convergence has yet occurred [Chua et al., 2007]. Examples of design standards where Web sites often vary include the service quality, the web quality, privacy and security control, brand/reputation, delivery/logistic, after sales services and incentive.

Further, some suggest that there are no de-facto standards for Web site design which is evident in a study where 126 different product configurations tools used by ecommerce sites in three different industries (electronics, apparel, automotive) were evaluated. This case study found that in fact there are more differences in how organizations present tools in their ecommerce sites than there are similarities [Streichsbier et al., 2009].

The literature also shows that different organizations use their ecommerce Web sites in varying ways that may or may not include standards in design. It could be argued that this lack of

congruence in the literature and in practice is due to the lack of a common method used to guide Web site design. In this paper we will evaluate and utilize human behavior factors that affect a user's perception of certain Web design components. As stated above, using the motivations in human behavior may offer insight into how a user's perceptions are formed about web design components. Next we examine the relevant literature on human behavior to explain the linkage of motivation to a user's perception of a Web site.

Motivation literature

Recently there has been a call to study motivation in the context of information and communication technology (ICT) [Zhang, 2008]. There are two basic questions that the motivation literature, in general, attempts to answer. First is what causes certain behavior and second why does behavior vary in intensity [Reeves, 2005]. By examining these issues within an ecommerce context we have the opportunity to study the factors that positively affect certain desirable online consumer behaviors (e.g. satisfaction, intent to return, and so on). The significance of studying motivation is clear as it offers a valuable association between *a priori* impetus and the end behaviors.

Although many times motivation is treated as a single or first-order construct, it is evident that people are moved to act by very different factors. There is also the issue of whether motivation is a state or trait. In psychology there has been a great deal of research on state versus trait. Cognitive traits are primal and stable propensities that are relatively invariant to situational stimuli, whereas a cognitive state is a dynamic and situational inclination [Webster and Martocchio, 1996]. We define motivation, similar to Deci [1975], as a state of mind that is influenced. Further, it must be pointed out that there is a clear distinction between motivation and personality and emotion [Deci and Ryan, 1985]. SDT posits that motivation can be formed

by external factors (e.g. strong external coercion) and by internalized factors (e.g. value an activity), these are called extrinsic and intrinsic factor respectively [Deci, 1975 ; Deci and Ryan, 1985 ; Ryan and Deci, 2000] or

“The term extrinsic motivation refers to the performance of an activity in order to attain some separable outcome and, thus, contrast with intrinsic motivation which refers to doing an activity for the inherent satisfaction of the activity itself.” [Ryan and Deci, 2000 p. 71].

Extrinsic and intrinsic are two fundamental types of motivation that have been used extensively in the information systems literature. For example, Davis and colleagues [1992] examined motivation in the context of computer use in the workplace. This research suggests that perceived usefulness can be a proxy for extrinsic motivation when using a system, whereas enjoyment is can be a proxy for intrinsic motivation.

Intrinsic motivation has also been linked to adoption and information system success. For instance, Venkatesh [1999] found that intrinsically motivated individuals, as measured by computer playfulness, positively affected acceptance of technologies. This study also demonstrated that specific training techniques aimed at increasing ones computer playfulness created a positive experience for the user and therefore increased the user’s satisfaction. In a subsequent study, Venkatesh [2000] suggested that intrinsic motivation can also influence a system’s ease of use which, in turn, affects intention to use.

Intrinsic motivation has also been studied in the context of enterprise resource planning (ERP) system adoption [Hwang, 2005]. Specifically, this field study examined how intrinsic

motivation affected satisfaction in the use of a mandatory systems³. Likewise, intrinsic motivation has also been studied in voluntary systems, such as ecommerce Web sites. The technology acceptance model (TAM) originally proposed by Davis and colleagues [Davis, 1989 ; Davis, 1993 ; Davis et al., 1989a ; Davis and Venkatesh, 1996] has been used as a framework for studying whether intrinsic and extrinsic factors can influence online behavior [Shang et al., 2005]. Interestingly, one of Davis' [Davis et al., 1992] preliminary studies suggests that the user's task influences the affects of intrinsic motivation. Also, this research found that there was no relationship between the type of task and the extrinsic motivation.

In sum, information system research, presents motivation as the psychological relationship between the external forces (extrinsic) and the internal forces (intrinsic). In a SDT framework [Deci, 1975 ; Deci and Ryan, 1985 ; Ryan and Deci, 2000] extrinsic and intrinsic factors form a continuum of nonself-determined and self-determined behavior. These are anchored by extrinsic motivational factors for the nonself-determined and intrinsic motivation for the self-determined anchor. Figure 1 is adapted from Ryan and Deci's [2000] conceptualization of SDT. This figure outlines how the continuum is conceptualized and gives examples.

Figure 1 below outlines how SDT connects Behaviors, Motivation, Regulatory Styles and Perceived Locus of Causality. Specifically, we are interested in the extrinsic and intrinsic continuum as developed by the nonself-determined and self determined behavior. This figure shows that extrinsic motivation can be categorized along the continuum by differing types of regulatory styles (e.g., external regulation, interjected regulation, identified regulation and

³ Mandatory systems are defined as the required use of software in an organization.

integrated regulation). Further these regulatory styles are informed by the type of perceived locus of control (e.g. from external to internal).

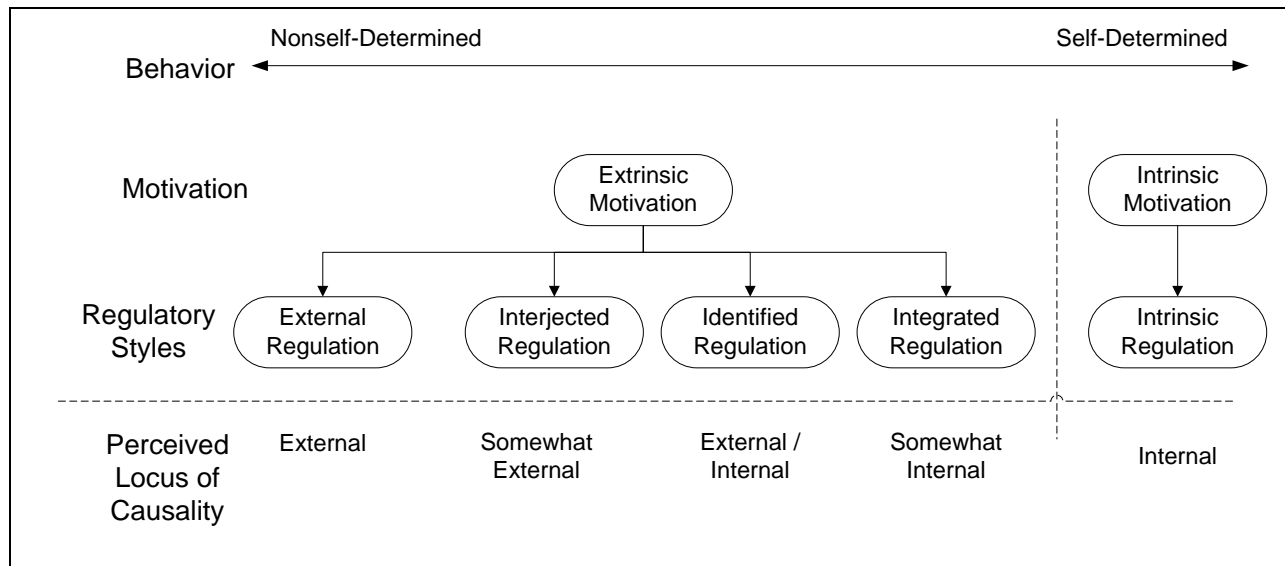


Figure 1. SDT in Information Systems

Although much of the past psychology literature has focused on the either intrinsic or extrinsic, as presented above, recent IS research has provided a conceptualization of the interplay between the two types of motivation [Malhotra et al., 2008]. This research based on Deci and Ryan’s organismic integration theory (OIT) which was originally introduced as a sub-theory within SDT [Deci and Ryan, 1985].

Malhotra and colleagues [2008] argue that an endogenous lens be used to apply OIT theory into an information system context. This research posits that motivation stems from a “collection” of sources rather than simplified extrinsic and intrinsic factors. Similar to the Malhotra’s concept of motivation our theoretical orientation leverages a similar users’ psychological state in term of perceived locus of causality (PLOC) to aid in measuring and defining motivation in an online context (See Figure 1 above). PLOC offers a richer

understanding that the interplay between intrinsic and extrinsic motivation, providing the ability to rectify the conflict between intrinsic beliefs and extrinsic pressures. By adopting an endogenous lens we can specify how extrinsic and intrinsic factors are internalized.

We advance the body of online consumer motivation research by offering a way to measure motivation based on the interplay between the two motivation factors (e.g., extrinsic and intrinsic). True to SDT, we view this interplay as a behavior continuum where a consumer could be highly extrinsically motivated or highly intrinsically motivated. Clearly, these two motivations factors are not orthogonal. For example, one could be highly extrinsically motivated and highly extrinsically motivated. We argue that when someone is high in both areas the relationship can be conceptualized as in the middle of the continuum.

Online consumer motivation

Online consumer motivation is emerging as a focal area of research within the IS discipline that has received recent attention [Cheung et al., 2005 ; Cheung et al., 2003]. A review of online consumer motivation research has shown that this areas of research draws heavily from psychology, consumer behavior and information systems literatures [Cheung et al., 2005 ; Cheung et al., 2003]. This include seminal research such as behavioral learning [Skinner, 1938], personality research [Folkes, 1988], attitude models [Fishbein and Ajzen, 1975 ; Fishbein and Middlestadt, 1995] and information processing [Bettman, 1979]. This body of research was used to describe the decomposition of online consumer behavior with some success. However, the application of these theories is not as simple of borrowing the respective components and applying them. It is clear, from this literature review that there are significant differences between conceptualizations of online consumer motivation. We suggest, as does Malhotra, Zhang and others [Malhotra et al., 2008 ; Zhang, 2008], that IDT offers a simplistic

parsimonious lens for understanding what consumers are looking for in an ecommerce transaction. Our conceptualization looks at the interplay between the intrinsic and extrinsic factors that may form a reasonable amount of influence over a consumer's overall motivation when in an ecommerce context. For this reason it is important to investigate ways to measure this motivation.

The next section presents a general structure of online consumer motivation that draws heavily from Deci and Ryan's IDT [Deci, 1975 ; Deci and Ryan, 1985 ; Ryan and Deci, 2000]. This conceptualization includes important factors that influence an online consumer's motivation (e.g., task and computer playfulness).

ONLINE CONSUMER MOTIVATION MODEL DEVELOPMENT

As discussed above, we believe that online consumer motivation can be conceptualized as the interplay between extrinsic and intrinsic motivation on a continuum. What is unclear is what specific antecedents affect a consumer's motivation in an ecommerce context. For this reason, the past literature on individual and consumer characteristics will be reviewed to provide a foundation for positing linkages to possible antecedents.

The characteristics of individuals have a long history of investigation within the information systems discipline [Zmud, 1979]. In the case of our research there are two factors that we believe have significant impacts on a consumer's motivation. The antecedents of online consumer motivation include the task (e.g. extrinsic forces / intrinsic forces) and individual difference in Web use (e.g. computer playfulness). These motivating factors have an obvious effect during the online experience. The following section outlines the extant literature for both task characteristics and computer playfulness.

First we will look at how online tasks can be influenced by and also influence a consumer's motivation. This will include an introduction to past ecommerce studies on online tasks. Second, computer playfulness, a heavily studied motivational factor will be introduced and integrated into the online consumer motivation model.

Research on Online Tasks

Ecommerce consumers can have very different intentions when visiting a Web site and can therefore behave differently. Some consumers can have a general idea of what they are looking for while others may have specific goals. For example, one user could be looking for cars without any specific requirement where another consumer could be searching for the best price for a certain used car that is located in her general vicinity.

The extant ecommerce literature has identified two general types of shopping tasks: 1) goal-directed and 2) experiential [Shang et al., 2005 ; van der Heijden, 2004 ; van der Heijden et al., 2001 ; Wells et al., 2005]. Unfortunately, there is no agreement for the terminology used in the consumer behavior and ecommerce literature. Further, in the consumer behavior literature there has been a focus on utilitarian and hedonic activities in both traditional offline settings and online settings [Hirschman, 1984 ; Hirschman and Holbrook, 1982 ; Novak et al., 2003a ; van der Heijden, 2004]. Hedonic task are unstructured using non-linear navigation and search techniques. On the other hand, utilitarian tasks are structured using linear navigation and search patterns [Novak et al., 2003a ; Wells et al., 2005].

As such, there are a wide variety of online ecommerce tasks a user may undertake. Prior research has created online task categories [Hargittai, 2004 ; Kau et al., 2003 ; Rohm and Swaminathan, 2004]. Further, the naming convention for these tasks has been somewhat inconsistent. Research on information systems training methods suggest that we differentiate

tasks as “programmed” and “non-programmed” in an automated environment [Simon et al., 1996], where programmed tasks are repetitive and routine and the non-programmed tasks are novel and unstructured. Other researchers identify the task on a continuum as “goal-directed” and “experiential” [Wells et al., 2005]. Clearly, searching and browsing are deemed to be distinct activities in ecommerce, researchers also recognized that they represent two ends of a continuum rather than a strict dichotomy. There are several conventions used to describe the anchors on task continuum. Table 1, adapted from [Wells et al., 2005] summarizes the terms used to describe task characteristics.

Table 1: Task Characteristics: Experiential vs. Search Directed		
Experiential Task Types	Search Task Types	Key Work
Experiential attributes	Search attributes	Alba et al. [1997]
Hedonic	Utilitarian	van der Heijden [2004], Wolfenbarger & Gilly [2001],
Unstructured	Structured	Hoffman & Novak [1997]
Non-directed search	Directed search	
Non-linear navigation	Linear navigation	
Perceptual attributes	Analytic processing	Mathwick et al. [2002]

Similar to the research on task characteristics in an ecommerce context this instrument development paper we will be describing tasks as either experiential or search oriented [Wells et al., 2005]. In order to contextualize task characteristics Table 2 gives some examples of ecommerce tasks that have been categorized as search or experiential.

Table 2: Examples of Online Ecommerce Tasks

Search	Experiential
Paying your cell phone bill online.	Examining at your overall spending patterns.
Looking for a certain song you heard on the radio.	Browsing for new music that interests you.
Booking the cheapest ticket to for an upcoming wedding.	Looking for possible vacation destinations for next Christmas.
Finding a textbook you need for school.	Looking at the current bestseller books to see if any interest you.

It must be noted that different consumers will have different views on whether certain tasks are search or experiential. We will introduce how individual differences, in the form of computer playfulness, can impact the perception of task and therefore influence a consumer's online motivation.

Research on Individual Differences

There are many different ways of examining how individual differences, particularly personality traits relate to ecommerce outcomes. Specific individual differences examined in the consumer behavior and ecommerce literature include privacy beliefs [Sheng et al., 2008], usability preferences [Palmer, 2002], interactivity preferences [Campbell and Wright, 2008], cognitive load [Shang et al., 2005], stimulation preferences [Hirschman and Holbrook, 1982] and so on. All of these personality traits have been shown to affect the outcomes in ecommerce.

As argued above it is our contention that task is an important component that affects motivation. Independent of task, the consumer's interaction with an ecommerce Web site is also

influenced by the inherent nature of the user [Goodhue, 1995 ; Goodhue and Thompson, 1995]. We believe that consumers can also have intrinsic or extrinsic personality traits in online ecommerce experiences. More specifically, we believe that online shopping motivations can vary from person-to-person in general. Zhou [2007] agrees by stating, “(intrinsic) shoppers always find more enjoyment in interactivity environments than in pure test environments.” [Zhou et al., 2007 p. 43]. On the other hand, research has shown that extrinsic shoppers are concerned with the shopping experience being timely, quick and efficient [Childers et al., 2001].

Venkatesh’s seminal paper on individual difference within information systems looks at intrinsic motivation as instantiated by computer playfulness [Venkatesh, 2000]. Our paper draws heavily on Venkatesh’s concept of intrinsic motivation [Venkatesh, 1999 ; Venkatesh, 2000]. Extending this thinking, computer playfulness is a good ideal for understanding how personality affects overall online consumer motivation. Table 3 summarizes the general computer playfulness based on intrinsic and extrinsic needs. For example, generally in any ecommerce context a person who has a high degree of computer playfulness (e.g., intrinsically motivated) will tend to browse around the Web site more and look for opportunities to explore. On the other hand, consumers who rate low on computer playfulness tend to look for a quick interaction and want to get the task completed efficiently.

Table 3: Examples of Online Individual User Differences

Extrinsic	Intrinsic
Usually gets in and out	Wants to tinker with the options
Likes a quick and easy option	What to view all aspects
Does not vary from the task at hand	Likes finding new things

The literature have posited that aspects of the task will account for more variance in outcomes than some individual differences [Simon, 1996]. What is not certain, and will be studied here, is how computer playfulness and the task will influence overall online motivation in an ecommerce environment. For this reason we conceptualized online consumer motivation as a second order factor that is influenced by both task type (e.g., search or experiential) and computer playfulness (e.g., intrinsic and extrinsic). Figure 2 depicts our conceptualization of how online consumer motivation is formed. This includes the effects of both task and computer playfulness.

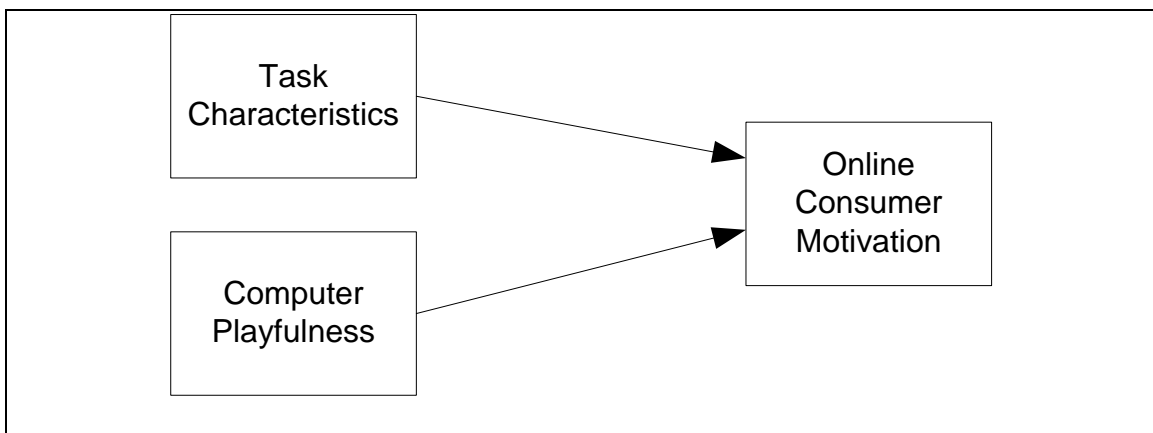


Figure 2. Online consumer motivation

INSTRUMENT DEVELOPMENT

In order to measure the constructs developed in this paper, it is necessary that instrumental validation should proceed any empirical validation [Cook and Campbell, 1979]. The instrument vetting process refers to the adequacy with which the scale (e.g., grouping of items that measure a construct) nomologically address the constructs while also measuring the convergent and discriminant validity [Straub et al., 2004]. The information system literature offers explicit guidance on validation guidelines for measurement instruments [Gefen et al., 2000 ; Straub, 1989 ; Straub et al., 2004]. Straub and colleague [2004] note that there are several different type of components to validity. This includes reliability, construct validity, content validity and manipulation validity.

The instrument creation process typically includes three steps: creating a set of possible items, developing the scales in their entirety, and finally testing of the items [Straub et al., 2004]. The instrument will be validated by one pilot test and two cross sectional studies.

Item generation

The first step in the instrument development process involved the creation of items to measure each of the three constructs (e.g., online consumer motivation, computer playfulness and task characteristics) theoretically argued as related above. First, the prior literature was reviewed at length to provide search for previously established measures. Having completed this, the next step included generating a large pool if candidate questions for initial evaluation of the constructs. The initial pool included 20 questions for the three dimensions – perception of task, computer playfulness and online consumer motivation.

As discussed above, computer playfulness is an established measure that has been used in information systems research for some time [Venkatesh, 2000]. Even though computer playfulness has been established in the literature this study included the items in the instrument development process as no study to our knowledge has linked computer playfulness to task and online motivation.

In this step content validity is examined. Content validity is how the content of the items actually measures the content of the construct and also the extent to which measurement reflects the intended domain [Straub et al., 2004]. A group of 5 ecommerce and psychology experts were consulted to analyze the potential items for nomological consistency. This group was given the definition for each construct as outlined by the literature and descriptions of the context for which these items will be used (e.g., ecommerce). The group was then asked to identify: 1) items that were incompatible with the constructs 2) identify items that do not clearly map to any of the constructs of interest and 3) and items that were poorly worded or vague.

Several items were dropped or were reworded based on this feedback. Also, several items were added to the established computer playfulness scale. These new items were added to attempt to provide an ecommerce context to the playfulness instrument. Further, the items were vetted for reading levels with the goal of providing a maximum overall Flesch-Kincaid Grade Level of 10. The rationale for this reading level was that the researchers wanted the target population of college students to easily read and understand the items. The Flesch Reading Ease statistic was 75.4 and the Flesch-Kincaid Grade Level was 8.9. Both statistics were deemed acceptable.

The second draft of the complete measure was then developed with 15 items per each construct. This draft was given to 30 undergraduate students to check for readability. Based on this

feedback the first version of the instrument was prepared. Several questions were asked in the negative. Negatively worded items were used as it has been shown that single items worded in the same direction performed poorly as compared to instruments that include both positive and negatively worded items [Curran et al., 1996]. The instrument had forty questions.

Rating anchors

A seven-point LIKERT scale was chosen with a neutral midpoint for the measurement computer playfulness and online task motivation. To measure task we used semantic differential anchors (See Appendix H). The items strongly match the typical LIKERT item - a declarative statement, followed by a response opinion. Also, summation across items are designed to yield a total score indicator of the construct. Finally, LIKERT will allow for a variety of response options for the subjects. The LIKERT scale used for the online consumer motivation and computer playfulness was as follows: 1)Strongly Disagree, 2)Disagree, 3)Slightly Disagree, 4)Neither Disagree nor Agree, 5)Slightly Agree, 6)Agree and 7) Strongly Agree. Table 4 outlines the construct in the initial version of the instrument.

Table 4: Initial Version of the Scales		
Constructs	Abbreviations	Number of Questions
Computer Playfulness (adapted from [Venkatesh, 2000])	CP	10
Task Type	TT	15
Online Consumer Motivation	OCM	15

MAIN EXPERIMENTAL TESTING

The development of this instrument included a controlled experiment and a survey. The samples were separate and independent. Exploratory analysis was conducted on the first sample. The second sample was analyzed using confirmatory means. The following will outline the data collection procedure. This includes the exploratory analysis, and the confirmatory analysis.

Experimental Study

The instructions were presented on a Web page for both data collections. This study consisted of a simple 1 X 8 full factorial design using 2 domains and 4 different Web sites. The Web sites were designed be either experiential sites, that were geared towards experiencing many different things and create an atmosphere of enjoyment, or goal-directed site, where the design enabled users to complete a certain set of tasks very easily. Appendix C show examples of the sites used. The two domains chosen were a vacation resort Web site and a news aggregation site. All the sites were developed to exemplify real commercial Web sites. An open API from Digg.com was used as a code basis for the news aggregation site. The vacation sites were developed from the ground up.

Both domains had an experiential Web site and a goal-directed Web site. The information that was presented for the Web sites in each domain was identical but the interface design differed as mentioned above. In the experiential vacation site, the interface presented a map of the resort which was used for navigation. The users could easily browse the different activities the resort had to offer but using the interactive resort map. The goal-directed site was very linear, in that the users could only chose different activities within a menu.

