

Research Article

Causal Relationships between Perceived Enjoyment and Perceived Ease of Use: An Alternative Approach¹

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Abstract

Identifying causal relationships is an important aspect of scientific inquiry. Causal relationships help us to infer, predict, and plan. This research investigates the causal relationships between two constructs, perceived enjoyment (PE) and perceived ease of use (PEOU), within the nomological net of user technology acceptance. PE has been theorized and empirically validated as either an antecedent or a consequence of PEOU. We believe that there are two reasons that account for this ambiguity the conceptual coupling of PE and PEOU and the limitations of covariance-based statistical methods. Accordingly, we approach this inconsistency by providing more theoretical reasoning and employing an alternative statistical method, namely Cohen's path analysis. Specifically, as suggested by previous research on the difference between utilitarian and hedonic systems, we propose the conditional dominance of causal directions. Empirical results from two studies using different technologies and user samples support the theoretical claim that the PE→PEOU causal direction outweighs the PEOU→PE direction for utilitarian systems. There are both theoretical and the methodical contributions of this research. The approach applied in this research can be generalized to study causal relationships between conceptually coupled variables, which otherwise may be overlooked by confirmatory methods. We encourage researchers to pay attention to causal directions in addition to causal connectedness.

Keywords: Causal relationships, user technology acceptance, perceived enjoyment, Cohen's path analysis.

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Introduction

It is obvious that user acceptance is critical to the success of information technologies (IT). System failure is ubiquitous, and the lack of user acceptance and ineffective system use are believed to account for many of those failures. Therefore, a better understanding of the various factors that influence users' acceptance and use of IT is crucial. This objective calls for studies focusing on theory-based discovery and assessment of causal relationships among user perceptual, attitudinal, and behavioral factors. Decades of effort have yielded a variety of research results including the technology acceptance model (TAM, Davis, 1989; Davis et al., 1989) and its expansion TAM 2 (Venkatesh and Davis, 2000), the motivational model of technology behavior (MM, Davis et al., 1992), task-technology fit (TTF, Goodhue and Thompson, 1995), and the unified theory of acceptance and use of technology (UTAUT, Venkatesh et al., 2003). Several robust factors such as perceived usefulness, perceived ease of use, perceived enjoyment, social influence (or social norms), and facilitating conditions have been identified to significantly influence user technology acceptance and use.

As an important dimension of causal relationships (including both connectedness and directionality), causal links in technology acceptance should receive more attention. Most of the above models follow the causal relationships suggested by reference theories. For instance, TAM follows the Theory of Reasoned Action (e.g., Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975), which proposes the basic "beliefs→attitude→intention→behavior" causal path. It works well for factors that belong to different categories in the above causal path, e.g., beliefs and intention. However, for factors in the same category, e.g., two beliefs, we have to assume causal directions based on theoretical reasoning. As a result, the causal directions between some factors in technology acceptance research are still unclear.

In this research, we are particularly interested in two factors—perceived enjoyment (PE) and perceived ease of use (PEOU)—in light of the fact that, as we will see in detail later, the casual link between them needs further exploration. In brief, PE has been conceptualized as either an antecedent (e.g., Agarwal and Karahanna, 2000; Venkatesh, 1999; Venkatesh, 2000; Venkatesh et al., 2002; Yi and Hwang, 2003), or a consequence (e.g. Davis et al., 1992; Igbaria et al., 1995; Igbaria et al., 1996; Teo et al., 1999; Van der Heijden, 2004), of PEOU. This inconsistency can be problematic because it further constrains our understanding of the relationships PE and PEOU have with other important factors such as perceived usefulness (PU) and behavioral intention (BI) of using IT, and subsequently might confuse our understanding of the mechanisms by which factors influence one another. In terms of practical implications, an unclear causal direction between PE and PEOU inhibits us from predicting user acceptance, designing training programs and system features appropriately to achieve higher user acceptance, and inferring what causes user acceptance/resistance. For example, to promote the PEOU of a system, game-based training programs or emoticons (a sequence of ordinary printable characters intended to represent a human facial expression and convey an emotion) may be used based on the confirmed PE→PEOU direction. Such ideas may not work if the PEOU→PE causal direction dominates; therefore, enhancements in PE do not contribute to enhancements in PEOU.

We approach these inconsistent arguments regarding the causal direction between PE and PEOU by specifying the contexts under which it is studied. We argue that the causal

direction between PE and PEOU is contingent upon the type of information systems being studied (utilitarian or hedonic). As a first step toward addressing this problem, we constrain our effort within the utilitarian system context without devaluating the importance of hedonic systems. Although we focus on utilitarian systems, we believe this research could also shed light on the causal relationship between PE and PEOU in hedonic system environments.

Methodologically, we highlight the limitation of the currently used approaches in detecting causal directions. Currently used covariance-based statistical methods are of a confirmatory nature and insensitive to causal directions. They usually allow only one causal direction between any two factors in a causal model. As we will see in the next section, these features limit us in drawing conclusions regarding causal directions.

Therefore, the main purposes of this research are twofold: (1) to explore the causal relationship – especially causal direction – between PE and PEOU within the utilitarian information systems context, and (2) to illustrate an approach that is helpful in exploring causal directions. Specifically, we refer to more theoretical reasoning about the causal direction between PE and PEOU and apply an alternative statistical method, namely Cohen's path analysis method, which is sensitive to causal directions (Cohen et al., 1993). Cohen's path analysis can be applied to other research contexts beyond the specific examples of PE and PEOU.

The remainder of this paper proceeds as follows. We first analyze the inconsistent findings in the literature regarding the causal directions between PE and PEOU, and illustrate the limitations of the commonly used analytic approach, especially covariance-based statistical methods, in detecting causal directions. Second, we allow for the coexistence of different causal relationships and develop two competing theoretical models and hypotheses, followed by a description of research methodology. Then we discuss the findings and methods and conclude this research with limitations, along with research and practical implications.

Theoretical Development

Existing Research on the Causal Directions between PE and PEOU

Perceived enjoyment (PE) is conceived as the extent to which the activity of using computers is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated (Davis et al., 1992). It has been confirmed that PE plays an important role in user technology acceptance and has great implications, especially for hedonic systems. PEOU, on the other hand, is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989 p.320). The correlation between PE and PEOU is well accepted.

Table 1 provides a summary of existing studies on the relationship between PE and PEOU. An examination of previous literature reveals that both causal directions between PE and PEOU ($PEOU \rightarrow PE$ and $PE \rightarrow PEOU$) have been proposed and confirmed (Table 1). First, the $PE \rightarrow PEOU$ direction is theoretically and empirically supported. Studies using this direction usually refer to the technology acceptance model (TAM) with the rationale that enjoyment makes individuals "underestimate" the difficulty associated with using the technologies since they simply enjoy the process itself and do not perceive it to

be arduous (Venkatesh, 2000). Second, the other direction (PEOU \rightarrow PE) has also been proposed and confirmed. This direction often appears in studies based on Deci's motivational theory (Deci, 1975) or Davis et al.'s work on the motivational model of technology acceptance (Davis et al., 1992). The rationale is that systems that are perceived as easier to use are more likely to be perceived as enjoyable (Teo et al., 1999). Igbaria et al. (1995) also cited Bandura's self-efficacy theory (Bandura, 1977; Bandura, 1986) to inform the relationship between PEOU and PE: self-efficacy has significant impacts on affect; therefore, PEOU (self-efficacy) is supposed to have significant impacts on PE (affect).