The news aggregation site was based on Digg.com, where users can submit stories that are rated by the community in terms of importance. In the goal-directed news site stories are present in a 25 stories per page list with the higher rated stories further up the list. The stories also can be sorted by many criteria such as different genres or timeliness of the story. This goal-directed site also presented changes to the news rankings in real time. The experiential presentation of the Web site involves a view of users as they jump from reading stories. The users are presented as small spheres that move from stories viewed as bubbles. The bubbles become larger as the story increases its ranking.

Also, the user of the experiential news site could watch users view stories in real time. Smaller user nodes were attached to the stories and jumped around to other stories as the user viewed the different stories. Although difficult to conceive this experiential interface provides a hedonic aspect as it allows people to experience news stories differently than the list of news stories would. For example, a user can watch stories grow, or watch a particular user with similar interests which may lead to stories that might not otherwise be found in a list type interface. See Appendix C for screen shots of the Web sites.

The methodological approach in this stage consists of a laboratory experiment in which student subjects are asked to take part in an evaluation of a Web site. The subjects in the study were randomly assigned to one of 8 conditions (See Table 5 for a list of the conditions). After the student complete the task (See Appendix D) the instrument was administered via a Webpage and the subjects were debriefed.

Table 5: Experimental Conditions

Task	Site	Site Description
Hedonic	News Aggregation - Experiential	This site, modeled after Digg.com – Swarm, allowed users to browse news stories based on a visualization of what stories were currently being rated real-time. This allowed users to also watch other users bounce from story to story.
Utilitarian	News Aggregation - Experiential	Same as above
Hedonic	News Aggregation - Goal-Directed	This site, modeled after Digg.com, allowed a community of users to rate stories which then provides the ranked list in which users can view the popular stories. The site is in a list like format with the most popular stories on the front page and progressively less popular stories going down the list.
Utilitarian	News Aggregation - Goal-Directed	Same as above
Hedonic	Vacation Site - Experiential	This vacation resort site allowed users to browse possible activities and amenities at the resort using an interactive resort map. This feature allowed the users to easily look at lots of different features in the resort.
Utilitarian	Vacation Site - Experiential	Same as above
Hedonic	Vacation Site - Goal-Directed	The site was also a vacation resort in which users could browse using typical menu based links. It was very linear in fashion.
Utilitarian	Vacation Site - Goal-Directed	

EXPLORATORY ANALYSIS

In this analysis section we will outline all the assumption and statistical test undertaken⁴.

This section begins proceed as follows: 1) description of the sample decision made by the

⁴ Unless otherwise noted SPSS 16.0 was used by the authors for all statistical descriptions and tests.

researchers, 2) demographics information reported, 3) description of data screening, 4) exploratory factor analysis, 5) reliability analysis, and 6) discrimination analysis.

Sample Decisions

The sample was 361 undergraduate business students in an introductory business class. This constitutes a non-probability sample as the participants were taken from a subject pool. While non-probability samples can be problematic in terms of generalizability, the task was relevant as all the subjects have had online buying experience. Although, the sample size is deemed acceptable due to: 1) there were ample amount of subject for three constructs being estimated, and 2) the authors will be undergoing exploratory factor analysis.

The author chose list-wise deletion to deal with missing data. This is deemed acceptable as exploratory research can absorb the lost subjects. Also, exploratory analysis is more sensitive to imputation for replacement of data. By using list-wise deletion the sample size decreased to 345 subjects. An ANOVA test was run to see if there were any differences between subjects that answered all questions and subjects that left out answers. There are no significant results for any of the variables (See Table 6 below).

Table 6: ANOVA results for Non-Response Bias

		Sum of Squares	df	Mean Square	F	Sig.
OCM	Between Groups	3.029	15	.202	.413	.975
	Within Groups	160.840	329	.489		
	Total	163.870	344			
CP	Between Groups	4.814	15	.321	.890	.576
	Within Groups	118.673	329	.361		
	Total	123.486	344			
TT	Between Groups	15.656	15	1.044	.745	.738
	Within Groups	460.957	329	1.401		
	Total	476.613	344			

In order to accomplish a non-response bias test the data included dummy coding of 0 - representing no data missing for the particular case and 1 – representing cases which were missing data. These results confirm that excluding the subjects with missing data was acceptable.

Demographics

In order to gain a complete understanding of the outcomes demographics must be reported and evaluated. In this study there are 201 males (58%). A one way ANOVA was conducted to evaluate if there were differences in sex and the variables. We found no significant differences using sex as the factor (See Table 7 below). The age of the subjects ranged from 18-28 with a mean age of 20.4.

Table 7: ANOVA results for sex bias

		Sum of Squares	df	F	Sig.
OCM	Between Groups	.871	1	1.832	.177
	Within Groups	162.999	343		
	Total	163.870	344		
CP	Between Groups	.055	1	.152	.697
	Within Groups	123.432	343		
	Total	123.486	344		
TT	Between Groups	1.962	1	1.418	.235
	Within Groups	474.651	343		
	Total	476.613	344		

Screening of Data

The next step taken in the process was simply looking for values outside the possible range for the particular scales. None of the items were outside the possible ranges for the seven-point LIKERT scale. Also, descriptive statistics were run and evaluated (See Appendix E). When evaluating the descriptive statistics we specifically pay attention to the skewness and the kurtosis statistics. With skew we evaluate the statistic simply if the value is + or – 3 [Devellis, 2003] and the kurtosis we evaluate using the + or – 10 [Kline, 2005]. All items were well within these ranges.

EXPLORATORY ANALYSIS RESULTS

To evaluate the newly generated items convergent validity an exploratory factor analysis (EFA) was undertaken using SPSS 16.0. Convergent validity is concerned with how an observed

variable of a latent construct correlate with another observed variable that represents the same construct [Straub et al., 2004]. The EFA included the assumption that there are 3 latent variables as mentioned in the introduction.

When conducting the EFA principle components extraction method was used and the number of factors was constrained to three, as per the above research model. Straub and colleagues suggest that principle components analysis is a , “statistical procedure employed to resolve a set of correlated variables into a smaller group of uncorrelated or orthogonal factors.” [Straub et al., 2004 p. 70]. Also, Varimax rotation with Kaiser Normalization was used in the extraction process.

Using the above extraction methods three factors were extracted in 12 iterations (See Appendix F). The goodness-of-fit test proved significant ($p < .001$) so the researchers felt comfortable moving on with the factor analysis. Both the KMO and the Barlett’s Test of Sphericity also encouraged the researchers to proceed with the EFA reporting values of .895 and $p < .001$ respectively (Appendix F).

The cutoff criteria for the factor loadings on each construct were 0.5. The analysis was done using a stepwise approach. The factor with the lowest loading was removed. This was done until all factor loadings were 0.5 or more. As you can imagine several items were removed.

We then vetted the instrument down to 5 items on each construct. This was based on content validity by our expert panel described above. Using SPSS 16.0 we then ran an EFA on this set of 15 items. There were three components that had initial eigenvalues over 1.0. These three components accounted for 65% of the variance explained by the dataset.

The pattern matrix included five TT items loading on component one above .8 and with no cross loadings above .2. Five OCM items loading on component two above .7 and no cross

loading above .2. When evaluating CP on component three there were five factors above .5 and again no cross-loading above .2 (See Appendix G).

CONFIRMATORY FACTOR ANALYSIS

After completing the EFA a confirmatory factor analysis using AMOS 16.0 was undertaken with another independent sample. A snowball sampling technique was used to recruit participants for this study. A snowball sample is a referral sampling methods that originated with in early survey research [Coleman, 1958]. This sampling technique uses a convenience sample as seeds. These recruit subjects are typically based on a set of criteria to participate in order to tap into different networks. This methodology is commonly used in consumer behavior and marketing research, see [Mick, 1996]. Snowball sampling is also known in the literature as link-tracing sampling and random-walk sampling [Hedman and Sharafi, 2004].

The seed group of participants were students in an introductory information systems course. This seed group of participants was given an incentive (extra credit worth about 1 % of the final grade) to recruit non-student subjects. Each student was instructed to solicit up to four individuals who use the internet for online purchases. Three hundred and thirty seven individuals (not including the seed sample of students) participated in this survey. The minimum age reported was 14 and the maximum was 72. The average age was 33 of the subjects (47 %) were male. An *a priori* power analysis was undertaken to see if the sample size was large enough for the model. This sample seemed to be adequate for testing this research model. The power analysis for this model is fairly uncomplicated as there are only three constructs represented by a few items each. Having over 300 participants easily satisfies the need of a minimum of five participants per estimated parameter in structural equation modeling [Kline, 2005].

Next the measurement model fit was examined. For the purpose of this analysis comparative fit index (CFI), goodness of fit (GFI), adjusted goodness of fit (AGFI) and the root-mean-squared error of approximation (RMSEA) will be used. The results showed an acceptable fit (See Table 8) therefore the items have been validated [Brown, 2006].

Table 8: Fit Statistics for the Measurement Model on the Vetted Items			
χ^2 / df	128 / 62	AGFI	0.948
CFI	0.980	RMSEA	0.044
GFI	0.965		

The criteria for the values used to evaluate the fit have been well established [Kline, 2005]. This includes that the CFI must be higher than .95, the GFI must be greater than .9, the AGFI must be greater than .8, and the RMSEA value be lower than .08. Next we will evaluate the instruments reliability.

Reliability Analysis

Reliability analysis is used to evaluate the internal consistency of a measurement instrument. The most common statistic for evaluating reliability is Cronbach's alpha. In this research where we are validating our instrument relative to a theoretical perspective we would like to see 0.8 or higher [Nunnally and Bernstein, 1994].

Using the items validated by the EFA a reliability analysis was undertaken. The instrument tested provided high reliability to the latent factors as measured (See Table 9). The results show that each item demonstrates convergence to its proper latent factor.

Table 9: Reliability	
Latent Factor	Cronbach's Alpha
OCM (5 Items)	.850
Task (4 Items)	.902
Computer Playfulness (4 Items)	.930

Composite Reliability was analyzed next on the final bank of items (see Table 10) to provide further reliability analysis. As shown, all reliabilities except two were greater than the recommended threshold of .7 [Hair et al., 1998]. These two items were removed (CP 4 and TT 10). We also evaluated the modification indices in the structure model and found both of these items to be problematic (e.g. the items had indices higher than 25).

Convergent Validity

As stated previously, convergent validation provides an understanding of which observed variable correlate with which latent factors. We will use SEM to assess the convergent validity of the final items. In this case we will evaluate validity using the average variance extracted for each construct. These values should be greater than .5 [Fornell and Larcker, 1981]. This condition has been met using this data set (see Table 11).

Table 10: Measurement Model: Composite Reliabilities

Items	Loadings	Composite
OCM3	.776	.887
OCM7	.845	
OCM9	.823	
OCM10	.671	
OCM15	.783	
CP2	.734	.875
CP5	.755	
CP6	.846	
CP7	.852	
TT8	.712	.878
TT9	.776	
TT11	.856	
TT12	.859	

Table 11: AMOS Estimated Squared Correlations and AVE

OCM	0.611
CP	0.638
TT	0.645

Discrimination Analysis

In order to completely detail the discriminant validity of this instrument this section will outline: 1) Correlation-based discrimination, 2) χ^2 analysis and finally 3) average variance extracted (AVE) evaluation. By providing a convergence in finding from these three statistical tests this should afford a robust finding for the instruments discrimination properties.

Correlation

This test of discrimination evaluates the correlations between two factors [Kline, 2005]. Based on the correlations between the constructs there is strong discriminant validity (See Table 12). Specifically, none of the constructs correlate higher than .85 [Kline, 2005]. This confirms our initial theoretical perspective. Further analysis must be under taken to provide additional evidence of discriminant validity.

	OCM	CP	TT
OCM	1		
CP	0.199	1	
TT	0.106	-0.026	1

χ^2 Analysis

Using the χ^2 analysis will provide further evidence of discriminant validity. This analysis simply tests the difference between the model with all latent factors are covaried and pairs of latent variables are statistically compared. Using this test every combination results in a significant decrease in fit (see Table 13). From this we can conclude that these constructs show discriminant fit using this method.

AVE Analysis

Average variance extracted can also be used in discrimination analysis. This method provides an understanding of how the observed variables account for variance in specific latent variables. If the AVE's are larger than all the squared correlation between constructs then it is said to be discriminant [Segars, 1997]. Table 8, shows that the AVE figures , on the diagonal, sue in fact show discriminant validity using this method.

Table 13: Pairwise Discriminant Analysis

Construct	df	χ^2
Original Model	62	129.9
OCM, TT	63	302.3
OCM, CP	63	282.6
CP, TT	63	340.3
χ^2 difference test for 1 df at $p < .005$ requires a difference of 7.88 in the χ^2 value [Cohen, 1988].		

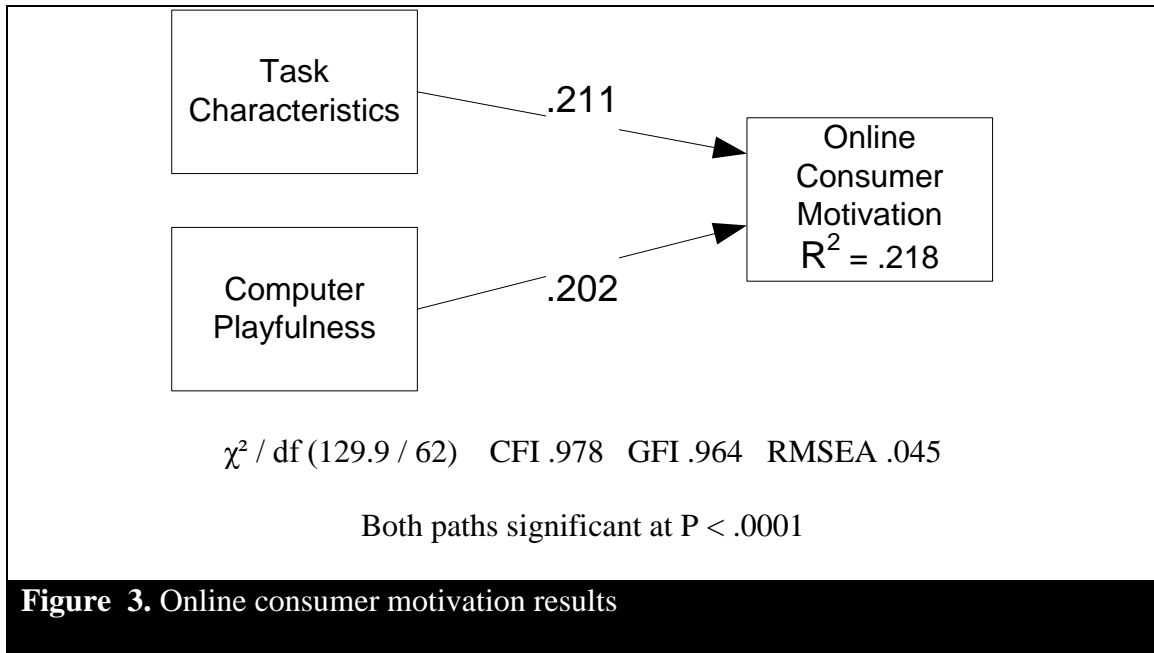
Table 14: AMOS Estimated Squared Correlations and AVE

	OCM	CP	TT
OCM	0.611		
CP	0.040	0.638	
TT	0.011	0.001	0.645
AVE statistics are shown in bold along the diagonal			

Final Research Model

Now that we have established the measurement model for these three constructs. The structural model will be tested. As stated above we are testing to see if the perceptions of the task and an individual's computer playfulness affect online consumer motivation. As before, AMOS 16.0 was used to test the model. As seen in Figure 3 below the model produced good fit for each indices. Further, all paths in the model were significant. Table 15 outlines the instrument.

Table 15: Final Group of items for each construct	
OCM1	I am likely to play while using this Web site.
OCM2	I would like to enjoy myself while interacting with this Web site.
OCM3	I am inclined to explore this Web site.
OCM4	I am likely to tinker while interacting with this Web site.
OCM5	I am inclined to spend some time and look around this Web site.
TT1	Directed/Meandering
TT2	Well-Organized/Unordered
TT3	To-the-Point/ Browsing
TT4	Direct/Not Direct
TT5	In-and-out/ Look around
CP1	. . . unimaginative
CP2	. . . creative
CP3	. . . playful
CP4	. . . unoriginal
CP5	. . . uninventive



CONCLUSION & DISCUSSION

This paper provides insight into the critical psychological factors that affect online consumer behavior. Further, this paper develops and validates an instrument to measure the factors that are attributed to online consumer motivation in an ecommerce context. The development of an online consumer motivation instrument is useful as it will allow researchers and practitioners alike to be able to measure and therefore predict which Web design tools will but suit the consumer.

The contributions of this paper are two-fold. First a conceptual model of the factors influencing online consumer motivation is presented. This model draws on SDT as well as the current practices used in Web design. The model adapts concepts from SDT [Deci, 1975 ; Deci and Ryan, 1985 ; Ryan and Deci, 2000], and references several components of use of motivation in design [Fang and Salvendy, 2000 ; Galletta et al., 2006 ; Palmer, 2002 ; Zhang, 2008].

Second, this paper presents an instrument that has been validated in both laboratory and field

tests. The above results show both discriminant and convergent validity for the measurement instrument based on both an exploratory and independent confirmatory sample.

All research has flaws and this instrument validation is no exception [Dennis and Valacich, 2001 ; McGrath, 1982]. One limitation of this study is that subjects used in the analysis. Student subjects were used in the initial sample. This limitation was controlled somewhat as the task that was executed mapped to the subjects' everyday experience. In other words, using student subjects to research online shopping and online consumer behavior can be seen as acceptable, as they are part of the core online shopping demographic.

ESSAY THREE: ONLINE CONSUMER MOTIVATION: AN EMPIRICAL EVALUATION

INTRODUCTION

A key challenge for organizations operating in the ecommerce arena is designing Web sites that fit the vast range of tasks (e.g., transactional, searching, browsing for pleasure, and so on) that are being executed by an increasingly heterogeneous consumer base⁵ (e.g., systems engineer, child in the third world, your grandfather, your daughter and so on). Organizations commonly design Web sites with a “one size fits-all” approach to try and address all, or at least most, of the tasks a consumer would need or want. To date, a primary focus of ecommerce Web site design research has focused on elements that can best suit the needs of all the possible needs of the consumer [Lazar, 2007 ; Shneiderman, 2000 ; Zeldman, 2003] .

There has been, however, less of a focus on how to design Web sites to best support specific tasks [Jahng et al., 2001 ; Zhou et al., 2007]. Further, there has been a call to focus on meeting the online consumer’s motivation for interacting with a particular type of Web site [Zhang, 2008]. Online consumer motivation is a state of mind prior to interacting with an ecommerce Web site that helps explain the underlying reasons why a user is at a particular Web site [Cheung et al., 2005 ; Cheung et al., 2003]. For instance, the consumer’s online motivation can be influenced by many things, including the task at hand (e.g., a user needing to pay a bill or

⁵ For this paper the authors consider user and consumer to be synonymous

trying to find a gift for your sibling) or one's personality (e.g., online impatience or computer playfulness). As such, both the task being performed and an individual's personality can inform, and possibly affect, an online consumer's motivation prior to interacting with a Web site.

When evaluating how certain individual personality differences interplay with tasks we draw from task-technology fit theory [Goodhue and Thompson, 1995]. Goodhue and Thompson [Goodhue, 1998 ; Goodhue and Thompson, 1995] posit that in any information system, the utilization focus (e.g., the technology's impact on utilization of a system) combined with the fit focus (e.g., the task and technology affect the performance) will provide a lens for understanding beliefs, affect, utilization and performance impacts in a given information system. In an ecommerce context, this means that both the consumer's task at hand and the inherent differences between consumers will influence performance and utilization of a particular Web site.

This research is based on the notion that we may be able to improve online purchase intention and satisfaction with the system, at the individual consumer level, by understanding the antecedents of online consumer motivation and subsequently being able to distinctly measure this new construct. Using data collected from several lab experiments and online surveys, we investigate: 1) online consumer motivation as a distinct construct, 2) the role that online consumer motivation plays in consumer behavior and 3) the possible ways online consumer motivation can be applied to improve the 'fit' of Web site design to consumer needs.

The goal of this research is twofold. First, given the interest in the interplay between task, individual differences, and technology characteristics, in an ecommerce context, task-technology fit offers a logical theoretical framework for understanding consumer motivation. As such, we propose a decomposed version of task-technology fit (TTF) that positions online consumer

motivation (OCM) as the focal construct. The second goal of this research is to offer practical guidance on how OCM can be measured, predicted, and ultimately used by organizations to improve Web site design that will subsequently affect purchase intention and satisfaction.

The following section will outline the appropriate prior research including the motivation literature and the task-technology fit research. This review will be followed by the theoretical underpinnings for this research which will lead to the presentation and abstraction of the research model. Next, the experimental and survey methods used for this research will be detailed followed by the results of these several studies. Finally the discussion and conclusion are presented.

PRIOR RESEARCH

Understanding how motivation can play an important role in consumer behavior and how task-technology fit can inform ecommerce design is central to this study. For this reason, we will be focusing our literature review on the prior motivation literature and then will examine how it can be integrated with task-technology fit theory has been used in the information systems literature.

The Motivation Literature

The motivation literature, primarily drawn from the field of psychology, attempts to answer two fundamental questions. The first basic question is how motivation causes certain types of behavior. The second question is why do certain types of behavior vary in intensity [Reeves, 2005]. Both of these questions lend themselves to ecommerce. Specifically, there is an opportunity to examine factors that affect sought-after ecommerce consumer behaviors (e.g., satisfaction, intent to return, and so on).

Many times motivation has been thought of as a first-order construct, it is now clear in the literature that different people are moved to act for very different reasons. For the purpose of our research we define motivation, similar to Deci and Ryan [Deci and Ryan, 1985 ; Ryan and Deci, 2000], as a state that is influenced by energy or direction and is linked directly to activation and intention. From this it can be inferred that people are motivated by very different types of factors. This includes motivation by strong external forces (e.g., the boss asks you to call a client) and internal forces that are driven by interests and values (e.g., reading the newspaper for enjoyment). There has been a great deal of work in the psychology discipline on how these two motivation factors interact. For example, those people who act in self-interest have more excitement and confidence which in turn enhances performance and creativity than those who are driven by external sources [Sheldon et al., 1996].

This interplay between external and internal motivation factors has been captured by a seminal theory in psychology called self-determination theory (SDT). SDT posits that motivation is created by both external factors and by internalized factors, more commonly referred to as extrinsic and intrinsic motivation respectively [Deci, 1975 ; Deci and Ryan, 1985 ; Ryan and Deci, 2000]. Deci and Ryan state that,

“The term extrinsic motivation refers to the performance of an activity in order to attain some separable outcome and, thus, contrast with intrinsic motivation which refers to doing an activity for the inherent satisfaction of the activity itself.” [Ryan and Deci, 2000 p. 71]

Moreover, intrinsic motivation describes how people are moved to act by spontaneous exploration and interest. SDT posits that feelings of competence will only occur when self-regulation is attached to intrinsic motivation. Further, some studies have suggested that positive

performance feedback enhances intrinsic motivation [Reeves, 2005]. Extrinsic motivation, on the other hand, is typically fostered by authorities (e.g., a boss, a teacher, parents, and so on) to induce certain types of behaviors.

In sum, motivation is typically regarded as the psychological relationship between the external forces (extrinsic) and the internal forces (intrinsic). It is important to note that contemporary research has also introduced differing regulatory styles for extrinsic motivation (See Figure 1 below). At the far left of the self-determination continuum is motivation that has the least amount of autonomy. This lack of autonomy is a type of extrinsic motivation called external regulation in the motivation literature [Deci and Ryan, 1985 ; Reeves, 2005 ; Ryan and Deci, 2000 ; Zhang, 2008]. The next type of extrinsic motivation is introjected regulation. This subset of extrinsic motivation typically stems from a controlled form of regulation that is also performed to avoid guilt [Ryan and Deci, 2000]. Moving further right on the motivation continuum a more autonomous form of extrinsic motivation is labeled regulation through identification. This is when the motivation is based on conscious valuing of goals and the action is personally important. Finally, internalized regulation is the most autonomy form of extrinsic motivation. This is when external pressures have been fully integrated with the self. Integrated regulation shares a great deal with intrinsic motivation although Ryan and Deci argue that enjoyment will not be as heightened by integrated regulation [Ryan and Deci, 2000].

Using SDT, we can see that motivation is anchored by extrinsic motivational factors for the nonself-determined and intrinsic motivation for the self-determined anchor. Figure 1, adapted from Ryan and Deci [2000] conceptualizes the differences in intrinsic and extrinsic motivations outlined above. Figure 1 exemplifies how SDT is traced from behavior to motivation which in

turn is broken into how a regulatory style affects both extrinsic and intrinsic motivation. Finally, the perceived locus of causality is examined to see to perceived source of the regulatory style.

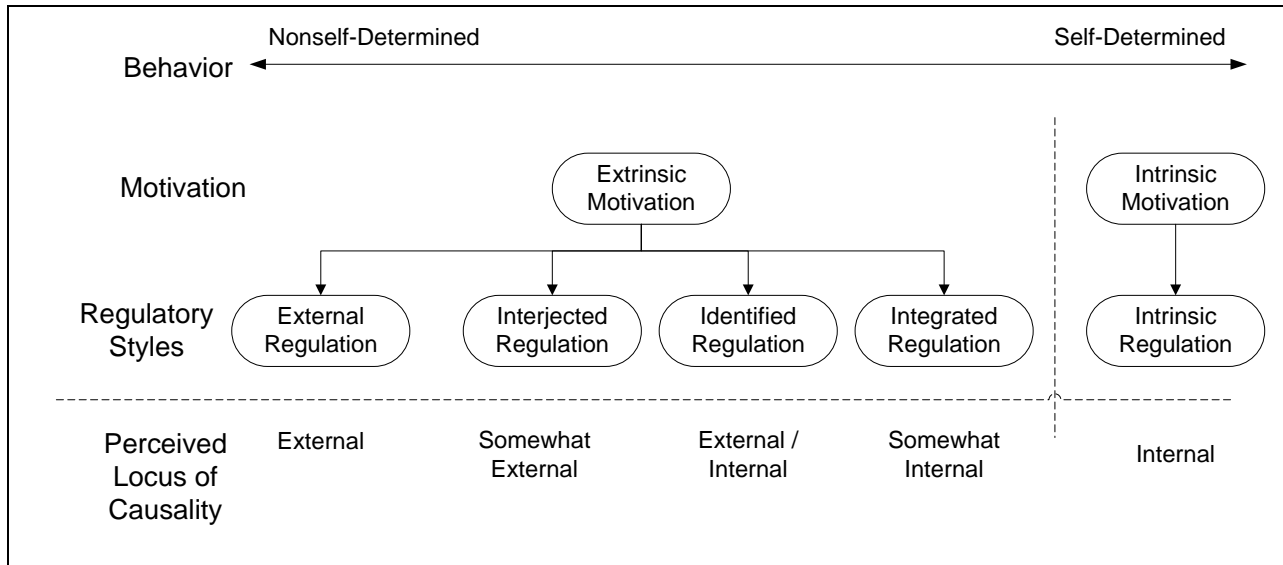


Figure 1. SDT in Information Systems

Motivation has also been studied extensively in information systems. For example, motivation has been investigated as a central construct in the use of computers in the workplace [Davis et al., 1992]. Davis and colleagues suggest that perceived usefulness can be a proxy for extrinsic motivation, whereas enjoyment can be a surrogate for intrinsic motivation. Taken together both intrinsic and extrinsic motivation are of consequential importance in information system acceptance.

Intrinsic motivation has also been linked to outcomes in information systems (e.g., information system success). Venkatesh [1999] found that intrinsically motivated individuals, in the form of computer playful users, positively affected technology acceptance. This study also demonstrated that certain training techniques that were aimed at increasing computer playfulness

to create a positive experience for the user and therefore increased the user's satisfaction. In a subsequent study, Venkatesh [2000] found that intrinsic motivation can also influence the ease of use which, in turn, affects intention to use. Both of these studies investigated how motivation can impact technology adoption and information system success.

Intrinsic motivation has also been studied in general Internet usage [Teo et al., 1999]. The Teo et al.'s study extended Davis et al. [1992] work to include Internet usage as the dependant variable rather than computer usage. By doing so they changed the context of the study to examine systems that were somewhat voluntary in nature. As expected, the researchers found that perceived enjoyment and perceived usefulness were related to system usage. The researchers also found that the diversity of Internet usage was not statistically related to perceived enjoyment and perceived usefulness. They argue the following, "although a wide diversity of tasks may be performed on the Internet, users are likely to enjoy a small subset of tasks." [Teo et al., 1999 p. 30]. Our research will also examine Internet use to see if task has an impact on motivation. Internet-based learning has also been studied in terms of how intrinsic and extrinsic motivation affects behavioral intention [Lee et al., 2005]. Specifically, the researchers were evaluating the underlying drivers to student adoption of Internet-based learning. They found, as predicted, that intrinsic and extrinsic factors both contribute to a student's adoption intention.

Much of the motivation literature in information systems, including the seminal work [Davis et al., 1992 ; Venkatesh, 1999 ; Venkatesh, 2000], has used intrinsic and extrinsic motivation as orthogonal factors with little or no relationship between the two types of motivation. It is clear from SDT that various aspects of extrinsic and intrinsic motivation are linked in some contexts. Likewise, recent research has provided a conceptual link relating the two types of motivation within the IS literature [Malhotra et al., 2008].

The Malhotra research [Malhotra et al., 2008] uses an approach to study motivation that examines how individuals internalize both external sources (e.g., their boss) and internal sources of motivation (e.g., like or dislike to do something). This endogenous lens approach is utilized to evaluate how SDT can be applied in information systems. Malhotra's research draws on Deci and Ryan's view of motivation [Deci and Ryan, 1985 ; Ryan and Deci, 2000] in that motivation stems from a "collection" of sources rather than simplified extrinsic and intrinsic factors. Similar to the Malhotra vein, our theoretical orientation is based on perceived locus of causality (PLOC) to aid in measuring and defining motivation in an online context. PLOC offers a rich understanding between the interplay of intrinsic and extrinsic motivation. This endogenous lens is able to rectify and subsequently capture the relationship between intrinsic beliefs and extrinsic pressures.

We advance the online consumer motivation research by offering a way to measure motivation based on interplay between extrinsic and intrinsic motivation. Figure 2 shows examples of how online tasks could be classified by an individual as it relates to extrinsic and intrinsic motivation. For example, it is possible that paying a bill online is a highly extrinsic task that has a high degree of external perceived locus of causality. Further, submitting homework online could be viewed as a task where the person does have external pressures but their motivation to do well in the course would also draw from intrinsic motivation. For this reason submitting homework could fall somewhere in the middle of the continuum. Finally, finding new music could be a very personal and very intrinsically motivated task for a person. Having said this, all of these examples are dependent on individual differences as each person could perceive the same task in unique ways.

The next section of the literature review will evaluate how task-technology fit can inform how online motivation could be constructed from the task-at-hand and an individual's level of computer playfulness.

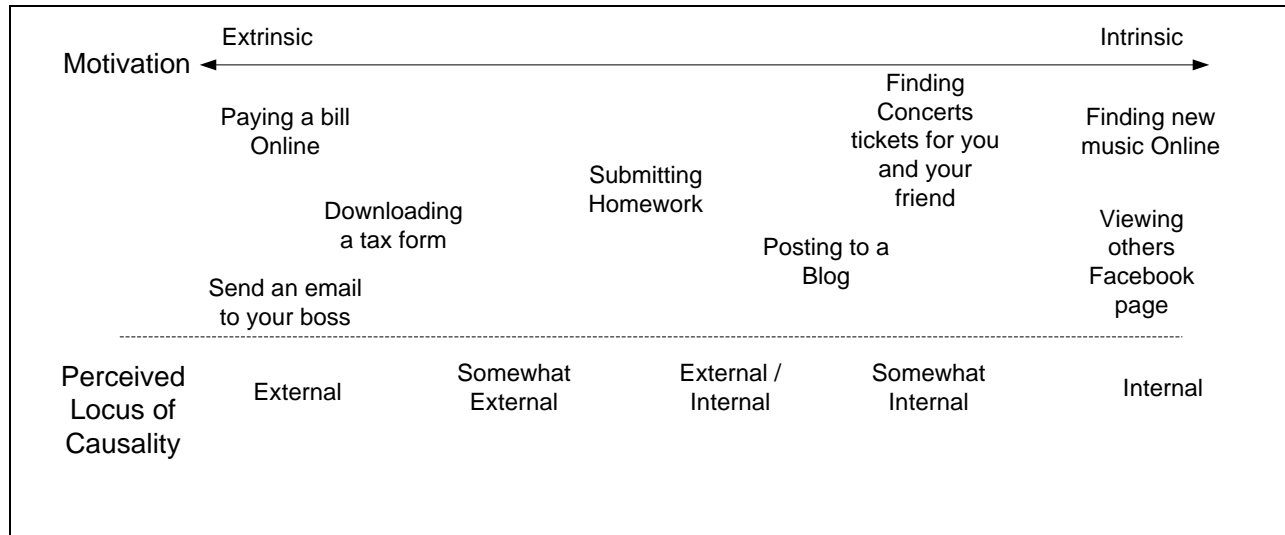


Figure 2. Example of Online Task on the Extrinsic / Intrinsic Continuum

Task-Technology Fit Literature

Issues with how graphs and tables are represented were an early focus of information systems presentation research [Benbasat and Dexter, 1982 ; Benbasat et al., 1986 ; Jarvenpaa and Dickson, 1988]. Building on this work on information presentation, subsequent research has addressed how task and certain individual personality differences can play an important role in information system success. The importance of the fit between the task characteristics and the technology presentation have been exemplified in several studies [Vessey, 1991 ; Vessey and Galletta, 1991]. The task-technology fit model (TTF) [Goodhue and Thompson, 1995] offers a conceptualization of a triad fit between the task characteristics, the technology characteristics and certain individual differences. TTF posits that the congruence between these three antecedents can lead to performance impacts (e.g. satisfaction with the system, retention of

information with the system, and so on). Goodhue and Thompson [Goodhue and Thompson, 1995] applied the TTF framework to understand the congruence between information system functionality and the task requirements that leads to positive user evaluation of the system and positive performance of the system (See Figure 3).

TTF has been used extensively to describe and evaluate the outcomes of individual performance when utilizing information systems [Goodhue and Thompson, 1995]. Outcomes in TTF theory include utility and performance; utility is typically measured as a subjective perception (e.g., satisfaction of the user, intention to use, and so on) while performance is typically measured objectively related to the task being performed by the user (e.g., timed task completion, accuracy, and so on). Usability in the form of the usefulness construct and performance in the form of ease of use has been extensively explored using models such as Technology Acceptance Model (TAM) [Davis, 1989 ; Davis et al., 1989b], Cognitive Fit [Vessey, 1991 ; Vessey and Galletta, 1991], and of course Task-Technology Fit [Goodhue, 1995 ; Goodhue, 1998 ; Goodhue and Thompson, 1995].

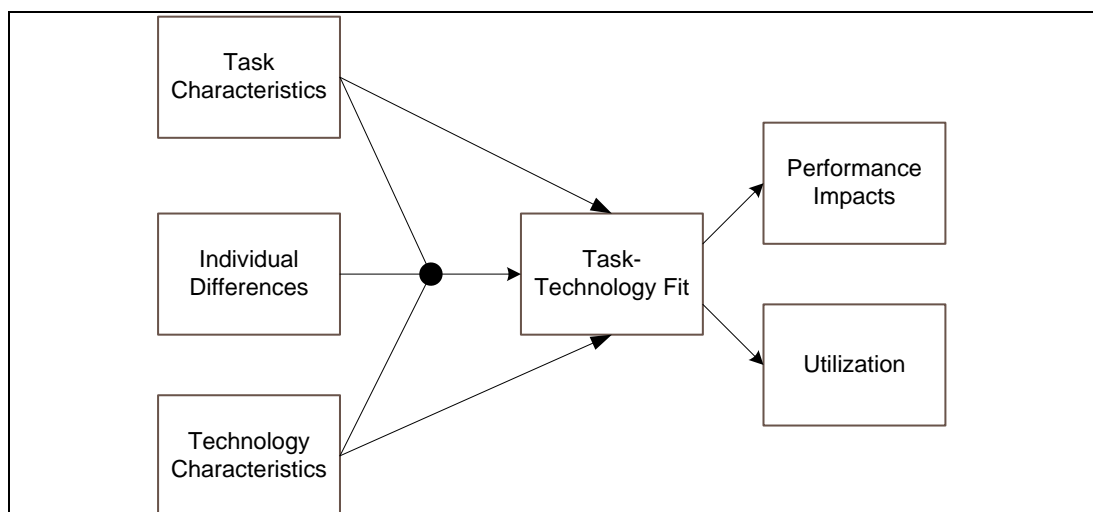


Figure 3. Individual Task-Technology Fit

The TTF framework has offered flexibility to study several areas beyond the voluntary and mandatory systems. While traditionally TTF research has focused on the intuitional end-users [Goodhue, 1995 ; Goodhue, 1998 ; Goodhue and Thompson, 1995], the model has also been applied to various other domains including ecommerce. This includes the application of ‘fit’ to explain ecommerce interactions between consumer and organization [Klopping and McKinney, 2004]. Nevertheless, the technology presentation characteristics in an ecommerce context are different from those in an organizational setting. Ecommerce uses web browsers as the medium to present information whereas there are several different platforms organizations can use to disseminate applications (e.g., terminal services, installed stand-alone programs, web browsers, virtualized services, and so on). Another difference from organization-level applications is ecommerce tends to be a choice, whereas in an organizational setting application use is typically mandatory.

TTF has also been used in describing different levels of analysis within an organization. The TTF literature has extended beyond the investigation of how individuals [Goodhue, 1995] interact with technology presentation to include how groups interact with technology presentation [Dennis et al., 2001 ; Zigurs and Buckland, 1998] based on task and certain individual differences.

Clearly there is evidence that ‘fit’ in technology presentation to the task-at-hand and certain individual difference affects performance and utilization of a system. The difficulty in using the TTF model lies within the complex interaction between the antecedents and the fit construct. Further, research has suggested that TTF is too general to describe most contexts in information systems today [Gebauer and Ginsburg, 2009]. As shown in Figure 3, the TTF framework is comprised of a three-way interaction between technology characteristics, task

characteristics and individual differences. This interaction causes a difficulty that makes modeling and testing TTF to a particular context (e.g., ecommerce) quite challenging. Additionally, the conceptualization of the fit construct is somewhat of a black box and offers little guidance for pragmatic application [Gebauer and Ginsburg, 2009].

We believe there is an opportunity to extend and combine the core motivation concepts as outlined by Deci and Ryan [Deci and Ryan, 1985 ; Ryan and Deci, 2000] and the TTF model [Goodhue and Thompson, 1995] to provide an omnibus model for online consumer motivation. The next section will outline how we conceptualize this model and the hypothesis associated with each proposed relationship.

RESEARCH MODEL

In order to operationalize the TTF model within an ecommerce environment, our research must reconcile how online consumer motivation (OCM) captures the interaction between task and individual characteristics. Subsequently, we must identify how OCM will act as a clearing house for the decomposition the inherent 3-way interaction. Our instantiation of OCM will include a temporal view of how task characteristics and certain individual differences lead to an understanding of OCM that in turn will affect performance and utilization in ecommerce.

The OCM model will center on how motivations, be it intrinsic or extrinsic as described above, is an ex ante state of mind prior to use of the ecommerce Web site. That is, a user will want a particular type of interaction with the ecommerce Web site prior to actually visiting the Web site. For example, a consumer could want to find flowers to send his wife for Valentine's Day. This user's OCM would be based on his perceptions of the task, (e.g., whether he enjoys looking for flowers or finding flowers feels like work) and his individual difference in how he interacts with websites (e.g., whether he likes browsing and tinkering with Web sites in general).

Using this logic and drawing from TTF, OCM would be influenced by both the task-at-hand and certain individual differences. The following outlines the importance of the task characteristics and the individual differences in OCM.

Online Tasks in Ecommerce

Online tasks can take many forms, especially when consumers are interacting with ecommerce Web sites. There has been several attempts to classify these tasks using different criteria [Hargittai, 2004 ; Kau et al., 2003 ; Rohm and Swaminathan, 2004] and more recently by Cheng and colleagues [Cheung et al., 2005 ; Cheung et al., 2003]. These classification schemas offer insight into the myriad of possible tasks that consumers are undertaking on ecommerce Web sites. Although useful, the basic direction they offer for practice is additive in nature. That is, they suggest adding tools and changing the interfaces to better suit the wide variety of task. This additive nature could overwhelm some consumer. Other research posits a more simplistic approach where shopping and ecommerce task can be captured along a continuum [Alba et al., 1997 ; Novak et al., 2003a ; Wells et al., 2005].

To date, there is no clear convention for the anchors on this task characteristic continuum. Simon and colleagues suggest [1996] that we distinguish tasks based on “non-programmed” and “programmed” attributes. Where non-programmed tasks are unstructured and free flowing and programmed tasks are routine and goal-directed. Others have used “goal-directed” and “experiential” to describe the anchors on the task characteristic continuum [Hoffman and Novak, 1996 ; Wells et al., 2005 ; Wolfinbarger and Gilly, 2001]. Van der Heijden uses yet another rubric, “hedonic” and “utilitarian” to describe the differences in tasks [van der Heijden, 2004]. Finally, Mathwick and colleagues use yet another convention to describe tasks characteristics – “perceptual attributes” and “analytic processing” [Mathwick et al., 2002]. Table , adapted from

Wells et al. [2005], summarizes all of the differing terminology used to describe the task continuum. For the purposes of our research we will refer to anchors on the task continuum as “experiential oriented” and “search oriented”.

Table 1: Task Characteristics: Experiential vs. Search Directed		
Experiential Task Types	Search Task Types	Key Work
Experiential attributes	Search attributes	Alba et al. [1997]
Hedonic	Utilitarian	van der Heijden [2004], Wolfenbarger & Gilly [2001]
Unstructured Non-directed search Non-linear navigation	Structured Directed search Linear navigation	Hoffman & Novak [1996]
Perceptual attributes	Analytic processing	Mathwick et al. [2002]

In the consumer behavior and the information systems literatures there has been a significant amount of focus on the impacts of search and experiential tasks in both traditional offline and online settings [Hirschman, 1984 ; Hirschman and Holbrook, 1982 ; Novak et al., 2003a ; van der Heijden, 2004]. Experiential tasks are relatively unstructured using non-linear search and navigation patterns. On the other hand, search tasks are rather structured using linear search and navigation patterns [Novak et al., 2003a ; Wells et al., 2005]. Taken in an ecommerce context, consumers engage in tasks that are relatively experiential (e.g., browsing for enjoyment) or relatively search oriented (e.g., finding a particular form), or somewhere between these two

extremes⁶. Table 2 below outlines some examples of both search tasks and experiential tasks typical in ecommerce.

Table 2: Examples of Online Tasks	
Search Task	Experiential Tasks
Find your checking account balance	Play a game
Submit an assignment to an instructor	Read a blog on the current state of the economy
Find the news story about a relative	Browse for interesting tech news
Download application form	Find new music
Access your competitor's Web site and see their client list for your boss	View myspace/facebook profiles

In sum, we posit that task characteristics can be classified on a continuum with “search” and “experiential” as anchors. Drawing from this we propose that:

Hypothesis 1: In ecommerce the task characteristics will influence online consumer motivation.

While task characteristics play an important role in determining online consumer motivation, it is only part of the dynamic. Next, we will discuss certain individual differences that can also influence a consumer's OCM.

⁶ It must be noted that many people might view the search rubric as synonymous with browsing for items or service online. In our research this is clearly not the case. A search oriented task is where a consumer is looking for a specific object and not interested in browsing for other items. Our strict definition of search tasks is drawn from the extant literature [Alba et al. 1997; Wells et al. 2005].

Individual Difference in Ecommerce

Individual characteristics have been positioned as an important factor than influence how consumers view technology presentation. In a traditional shopping context, consumers can be described generally as either “problem solvers” or seeking “fun, fantasy, arousal, sensory stimulation, and enjoyment” [Hirschman and Holbrook, 1982]. Similar to traditional shopping, ecommerce consumers have general utilitarian or hedonic preferences [van der Heijden, 2003 ; van der Heijden, 2004 ; Wells et al., 2005]. This dichotomy is considered part of the consumer’s personality trait. Personality has been found to be an important factor that can influence technology interaction outcomes [Aykin and Aykin, 1991]. Research has addresses the influence of personality on ecommerce outcomes using the Myers-Briggs Types Indicator, the Big Five Factor Model and others prominent personality scale [Jahng et al., 2002 ; Woo et al., 2007 ; Woo and Shirmohammadi, 2008]. This preliminary research has shown that individual characteristics in the form of personality traits do impact ecommerce outcomes.

Ecommerce researchers have also stated that shopping motivations can vary from person-to-person. Specifically, “experiential shoppers always find more enjoyment in interactivity environments than in pure test environments” [Zhou et al., 2007 p. 50]. On the other hand, utilitarian shoppers are concerned with the shopping experience being efficient and timely [Childers et al., 2001]. We agree with the extant literature and posit that online consumer motivation is guided by personality factors. Next the information system literature is examined in order to provide guidance on what personality factors affect online consumer motivation in general.

Venkatesh’s seminal paper offers this guidance on individual difference by suggesting how intrinsic motivation can be instantiated by computer playfulness [Venkatesh, 2000]. Our

research draws heavily on the concept of intrinsic motivation [Venkatesh, 1999 ; Venkatesh, 2000]. Specifically, we are interested in the theoretical and logical linkages between computer playfulness and motivation posited by Venkatesh’s work. Table 3 gives some example of how computer playfulness can be assessed based on intrinsic and extrinsic motivational needs. For example, one consumer using an ecommerce Web sites in general may have a high degree of computer playfulness (e.g., the consumer is intrinsically motivated). This consumer may tend to tinker with the Web site and find opportunities to explore the Web site. Conversely, another consumer who is not as interested in computer playful activities will, in general, try for an efficient interaction and want to get the task completed quickly. Venkatesh [1999] describes these individuals as having intrinsic and extrinsic motivations respectively.

Table 3: Examples of Computer Playfulness Motivations	
Extrinsic	Intrinsic
Business like interaction	Wants to play with the features
Wants an efficient option	Wants to browse for all the available options
Likes an quick interaction	Likes an full featured experience on the Web site

Extending the research on intrinsic motivation [Venkatesh, 1999 ; Venkatesh, 2000], we posit that computer playfulness is an antecedent to OCM. For this reason we conceptualize OCM as a second order factor that with both task type (e.g., search or experiential tasks) and computer playfulness (e.g., intrinsic and extrinsic motivations) as antecedents. Therefore:

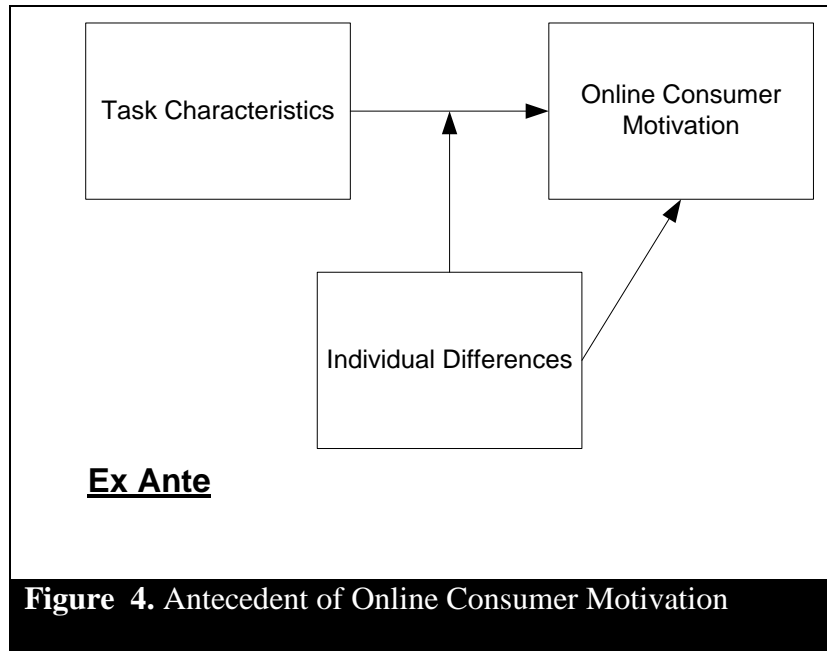
Hypothesis 2: A consumer's computer playfulness will influence online consumer motivation.