Some researchers have noted the inconsistent findings regarding the causal direction between PE and PEOU. For instance, Venkatesh, when proposing a PE \rightarrow PEOU direction, footnoted this problem:

"It is possible to argue that perceived ease of use should influence intrinsic motivation, rather than intrinsic motivation influence perceived ease of use... the causal flow from perceived ease of use to intrinsic motivation would be consistent with a motivational model where extrinsic and intrinsic motivation are the key predictors of intention/behavior, result in perceived ease of use being examined as a determinant of intrinsic motivation... given the focus on TAM, an outcome and process expectancy model, intrinsic motivation is expected to influence perceived ease of use" (Venkatesh, 2000, p.348).

In this case, the differences between TAM and motivational models were used as the reason for selecting a PE \rightarrow PEOU direction.

From other perspectives, researchers have also noted a similar "precedence" problem and suggested that the nature of the system should be considered to study the precedence of intrinsic and extrinsic motivations (Atkinson and Kydd, 1997; Van der Heijden, 2004). However, their studies were limited to the magnitudes of the constructs' connectedness, and did not examine causal directions. Therefore, we complement this stream of research by studying the conditional dominance of causal direction.

In summary, the selection of the causal direction between PE and PEOU has depended largely on which model the researchers chose: TAM (Davis et al., 1989) or motivational models (Davis et al., 1992). System characteristics such as its utilitarian or hedonic nature, albeit important, have rarely been considered in proposing causal directions.

Utilitarian vs. Hedonic Systems

The differences between utilitarian and hedonic systems have gradually drawn significant attention from IS researchers. Utilitarian systems aim to provide instrumental value to the user, e.g., information to perform a task. Hedonic systems refer to those that provide self-fulfilling value to users, e.g., enjoyment (Van der Heijden, 2004). Existing research on user technology acceptance often emphasizes the utilitarian aspect of information systems (Legris et al., 2003; Van der Heijden, 2004), while hedonic systems are different from utilitarian systems in terms of the relative importance of perceptual factors such as PU, PE, and PEOU in forming behavioral intentions. For example, existing empirical evidence indicates that PE has stronger impacts on BI for hedonic systems (Atkinson and Kydd, 1997; Van der Heijden, 2004).

Table 1 indicates that the utilitarian/hedonic system type is often not carefully considered in proposing the causal direction between PE and PEOU. Motivated by prior research, we argue that these distinctions should be considered in selecting the causal direction between PE and PEOU. It should be noted that the boundary between utilitarian and hedonic systems is not as apparent as their names suggest. The utilitarian/hedonic dimension is task-dependent. It is especially true for mixed systems, which can be used for both utilitarian and hedonic purposes. For example, it is hard to say whether the Internet, which has been used in prior research, is a utilitarian or a hedonic system. Users can perform various tasks such as searching for a job (utilitarian) or simply surf the net for fun (hedonic). Therefore, it is possible that systems have both utilitarian and hedonic aspects, but to different degrees depending on what tasks they are used for. Moreover, users' attitudes toward a task (e.g., using a system to do something) "may quite simply be influenced by labeling a task as 'work' or 'play'" (quoting from Venkatesh, 1999, Webster and Martocchio, 1993). Therefore, we say a system is utilitarian when it is aimed mainly at outcome-oriented tasks, in other words, when its users are mainly driven by an external locus of causality. When we say a system is hedonic, on the other hand, we mean it supports tasks focusing mainly on the process, and users have an internal locus of causality. A system can be used for both purposes and users can be driven by both external and internal loci of causality. Therefore, when we define a system to be utilitarian or hedonic, the nature of tasks should be taken into account.

It is interesting to note that the literature shows PE always has significant impacts on PEOU for utilitarian systems, which implies the significance of this direction in a utilitarian system environment. The causal direction in hedonic system environments may be reversed given their differences from utilitarian systems. Yet, we are aware that we cannot draw any conclusions about the conditional dominance of causal direction from this finding without further theoretical reasoning.

Reasons for the Inconsistency and Possible Solutions

Two reasons might account for the inconsistent arguments regarding the causal direction between PE and PEOU. First, PE and PEOU are conceptually close to each other. Both are conceived as intrinsic motivation variables and show similar patterns in influencing user technology acceptance (Atkinson and Kydd, 1997). Moreover, a brief examination of existing literature on PE and PEOU shows that they are usually significantly correlated (Table 2). We can see from Table 2 that PE and PEOU are correlated at a significant level in all studies that the significance statistic (p value) is available. Given this high conceptual coupling, it is difficult to distinguish their impacts from each another, and a temporal precedence between PE and PEOU is hard to detect.

Second, currently used covariance-based statistical methods (e.g., structural equation modeling (SEM)), albeit robust in examining causal connectedness, are limited in detecting causal direction. SEM incorporates the traditional Wright's path analysis (Wright, 1921) and factor analysis and allows latent variables in the model. Based mainly on the covariance matrix, SEM is also called "covariance structure analysis" (Bollen, 1989). It is of a confirmatory nature and researchers have to "hypothesize a causal relationship (or link) before collecting or analyzing data" (Goldberger, 1972). In addition, currently used methods usually allow only one causal relationship between any two factors in a causal model. Table 3 illustrates the limitations of SEM, from which we can see that SEM yields the same results despite the different conceptualizations of the causal direction between PE and PEOU.

Table 1. A Review of the Existing Literature on Causal Relationships Between PE and PEOU

Article ID	Systems	Types of systems	Subjects	Analytic methods	Used theories	Major findings
PE→PEOU						
(Venkatesh, 1999)	Virtual Workplace System	Utilitarian	Knowledge workers	Regression analysis	TAM + MM	Perceived enjoyment has a significant impact on perceived ease of use and the effect of perceived ease of use on behavioral intention to use is much higher in game-based training.
(Agarwal and Karahanna, 2000)	WWW	Mixed	Students	SEM (PLS)	Extended TAM	Heightened enjoyment, which is measured the same as perceived enjoyment, is one dimension of Cognitive Absorption (CA); CA has a significant impact on PEOU. An interesting finding is that CA also has a direct impact on BI whereas PEOU does not.
(Venkatesh, 2000)	Study 1: Online help desk Study 2: multimedia system for property management	Utilitarian	Employees	SEM (PLS)	TAM	PE has significant effects on PEOU. PE's impacts on PEOU increase along with increasing experience. PEOU's impact on BI, on the other hand, decreases.
(Venkatesh et al., 2002)	Virtual Workplace System	Utilitarian	Knowledge workers	SEM (EQS)	TAM + MM	PE does not have direct impacts on BI. Instead, its effects are fully mediated by PU and PEOU.
(Yi and Hwang, 2003)	Web-based class management system	Utilitarian	Students	SEM (PLS)	Extended TAM	PE has significant effects on PEOU and PU. No direct impact of PE on BI was proposed.

Table 1. A Review of the Existing Literature on Causal Relationships Between PE and PEOU

Article ID	Systems	Types of systems	Subjects	Analytic methods	Used theories	Major findings
PEOU→PE						
(Davis et al., 1992)	Two graphics systems	Utilitarian	Students		MM	PEOU is found to significantly influence PE. PE has a significant impact on BI in study 1, but not in study 2.
(Igbaria et al., 1995)	Computer	Mixed	Employees	Path analysis with least squares regression	MM	PEOU significantly influences PE and BI whereas PE's impacts on BI are very weak.
(Teo et al., 1999)	Internet	Mixed	General Internet users	Path analysis with ordinary least square regression	MM	PEOU has a stronger impact on Internet usage, which is larger than indirect impacts over PU and PE. Moreover, PEOU's direct impact on usage is larger than that of PE.
(Igbaria et al., 1996)	Mixed system: Microcomputer	Mixed	Managers and professionals	SEM (PLS)	TRA, TAM, and Deci's motivational theory.	PEOU (complexity) has significant impacts on PE and PU at almost the same magnitudes. PEOU has significant direct and indirect impact over PU and PE on system usage.
(Van der Heijden, 2004)	A Dutch movie website	Hedonic	Internet users	SEM	Deci's motivational theory	PEOU has significant impacts on PU, PE, and direct impacts on BI over PU and PE.
Analytic methods: SEM (Structural Equation Modeling); PLS (Partial Least Square) Used theories: TAM (Technology Acceptance Model); MM (Motivational Model); TRA (Theory of Reasoned Action)						