Although individual differences in online shopping are influencing factors for online consumer motivation, they cannot be studied in a vacuum. TTF, and other theoretical perspectives, strongly link the impact of individual differences with task characteristics [Goodhue, 1998 ; Goodhue and Thompson, 1995]. Past research suggests that both individual differences and task will affect the outcomes in information systems success but task does account for more variance in outcomes as compared to individual differences [Simon, 1981].

We argue that the task characteristics and the individual differences are not orthogonal constructs as each individual views task characteristics differently. Returning to the example of the consumer buying flowers for his wife; it might be possible that one consumer is interested in flowers and another consumer that has no interest in flowers. These two consumers would have very differing views of the task-at-hand. Further, it is possible that one consumer finds the online shopping in general very rewarding and enjoys looking at the different options where another consumer might dislike online shopping and therefore would view the task very differently. Due to this possible diversity in task characteristic perception we posit that individual differences moderate the influence of the task characteristics on online consumer motivation (see Figure 3 for the complete ex ante model). Therefore:

Hypothesis 3: Computer playfulness will moderate the perception of the task characteristics on online consumer motivation.

The next section of this paper will explore how online consumer motivation as a construct is conceptualized while also examining how OCM is hypothesized to affect performance and utilization in an ecommerce context.



Online Consumer Motivation

As outlined above, OCM is hypothesized to be influenced by computer playfulness, task characteristics and the interaction between computer playfulness and task characteristics. OCM therefore is the reason and/or rationale that a consumer has prior to the specific ecommerce context or encounter. For instance, a consumer’s OCM might include looking for an effective and efficient execution of a specific shopping goal. Conversely, another consumer’s OCM could consist of a consumer wanting an unstructured interaction where they could browse without an associated shopping goal [Arnold and Reynolds, 2003 ; Childers et al., 2001 ; Wells et al., 2005]. Marketing research has pointed to this dichotomy as search vs. experiential [Arnold and Reynolds, 2003 ; Childers et al., 2001 ; Hargittai, 2004]. More fundamentally, psychology research uses an intrinsic vs. extrinsic motivation continuum to relate to this type of motivation [Davis et al., 1992 ; Deci, 1975]. Consistent with Davis et al., we will use intrinsic motivation and extrinsic motivation as the anchors to the state of online consumer motivation.

This process of forming OCM is ex-ante to the introduction of the technology and therefore the consumer has not been influenced by the technology presentation yet. That is, the ‘fit’ component of the interaction between the consumer and technology presentation is heavily reliant on one’s OCM state (e.g., intrinsic or extrinsic motivation). This does not include the direct effects of task characteristics. OCM is the mediating factor. For example, if a consumer went online to pay a bill (e.g., search task) and was generally very playful in their use of the Internet, then the overall OCM would be able to reconcile any discrepancies between individual and task characteristics. OCM would classify a consumer by both the task characteristics (e.g., search/ experiential) and the individual differences factors (intrinsic/extrinsic). The consumer’s preconceived OCM is based on the task, the individual’s computer playfulness and the interaction between task and computer playfulness.

OCM can be classified into one of four typologies (see Figure 5 below). The two extremes of OCM are captured in Type II and Type III of the matrix. OCM Type II is when the consumer is low in computer playfulness and also has a search oriented task. OCM Type III captures a consumer with an experiential task and has a tendency to be a very computer playful person. These extremes will provide the anchors to measurement of the OCM construct. Both Type I and Type IV consumers have a mixed task and individual characteristic that is typically already being met by today’s one size fits all interface design (e.g., the hybrid design). Figure 6 shows the proposed measurement of OCM that captures the each type of OCM. This includes the two anchors (Intrinsic OCM and Extrinsic OCM). The middle of the OCM continuum will consist of the consumers that have the mixed motivation. Now that we have examined the ex-ante OCM we will now propose how OCM will influence performance and utilization. These outcomes in our research model has also been based on the TTF framework.

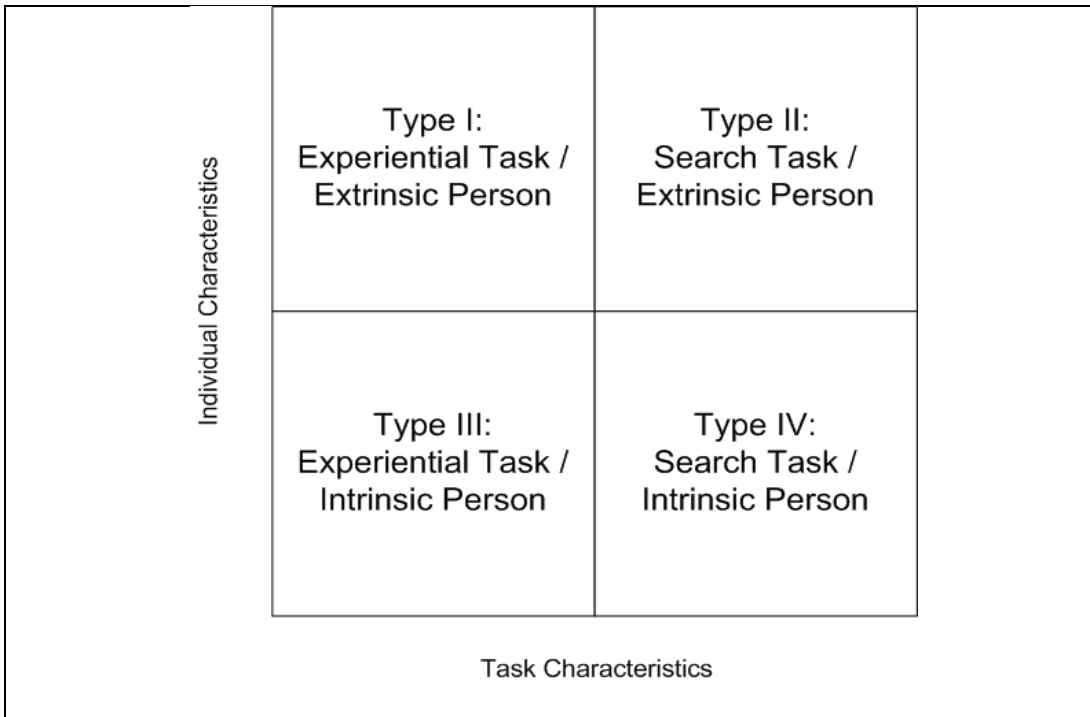


Figure 5. Differing Types of Online Consumer Motivation

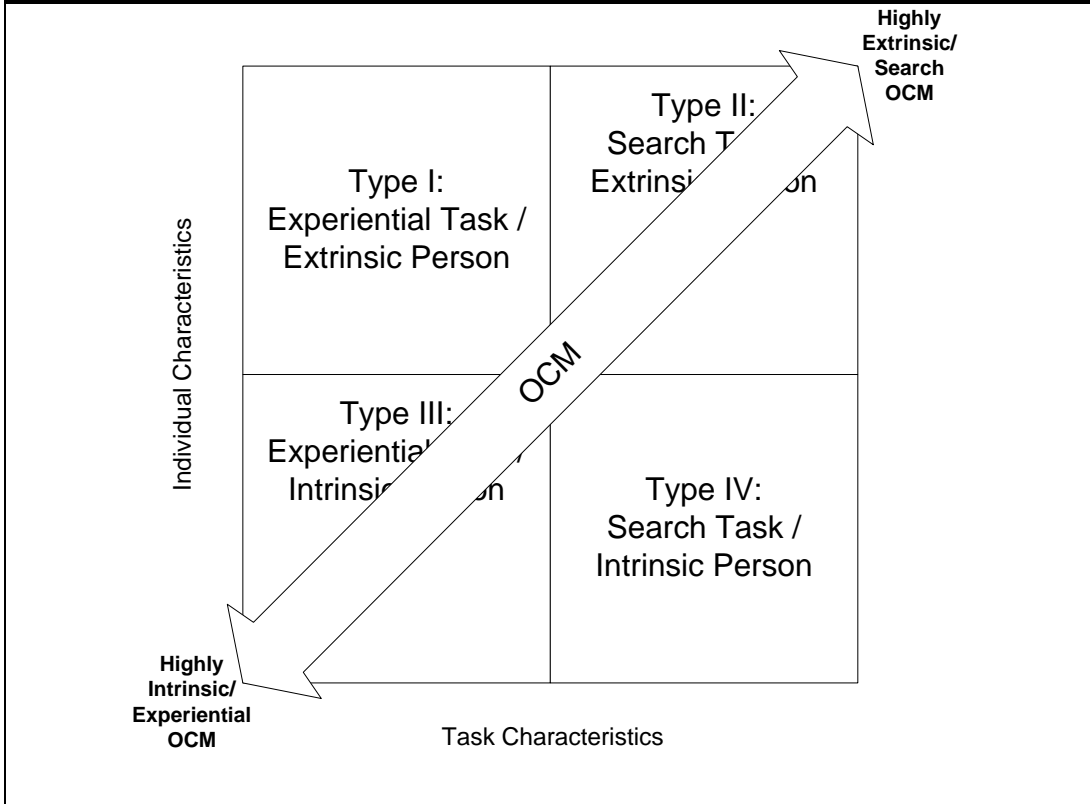


Figure 6. Example of Online Consumer Motivation Measurement

The Influence of Technology Characteristics

The traditional TTF model uses a distinct ‘fit’ construct (e.g., Task-Technology Fit) to capture the interplay between the three antecedents (e.g., task characteristics, technology characteristics and individual differences [Goodhue, 1998]. Recently, research has used the variance in the model’s outcomes to test proper fit [Gebauer and Ginsburg, 2009 ; Junglas et al., 2008 ; Zigurs and Buckland, 1998]. It can be argued that measuring fit then measuring perceptual factors can cause bias problems. For example, if a user answered that the technology presentation was a ‘fit’ then intuitively that user should also indicate that the technology presentation is satisfying and they intended to use the technology. Assessing ‘fit’ based on the outcomes (e.g., satisfaction with the system, intention to use the system, and so on) would be more appropriate especially in the ecommerce domain.

Given that we are interested in the interplay between task, individual, and technology (i.e., interface) characteristics, TTF offers a logical theoretical framework for understanding this phenomenon. Thus, we are proposing a temporal version of TTF that positions online consumer motivation (OCM) as the focal construct. We posit that the technology characteristics will only influence the outcomes ex post the OCM formation (see Figure 7 below). Next we will discuss the metrics used in evaluating the impact of an ecommerce system.

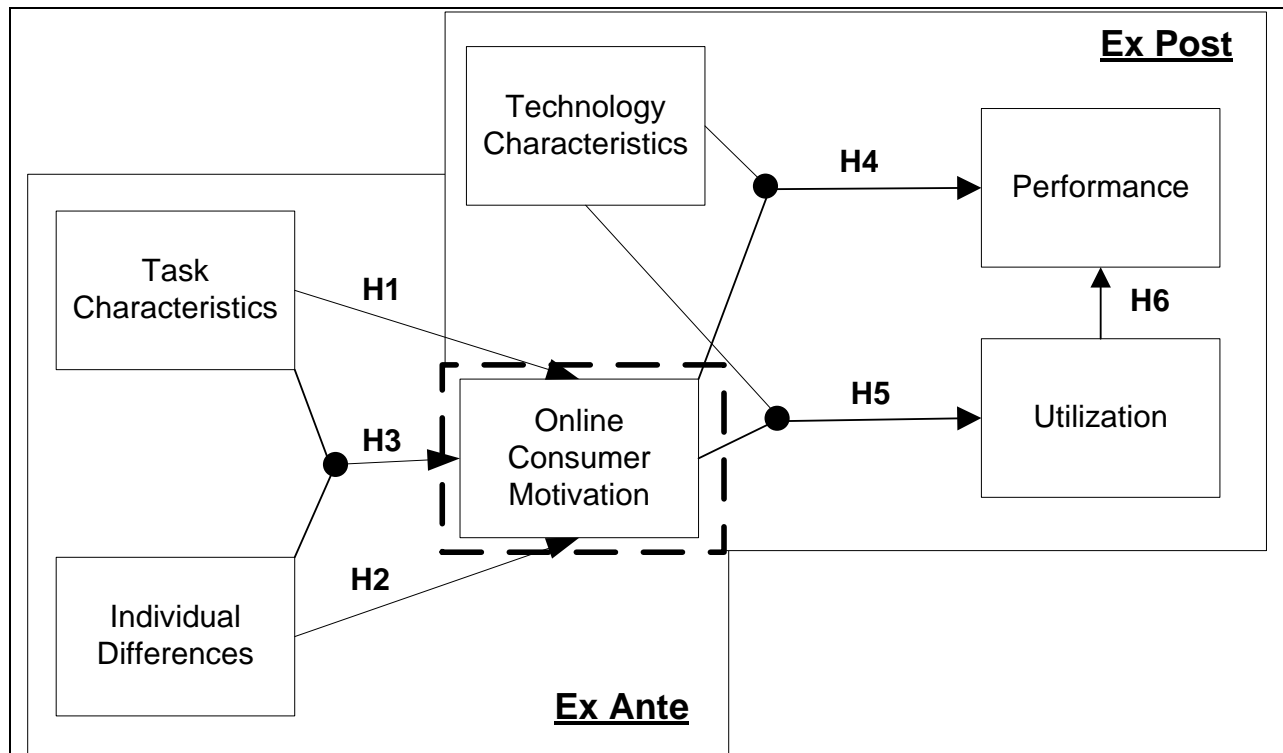


Figure 7. Example of Online Consumer Motivation Measurement

Dependent Variables

In the consumer behavior literature there has been a focus on how information presentation can affect one's ability to process and store information [Pitkow and Kehoe, 1996]. Further, information systems studies have also shown that different presentation characteristics impact users performance [Vessey, 1991 ; Vessey and Galletta, 1991]. Both of these studies use performance in the task as the dependant variable. Give our desire to measure the impact that OCM has on perception of Web site design characteristics it is appropriate that we use a performance metric as the dependent variable for this study. There we propose:

Hypothesis 4: Online consumer motivation will moderate the technology characteristics when affecting performance of the consumer in an ecommerce context.

For the purposes of this study, we are also interested to see if OCM provides for a possible fit given a certain Web site interface experience. This can be measured for both highly extrinsic OCM consumers and highly intrinsic OCM consumers. Information presentation has also been studied in ecommerce in terms of interface metaphors and how they map to tasks [Wells et al., 2005]. The Wells et al. investigation highlights the importance of mapping the task to the interface characteristics. A manipulation of the interface experience was used to provide evidence that the interaction between different interface characteristics (experiential or search) and the task (experiential) would influence performance. Specifically, when an experiential interface was matched to a experiential task, retention and recall was significantly improved. Conversely, when a search interface was matched with an experiential task, retention and recall significantly decreased. Consequently, it is intuitive that technology characteristics can either inhibit or enhance performance. For this reason, we posit that if an experiential interface was given to a highly intrinsic OCM consumer both performance and utilization would be higher than if a highly intrinsic OCM consumer was given a very linear and structured Web site experience. There we propose:

Hypothesis 4a: A highly intrinsic OCM consumer will perform better using an experiential Web site.

Hypothesis 4b: A highly extrinsic OCM consumer will perform better using a linear Web site.

Given our desire to measure both the subjective and objective outcomes associated with using a particular Web site, OCM will draw from TTF to employ both performance and utilization as the dependent variable for this study. Further, TTF will be used as the foundation for explaining the interplay of how the user's task and individual characteristics affect user

motivation, and ultimately the subjective and objective outcomes of using a particular Web site. Many studies have employed utilization as a dependent variable in ecommerce. This broad construct has been operationalized by the following measures: attitude toward the system [Malhotra et al., 2008], service quality [Yang et al., 2005], usefulness [Davis et al., 1992], and so on. Being that this research is focused on ecommerce, we will stay consistent with the extant literature [Campbell and Wright, 2008 ; Childers et al., 2001 ; Hoffman and Novak, 1996 ; Sheng et al., 2008 ; Tam and Ho, 2006] and use the satisfaction with the Web site measure as a proxy for utilization. Therefore, we propose the following:

Hypothesis 5: Online consumer motivation will moderate the technology characteristics when affecting utilization in an ecommerce context.

As with the hypotheses examining interaction that affects the performance DV we are interested in understanding further the interaction that affects utilization. Similar to the effects measured by performance highly extrinsic OCM consumers will typically look for a quick, in-and-out type of interaction with a Web site. Therefore we propose:

Hypothesis 5a: A highly extrinsic OCM consumer will have a higher satisfaction with a linear Web site.

Hypothesis 5b: A highly intrinsic OCM consumer will have a higher-level of satisfaction with an experiential Web site.

Similar to past research on fit we will also examine the impact of utilization on performance [Gebauer and Ginsburg, 2009 ; Goodhue, 1998 ; Goodhue and Thompson, 1995 ; Junglas et al., 2008 ; Sismeiro and Bucklin, 2004 ; Zigurs and Buckland, 1998]. Therefore we propose:

Hypothesis 6: The utilization of an ecommerce system will directly influence a consumer's performance in the system.

In summary, consistent with considerable recent research on motivation and TTF we have defined a conceptual construct labeled online consumer motivation. We expect OCM to play a pivotal role in our understanding of consumers' behaviors towards ecommerce Web sites via its effect on the technology presentation. OCM has been theorized to be influenced by task characteristics, certain individual differences and the interaction between these antecedents. The operationalization of OCM as well as the empirical testing of the hypothesis are discussed next.

METHODS

To test the relationships between the constructs outlined in the research model, we first designed a laboratory experiment where we could manipulate task and technology characteristics to cause variance in online consumer motivation and subsequently performance and satisfaction. This laboratory experiment included developing four functional Web sites for use in this study. As with most laboratory situations the goal of the first study was to isolate the effects of interest by controlling the environment. As argued by Cook and Campbell, experimental setting ensures internal validity and while allows evaluating the proposed theoretical perspective [Cook and Campbell, 1979]. The limitation of an experimental environment is generalizability. For this reason, a survey methodology was used to collect data that can be generalized to a greater degree. In the survey study, we used real Web sites in order to test the research model. The analysis for both studies was done using MPLUS 5.1 and SPSS 16.0 software. This two stage approach to testing of the research model address the key components of any research study – realism, precision and generalizability [Dennis and Valacich, 2001 ; McGrath, 1982]. Specifically, the laboratory experiment has been designed to maximize precise measurement of

the proposed constructs and relationships while the study using surveys and real web sites take full advantage of both generalizability and realism.

Instrumentation and Pilot Studies

All research variables were measured using a multi-item scale (See Appendix H for the vetted item). Scales for task characteristics were adapted from those proposed by Well and colleagues [2005]. The scale for computer playfulness was adapted from Venkatesh [1999], while satisfaction was measured using the recommendations of Bhattacharjee [2001]. The performance metric is an objective measure that will be described later due to its unique context for each study. Scales to measure online consumer motivation were developed using multiple stages. First, existing scales were reviewed to evaluate their fit with the current study. Next, an initial scale was developed. This scale was pilot tested twice using samples of 36 and latter 261 student subjects. Results of these two pilot studies lead to further refinement of the scales.

Next a statistical power analysis was conducted in order to establish an appropriate sample size for testing the research structural model. In structural equation modeling there are two typical methods for conducting power analysis [Brown, 2006]. The first method developed by Satorra and Saris focuses on a χ^2 difference test to evaluate specification errors associated with any one parameter. This method is limited as it does not address the precision of the parameter estimates [Brown, 2006]. Further, the Satorra and Saris method does not take non-normality into account. The second approach, Monte Carlo simulation, is more robust as it estimates precisely for each parameter. For this reason, the Monte Carlo approach is more appropriate for power analysis in this instance.

For the Monte Carlo approach to power analysis we will assume normally distributed indicators, which was shown to be true in both pilot studies and a sample size of at least 300.

Further we assume that the population parameter estimates for indicators are .8 or greater [Muthen and Muthen, 2007]. Muthen and Muthen also outline specific criteria for determining if the sample size is appropriate. These criteria include that the bias of the parameter and the associated standard errors do not exceed 10% for any parameter, any factor covariance standard error does not exceed 5%, and the coverage at then 95% confidence is between .91 and .98.

A Monte Carlo simulation was conducted with MPLUS 5.1 and provided evidence that the scales would cause power problems in our data collection at sample sizes of 200, 300, and 400. We found that the confidence intervals and the bias of the satisfaction parameters did not fall within the Muthen and Muthen's specifications. For this reason, we abbreviated the task characteristic scale to include 4 of the 5 items (See Table 4 below for the complete list of vetted items). Also, the original 8-item computer playfulness measure was modified based on the pilot results and by face validity of the items, and was scaled down to four items. We then ran a power analysis on the research model with the abbreviated scales. Using the vetted scales all of the power criteria provided by Muthen and Muthen [2007] were met in this next iteration of the Monte Carlo simulation.

Table 4: Final Group of items for each construct

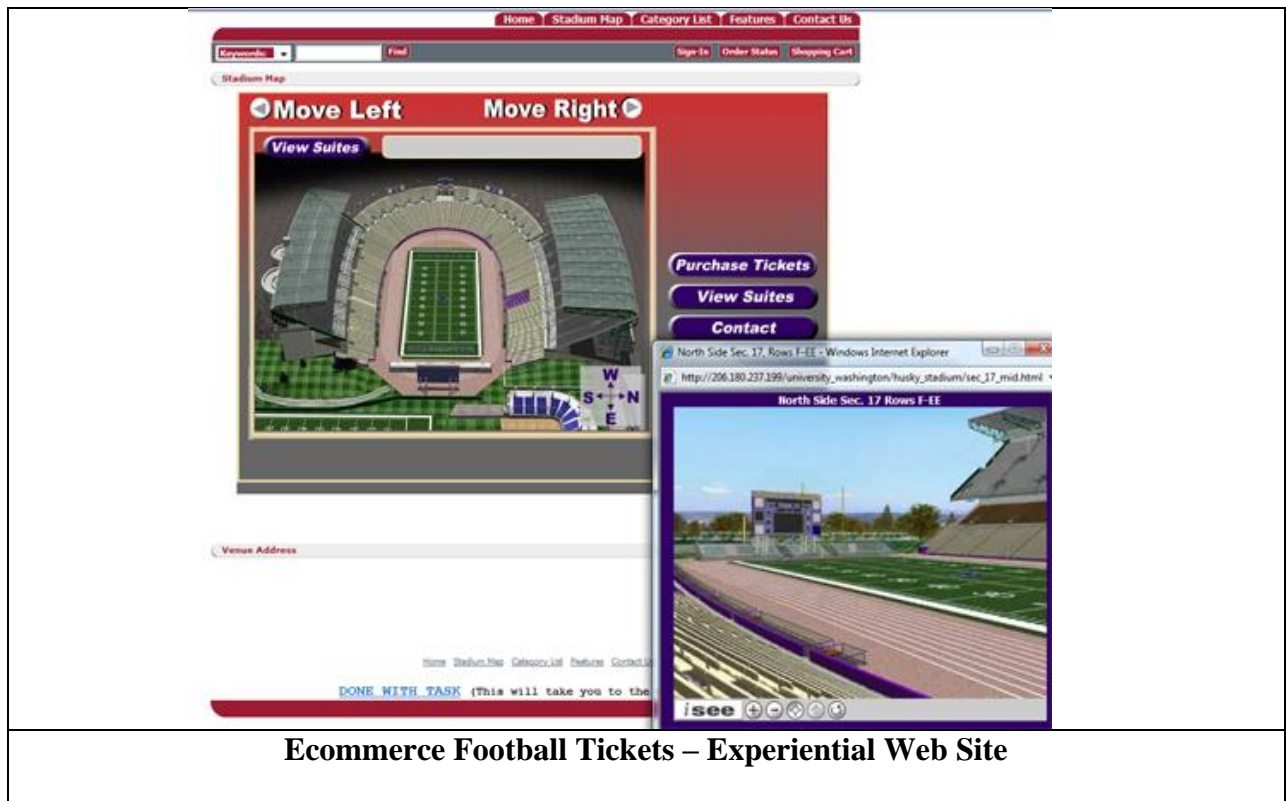
Going into this Web site...	
OCM1	I am likely to play while using this Web site.
OCM2	I would like to enjoy myself while interacting with this Web site.
OCM3	I am inclined to explore this Web site.
OCM4	I am likely to tinker while interacting with this Web site.
OCM5	I am inclined to spend some time and look around this Web site.
The following questions ask you how you would characterize the task you have been given:	
TC1	Directed/Meandering
TC2	To-the-Point/ Browsing
TC3	Direct/Not Direct
TC4	In-and-out/ Look around
The following questions ask you how you would characterize your-self when you use the Internet in general:	
CP1	. . . unimaginative
CP2	. . . creative
CP3	. . . playful
CP4	. . . unoriginal
How do you feel about your overall experience with this Web site:	
SAT1	Very dissatisfied Very Satisfied
SAT2	Very displeased Very pleased
SAT3	Very frustrated Very contented
SAT4	Absolutely terrible Absolutely delighted
OCM - Online Consumer Motivation, TT – Task Characteristics, CP – Computer Playfulness, SAT – Satisfaction	

Laboratory Experiment

Web sites were developed to represent the university’s football ticketing ecommerce environment. Specifically, three Web sites were developed that were designed to offer different levels of experiential ability. The first Web site was designed to offer a straight forward experience for users wanting to browse or buy tickets. This linear Web site provided lists of tickets that consumers could use to evaluate their possible choice. The goal of this Web site was

to offer the user an easy and quick interaction with the information. The second Web site offered an experiential environment where consumers could pull up a virtual stadium to see where all the available seats were located, prices for these tickets, and the view from the particular seat. Also, consumer could manipulate the stadium map so they could see turn the stadium map in any orientation to best fit their needs. Further, subject could see the view from any available seat. The goal of this Web site was to offer a completely immersive ticketing environment.

The third Web site was designed to offer a one-size fits all approach that is common in the most ecommerce Web site today. The consumer could bring up a list of tickets available and sort through the available tickets easily while also allow using the virtual stadium as well (See Figure 8 below for examples of all three Website). Care was taken so that each of the three Web sites had exactly the same information. This included the use of an identical shopping cart so that at the point of purchase the transactions would be exactly the same in each condition.



[Home](#) | [Stadium Map](#) | [Category List](#) | [Features](#) | [Contact Us](#)

Keywords:

[Sign-In](#) | [Order Status](#) | [Shopping Cart](#)

[Ticket Information](#) | [Category](#)

Tickets are selling out fast.

Max. 6 tickets per customer

After you select the tickets you have 10 minutes to complete the sale or the tickets will be released back to the public.

Apple Cup Tickets > Lower Deck

[Category Items](#)

Description	Item #	Price / ea.
Lower Deck Section 25 Row L Buy Now More Info	LD254	\$89.95
Lower Deck Section 24 Row G Buy Now More Info	LD124	\$89.95
Lower Deck Section 21 Row T Buy Now More Info	LD144	\$69.95
Lower Deck Section 21 Row U Buy Now More Info	LD411	\$69.95
Lower Deck Section 18 Row P Buy Now More Info	LD5412	\$49.95

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Ecommerce Football Tickets – Search Web Site

[General Admission](#)
[Lower Deck](#)
[Upper Deck](#)

Featured Items

General Admission
 General Admission standing room Westside.
 Tickets Available
 Item #GAW144
\$19.95

Don James Suites
 Don James Center Suites
 Tickets Available
 Item #DJC4
\$149.95

66 Seats Available in 19 Locations

Lower Deck


- [Section 1 Row B - 6 Tix](#)
- [Section 7 Row P - 3 Tix](#)
- [Section 9 Row Y - 2 Tix](#)
- [Section 18 Row P - 6 Tix](#)
- [Section 21 Row T - 1 Tix](#)
- [Section 21 Row U - 3 Tix](#)
- [Section 25 Row L - 1 Tix](#)
- [Section 24 Row G - 4 Tix](#)

[West General Admission - 4 Tix](#)
[South General Admission - 5 Tix](#)
[North General Admission - 6 Tix](#)

Upper Desk

- [Section 38 Row AA - 2 Tix](#)
- [Section 41 Row F - 6 Tix](#)
- [Section 44 Row C - 2 Tix](#)
- [Section 45 Row B - 2 Tix](#)
- [Section 50 Row AA - 2 Tix](#)

Bleachers
[NE Bleachers - 5 Tix](#)
[SE Bleachers - 3 Tix](#)
[Don James Center - 3 Tix](#)



[Venue Address](#)

Husky Stadium - Seattle, WA
 University of Washington 3800 Montlake Blvd.
 Seattle, WA 98195

[Home](#) | [Stadium Map](#) | [Seating Sections](#) | [Features](#) | [Contact Us](#)

Ecommerce Football Tickets – Hybrid Web Site

Figure 8. Example of the Experimental Web Sites

Task

To simulate an ecommerce transaction a scenario was used where the subjects were asked to complete one of two experimental tasks. The first task was a search task in which the subject was asked to find two tickets with specific parameters. The other task was more experiential in nature and in which the subject was asked to browse the Web site to find possibilities for seating (See Appendix I for the task). The tasks were given on a sheet a paper so the subjects could refer back to the instructions if need be.

Subjects were randomly assigned to one of the six conditions in this 2 X 3 experiment (e.g., two types of task by the three types of Web sites). First the subjects were given their randomly assigned task then they were asked to complete a short survey with the following scales: task characteristics, computer playfulness, and online consumer motivation as described above. Upon completion of this online survey subjects were automatically taken to one of the three experimental Web sites.

For the purposes of the objective performance measure for the search task the subjects were asked to actually go through the purchasing process for the tickets that best met the requirements listed on the task sheet. This included location, price for each ticket and the total amount of the purchase, number of tickets and seats that were together needed. The Web sites were designed to only have one seating option that fit all the criteria asked of the subject. There were 65 tickets available in total with 20 different seating options (e.g., seats that were together). Students were rated on a scale of 0 to 5 with how they did in locating and purchasing the tickets on the Web site. A zero score would mean that either failed to meet any requirements, a score of

one would mean that the subject met one of the requirement (e.g., location, price for each ticket and the total amount, number of tickets and seats that were together) and so on.

The subjects that were asked to browse the Web site (e.g., the experiential task) also had the same performance metric though it was measured after they left the Web site. Specifically, after the student was content that they investigated all the possible seating options available they exited the Web site and were asked to identify tickets that best met the same criteria as the search task (e.g., location, price for each ticket and the total amount, number of tickets and seats that were together). The subjects choices of seats were evaluated using the same criteria as the search directed task condition. Subjects were given a map of the stadium in order to help with the recall of their choices. By using the same criteria for both the search and experiential task we are able to evaluate both conditions in an omnibus model.

Subjects

559 Students enrolled in a sophomore-level introduction to management information systems class in the college of business were used in this study⁷. This was a required course for all business majors; therefore it was a good representation of the entire scope of majors in the college. All the subjects had previous ecommerce experience and had purchased something online in the past two years. The average age for the subjects were 20.4 and 46% of the subjects were female.

⁷ Subjects received course credit for participating in this study. The approximate amount of course credit a student could earn was one percent.

Measurement Model

A measurement model was administered to evaluate the discriminant and convergent properties of the four scales used in this experiment as noted above. Being that performance is an objective measure, this parameter was not included in the measurement model. For the measurement model fit testing, the Comparative Fit Index (CFI), the Goodness-of-Fit-Index (GFI), the Adjusted Goodness-of-Fit-Index (AGFI) and the Root-Mean-Squared Error of Approximation (RMSEA) will be used in accordance with Brown [2006].

The criteria, suggested by Brown [2006], used to evaluate the model fit includes a CFI value of over .95, the GFI value need to be greater than .90 and the AGFI value should be above .80 and cannot exceed a difference of .1 from the GFI [Hu and Bentler, 1995]. Further, RMSEA values must be lower than .08 with a confidence interval no higher than .1 [Hu and Bentler, 1995]. The measurement model undertaken for these scales exceeded all of the above criteria (See Table 5 below).

Table 5: Measurement Model			
Fit Statistics			
χ^2 / df	245.4 / 113	AGFI	.934
CFI	.975	RMSEA	.047
GFI	.951	RMSEA (Upper / Lower Bounds)	.039 / .055

Reliability Analysis

A reliability analysis was also undertaken for these scales. This was done by using the Cronbach alpha and composite reliabilities for each of the scale⁸ [Werts et al., 1974]. The Cronbach alpha value for each scale is as follows: online consumer motivation (OCM) is 0.852, task characteristics (TC) is .855, computer playfulness (CP) is .809 and satisfaction (SAT) is .935. Each of these scales met the recommendation that Cronbach alpha should be above 0.70 [Hair et al., 1998]. As shown in Table 6 below all composite reliability scores were also greater than the recommended .70 threshold [Hair et al., 1998]. Together this analysis suggests that the measurement of these constructs is reliable.

Table 6: Measurement Model: Loadings and Composite Reliabilities					
Items	Standardized Loadings	Composite Reliabilities	Items	Standardized Loadings	Composite Reliabilities
OCM1	0.580	0.875	CP1	0.734	0.822
OCM2	0.843		CP2	0.455	
OCM3	0.825		CP3	0.847	
OCM4	0.781		CP4	0.852	
OCM5	0.770				
TC1	0.859	0.878	SAT1	0.949	0.937
TC2	0.710		SAT2	0.952	
TC3	0.774		SAT3	0.801	
TC4	0.858		SAT4	0.842	
Standardized Loadings (all loadings p<.0001)					

⁸ Composite reliability scores were calculated as $(\sum \lambda_i)^2 / [(\sum \lambda_i)^2 + \sum \text{Var}(\epsilon_i)]$ where λ_i is the indicator loading and $\text{Var}(\epsilon_i) = 1 - \lambda_i^2$.

Convergent Validity

Convergent validity analysis is used to see to what extent the items in a given scale are measuring the same construct. Convergent validity is assessed by examining the factor loadings. Factor loadings need to exceed .707 [Hair et al., 1998 ; Segars, 1997]. Most factor loadings indicate compliance with the prescribed criteria except OCM1 which was estimated at .580 and CP2 at .455. For the purposes of further testing these two measures will be removed. Another assessment of convergent validity is that the Average Variance Extract (AVE)⁹. Past literature has recommended that any construct should have an AVE above .50 [Fornell and Larcker, 1981]. The AVE for each of the construct is as follows: OCM (4 items) is 0.649, TC (4 items) is 0.644, CP (3 items) is 0.661 and SAT (4 items) is 0.789. From this analysis we can assume convergent validity.

Discriminant Validity

AVE is used again to assess discriminant validity. This analysis allows us to evaluate the construct to see if the construct are statistically distinct from one another. The AVE for each construct was computed and compared to the squared correlation of each construct [Segars, 1997]. The results presented in Table 7 suggest that these construct are distinct and discriminant.

⁹ AVEs were calculated as $(\sum \lambda_i^2) / [(\sum \lambda_i^2) + \sum \text{Var}(\epsilon_i)]$ where λ_i is the indicator loading and $\text{Var}(\epsilon_i) = 1 - \lambda_i^2$.

Table 7: Estimated Squared correlations and AVE

	OCM	TC	CP	SAT
OCM	0.65			
TC	0.01	0.64		
CP	0.04	0.01	0.66	
SAT	0.07	0.03	0.01	0.79
AVE figures are shown in bold along the diagonal				

Structural Model

A structural model is used to test hypothesis 1 through 5. Again included in the structural model is the performance metric as describe above. Being that the structural model has three interactions (e.g., computer playfulness moderation on task, technology characteristics moderation on online consumer motivation for both satisfaction and performance outcomes) we will need to take a two step approach that includes model difference testing based on the likelihood ratio approach as outlined by Klien and Mossbrugger [Klein and Moosbrugger, 2000]¹⁰. Currently, chi-square and related fit statistics are not available for interactions containing continuous latent variable (e.g. SAT, CP, OCM) and observed latent variables (e.g. Performance). Nested models are often compared using -2 times the loglikelihood different which has a chi-squared distributed [Klein and Moosbrugger, 2000]. Typically, maximum likelihood is the contemporary calculation technique for these types of models. The first step of

¹⁰ Often partial least squared (PLS) modeling approach is used when interactions are nested within a structural model. For our research we made the decision to use a contemporary structural equation approach as we believe, like other researchers, that the structural CFA model approach to vetting new constructs is current the best available technique. It therefore is intuitive that using MPLUS for both the measurement model and the structural model is the best currently available choice for this approach as MPLUS is able to calculate the type of interactions needed to evaluate this model.

the approach is to calculate the structural model using only main effects (See Figure 9). In this model we found that all main effect path were significant at $p = 0.05$ except for the affect of OCM on performance. These results were expected but cannot be related directly to the hypothesis. In order to evaluate the interactions, another model will be calculated that include the three interactions and then compared to the main effects model.

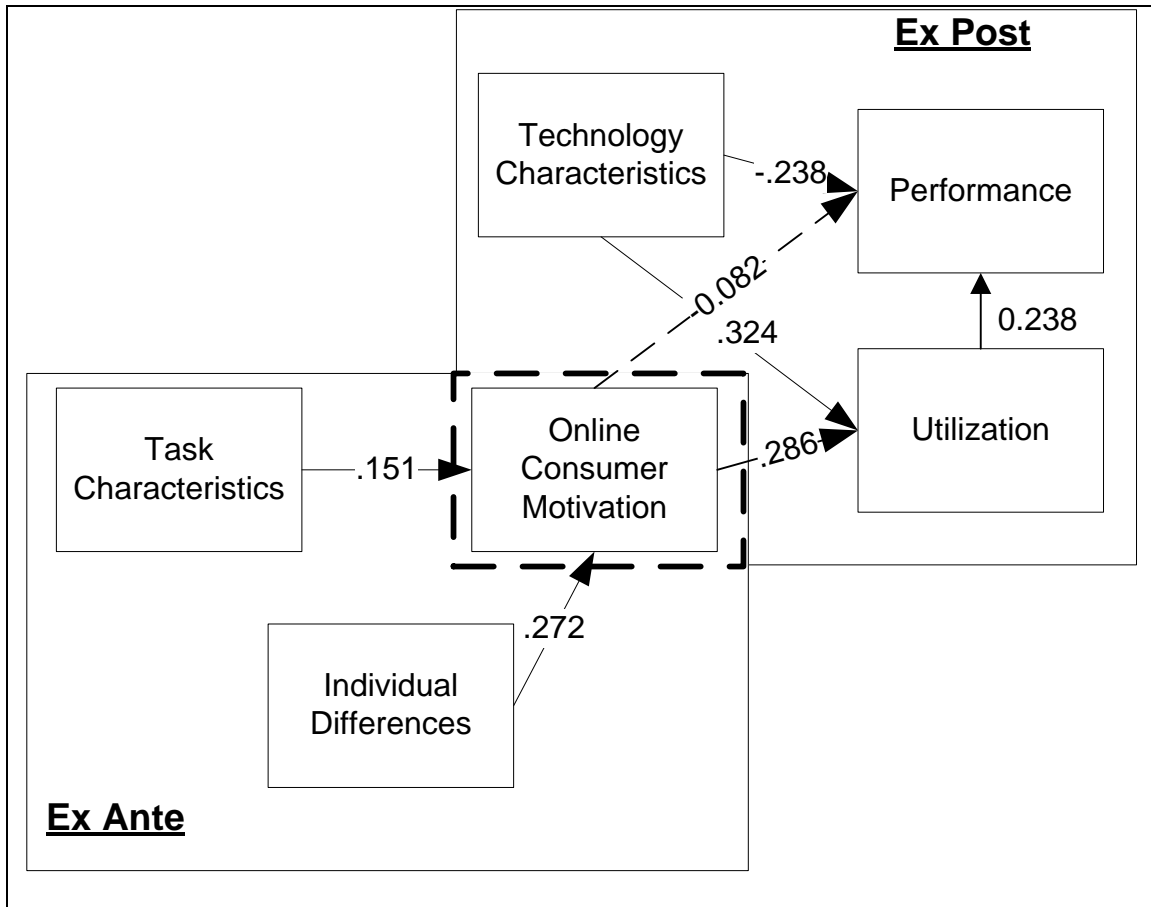


Figure 9. Structural Model with just Main Effects

Table 8: Test of Model Fit for Main Effect Model

Loglikelihood			
HO Value	-13281.18		
Information Criteria:			
Number of free Parameters	60	Sample-Size Adjusted BIC ¹¹	26749.3
Akaike (AIC)	26682.4		
Bayesian (BIC)	26939.7		

Typically to evaluate these models the different between the -2 times the loglikelihood is used to test a difference in fit. Since both models entail 60 freely estimated parameters (df = 60) this test cannot be used. To compare the models the AIC, the BIC and the A-BIC will be calculated to test if the interaction model better fits the data [Marsh et al., 2004]. The smaller value for these indices indicates a better fit for the data. All of these indices are smaller in the model that includes interactions. In the second model we see that all paths are significant at $p=0.05$ except for the effect of the interaction to OCM (See Figure 10). This analysis suggests that the model including the interaction terms is a better fit to the data than the main effects model.

¹¹ $(n^* = (n + 2) / 24)$

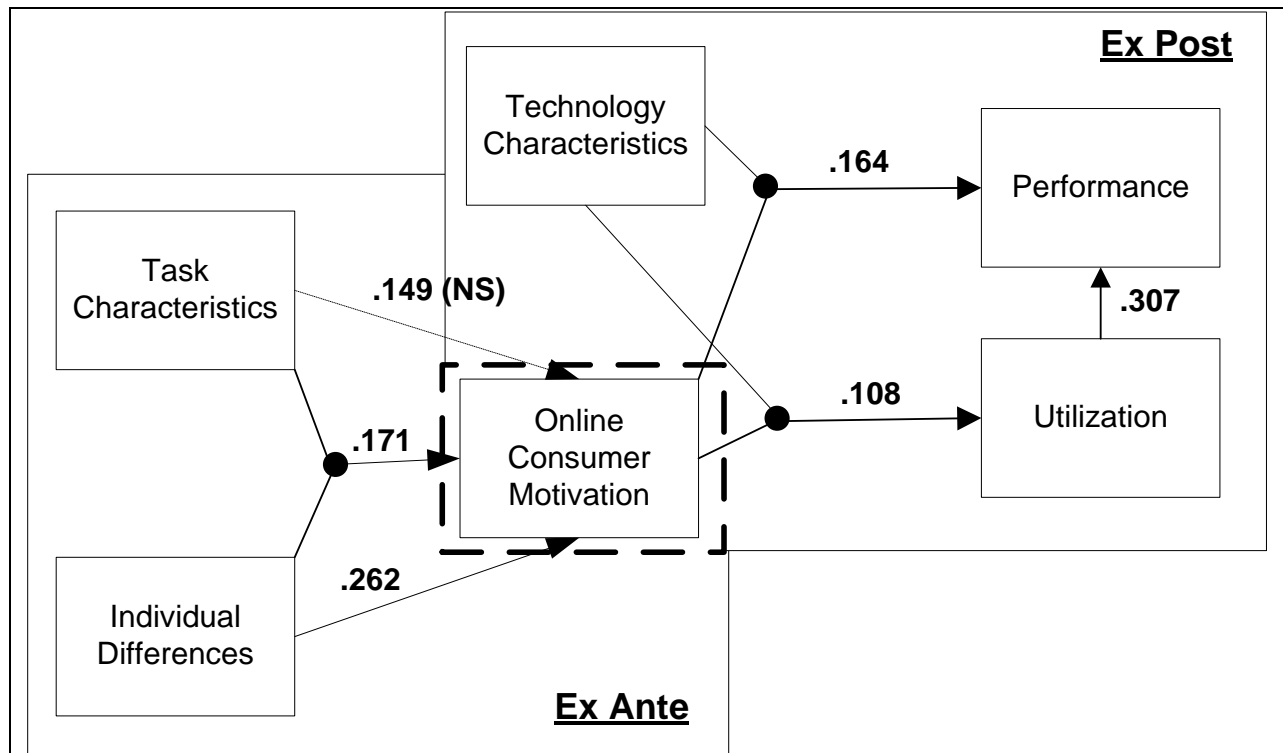


Figure 10. Structural Model with the Interactions

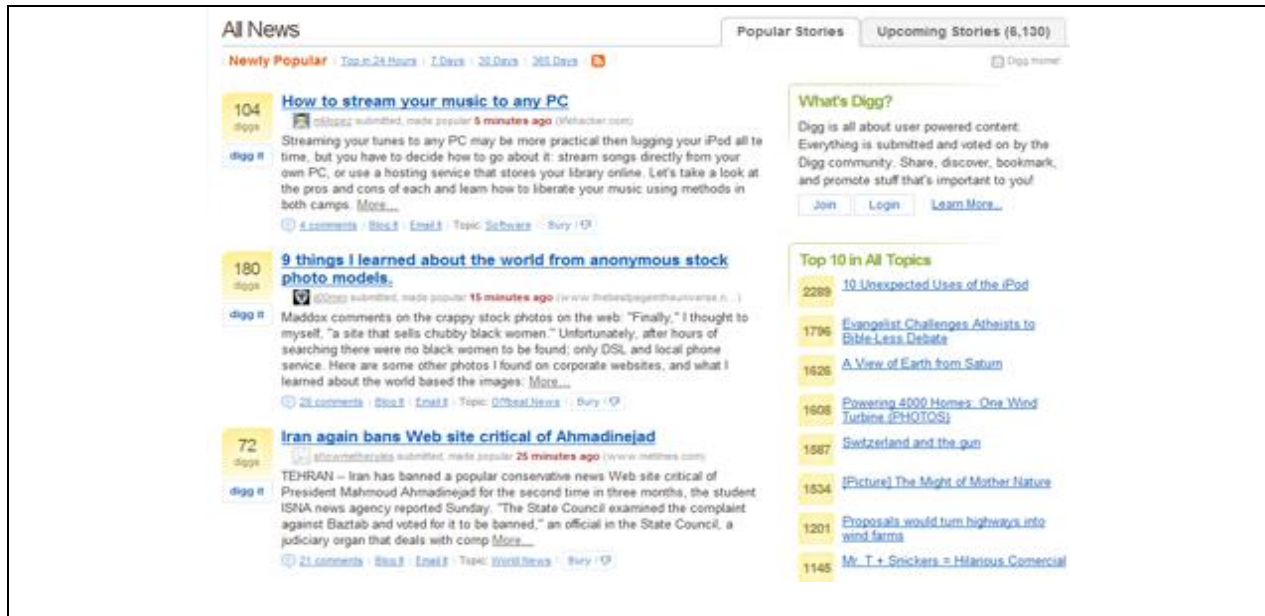
Table 9: Test of Model Fit for Interaction Effect Model			
Loglikelihood			
HO Value	-13206.12		
Information Criteria:			
Number of free Parameters	60	Sample-Size Adjusted BIC ¹²	26699.1
Akaike (AIC)	26632.2		
Bayesian (BIC)	26889.6		

¹² $(n^* = (n + 2) / 24)$

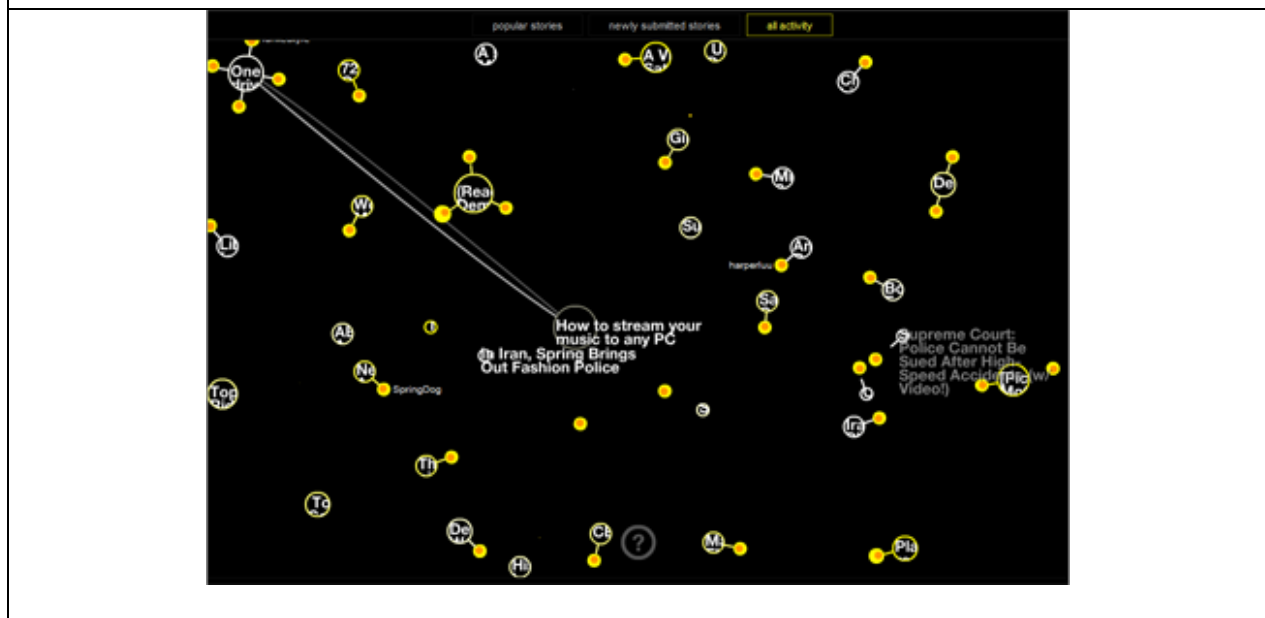
Survey Study

In order to provide generalizability to our analysis of this research model a survey study was undertaken using non-student subjects. For this study a seeded sampling technique was used to recruit participants [Coleman, 1959]. A seeded sample is common in marketing survey research as it can tap into a heterogeneous population [Mick, 1996]. Seeded sampling is also known as link-tracing, snowball sampling and random-walk sampling [Hedman and Sharafi, 2004]. In seeded sampling a group of students enrolled in an online distance degree program that were participating in an introductory to management information system class was selected as the seeds to the sample. These participants were then given course credit (i.e., about 1% of their final grade) to recruit non-student subject to partake in this survey research. Each student was instructed to solicit five individuals for this survey. Three hundred and four non student subjects were recruited for this survey. The average age for the sample was 32.4 with 42% females.