Table 2: The Correlations between PE and PEOU in Previous Empirical Studies

	Correlations between PE and PEOU
(Agarwal and Karahanna, 2000)	0.55 (p-value not indicated)
(Venkatesh, 2000)	0.06, 0.25*, 0.29* (at three points of time)
(Venkatesh et al., 2002)	0.30*, 0.33* (for traditional and game-based training groups respectively)
(Yi and Hwang, 2003)	0.54 (p-value not indicated)
(Igbaria et al., 1995)	0.35*
(Teo et al., 1999)	0.34*
(Igbaria et al., 1996)	- 0.44* (perceived complexity is used.)
* Significant correlation	

Table 3. Illustrations of the Limitations of SEM Method

<p style="text-align: center;">Illustration I: The SEM algorithm</p> <p>Consider two models of different causal directions (Goldberger, 1972):</p> $\left\{ \begin{array}{l} \text{Model 1: } X_1 = b_{12}X_2 + e_1 \\ \text{Model 2: } X_2 = b_{21}X_1 + e_2 \end{array} \right.$ <p>One cannot determine which model is a better fit to the data from conventional regression analyses. Using SEM terminology, both models are saturated on the covariance matrix of (X_1, X_2). No modifications are proposed regarding causal directions.</p>	
<p style="text-align: center;">Illustration II: An example of the causal direction between PE and PEOU</p> <p>To briefly illustrate the limitation using real data, we can refer to Figure 2 and the goodness of fit criteria depicted in Appendix I. We can see that despite the different conceptualizations of the causal relationships between PE and PEOU, the covariance based statistical methods provide us the same coefficients, R squares (Figure 2) and goodness of fit values (Appendix I) for Model 1 and Model 2 in each study. Based on Figure 2 and Appendix I, both Model 1 and Model 2 can be empirically confirmed with the same statistics using SEM. We cannot obtain additional statistical inferences regarding the causal direction between PE and PEOU.</p>	

To overcome the first reason, the conceptual coupling, we look for more theoretical reasoning regarding the causal direction between PE and PEOU, as will be explored in detail in the next subsection.

To address the limitation of the covariance-based statistical method, we refer to alternative statistical methods. Researchers have proposed several alternative methods to determine causal direction, among which two basic algorithms are useful. The first approach uses *longitudinal data* in which one observes variables X_1 and X_2 twice at time 1 (t) and time 2 (t') and constitutes the following models:

$$\left\{ \begin{array}{l} X_1(t') = b_{11}X_1(t) + b_{12}X_2(t) + e_1 \\ X_2(t') = b_{21}X_1(t) + b_{22}X_2(t) + e_2 \end{array} \right.$$

Then statistical significance concerning the parameters b_{11} , b_{12} , b_{21} and b_{22} will provide important information about the causal direction.

This longitudinal method, however, is not applicable to the current research because, as mentioned earlier, we cannot decide which one of PE and PEOU takes temporal precedence, given that they are conceptually closely related and appear almost simultaneously. In addition, the temporal precedence, as one of the three elements (the other two are contiguity in time and space and constant conjunction) in the cause-effect relation proposed by Hume and his followers (Hume, 1977), has been subjected to much criticism (Lee et al., 1997; Sobel, 1995). Opponents of the Humean school of thought, such as “realists” or “natural necessity theorists,” argued that the focus on temporal precedence does not recognize the possibility of contemporaneous causation and events that may take place between the occurrences of a cause and its effect (Lee et al., 1997; Simon, 1953).

Therefore, we turn to the other strategy, which underlies Cohen's path analysis method that will be introduced and applied later. This strategy proposes to situate the two factors of causal direction of interest into a nomological net with other factors of well-defined causal relationships. Then statistical tools are applied to compare the competing models with different causal directions.

Competing Research Models and Hypotheses

Figure 1 depicts two competing models including each causal direction between PE and PEOU. These models include two other major factors in user technology acceptance, perceived usefulness (PU) and behavioral intention (BI), to form a nomological net of causal relationships. These two factors are studied extensively in both TAM and motivational models. As a result, these two models, as we can see in Figure 1, are extensions of the TAM and Motivation Model, respectively.

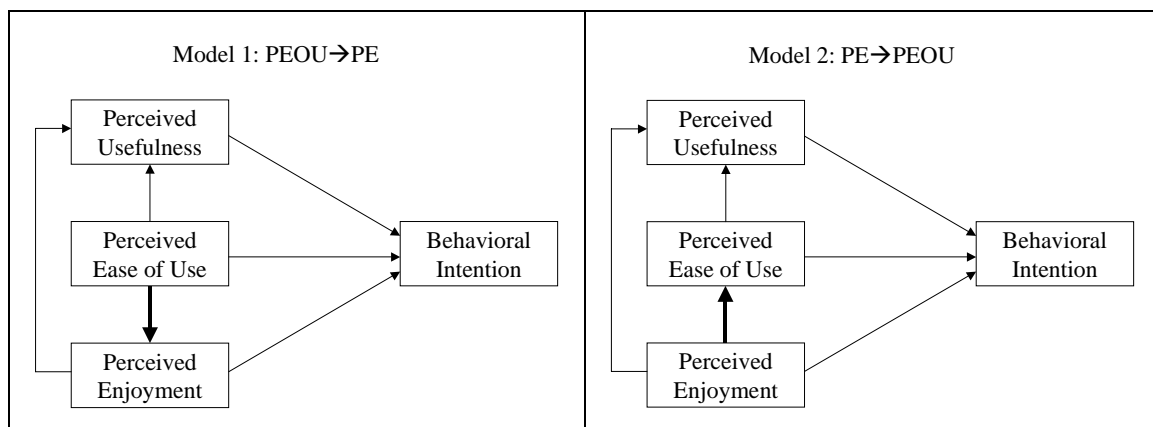


Figure 1. The Competing Models of the Relationship between PE and PEOU

The only difference between Models 1 and 2 is the causal direction between PE and PEOU. We first look for more theoretical reasoning about this difference. Then we will discuss other relationships in the model briefly because these relationships have been well-studied and are not the focus of this paper.

To enrich our understanding of causal relationships between PE and PEOU, we followed the stimulus-organism-response (S-O-R) model for describing causal relationships, as advocated by opponents of the Humean School (Bagazzi, 1980). This model was

considered to be richer than the Humean School's models using a S-R model. In short, we focus on not only "what" (i.e., $PE \rightarrow PEOU$ or $PEOU \rightarrow PE$), but also "why" (i.e., the mechanisms through which the $PE \rightarrow PEOU$ direction dominates) and "when" (i.e., the conditions under which the $PE \rightarrow PEOU$ direction dominates) particular causal relationships exist.

First, we should be aware that bi-directional relationships are possible and actually widely exist. More importantly, one direction dominates the other one in certain conditions, and when conditions change, the other direction dominates. Modern theories of behavioral development have suggested that there is a ubiquity of bi-directional relationships in user behavior (Flay, 2002). Bi-directional relationships have also been observed in other IS constructs (Sun and Zhang, 2006a). Therefore, the basic assumption of a bi-directional relationship between PE and PEOU is valid.