In this study we used real Web sites to provide generalizability. This consisted of a 2 Web sites from Digg.com. The Web sites used in the survey were either experiential (e.g., geared towards experiencing many different things and create an atmosphere of enjoyment), or goal-directed site (e.g., design enabled users to complete a certain set of tasks very easily). Figure 11 show examples of the sites used.



News Aggregation – Search Web Site



News Aggregation – Experiential Web Site

Figure 11. Screen shots of the Web sites used in Study 2.

Digg.com is a news aggregation Web site where users can submit stories that are rated by the community in terms of importance. In the goal-directed news site stories are present in a 25

stories per page list with the higher rated stories further up the list. The stories also can be sorted by many criteria such as different genres or timeliness of the story. On the other hand, the experiential presentation of Digg.com involved a view of users as they jump from reading stories. The users are represented as small spheres that move from stories viewed as bubbles. The bubbles become larger as the story increases its ranking. Also, the user of the experiential Digg.com site could watch users view stories in real time or browse the different stories themselves. Although difficult to conceive this experiential interface provides a hedonic aspect as it allows people to experience news stories differently than the list of news stories would. For example, a user can watch stories grow, browse the up and coming stories, or watch a particular user with similar interests which may lead to stories that might not otherwise be found in a list type interface.

The subjects in the study were randomly assigned to one of four conditions (See Table 10). After the subjects were given the task to complete on the Web site (e.g. a search task or an experiential task; See Appendix I) the TC, CP, and OCM instruments was administered via a Web page. The subjects were then taken directly to their assigned web site upon completion of the pre-survey. After the subjects were done with the task they were given a short survey that included satisfaction [Bhattacharjee, 2001]. In this generalizability study performance was not measured. Although not measuring an objective performance metric is not as desirable the second study allowed us to examine the all other aspects on this model.

Table 10: Study 2 Conditions

Task	Site	Site Description
Experiential	News Aggregation - Experiential	This site, modeled after Digg.com – Swarm, allowed users to browse news stories based on a visualization of what stories were currently being rated real-time. This allowed users to also watch other users bounce from story to story.
Search	News Aggregation - Experiential	Same as above.
Experiential	News Aggregation - Search	This site, modeled after Digg.com, allowed a community of users to rate stories which then provides the ranked list in which users can view the popular stories. The site is in a list like format with the most popular stories on the front page and progressively less popular stories going down the list.
Search	News Aggregation - Search	Same as above.

Measurement Model

As with the experimental study a measurement model was administered to evaluate the properties of the five scales used in this study. For the model fit testing, as with the experimental study, we calculated Comparative Fit Index (CFI), the Goodness-of-Fit-Index (GFI), the Adjusted Goodness-of-Fit-Index (AGFI) and the Root-Mean-Squared Error of Approximation (RMSEA) in accordance with Brown [2006]. Again the criteria suggested above was used again used to evaluate the model fit [Brown, 2006 ; Hu and Bentler, 1995]. The measurement model undertaken exceeds or is close to all of the above criteria (See Table 11 below).

Table 11: Measurement Model

Fit Statistics			
χ^2 / df	304.4 / 160	AGFI	.896
CFI	.970	RMSEA	.051
GFI	.921	RMSEA (Upper / Lower Bounds)	.042 / .060

Reliability Analysis

Similar to the experimental study a reliability analysis was also administered for these five scales. This was done, as with the previous study, by using the Cronbach alpha and composite reliabilities for each of the scale¹³ [Werts et al., 1974]. The Cronbach alpha value for each scale is as follows: online consumer motivation (OCM) is 0.847, task characteristics (TC) is .902, computer playfulness (CP) is .863, and satisfaction (SAT) is .956. Each of these scales, similar to our previous findings meet the recommendation that Cronbach alpha (0.70) [Hair et al., 1998]. As shown in Table 12 below all composite reliability scores were also greater than the recommended .70 threshold [Hair et al., 1998]. Together this analysis suggests that the measurement of these constructs is reliable.

¹³ Composite reliability scores were calculated as $(\sum \lambda_i)^2 / [(\sum \lambda_i)^2 + \sum \text{Var}(\epsilon_i)]$ where λ_i is the indicator loading and $\text{Var}(\epsilon_i) = 1 - \lambda_i^2$.

Table 12: Measurement Model: Loadings and Composite Reliabilities					
Items	Standardized Loadings	Composite Reliabilities	Items	Standardized Loadings	Composite Reliabilities
OCM1	0.510	0.761	CP1	0.704	0.761
OCM2	0.821		CP2	0.550	
OCM3	0.866		CP3	0.878	
OCM4	0.805		CP4	0.856	
OCM5	0.820				
TC1	0.887	0.878	SAT1	0.971	0.957
TC2	0.773		SAT2	0.970	
TC3	0.815		SAT3	0.855	
TC4	0.865		SAT4	0.878	
All loadings p<.0001					

Convergent Validity

Convergent validity again is assessed by examining the factor loadings. All factor loadings have to exceed .707 [Hair et al., 1998 ; Segars, 1997]. Most factor loadings indicate compliance with this standard except OCM1 at .510 and CP2 at .550. This is similar to the finding of the first experimental study and suggests that these items are problematic in general. For the purposes of further testing these two measures will be removed and should be also removed in any subsequent study. Again convergent validity is assessed using the Average Variance Extract (AVE)¹⁴ for each construct. AVE should be above .50 [Fornell and Larcker, 1981]. The AVE for each of the construct is as follows: OCM is 0.761, TC is 0.878, CP is 0.761 and SAT is 0.957. From this analysis we can assume convergent validity.

¹⁴ AVEs were calculated as $(\sum \lambda_i^2) / [(\sum \lambda_i^2) + \sum \text{Var}(\epsilon_i)]$ where λ_i is the indicator loading and $\text{Var}(\epsilon_i) = 1 - \lambda_i^2$.

Discriminant Validity

AVE is used to assess discriminant validity also. The AVE for each construct was compared to the squared correlation of each construct as directed by Segars [1997]. The results are presented in Table 13 suggest that these construct are distinct and discriminant.

Table 13: Estimated Squared correlations and AVE

	OCM	TC	CP	SAT
OCM	0.59			
TC	0.05	0.70		
CP	0.02	0.02	0.52	
SAT	0.04	0.01	0.01	0.85

AVE figures are shown in bold along the diagonal

Structural Model

The structural model is very similar to the experimental study but again performance is now subjectively measured. The two step approach will again be used to evaluate the interaction terms (e.g., computer playfulness moderation on task, technology characteristics moderation on online consumer motivation for both satisfaction and performance outcomes) as per Klien and Mossbrugger [2000].

In this model we found that all main effect path were significant at $p = 0.05$ except for the affect of the task characteristic on OCM and the affect of the technology on satisfaction (See Figure 12). Again, these results cannot be related directly to the hypothesis. In order to evaluate the interactions, another model will be calculated that include the three interactions and then compared to the main effects model.

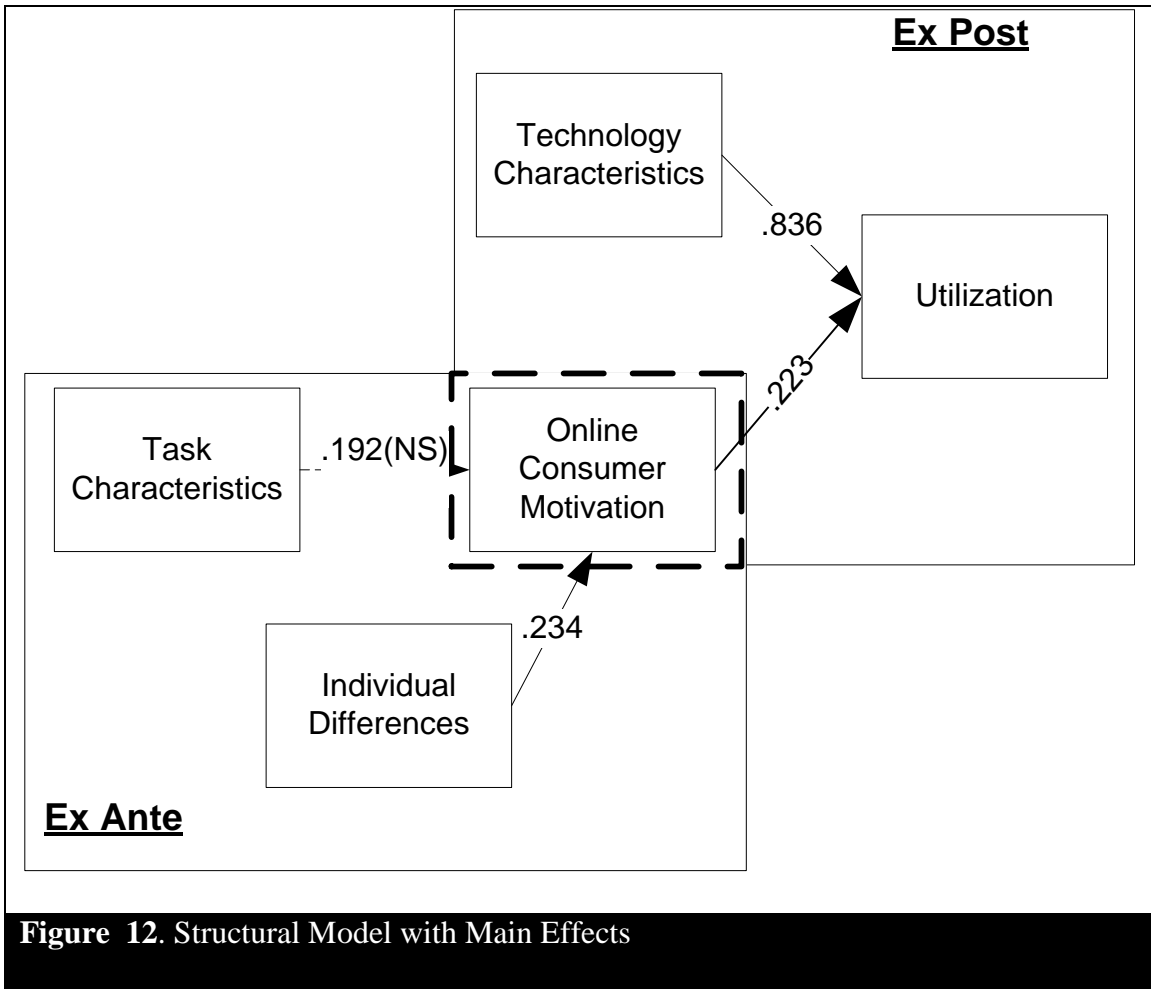


Figure 12. Structural Model with Main Effects

Table 14: Test of Fit for Main Effect Model			
Loglikelihood			
HO Value	-6838.69		
Information Criteria:			
Number of free Parameters	54	Sample-Size Adjusted BIC ¹⁵	13814.67
Akaike (AIC)	13785.39		
Bayesian (BIC)	13985.93		

¹⁵ (n* = (n + 2) / 24)

In the second model we see that all paths are significant at $p = 0.05$ except for the path from the task characteristics to OCM (See Figure 13). Again using we used March's criteria when evaluating the models using AIC, the BIC and the A-BIC [Marsh et al., 2004]. Again, all of these indices are smaller in the model that includes interactions. This analysis suggests that the model including the interaction terms is a better fit to the data than the main effects model.

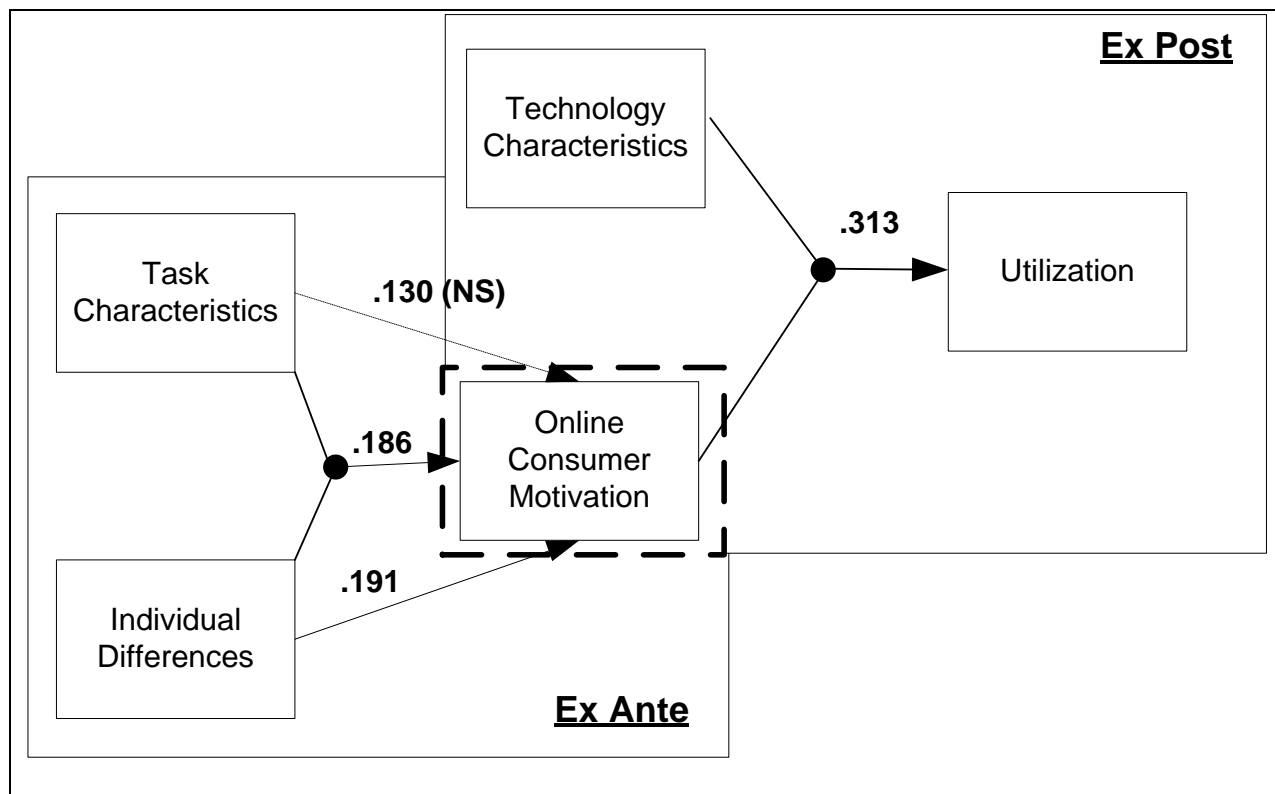


Figure 13. Structural Model with the Interactions Effects

Table 15: Test of Fit for Interaction Effect Model

Loglikelihood			
HO Value	-6852.45		
Information Criteria:			
Number of free Parameters	55	Sample-Size Adjusted BIC ¹⁶	13824.73
Akaike (AIC)	13804.91		
Bayesian (BIC)	14009.16		

Interactions

In order to tease out the effects of OCM on both the performance and the utilization constructs we need to evaluate the performance and satisfaction levels for highly intrinsic OCM subjects and highly extrinsic OCM subjects. This additional analysis is directed at answering questions regarding the fit between a consumer's OCM and the technology presented by an ecommerce Web site (e.g., hypothesis 4b, 4c, 5b and 5c). In order evaluate the interactions we have artificially dichotomize OCM into highly intrinsic and highly extrinsic users. This was accomplished by standardizing the OCM scores (e.g., the average of the four items measured) and then dividing this into quartiles. The quartile with the lowest standard score (n=150) was categorized as the Highly Extrinsic OCM group and the quartile with the highest standard scores was categorized as the Highly Intrinsic OCM group (n=136). Simple ANOVAs were undertaken to see if there were any differences between these groups in age and sex. No differences were found (age: $p = 0.89$ sex: $p=0.43$).

¹⁶ $(n^* = (n + 2) / 24)$

It must be noted that several methodologists caution against splitting continuous data to categorize the subjects [Cohen, 1988 ; Maxwell and Delaney, 1993 ; Pedhazur, 1982]. Having said that, most of these researchers have agreed that there are instances in which dichotomizing a variable might be appropriate. Pedhazur [1982] offers a situation that dichotomizing a variable is practiced commonly and is appropriate. In his example, the personality trait of masculinity and femininity is used to create categories. Also, Maxwell and Delany [1993] states that the, “primary argument against this practice has been that it underestimates the strength of relationships and reduces statistical power.” We do understand these limitations. Further Maxwell and Delaney argue that dichotomizing one variable can be appropriate but dichotomizing multiple continuous predictors, “not only may lose power to detect true predictor-criterion relationships in some situations but also may dramatically increase the probability of Type I errors in other situations”. For these reasons we proceed with this post hoc analysis with caution.

Using the data presented in Study 1 we performed a quartile split, as stated above, for the OCM variable to understand how OCM can affect outcomes (e.g., satisfaction and performance). Study 1 was used as it had three types for the Web site (e.g., experiential, hybrid, and search). The means for the two groups can be seen in Table 16. T-tests were calculated for each Web site condition using the OCM group as the factor. Both the search Web site and the experiential Web site had significant differences between the two groups for both performance and satisfaction. Inherently and consistent with the past motivation literature, we found a difference in performance between the two groups in general [Deci and Ryan, 1985 ; Ryan and Deci, 2000].

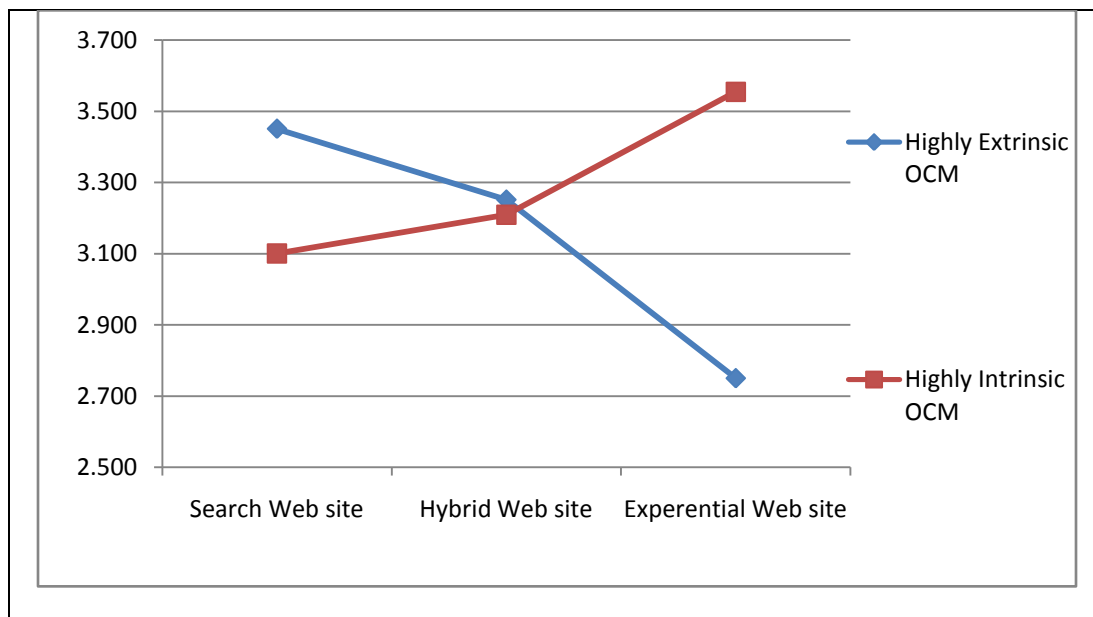
Table 16: Study 1 Summary of OCM classifications

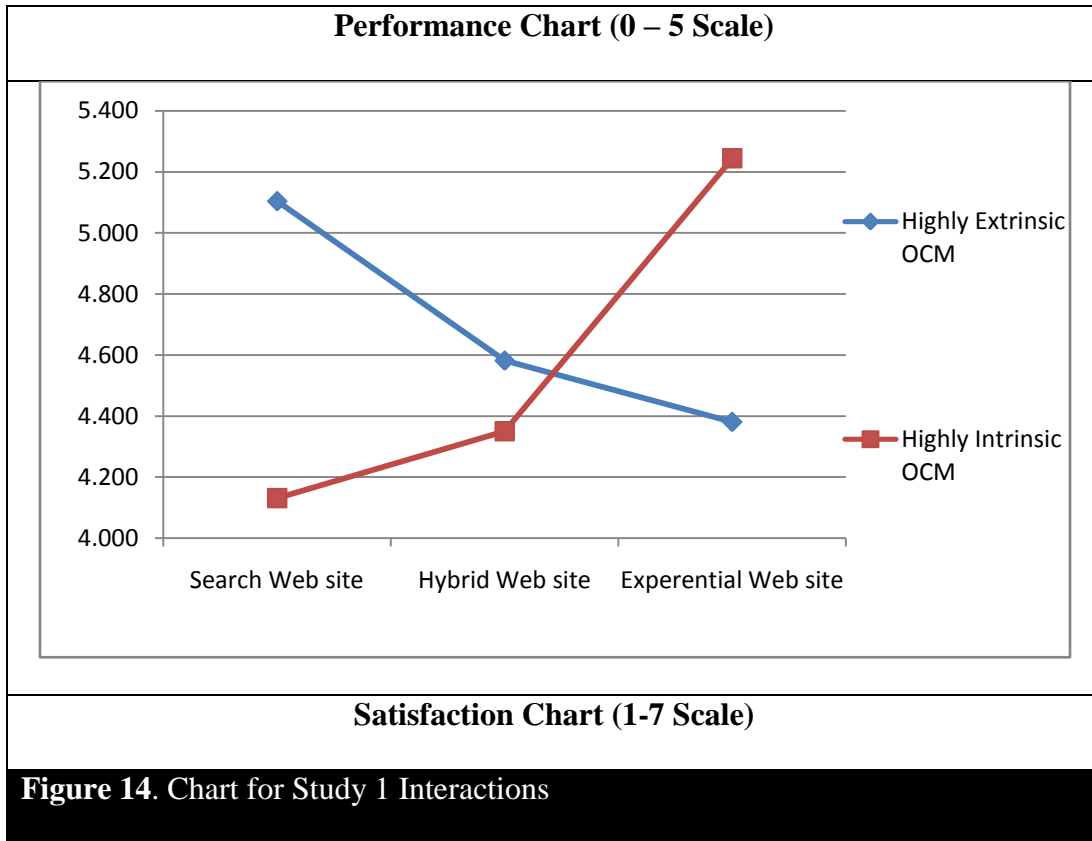
Performance Mean (Scale of 0-5)				
	Search Web Site	Hybrid Web Site	Experiential Web site	All the Web sites (Grand Mean)
Highly Intrinsic OCM	3.10	3.21(ns)	3.55	3.30 (ns)
Highly Extrinsic OCM	3.45	3.25 (ns)	2.75	3.13 (ns)

Satisfaction Grand Mean (Scale of 1-7)				
	Search Web Site	Hybrid Web Site	Experiential Web site	All the Web sites (Grand Mean)
Highly Intrinsic OCM	4.13	4.35 (ns)	5.24	4.59 (ns)
Highly Extrinsic OCM	5.10	4.58 (ns)	4.50	4.70 (ns)

(ns) = no significant different between the two groups at p=0.05.

Figure 14 illustrates the crossover interaction effect that was found as line graphs. The mean for each type of Web site by group is plotted for both satisfaction and performance.





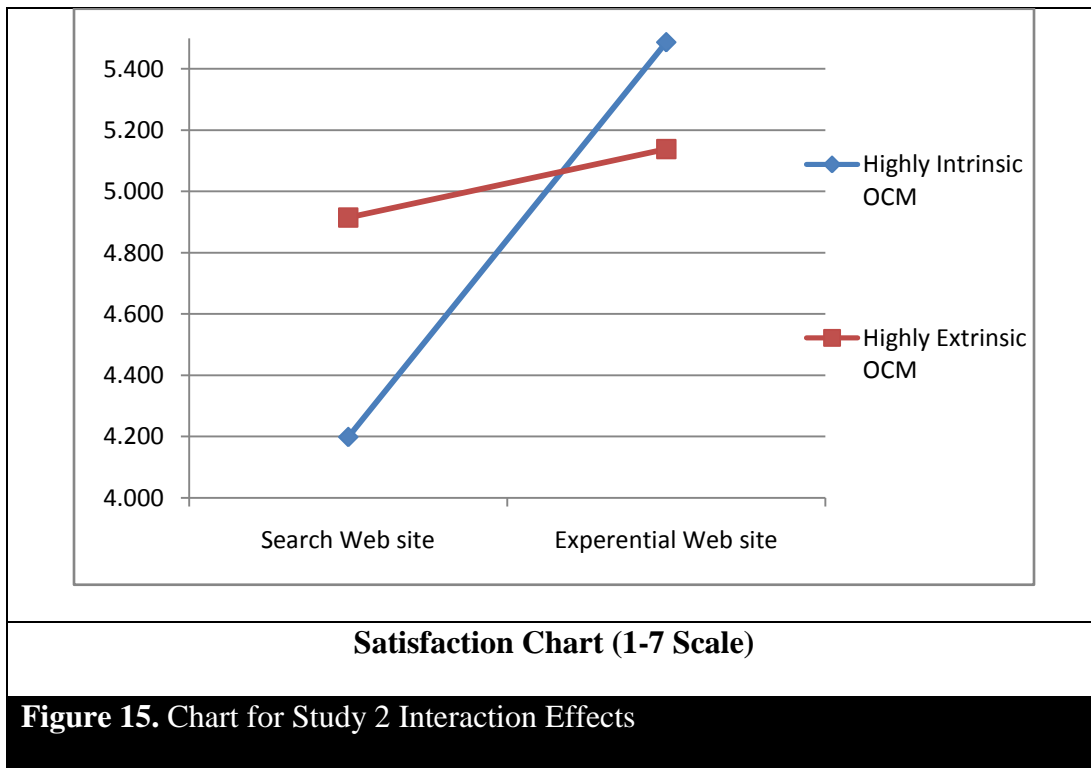
Using the data presented in Study 2 we performed the same quartile split, as stated above, for the OCM variable. Study 2 has only two types of interfaces (e.g., experiential and search). The means for the two groups can be seen in Table 16. Again, T-tests were calculated for each Web site condition using the OCM group as the factor. Both the search Web site and the experiential Web site had significant differences between the two groups for satisfaction. Again, we found a difference in performance between the two groups in general.

Table 17: Study 2 Summary of OCM classifications

Satisfaction Grand Mean (Scale of 1-7)			
	Search Web Site	Experiential Web site	All the Web sites (Grand Mean)
Highly Intrinsic OCM	4.20	5.49	5.02
Highly Extrinsic OCM	4.92	5.14	4.63

(ns) = no significant different between the two groups at p=0.05.

Figure 15 illustrates the crossover interaction effect that was found as line graphs which was similar to the first study. The mean for each type of Web site by group is plotted for satisfaction.



Our results indicate that “fitting” and the correct interface to a particular type of OCM does affect both satisfaction and performance. For this reason we cautiously conclude that hypothesis 4 b, 4c, 5b and 5c were all supported.

Results

The results of studies 1 and 2 are summarized in Table 18. These two studies show the effect that OCM has on both dependant variables (e.g., satisfaction and performance). Also, the ‘fit’ between the type of online consumer motivation and the type of Web site was also shown to be have an impact on satisfaction and performance.

Table 18: Summary of Results for Study 1 and Study 2

		Study 1	Study 2
H1	In ecommerce the task characteristics will influence online consumer motivation.	Not Supported	Not Supported
H 2	A consumer’s computer playfulness will influence online consumer motivation.	Supported	Supported
H3	Computer playfulness will moderate the perception of the task characteristics on online consumer motivation.	Supported	Supported
H4	Online consumer motivation will moderate the technology characteristics when affecting performance of the consumer in an ecommerce context.	Supported	Not Tested
H4a	A highly intrinsic OCM consumer will perform better using an experiential Web site.	Supported	Not Tested
H4b	A highly extrinsic OCM consumer will perform better using a linear Web site.	Supported	Not Tested
H5	Online consumer motivation will moderate the technology characteristics when affecting utilization in an ecommerce context.	Supported	Supported

H5a	A highly extrinsic OCM consumer will have a higher satisfaction with a linear Web site.	Supported	Supported
H5b	A highly intrinsic OCM consumer will have a higher-level of satisfaction with an experiential Web site.	Supported	Supported
H6	The utilization of an ecommerce system will directly influence a consumer's performance in the system.	Supported	Supported

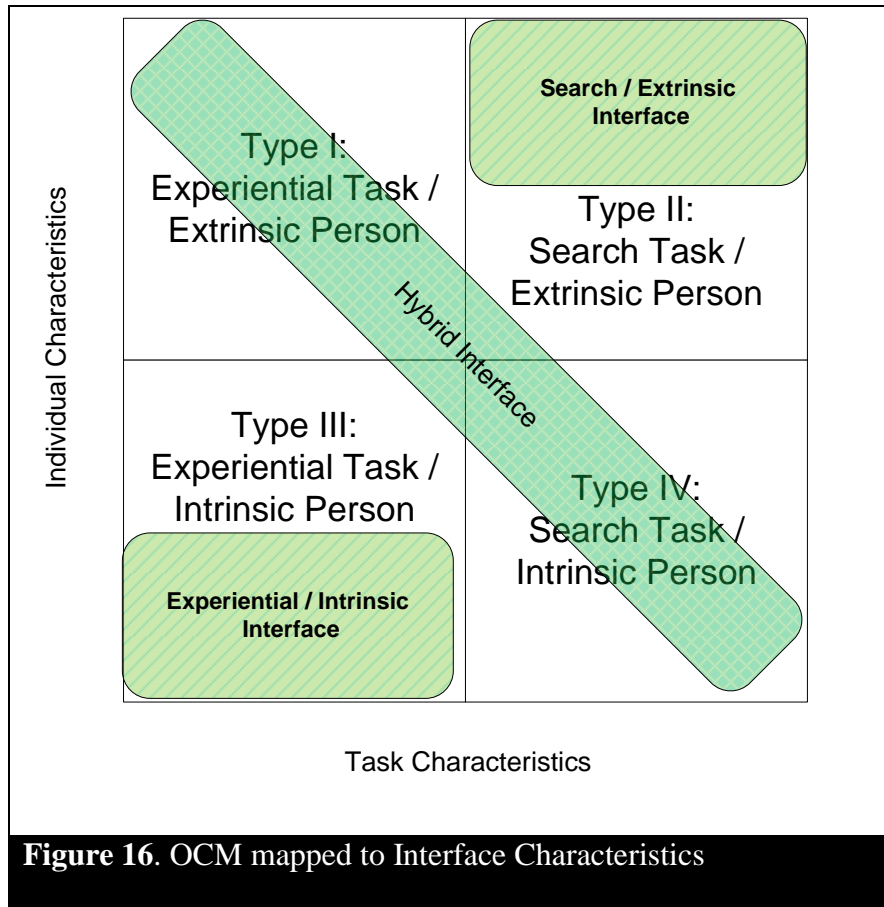
DISCUSSION AND CONCLUSION

This paper provides insight into the critical psychological factors that affect online consumer behavior. In order to accomplish this we first developed and validated an instrument to measure the *a priori* state of mind that a consumer has going into an ecommerce Web site. We called this online consumer motivation (OCM). Although the central motivation of this research was theoretically developing and empirically testing the existence of OCM we were also interested in the affect of a consumer's OCM towards performance and satisfaction. To this end we suggested that OCM can affect outcomes in an ecommerce context. Further, this construct synthesizes both the task and any individual difference in computer playfulness.

In terms of contribution to practice we believe that we offer an interesting avenue for further exploration. Specifically this could include ways of tailoring Web sites. Tailorable technology has been introduced by Germonprez and colleagues [2007], as a technology that is modified in the context of use. Rayport and Jaworski [2005] define personalization as something the consumer creates and tailoring as something the organization creates. More specifically, in our research, a tailored Web site is an interface that is customized by an organization for every unique user to optimize the online consumer experience.

Although there is a lot of hype surrounding Web site tailoring in the popular press, there is, however, little agreement in the academic literature as to how tailoring Web sites should be undertaken [Ho and Tam, 2005 ; Light et al., 2002] as well as how outcomes should be measured [Alpert et al., 2003 ; Benyon, 1993 ; Blake et al., 2005 ; Tam and Ho, 2006]. Browne [2006 p. 330] states that, “Individual customization presents new problems... that may require new techniques, templates and categorization schemes for users”. Our research shows that by using task-technology fit as a framework online consumer motivation can be used for individual customization. OCM could offer insight into possible tailoring techniques.

We investigated whether the typical design paradigm for ecommerce Web sites, “one-size fits all”, best suits the needs of consumers with differing motivations. We found support that although the one-size fit all approach is appropriate in some instances, if motivations are high for an experiential interface or moreover if motivations are high for a quick interaction, then giving consumers the experience that best fits their motivations can lead to improvements in ecommerce outcomes. Looking at the type of OCM detailed in Figure 15 we can suggest possible tailored interfaces that can be given to the user to best suit the consumer’s needs.



Further, if OCM can be measured in a finer grain approach it is possible to have several or “n” interfaces that are based on this real-time measurement of OCM (See Figure 16). With today’s sophisticated Web analytics, this can be possible. There are several ways in which in which modern system could provide the real-time click stream analysis to detect task include complex decision trees, cluster analysis, etc. The most promising analytic technique for predicting task our prescriptive research is the use of neural networks. Neural networks has been used extensively in business analytics and data mining [Swingler, 1996 ; Witten and Frank, 2005].

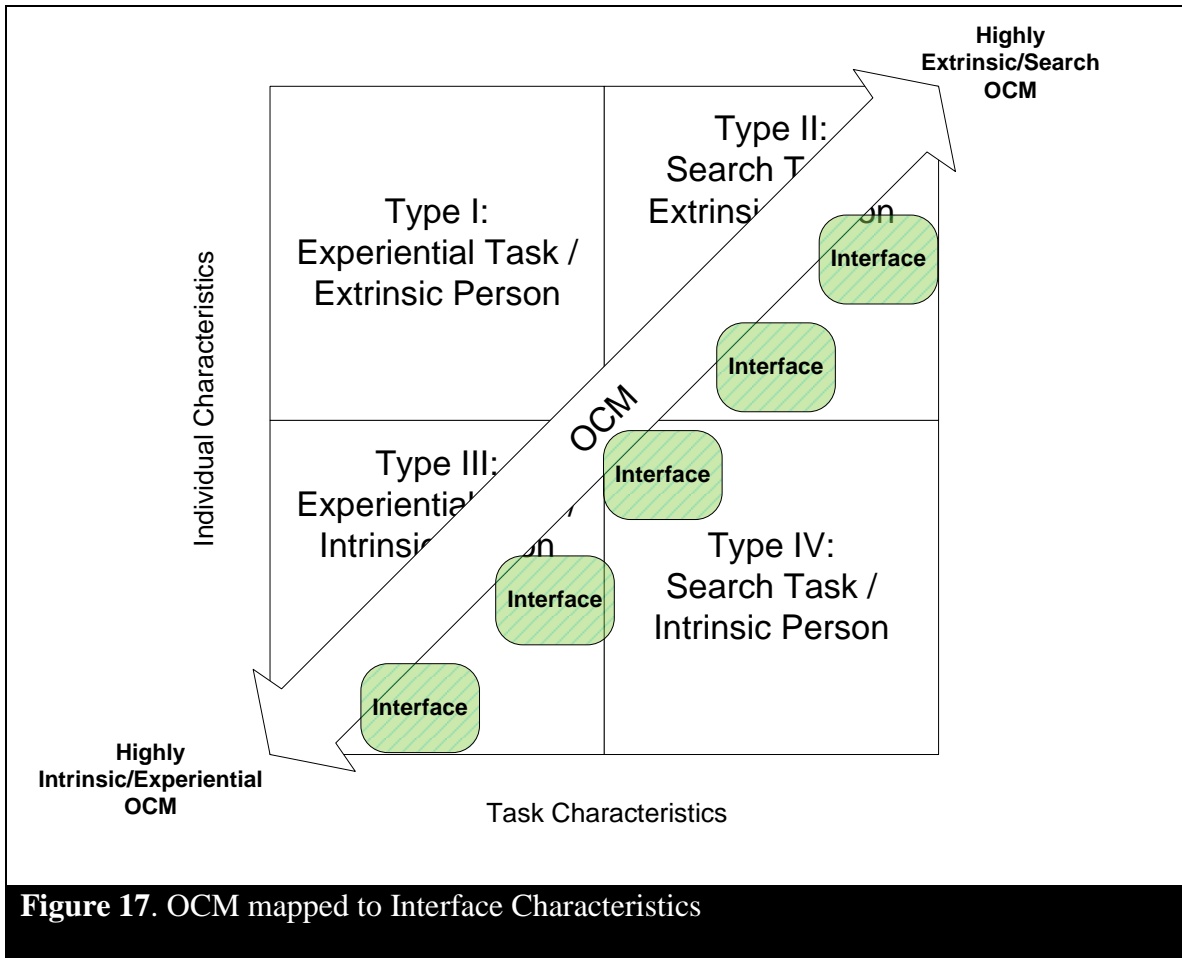


Figure 17. OCM mapped to Interface Characteristics

Similarly, individual personality differences, specifically in our case computer playfulness, can be diagnosed in several different fashions. Cluster modeling is one candidate. This is when organizations track every aspect of a consumer's Web site interactions and then infer individual differences. The easiest method, which could be an intermediate step, to understanding a user's playfulness is to measure this through a three to five item scale during the registration process. This would be the most effective way to create a baseline measurement for playfulness.

The practical implications to this research focused on providing a prescriptive approach for tailoring an ecommerce interaction. If successful, this research will develop a clear protocol for guiding designers and developers on how to affect behavior and cognitive processes by presenting certain technology characteristics based on task type and individual differences. More specifically, if the Web site knows some individual traits about the user *ex ante* the interaction and can prompt the user for the type of task being executed, they can tailor the interface for optimal user interaction.

There are also important theoretical contributes to this work. Conceptually, TTF is an elegant and useful model in information systems research, but has been difficult to investigate empirically due to the 3-way interaction. Our research expands the context of the TTF framework so that the interactions will be presented temporally, rather than as a single instance. By developing an extension to TTF this research contributes to both the Information Systems discipline as well as reference disciplines that are likely to use TTF. Second, the successful application of TTF also has implications for HCI research. Specifically given that much of the prior research concerning the tailoring of interfaces has been somewhat atheoretical in nature, providing a method for applying TTF will aid in future empirical studies in HCI.

Conclusion

The proposed research focuses on extending TTF to include a temporal component that predicts how motivation plays an important role when tailoring a Web site. Online consumer motivation can inform future HCI research but also guide the design of organizational Web sites. This research provides a foundation for pursuing these parallel objectives.

In conclusion, the overarching goal of this paper was to enrich our understanding of *a priori* motivations in ecommerce. We describe this motivation as online consumer motivation

and showed that it played a significant role in the outcome of an ecommerce transaction. This research can clear theoretical underpinning while also guiding ecommerce practice. There are several avenues in which future work can build on this preliminary empirical study. Clearly, much work remains.

CONCLUSION

In conclusion, the overarching goal of this dissertation was to enrich our understanding of *a priori* motivations in ecommerce. We describe this motivation as online consumer motivation and suggested that OCM plays a significant role in the outcome of an ecommerce transaction. This dissertation has outlined a theoretical framework for discerning how online consumer motivation can play an important role in ecommerce. The initial studies first helped us understand the measurement of online consumer motivation. This development process vetted several items and left us with a parsimonious scale that could be used to measure the construct of interest. Further, we established the relationship between online consumer motivation and both task characteristics and computer playfulness. Next this dissertation place online consumer motivation as the focal construct in a task-technology fit framework. Further this dissertation posits that online task motivation is an *a priori* state of mind that can affect the outcomes for an ecommerce transaction.

Next, this dissertation applies two studies, one using a laboratory experiment and the other using survey methodology to test the omnibus model. Results were promising as they suggest that online consumer motivation is the central construct within a task-technology fit framework.

Finally, this dissertation offered guidance to both researchers and practitioners. Specifically, we offer possible way that researchers can test the proposition using design science. Also, we challenge practitioners to utilize our concepts to better suit the needs of the heterogeneous ecommerce consumer.

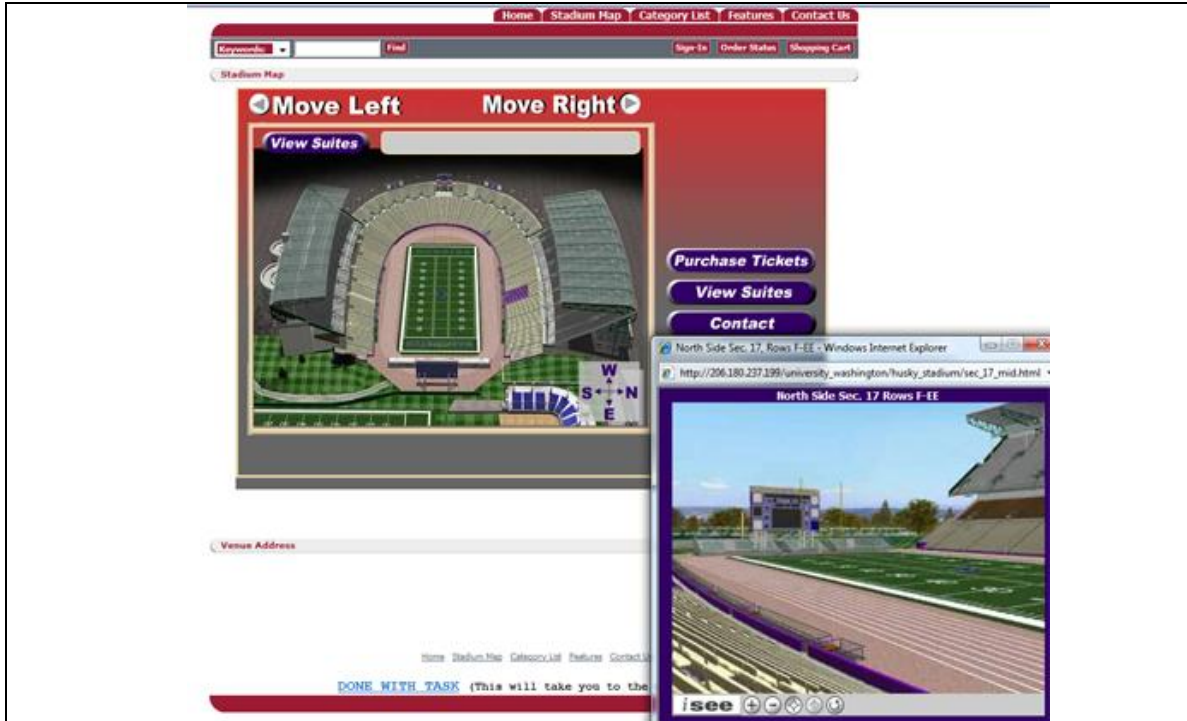
APPENDIX A: EXAMPLE ONLINE CONSUMER MOTIVATION ITEMS

The metric will be a 7-point LIKERT scale with the anchors Strongly Disagree to Strongly Agree.