Second, acknowledging that both $PE \rightarrow PEOU$ and $PEOU \rightarrow PE$ could be true in some circumstances, we argue that the $PE \rightarrow PEOU$ direction is dominant in a utilitarian systems environment. The differences between PEOU and PE should be noted at this point. While both can be considered as intrinsic motivation, PE is more likely to be influenced by the hedonic value of systems. If we conceive PE and PU as the two extremes of the intrinsic/extrinsic dimension (Davis et al., 1992), PEOU can be seen as a factor in between and related to both of them. In fact, as an intrinsic motivation, PEOU has been confirmed to be closely related to PU and facilitates people's productive use of systems (Davis et al., 1989; Mathieson, 1991). Users consider a system to be more useful if it is easy to use, therefore, they can finish more tasks within the same period of time. On the other hand, PEOU is also closely related to PE as shown above (Table 1). PEOU has been viewed as a critical system development variable in both utilitarian and hedonic systems (Van der Heijden, 2004).

Users pay attention to different design factors according to the nature of the system (Atkinson and Kydd, 1997; Van der Heijden, 2004), and it is the nature of the system that determines "which belief takes precedence" (Van der Heijden, 2004). Therefore, in utilitarian system environments, information gathered will be more likely to be guided by an expectation of potential impacts of this task on job performance (usefulness) and the facilitators of such impacts (PEOU) (Atkinson and Kydd, 1997). Hence, PEOU is more likely to be changed and accounts for changes in PU and BI rather than PE, in light of the fact that users are more likely to be driven by outcomes, i.e., the external locus of causality. In other words, PEOU is more "closely" related to BI and PU than PE. PE functions as a facilitator of PEOU and hence a $PE \rightarrow PEOU$ direction makes more sense. The rationale of this direction is that enjoyment makes individuals "underestimate" the difficulty associated with using the technologies since they simply enjoy the process itself and do not perceive it to be arduous (Venkatesh, 2000). In other words, enjoyment creates a lower cognitive burden because the individual is experiencing pleasure from the activity and is willing to expend more effort on it (Agarwal and Karahanna, 2000; Deci, 1975). Empirical evidence also suggests that information systems that are visually attractive, and therefore are more likely to be perceived as enjoyable, are also considered easy to use (Tractinsky et al., 2000).

A simple meta-analysis of existing empirical findings in Table 1 also supports the dominance of $PE \rightarrow PEOU$ direction for utilitarian systems. Prior research indicates that when a $PE \rightarrow PEOU$ direction is assumed, PEOU usually mediates PE's impacts on BI completely. Venkatesh and his colleagues argued that PE had no direct effect on

behavioral intention over and above PEOU and PU (Venkatesh et al., 2002). Similarly, in studying students' usage of Blackboard, a course managing system, Yi and Hwang (2003) also found a significant indirect impact of PE on behavioral intention to use via PU and PEOU. Moreover, by manipulating the level of PE (Venkatesh, 2000), found that not only was the level of PEOU enhanced, but the salience of PEOU as a determinant of behavioral intention also increased, suggesting that PEOU can be influenced by PE.

When the PEOU→PE direction is proposed, however, PE does not completely mediate the PEOU's effects on users' behavioral intentions or actual usage. When studying employees' computer usage, Igbaria et al. (1995) failed to confirm a significant relationship between PE and computer usage. Instead, PEOU had a significant direct and indirect impact on computer usage over PE. In studying Internet usage, Teo et al. (1999), also found similar results. While PEOU→PE was assumed, PE did not completely mediate PEOU's impact on Internet usage as hypothesized. Instead, a strong direct effect of PEOU on Internet usage was present, which was even greater than PE's direct impact on Internet usage. The total impact (including direct and indirect impacts) of PEOU was also larger than that of PE. Igbaria and his colleagues also found that PEOU (measured as perceived complexity) had a significant direct impact on employees' microcomputer usage over PU and PE, and the total impact of PEOU was larger than that of PE (Igbaria et al., 1996).

In brief, while PEOU→PE is often assumed, PEOU usually has significant direct impacts on behavioral intention or actual usage over PE. The magnitude of PE's impact on BI or actual usage is small or even non-significant (e.g., Davis et al., 1992). Therefore, given the bi-directional relationship between PE and PEOU, we argue that the PE→PEOU direction outweighs the PEOU→PE direction for utilitarian systems. So we hypothesize that:

H1: The PE→PEOU causal direction is more appropriate than the PEOU→PE causal direction for utilitarian systems.

We now turn to other relationships in the research models in Figure 1. Rooted in the traditional stream of research on the technology acceptance model (TAM), relationships among behavioral intention, perceived usefulness, and perceived ease of use have been studied extensively (see Sun and Zhang, 2006b for a review). First, defined as "the degree to which a person believes that using a particular technology will enhance his performance" (Davis, 1989 p.320), PU has been confirmed in numerous previous empirical studies to be a robust determinant of BI. Several similar counterpart constructs in other models, such as outcome expectation in the computer self-efficacy model (Compeau and Higgins, 1995a; Compeau and Higgins, 1995b) and performance expectancy in the UTAUT model (Venkatesh et al., 2003), have also been studied.

It is not surprising that people tend to have higher intention to use a system if it is perceived to be useful. Similarly, perceived ease of use has also been confirmed to be an important antecedent of behavioral intention. The rationale is that when a system is perceived to be easy to use, users are more likely to have higher intention to accept it. The importance of perceived ease of use and similar concepts (e.g., effort expectancy) in influencing users' decisions on technology acceptance has garnered a vast body of theoretical and empirical support (Agarwal and Karahanna, 2000; Davis et al., 1989; Gefen and Straub, 2000; Van der Heijden, 2003; Van der Heijden, 2004; Venkatesh and Davis, 1996; Venkatesh et al., 2003). Moreover, PEOU also has indirect impact on BI via

PU (Davis, 1989; Davis et al., 1989; Mathieson, 1991; Szajna, 1996; Taylor and Todd, 1995a; Taylor and Todd, 1995b; Venkatesh, 2000). When a system is perceived to be easy to use, users can finish more work in the same amount of time and therefore perceive it to be useful. Combining these, we hypothesize that:

H2: *Perceived usefulness has a significant impact on behavioral intention.*

H3: *Perceived ease of use has a significant impact on behavioral intention.*

H4: *Perceived ease of use has a significant impact on perceived usefulness.*

The relationship between PE and BI has received theoretical and empirical support. The rationale is that individuals who experience pleasure or enjoyment from using an information system are more likely to form intentions to use it than others (e.g. Davis et al., 1992). The significance of this relationship has received empirical support (Agarwal and Karahanna, 2000; Igbaria et al., 1995; Igbaria et al., 1996; Teo et al., 1999; Van der Heijden, 2004).

The relationship between PE and another important construct, PU, is relatively understudied (Yi and Hwang, 2003). An intrinsic motivation variable such as PE is argued to increase the deliberation and thoroughness of cognitive processing and lead to enhanced perceptions of an extrinsic motivation variable such as PU (Bagozzi et al., 1999; Batra and Ray, 1986; Venkatesh et al., 2002). In the literature, however, little research has studied this relationship. Davis et al. (1992) examined the relationships between PE and BI and between PU and BI, respectively, but they did not examine the direct impacts of PE on PU. Venkatesh and his colleagues empirically confirmed such a link between PE and PU (Venkatesh et al., 2002). Similarly, Yi and Hwang (2003), while acknowledging that “the effect of enjoyment on perceived usefulness is relatively unknown” (p. 435), proposed and empirically confirmed this relationship. Li et al. (2005) also empirically confirmed the significant impact of PE on PU. In the study on cognitive absorption, Agarwal and Karahanna confirmed that cognitive absorption, described as “a state of deep involvement with IT,” has significant impacts on PU, whereas perceived enjoyment is one of the components of cognitive absorption (Agarwal and Karahanna, 2000). Therefore, it is reasonable to expect a significant effect of PE on PU after other components of CA (i.e., curiosity, control, temporal dissociation, and focused immersion) are controlled.

Combined, we hypothesize that:

H5: *For utilitarian systems, perceived enjoyment has a significant impact on behavioral intention.*

H6: *For utilitarian systems, perceived enjoyment has a significant impact on perceived usefulness.*

Methodology

We conducted two empirical studies using different types of subjects and different information technologies. The use of subject types in our studies is congruent with contemporary studies on technology acceptance (Lee et al., 2003; Legris et al., 2003). The importance of specifying subject samples lies in the significant influence of

environments. Students are different from employees in terms of their perceptions and behaviors because students “function in a simpler environment” (Legris et al., 2003 p.202). Prior research has demonstrated that research findings grounded in student samples are different from those grounded in non-student samples. In this research, we use both students and employees to control for possible influences of user types and to enhance the generalizability of the findings in light of the fact that employees and students represent different user groups.

Study 1: Employees’ Acceptance of Internet-based Search Engines

Study 1 was an online survey of employees’ acceptance of Internet-based search engines. A total of 750 recruitment emails were sent out via an online survey project. Subjects were asked to use Internet-based search engines to complete two simple tasks and then fill out the questionnaires. Among the 240 returns, 169 had complete responses for all measures and were used for data analysis. Among the respondents, 43% were male. Ages ranged from 19-24 (15.6%), 25-34 (42.5%), 35-44 (20%), to older than 45 (21.9%). Sixty-eight percent of respondents had more than five years’ experience with search engines. Eighty-three percent of subjects chose Google even though they were allowed to use whichever search engines they preferred.

To ensure the tasks were utilitarian, we asked the users to finish two simple tasks (“find the historical events” and “find solutions to a problem you have in work”) and report the results. These tasks were designed purposely to force the locus of causality to be external and to make sure users focused on the outcomes instead of the process.

Study 2: Students’ Acceptance of University Website

Study 2 was a field experiment using college students. Participants were 194 undergraduate and graduate students in a northeastern U.S. university, who were asked via a questionnaire use a Web browser available in class to visit the university’s website and explore it to see whether this site could be *useful* for his or her university life. The questionnaire continued with measures of related constructs, and all questionnaires were collected during the class session. Among the subjects, 62% were male. Average age was 21 with a standard deviation of 4.5.

As in Study 1, the second environment was utilitarian. We designed the tasks so the users paid attention to some “external” purposes instead of their interaction with the technology itself.

It is noteworthy that using searching engines and university websites includes both physical and conceptual tasks. While the physical tasks are simple, the conceptual tasks are extensive and “deep.” For example, a user of search engines may be able to input the keywords (physical task) very quickly, but it may take quite some time to go through the results (conceptual task) and adjust the keywords. During this process, users may have various experiences. This aspect should also be considered as part of interacting with the technology. One similar example is hedonic websites that have been used as the target technology (e.g., Van der Heijden, 2004). For instance, Van der Heijden(2004) used entertainment websites in his research on hedonic systems. Use of these websites requires simple physical tasks, such as browsing, and extensive conceptual tasks, such as comparing and selecting results, to name a few.

Operationalization of Constructs

We measured constructs by validated scales: four items were used to measure PU (Davis, 1989, Davis et al., 1992), three items were used to measure PE (Davis et al., 1992, Venkatesh, 2000), four items were used to measure PEOU (Davis et al., 1989), and two items were used to measure behavioral intention (Venkatesh, 2000). Appendix II lists all measures.

Analytic Method

To assess the psychometric properties and evaluate the structural models, we used Partial Least Squares (version PLS-graph 03.00), a component-based structural equation modeling technique. Given the nature of this research, we chose PLS over LISREL because it supports exploratory research, whereas LISREL requires a sound theory base (Barclay et al., 1995).

We evaluated the measurement model using item loadings and reliability coefficients (composite reliability), as well as convergent and discriminant validities. Item loadings greater than 0.70 are considered adequate (Fornell and Larcker, 1981), and a composite reliability of .70 or greater is considered acceptable (Fornell and Larcker, 1981). Average variance extracted (AVE) measures greater than .50 are considered acceptable (Barclay et al., 1995). For discriminant validity, items should load more on their own construct than on other constructs in the model, and the average variance shared between each construct and its measures should be greater than the variance shared between the construct and other constructs (Compeau et al., 1999). Path coefficients and explained variance were used to assess the structural models.

In addition to the regular analysis of psychometric properties and structural models, we introduce and highlight Cohen's path analysis. Cohen's path analysis is ideal for this research because of its sensitivity to causal direction. Cohen's path analysis method is rooted in the well-known Wright's "method of path coefficients" (Wright, 1921) but extends it by "taking into account the way an arrowhead enters a node" (Sanguesa and Cortes, 1997, p. 43) and identifying explicitly the evaluative criteria of different causal models (Cohen and Bacdayan, 1994; Cohen et al., 1993). The usefulness of Cohen's method is also acknowledged by several experiments and simulations (e.g., Anderson et al., 1995, Cohen et al., 1993). Sanguesa and Cortes (1997) argued that "(other than Cohen's algorithm), no other algorithm has been created for recovering path models" (p. 57).

The underlying rationale of Cohen's path analysis is that estimated correlations based on path analysis should be as close as possible to the actual correlation. The "paths" including both connectedness and direction are therefore critical for calculating the estimated correlations. That is to say, changes in causal direction cause changes in estimated correlations and subsequently influence the errors between actual and estimated correlations, which are measured specifically by Total Squared Error (TSE). TSE can be used to indicate which of several alternative theoretical models with different causal directions holds in the data.

Cohen's path analysis follows a series of steps. First, it requires a prediction model and a corresponding path diagram. The prediction model can be described as

$\bar{Y} = \rho_{YX_1}X_1 + \rho_{YX_2}X_2 + \rho_{YX_3}X_3$ (a hypothetical model with three independent variables). The path coefficients are denoted by ρ . The second step is to tag each arc as a correlation or a beta coefficient (ρ). In a multi-variable situation (X_1, X_2, X_3 as independent variables pointing to Y as the dependent variable), the rule is: (1) if X_1, X_2, X_3 are independent causes of \bar{Y} , then the path coefficients ($\rho_{YX_1}, \rho_{YX_2}, \rho_{YX_3}$) are the correlation coefficient; (2) if X_1, X_2, X_3 are not independent causes of \bar{Y} (i.e., there exist causal relationships among them), then the path coefficients are standardized partial regression coefficients. Then, we can estimate the correlations between X_1, X_2, X_3 and \bar{Y} . This step involves finding the paths, direct or indirect, from each X variable to Y , and summing the weights of the paths. To find the legal paths, Cohen et al. provide some rules: (1) a path cannot go through a node twice; (2) there must be a path from every variable to the dependent variable; and (3) once a node has been entered by an arrowhead, no node can be left by an arrowhead.

It should be noted that Wright's path analysis (Wright, 1921) also underlies the development of several other contemporary statistical methods such as hierarchical multiple regression (e.g., ordinary least squares). However, initially for automatic discovery of theory-based causal relationships, Cohen's method lays out the process and evaluative criteria explicitly and is easy to compute. Therefore, Cohen's method is an ideal exploratory tool to investigate an unclear causal relationship by comparing competing models, in this case, the causal direction between PE and PEOU.