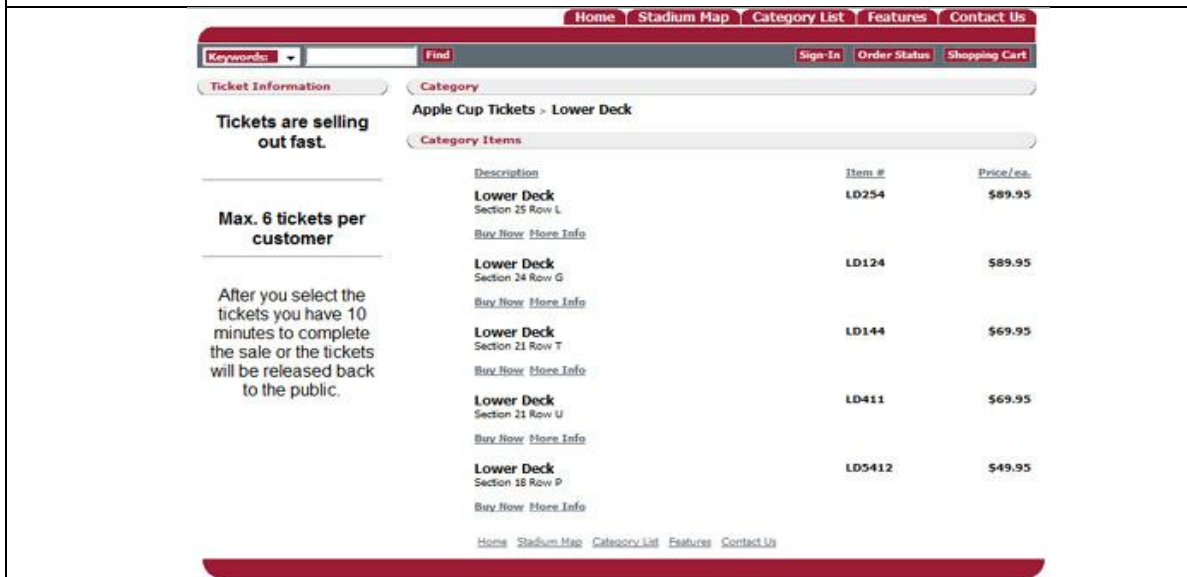
- 1 I am inclined to take my time on this Web site.*
- 2 I am looking for a quick interaction with this Web site.
- 3 I am likely to relax myself while using this Web site. *
- 4 I am likely to play while using this Web site. *
- 5 I am looking for an efficient interaction with this Web site.
- 6 I am hoping to spend as little time as possible at this Web site.
- 7 I would like to browse around this Web site.*
- 8 I would like to enjoy myself while interacting with this Web site.*
- 9 I am inclined to explore this Web site.*
- 10 I am likely to tinker while interacting with this Web site.*
- 11 I would like to get in and get out quickly when using this Web site.
- 12 I am likely to be very directed when using this Web site.
- 13 I am looking to see what this Web site can offer.*
- 14 I would like the shortest experience possible.
- 15 I am inclined to spend some time and look around this Web site.*

* Denotes reverse coded items.

APPENDIX B: EXAMPLE RESEARCH WEB SITES

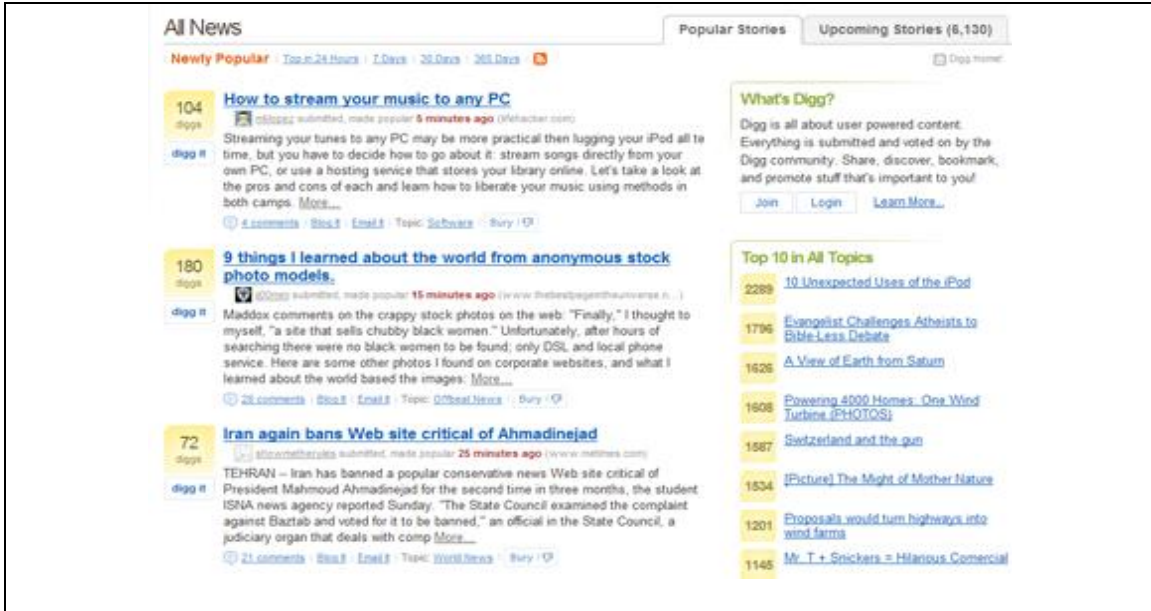


Ecommerce Ticket to Buy Football Tickets – Experiential Web Site

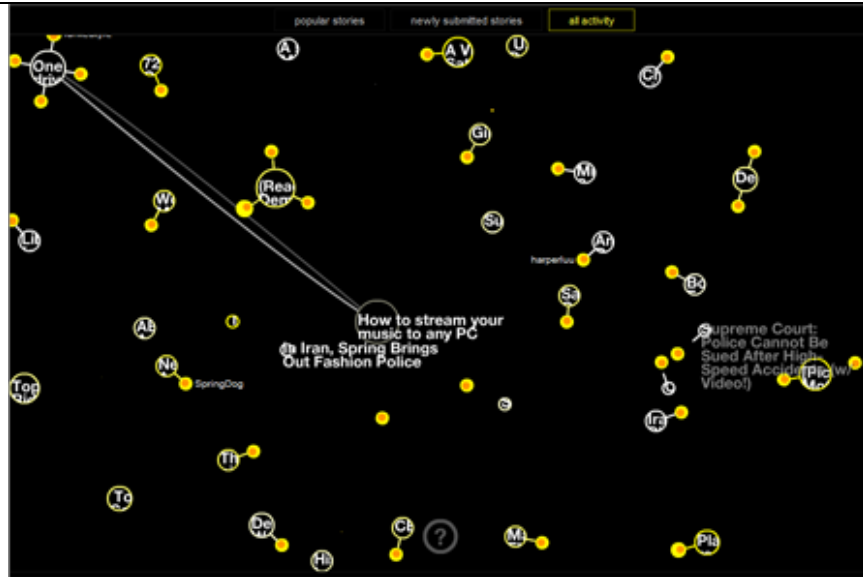


Ecommerce Ticket to Buy Football Tickets – Search Web Site

APPENDIX C: SCREEN SHOTS OF THE EXPERIMENTAL WEB SITES



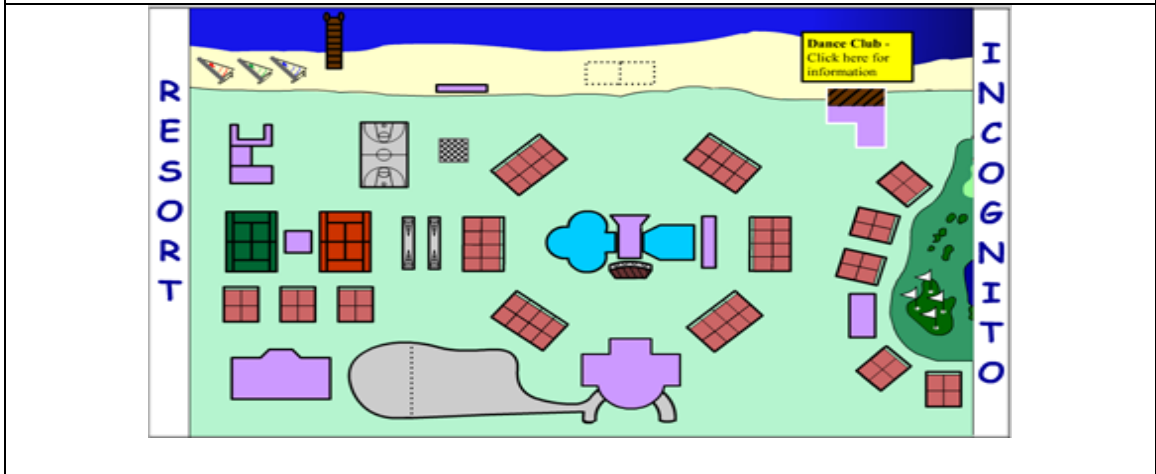
News Aggregation – Search Web Site



News Aggregation – Experiential Web Site

 <p> Description Location Resort Layout Accommodations Amenities Activities Dining Entertainment </p>	<h2>Resort Activities</h2> <p> Golf Tennis Diving Weights and Aerobics Water Activities (Includes water volleyball, water polo, and sailing) Miscellaneous Activities (Includes basketball, chess, shuffleboard, and sand volleyball) </p>
---	---

Vacation Resort – Search Web Site



Vacation Resort – Experiential Web Site

APPENDIX D: EXPERIMENTAL TASKS

Treatment 1 – Experiential News Aggregation Site with the Hedonic Task

Research Study #5 (eCommerce)	
You will be asked to complete a task online. Please do the following:	
<input type="checkbox"/>	View Your Task: CLICK HERE (You can view this task as much as you want).
<input type="checkbox"/>	Complete the first survey about the task: CLICK HERE Your Survey Code is: 101
<input type="checkbox"/>	CLOSE Your Task Window
<input type="checkbox"/>	1 - Go to the Web site (Maximize the window) and complete the task you were given. 2 - Digg.com is a Web site that users can post current stories and readings can rate these stories. 3 - You can spend up to 15 minutes on this Web site completing the task. CLICK HERE to open the Web site
<input type="checkbox"/>	Now Complete the Survey CLICK HERE Your Survey Code is: 101

Your Task

Please read the following:

- During some spare time, you are browsing the Web looking for interesting news.
- You find a new Web site with several different types of stories that might interest you.
- Check out the Web site and its features to see if this is something you might use again.
- Be sure to approach this information-browsing task from a broad-minded perspective.

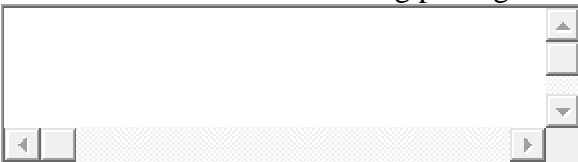
Treatment 2 – Experiential News Aggregation Site with the Utilitarian Task

Research Study #5 (eCommerce)							
You will be asked to complete a task online. Please do the following:							
<input type="checkbox"/>	View Your Task: CLICK HERE (You can view this task as much as you want).						
<input type="checkbox"/>	Complete the first survey about the task: CLICK HERE Your Survey Code is: 202						
<input type="checkbox"/>	CLOSE Your Task Window						
<input type="checkbox"/>	1 - Go to the Web site (Maximize the window) and complete the task you were given. 2 - Digg.com is a Web site that users can post current stories and readings can rate these stories. 3 - You can spend up to 15 minutes on this Web site completing the task. No More. CLICK HERE to open the Web site (Give it a couple moments to open)						
<input type="checkbox"/>	1st Story - <table style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th style="width: 33%; text-align: center;">Article Title</th> <th style="width: 33%; text-align: center;">Original Source</th> <th style="width: 33%; text-align: center;">Submitted By</th> </tr> </thead> <tbody> <tr> <td style="text-align: center;"><input type="text"/></td> <td style="text-align: center;"><input type="text"/></td> <td style="text-align: center;"><input type="text"/></td> </tr> </tbody> </table>	Article Title	Original Source	Submitted By	<input type="text"/>	<input type="text"/>	<input type="text"/>
Article Title	Original Source	Submitted By					
<input type="text"/>	<input type="text"/>	<input type="text"/>					
<input type="checkbox"/>	2nd Story - <table style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th style="width: 33%; text-align: center;">Article Title</th> <th style="width: 33%; text-align: center;">Original Source</th> <th style="width: 33%; text-align: center;">Submitted By</th> </tr> </thead> <tbody> <tr> <td style="text-align: center;"><input type="text"/></td> <td style="text-align: center;"><input type="text"/></td> <td style="text-align: center;"><input type="text"/></td> </tr> </tbody> </table>	Article Title	Original Source	Submitted By	<input type="text"/>	<input type="text"/>	<input type="text"/>
Article Title	Original Source	Submitted By					
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<input type="checkbox"/>	3rd Story - <table style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th style="width: 33%; text-align: center;">Article Title</th> <th style="width: 33%; text-align: center;">Original Source</th> <th style="width: 33%; text-align: center;">Submitted By</th> </tr> </thead> <tbody> <tr> <td style="text-align: center;"><input type="text"/></td> <td style="text-align: center;"><input type="text"/></td> <td style="text-align: center;"><input type="text"/></td> </tr> </tbody> </table>	Article Title	Original Source	Submitted By	<input type="text"/>	<input type="text"/>	<input type="text"/>
Article Title	Original Source	Submitted By					
<input type="text"/>	<input type="text"/>	<input type="text"/>					
<input type="checkbox"/>	Now Complete the Survey CLICK HERE Your Survey Code is: 202						
Your Task							
Please read the following: Your boss has asked you to come up with 3 technology related articles that could be used to help your business. Please find three different and relevant articles that can be presented in at the next meeting as ideas. Please list the three articles on the work sheet (include the original Web site's source information and submitters username).							

Treatment 3 – Experiential Vacation Resort with the Hedonic Task

Research Study #5 (eCommerce)	
You will be asked to complete a task online. Please do the following:	
<input type="checkbox"/>	View Your Task: CLICK HERE (You can view this task as much as you want).
<input type="checkbox"/>	Complete the first survey about the task: CLICK HERE Your Survey Code is: 303
<input type="checkbox"/>	CLOSE Your Task Window
<input type="checkbox"/>	1 - Go to the Web site (Maximize the window) and complete the task you were given. 2 - Digg.com is a Web site that users can post current stories and readings can rate these stories. 3 - You can spend up to 15 minutes on this Web site completing the task. No More. CLICK HERE to open the Web site
<input type="checkbox"/>	Now Complete the Survey CLICK HERE Your Survey Code is: 303
Your Task	
Please read the following:	
<ul style="list-style-type: none">• You and a group of your friends and/or family are planning a vacation to an all-inclusive resort.• This group has requested that you go to the Web site for a particular resort and check it out.• You will be meeting them for dinner later tonight to make your report.• Keep in mind that your overall goal is to convey to your friends and/or family what type of experience they could expect by going to this resort.	
Therefore, be sure to approach this information-browsing task from a broad-minded perspective.	

Treatment 4 – Experiential Vacation Resort with the Utilitarian Task

Research Study #5 (eCommerce)	
You will be asked to complete a task online. Please do the following:	
<input type="checkbox"/>	View Your Task: CLICK HERE (You can view this task as much as you want).
<input type="checkbox"/>	Complete the first survey about the task: CLICK HERE Your Survey Code is: 606
<input type="checkbox"/>	CLOSE Your Task Window
<input type="checkbox"/>	1 - Go to the Web site (Maximize the window) and complete the task you were given. 2 - Resort Incognito is the Web site you will be using. 3 - You can spend up to 15 minutes on this Web site completing the task. No More. CLICK HERE to open the Web site
<input type="checkbox"/>	1. What are the various diving packages that are offered at the resort? 
<input type="checkbox"/>	2. How to go about reserving a tennis court at the resort?
<input type="checkbox"/>	3. What are the dining alternatives offered at the resort?
<input type="checkbox"/>	Now Complete the Survey CLICK HERE
Your Task	
Please read the following:	
You are asked by your boss at work to find some information out about his upcoming trip. Please find the following and note these on the work sheet provided.	
1 - What are the various diving packages that are offered at the resort? 2 - How to go about reserving a tennis court at the resort. 3 - What are the dining alternatives offered at the resort?	

APPENDIX E: DESCRIPTIVE STATISTICS

	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
TM1	1	7	5.02	1.273	-.704	.131	-.080	.262
TM2	1	7	2.90	1.365	1.008	.131	.672	.262
TM3	1	7	4.95	1.207	-.619	.131	-.041	.262
TM4	1	7	4.17	1.426	-.164	.131	-.881	.262
TM5	1	7	2.27	1.014	1.265	.131	2.512	.262
TM6	1	7	3.72	1.633	.264	.131	-.929	.262
TM7	1	7	4.75	1.388	-.714	.131	-.117	.262
TM8	1	7	5.42	1.108	-1.063	.131	1.552	.262
TM9	1	7	4.88	1.320	-.777	.131	-.048	.262
TM10	1	7	4.53	1.318	-.478	.131	-.437	.262
TM11	1	7	3.53	1.475	.277	.131	-.784	.262
TM12	1	7	2.94	1.118	.812	.131	.613	.262
TM13	1	7	5.29	1.194	-1.084	.131	1.150	.262
TM14	1	7	3.67	1.435	.143	.131	-.608	.262
TM15	1	7	4.80	1.273	-.624	.131	-.117	.262
IC1	1	7	4.77	1.245	-.814	.131	.241	.262
IC2	2	7	4.66	1.205	-.407	.131	-.494	.262
IC3	1	7	5.23	.995	-.983	.131	1.578	.262
IC4	1	7	4.92	1.131	-.736	.131	.302	.262
IC5	2	7	5.05	1.118	-.624	.131	.068	.262
IC6	1	7	4.49	1.242	-.304	.131	-.280	.262
IC7	1	7	4.62	1.198	-.341	.131	-.162	.262
IC8	1	7	3.06	1.280	.747	.131	.439	.262
IC9	1	7	3.48	1.368	.241	.131	-.663	.262
IC10	1	7	3.75	1.411	.180	.131	-.634	.262
TC1	1	7	3.73	1.860	.057	.131	-1.145	.262
TC2	1	7	3.35	1.739	.319	.131	-1.065	.262

TC3	1	7	3.26	1.623	.419	.131	-.849	.262
TC4	1	7	3.68	1.705	-.054	.131	-.998	.262
TC5	1	7	3.38	1.575	.316	.131	-.758	.262
TC6	1	7	3.68	1.533	.007	.131	-.787	.262
TC7	1	7	3.40	1.524	.354	.131	-.690	.262
TC8	1	7	3.23	1.528	.479	.131	-.582	.262
TC9	1	7	3.25	1.470	.491	.131	-.514	.262
TC10	1	7	3.65	1.733	.192	.131	-1.086	.262
TC11	1	7	3.31	1.425	.273	.131	-.576	.262
TC12	1	7	3.26	1.480	.425	.131	-.519	.262
TC13	1	7	3.48	1.358	.150	.131	-.322	.262
TC14	1	7	3.83	1.330	-.212	.131	-.172	.262
TC15	1	7	4.21	1.667	-.150	.131	-.845	.262
Valid N (355)								

APPENDIX F: INITIAL FACTOR ANALYSIS

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.895
Bartlett's Test of Sphericity	Approx. Chi-Square	7619.021
	df	780
	Sig.	.000

Rotated Component Matrix^a

	Component							
	1	2	3	4	5	6	7	8
TT12	.856						-.112	
TT11	.834				.154	-.110		
TT8	.818	.100					.117	
TT9	.818		-.150					
TT7	.797						.137	
TT13	.791	.116			.104	-.103	-.129	
TT3	.790					.133		
TT10	.767	.124						.115
TT5	.751					.105	.172	
TT2	.680					.264	.143	-.102
TT6	.641				-.102	.317	.216	
TT4	.624	.254		-.131		.423	.273	
TT14	.607	.255					-.111	
TT1	.599	.154				.441	.340	
TT15	.503	.389			.167	.120	-.175	.283
OCM9	.125	.851						
OCM7	.137	.809					.148	
OCM15		.795			.205	.128	.170	
OCM1		.697		.102		.124	-.150	
OCM13	.103	.657			-.276	.234		
OCM10		.626		.117	.107	-.145	.458	.128
OCM3	.177	.551		.207	-.195		.142	
OCM8	.160	.547			-.410	.123		.181

CP6			.844	.183				
CP7			.803	.280				
CP2			.684	.188				.158
CP10			-.667	.219				.214
CP4		.161	.347	.716			.120	
CP3		.160	.125	.670	-.108	-.178		
CP1				.664		.169		
CP5	-.198	.124	.229	.585		.117	.314	.173
OCM5	.155	-.334			.700		.173	
OCM2		.180			.687	.248	-.242	
OCM12	.255				.623			.282
OCM11	.398	.321			.201	.586		.172
OCM14	.428	.372			.186	.547	-.106	.193
OCM6	.368	.343			.167	.483		
OCM4	.153	.288		.126			.732	.156
CP8		-.137					.262	.771
CP9		.134	.113	.155	.264	.118		.686

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 12 iterations.

APPENDIX G: FINAL EFA LOADINGS

Rotated Component Matrix^a

	Component		
	1	2	3
TT11	.870		
TT12	.869		
TT9	.858		-.132
TT8	.849	.144	
TT7	.833		
OCM9	.116	.863	
OCM7	.118	.852	
OCM15		.827	
OCM1		.722	
OCM13		.721	
CP7			.848
CP6			.830
CP2			.734
CP4		.182	.670
CP5	-.198	.196	.556

Extraction Method: Principal

Component Analysis.

Rotation Method: Varimax with Kaiser

Normalization.

a. Rotation converged in 5 iterations.

APPENDIX H: VETTED ITEMS

A seven-point scale was used for computer playfulness, task characteristics, online consumer motivation, and satisfaction.

Computer Playfulness [Venkatesh, 2000]

7-point scale using “Strong Disagree, Disagree, Slightly Disagree, Neither Agree nor Disagree, Slightly Agree, Agree and Strongly Agree”

The following questions ask you how you would characterize your-self when you use the Internet in general:

... spontaneous

... unimaginative

... flexible

... creative

... playful

Task Characteristics adapted from [Wells et al., 2005]

7-Point scale using anchors and 5 intermittent choices.

The following questions ask you how you would characterize the task you have been given:

Business oriented Pleasure oriented

Work Play

Directed Meandering

In-and-out Browsing

Succinct Roundabout

Online Consumer Motivation

7-point scale using “Strong Disagree, Disagree, Slightly Disagree, Neither Agree nor Disagree, Slightly Agree, Agree and Strongly Agree”

Going into this Web site...

. . . I am looking for a quick interaction

. . . I am likely to play while using this Web site

. . . I am looking for an efficient interaction with this Web site

. . . I am inclined to explore this Web site

. . . I am inclined to browse around this Web site

Satisfaction adapted from [Bhattacharjee, 2001]

7-Point scale using anchors and 5 intermittent choices.

How do you feel about your overall experience with this Web site:

Very dissatisfied Very Satisfied

Very displeased Very pleased

Very frustrated Very contented

Absolutely terrible Absolutely delighted

Performance

No specific items were used in the laboratory experiment. Performance was measured by how close the subject got to select the optimal tickets. In the next study performance was measured using behavioral intention items adapted from [Davis et al., 1989b].

7-point scale using “Strong Disagree, Disagree, Slightly Disagree, Neither Agree nor Disagree, Slightly Agree, Agree and Strongly Agree”

I would probably come back to this Web site again.

I would probably use this Web site again for this type of information.

How likely or unlikely would you be to revisit this Web site?

Assuming that I was interested in one of their products or services, I could see myself returning to this Web site.

APPENDIX I: EXPERIMENTAL TASKS

Search Task

You and a friend want to go to the Apple Cup in Seattle. Tickets have gone on sale this week and the game is very close to selling out.

Your friend has tasked you with buying tickets for the game. They have a couple of constraints though. They are as follows:

- 1 – You need 2 tickets.
- 2 – Anywhere on the Husky bench side (North Side) of the field.
- 3 – As close to the 50 yard line as possible.
- 4 – You have a total budget of \$60 (\$30 / ticket).

Experiential Task

You and a friend have been talking about going to the Apple Cup in Seattle. Tickets have gone on sale this week. You have offered to check out seating possibilities for the game and report back to him.

Take your time and browse around the website to see what is available and interesting.

Make sure you check out all the options (e.g., location, price, available tickets, and so on) as you'll be asked for your recommendation by your friends after you browse the website. You can take notes if need be.

APPENDIX J: DIGG.COM TASK FOR THE SURVEY STUDY

Browse Task

Please read the following:

- During some spare time, you are browsing the Web looking for interesting news.
- You find an new Web site with several different types of stories that might interest you.
- Check out the Web site and its features to see if this is something you might use again.
- Be sure to approach this information-browsing task from a broad-minded perspective.

Search Task

Please read the following:

- Your boss has asked you to come up with 3 technology related articles that could be used to help your business.
- Please find three different and relevant articles that can be presented in at the next meeting as ideas.
- Please list the three articles on the work sheet (include the original Web site's source information and submitters username).

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