Results

We assessed the psychometric properties of the scales in terms of item loadings, discriminant validity, and internal consistency. As we can see from Tables 3 through 5, the psychometric properties of the scales are satisfied in both studies. Specifically, item

Table 4. Cross - Loadings in Study 1 and 2

	Study 1				Study 2			
	PE	PEOU	PU	BI	PE	PEOU	PU	BI
PE1	0.97	0.67	0.57	0.43	0.87	0.30	0.35	0.13
PE2	0.97	0.71	0.56	0.39	0.88	0.31	0.33	0.11
PE3	0.96	0.63	0.59	0.43	0.82	0.34	0.38	0.18
PEOU1	0.58	0.92	0.53	0.52	0.30	0.81	0.42	0.28
PEOU2	0.68	0.92	0.48	0.47	0.25	0.84	0.28	0.25
PEOU3	0.64	0.92	0.53	0.48	0.36	0.88	0.45	0.28
PEOU4	0.67	0.94	0.54	0.53	0.34	0.91	0.43	0.25
PU1	0.55	0.52	0.95	0.54	0.37	0.44	0.90	0.42
PU2	0.56	0.54	0.90	0.55	0.36	0.40	0.89	0.41
PU3	0.56	0.54	0.93	0.63	0.34	0.46	0.84	0.58
PU4	0.53	0.51	0.94	0.58	0.36	0.29	0.78	0.40
BI1	0.42	0.47	0.66	0.94	0.13	0.29	0.53	0.95
BI2	0.37	0.55	0.48	0.92	0.17	0.31	0.52	0.96

Table 5. Reliability, Convergent and Discriminant Validity Coefficients (Study 1)

	CR	AVE	1	2	3	4
1. PE	0.977	0.935	0.967			
2. PEOU	0.959	0.853	0.694	0.924		
3. PU	0.962	0.864	0.594	0.565	0.930	
4. BI	0.929	0.867	0.427	0.542	0.619	0.931

CR: Composite Reliability; AVE: Average Variance Extracted.

Diagonal Elements are the square root of the variance shared between the constructs and their measurement (AVE). Off diagonal elements are the correlations among constructs. Diagonal elements should be larger than off-diagonal elements in order to exhibit discriminant validity.

Table 6. Reliability, Convergent and Discriminant Validity Coefficients (Study 2)

	CR	AVE	1	2	3	4
1. PE	0.893	0.737	0.858			
2. PEOU	0.920	0.743	0.367	0.861		
3. PU	0.916	0.731	0.414	0.471	0.855	
4. BI	0.965	0.902	0.167	0.309	0.538	0.950

loadings are larger than the suggested 0.7 criterion (Fornell and Larcker, 1981) and composite reliabilities in Study 1 and Study 2 are larger than the suggested 0.70 criteria. AVEs are all well above the suggested 0.50 criterion (Barclay et al., 1995). As for discriminant validities, the loading of each measurement item on its assigned latent variables is larger than its loadings on any other constructs (Chin, 1998, Straub et al., 2004). Moreover, the square roots of AVEs are larger than corresponding correlations, indicating satisfactory discriminant validities in both Study 1 and 2 (Table 5 and 6).

Structural Models

The structural models in Figure 2 present empirical support for Hypotheses 2, 4, and 6. PU has significant effects on BI in both studies. PEOU has significant impacts on PU. PE has significant effects on PU. However, Hypothesis 3 is partially supported. PEOU has significant effects on BI in Study 1 (employees' use of search engines) but not in Study 2 (students' use of University website). Hypothesis 5 is not supported. PE has no significant impacts on BI in either study.

Causal Directions

Following the methods proposed by Cohen et al. (1993), we conducted path analysis on the two competing models, respectively. Regression coefficients obtained from a standard SEM analysis (Figure 2) were used as the path coefficients because PU, PEOU and PE also influence each other (i.e., they are not independent causes of BI). Following Cohen's rule, we calculated the estimated correlations by identifying all legal paths, and also calculated the actual correlations. Then we compared the estimated and actual correlations. The processes and results are summarized in Table 7.

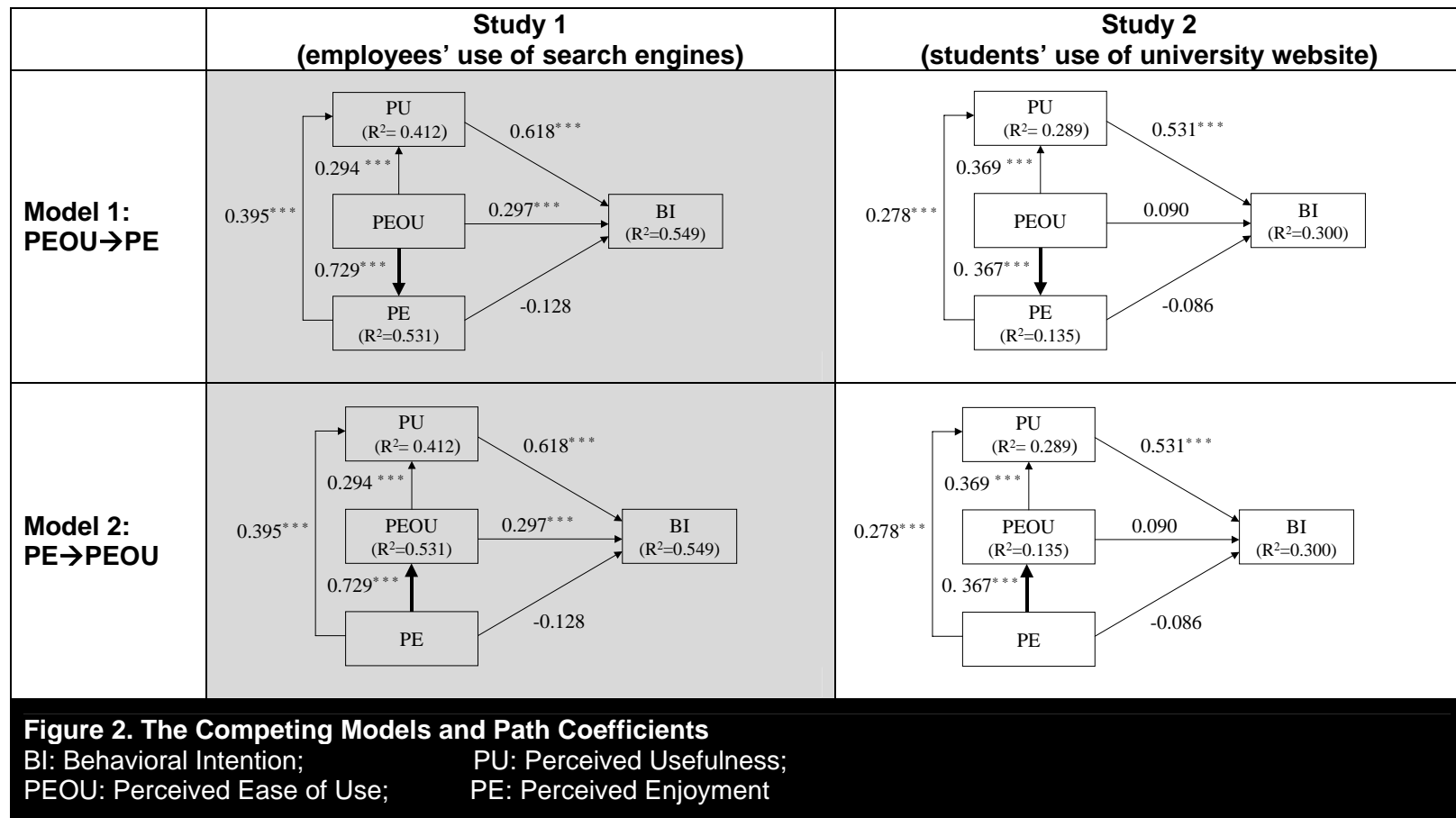


Table 7. The Results of Path Analysis

	Direct Paths	Indirect Paths	Study 1			Study 2		
			Estimated Correlation	Actual Correlation	Squared Error	Estimated Correlation	Actual Correlation	Squared Error
Model 1: PEOU→PE			Total Squared Error: 0.2201			Total Squared Error: 0.0609		
BI: PU	PU→BI	N/A	0.6182	0.7554	0.0188	0.5298	0.5661	0.0013
BI: PEOU	PEOU→BI	PEOU→PU→BI; PEOU→PE→BI; PEOU→PE→PU→BI;	0.5642	0.6007	0.0013	0.3234	0.3464	0.0005
BI: PE	PE→BI	PE→PU→BI	0.1165	0.4938	0.1424	0.0231	0.1590	0.0185
PU: PEOU	PEOU→PU	PEOU→PE→BI	0.5823	0.6101	0.0008	0.4963	0.5361	0.0016
PU: PE	PE→PU	N/A	0.3951	0.6318	0.0560	0.2748	0.4679	0.0373
PEOU: PE	PEOU→PE	N/A	0.7288	0.7570	0.0008	0.3818	0.4227	0.0017
Model 2: PE→PEOU			Total Squared Error: 0.1353			Total Squared Error: 0.0271		
BI: PU	PU→BI	N/A	0.6182	0.7554	0.0188	0.5298	0.5661	0.0013
BI: PEOU	PEOU→BI	PEOU→PU→BI;	0.4793	0.6007	0.0147	0.3146	0.3464	0.0010
BI: PE	PE→BI	PE→PEOU→BI; PE→PU→BI; PE→PEOU→PU→BI;	0.4658	0.4938	0.0008	0.1432	0.1590	0.0002
PU: PEOU	PEOU→PU	N/A	0.2944	0.6101	0.0997	0.3914	0.5361	0.0209
PU: PE	PE→PU	PE→PEOU→PU	0.6097	0.6318	0.0005	0.4242	0.4679	0.0019
PEOU: PE	PE→PEOU	N/A	0.7288	0.7570	0.0008	0.3818	0.4227	0.0017
BI: Behavioral Intention; PU: Perceived Usefulness; PEOU: Perceived Ease of Use; PE: Perceived Enjoyment								

Study 1

We first checked error changes from Model 1 to Model 2. The total squared error (TSE) is changed by -38.53% (= (0.1353-0.2201)/0.2201). The effect size is -0.76. The effect size is medium according to Cohen's criteria (Cohen, 1988).² The negative sign means that when we change the causal direction from Model 1 to Model 2, the TSE is actually reduced (or deteriorated in Cohen's terminology). Moreover, the large error terms associated with PE in Model 1 are much improved in Model 2. Then, we checked error changes in reverse order: from Model 2 to Model 1. The TSE is changed by 62.69% (= (0.2201-0.1353)/0.1353). The effect size is 0.76. The positive sign means the TSE is actually increased (or improved in Cohen's terminology) from Model 2 to Model 1.

Study 2

Following the same procedure for Study 1, we first checked error changes from Model 1 to Model 2. The total squared error (TSE) is changed by -55.47% (= (0.0271-0.0609)/0.0609). The effect size is -0.90 (large according to Cohen's criteria). The negative sign means that when we change the causal direction from Model 1 to Model 2, the TSE is actually reduced.

Then, we checked error changes in the reverse order: from Model 2 to Model 1. The TSE is changed by 124.58% (= (0.0609-0.0271)/0.0271). The effect size is 0.90. The positive sign means the TSE is actually increased from Model 2 to Model 1.

In summary, we can see that both studies have consistent findings regarding the causal direction between PE and PEOU. The effect sizes for Study 1 and Study 2 are satisfactory (0.76 (medium) and 0.90 (large), respectively). We thus conclude that the PE→PEOU causal direction holds better in the data than the reverse direction. Hypothesis 1 is supported.

Discussion

In this section, we discuss the approach we used to investigate the causal direction between PE and PEOU, as illustrated above. A prior methodological study (Lee et al., 1997) merits mention at this point. Based on a review of existing MIS research, Lee et al.'s research (1997) calls strongly for the *theory-based discovery of causal relationships*. They argued that, because of the "lack of theories and methodological weakness" (p.109), we need the "systematic discovery of causal relationships based on theory development, improved model representation and analysis techniques" (p.111). To build a "richer model," they suggest we should use more flexible tools and techniques in light of the fact that "weak exploratory phase tools and approaches may allow violations of causal assumptions to pass undetected to the confirmatory phase" (p.109). Based on the belief that exploratory research is "at least equally important in MIS" as

² Here we use Cohen's d to calculate the effect size, which defines the effect size as

$$f^2 = \frac{M_2 - M_1}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}}. \text{ According to Cohen (1988), effect size of 0.2 is defined as small, 0.5 as}$$

medium, and 0.8 and above as large.

confirmatory research, Lee et al. identified the shortcomings and statistical pitfalls of confirmatory statistic tools and accordingly recommended TETRAD (Glymour et al., 1987), a non-parametric modeling tool.

From this methodological perspective, the current study concurs with Lee et al.'s arguments in spirit. First, we built richer models by allowing the coexistence of conflicting causal directions based on theoretical reasoning. Competing models were developed and compared theoretically. We also further proposed the concept of "conditional dominance." We specified the mechanism and conditions for the causal direction between PE and PEOU. Second, this research applies Cohen's path analysis method to echo Lee et al.'s call for alternative flexible statistical methods in the exploratory stage.³ This strategy also echoes Robey and Boudreau's recommendation that we should consider 'logic of opposition' and recognize implicit contradictions and opportunities by focusing on theories that promote and oppose social change and explain a wider range of outcomes (Robey and Boudreau, 1999). They further proposed that researchers should identify opposing forces, incorporate opposing hypotheses in research design, and pay attention to multiple interpretations. In our research, we identify the inconsistent findings regarding the causal direction between PE and PEOU and attribute this inconsistency to the technological differences (utilitarian and hedonic) as "opposing forces." Further, we consider the possibilities of both causal directions and incorporate them in competing models. We refer to the differences between utilitarian and hedonic and individual's psychological reactions to them, respectively, for multiple interpretations. In this way, we overcome one-sided interpretations. It is noteworthy that, as pointed out by Robey and Boudreau, overcoming one-sided interpretations is "more fundamentally related to an open-minded approach to inquiry" (Robey and Boudreau, 1999 p.181), and the essential implication of multiple interpretation is to be open to new interpretations by freeing oneself from any single perspective. We thus use Cohen's path analysis method as a supplementary tool to empirically examine the competing models and draw conclusions about the relative significance of multiple interpretations.

In summary, this research confirms the usefulness of combining richer models and more flexible tools in the exploratory stage, as advocated by Lee et al. Cohen's path analysis method can give us more insight into the causal direction, which could be otherwise ignored by confirmatory tools such as SEM. Table 8 summarizes the differences between SEM and Cohen's method.

While we have discussed the strengths of the method, especially its sensitivity to causal direction and its ease of use, Cohen's path analysis also has weaknesses. For instance, since we refer to the error terms (TSE) as the indicator of model fitness, we should be

³ In fact, TETRAD, proposed by Lee et al. (1997), and the Cohen's method used in this research share the same rationale. That is, the estimated correlation statistics should represent the actual correlations. As we said earlier, Cohen's method uses the total squared error (TSE) between estimated and actual correlation data to evaluate the proposed causal models. TETRAD, on the other hand, applies analysis of vanishing partial correlation (VPC) as the primary evaluative method, which refers to the vanishing correlation between undirected variables (i.e., correlation without causality) with respect to variables mediating (or connecting) them. VPCs calculated based on a causal model are then compared with the sample correlation matrix (actual correlations) to determine if the VPCs indeed hold in the data. If they do not, the hypothesized causal relationship is falsified (Lee et al., 1997). Then, a new causal model based on theoretical reasoning should be proposed and retested following the same procedure.

careful about the disturbance of error from other sources. Although differentiating the error terms associated with changing causal direction and those from other sources is beyond the scope of this research, we at least should be open-minded to the possibility of drawing incorrect conclusions. A possible solution is to use multiple datasets, as we did in this research, although this brings complexity to research design.

Table 8: A Comparison between SEM and Cohen's Method		
	Covariance-based SEM	Cohen's method
Nature of the method	Confirmative	Exploratory
Allows opposing hypotheses?	No	Yes
Sensitive to Causal direction?	No	Yes
Application context	Appropriate for factors that have clear causal directions, e.g., factors belonging to different categories in the reference theory that proposes clear inference about causal directions.	Ideal for factors that are: (1) conceptually coupled, e.g., factors belonging to the same categories in the reference theory; (2) hard to examine the temporal precedence in nature; and (3) conceptualized in previous literature to have contradictory causal directions.

Conclusion

Both causal directions between PE and PEOU, $PE \rightarrow PEOU$ and $PEOU \rightarrow PE$, have been proposed and confirmed in prior literature on user technology acceptance. The conceptual closeness between PE and PEOU and the limitations of confirmatory covariance-based statistical methods in detecting causal direction are believed to account for this inconsistency. As a result, researchers have selected one direction without considering an alternative direction. In the present study, we refer to more theoretical reasoning and an alternative method, Cohen's path analysis, to investigate the causal direction between PE and PEOU. We propose the conditional dominance of causal direction to study this causal relationship. Using data from two empirical studies involving different samples and technologies, this research argues that the $PE \rightarrow PEOU$ direction has an overall dominance over the $PEOU \rightarrow PE$ direction in utilitarian system environments.

The primary contributions of this research are two-fold: (1) exploring the conditional dominance of the causal direction between PE and PEOU, and (2) demonstrating a methodologically innovative approach to exploring causal directions. For the former contribution, two empirical studies work in favor of a $PE \rightarrow PEOU$ direction for utilitarian

systems. This direction is significantly better than the reverse direction from PEOU to PE. PE does not have a direct impact on BI; instead, PU and PEOU fully mediate its impacts.

The second, but not less important, contribution of this research is the demonstration of the usefulness of Cohen's path analysis, which is applicable to many other research contexts beyond the specific example of PE and PEOU. To our best knowledge, this method has rarely been used in contemporary IS research. Our results demonstrate the usefulness of Lee et al.'s approach (Lee et al., 1997) (see the Discussion section) in studies where conceptually highly coupled factors are theorized reciprocally, and their mutual impacts could be overlooked based merely on confirmatory methods. Richer models and flexible statistical tools, advocated by Lee et al., are valuable for these types of studies. To make results more convincing and accurate, we encourage researchers to address causal directionality between two conceptually-coupled concepts in a paper's theoretical development section by exploring alternative causal directionality and finding stronger theoretical reasoning, and in an analysis section by using flexible statistical tools, such as Cohen's path analysis, that are sensitive to causal directions.

The importance of the current study lies in the importance of causal relationships in general. Causal relationships are without a doubt important and ubiquitous in explaining human behaviors including acceptance of technology. Specifically, established causal relationships help us in predicting (foreseeing what will happen), planning (specifying an action to achieve the goal), and inference (inferring what (unobserved) actions may have occurred to account for what happened) (Pazzani, 1991).

The limitations of this study should be noted. The first limitation relates to external validity. We have two datasets representing different samples and technologies. While we believe this research design is helpful in enhancing generalizability, more empirical studies are needed. Second, the current study does not use longitudinal data. While our approach avoids methodological problems associated with the multiple administration of the same instrument (Cook and Campbell, 1979; Yi and Hwang, 2003), this research does not capture the changes that might result from continued use. The impact of continued use has been demonstrated in prior research. Whether direct experience affects the PE \rightarrow PEOU direction is an interesting topic in itself. Third, as our first attempt, we focus our attention on utilitarian systems because most of the prior research focused on the utilitarian aspect of information systems (see Legris et al., 2003, for a review), and, therefore, our findings can be more comparable. By doing so, we avoid being overly complex and are able to focus on the analytic approach. But obviously, the causal direction between PE and PEOU in hedonic systems environments is an interesting topic for future research.

It should be noted that by no means do we imply that we have solved the problem associated with causal directionality. After all, causal relationships are extremely complex and there does not exist a final answer about them, even in mathematics and statistics (DeLong and Summers, 1994). The complexity of causal direction is ubiquitous for human perceptions. With no intention to step into the debate of verisimilitude (closeness to the truth or likeliness of truth) and in light of the fact that all psychological theories are incomplete and almost all of them contain postulates that are literally false (Meehl and Waller, 2002), what we have done is to raise a problem associated with causal directions, point out the importance of them, and provide a possible approach to give us more confidence to believe one direction has an overall conditional dominance in

certain environments. Given the importance of causal relationships mentioned earlier, this attempt is worthy and should attract more attention from contemporary IS researchers.

This research also has practical implications. As we pointed out earlier, understanding causal relationships helps in prediction, planning, and inference. The conditional dominance of the PE→PEOU causal direction in utilitarian systems environments suggests that PE can be used as an enabler of PEOU, considering the significant variance in PEOU explained by PE, especially for employees ($R^2 = 0.531$). This is especially important when PEOU is considered important in determining intention to use. Sun and Zhang identified a list of conditions under which PEOU is important (Sun and Zhang, 2006b). For example, users are more likely to think PEOU is important when the system is complex. PEOU has also been proposed to be important in influencing intention to use for female and older users and users with less experience and intellectual capability (Sun and Zhang, 2006b). Therefore, for complex systems and the user groups mentioned above, we should pay special attention to PE and may use it as the enabler to enhance users' PEOU. To use this enabler, practitioners can design game-based training programs (Venkatesh, 1999), add affective components such as emoticons, or include productive and involving metaphors and useful sound and graphics in interface design (Malone, 1982).

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Appendix I: Goodness-of-fit of Model 1 and Model 2

	Criteria	Study 1		Study 2	
		Model 1 (PEOU→PE)	Model 2 (PE→PEOU)	Model 1 (PEOU→PE)	Model 2 (PE→PEOU)
Regression equations		BI=PU+PEOU+PE PU=PEOU+PE PE=PEOU	BI=PU+PEOU+PE PU=PEOU+PE PEOU=PE	Same as Study 1	Same as Study 1
Chi-Square	Chi-Square/DF	236.0285	236.0285	152.0851	152.0851
Chi-Square DF		59	59	59	59
Pr > Chi-Square	< 2	<.0001	<.0001	<.0001	<.0001
RMSEA Estimate	<0.06	0.1361	0.1361	0.0906	0.0906
Bentler's Comparative Fit Index	>0.9	0.9276	0.9276	0.9432	0.9432
Bentler & Bonett's (1980) Non-normed Index	>0.9	0.9042	0.9042	0.9249	0.9249
Bentler & Bonett's (1980) NFI	>0.9	0.9064	0.9064	0.9114	0.9114

Appendix II: Instruments

Seven-point Likert Scale was used for all items.

Perceived Enjoyment:

PE1: I find using (the system's name) to be enjoyable

PE2: The actual process of using (the system's name) is pleasant

PE3: I have fun using (the system's name)

Perceived Ease of Use:

PEOU1: Learning to operate (the system's name) is easy for me

PEOU2: I find it easy to get (the system's name) to do what I want it to do

PEOU3: It is easy for me to become skillful at using (the system's name)

PEOU4: I find (the system's name) easy to use

Perceived Usefulness:

PU1: Using (the system's name) enhances my effectiveness in work

PU2: Using (the system's name) enhances my productivity

PU3: I find (the system's name) useful in my work

PU4: Using (the system's name) improves my performance in work

Behavioral Intention:

BI1: I intend to use (the system's name) in the future

BI2: I predict I would use (the system's name) in the in the future

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