Exploring the Interdependence of Codified and Personalized Knowledge Use on Knowledge Management System Success

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ABSTRACT

Knowledge management systems (KMS) provide access to both codified and personalized knowledge so that knowledge workers can perform with higher expertise. Yet the knowledge management literature is not clear on how accessing both kinds of this knowledge influence one another and thus in combination influence KMS success. In this research I utilize a learning-based theory focused on the development of expertise to investigate outcomes from the temporal use of codification-based KMS and personalization-based KMS in the domain of technical problem-solving support, using Hierarchical Linear Modeling (HLM) as my method of analysis. Contributions to knowledge from this research include: (1) investigating how the use over time of both codified and personalized knowledge from KMS complement one another and influence KMS success; (2) clarifying the conceptual structure underlying the use of KMS in problem-solving knowledge work to better-include the human element in the immediate nomological net of the IT artifact, while at the same time suggesting that IT artifacts – such as personalized and codified knowledge contained within KMS – can have a significant impact on human performance; (3) explaining one approach – HLM – to the analysis of KMS use over time data in a unique setting; and (4) providing insights on how knowledge worker experience may be conceptualized in regards to knowledge worker use of information technologies.

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CHAPTER 1. INTRODUCTION

In this time of increased expectations for increasingly improving results from organizational knowledge-based work, it is important for knowledge workers to have highly effective knowledge management tools. Some scholars have situated the problem of ever-more-demanding expectations for knowledge-based work in terms of effectively developing intellectual capital (developing minds). But in this dissertation I situate the problem (of knowledge access for problem solving) within the information processing and information technology (IT) literatures – and therefore in terms of effectively developing knowledge management systems (extending minds) such that higher expertise is possible due to IT.

Thus, while it is commonly appreciated that intellectual capital is a significant determinant of success (and one form of intellectual capital is the capacity for conducting high-utility knowledge-based work, such as access to the collective knowledge of workers in an organization (Grant, 1996a, 1996b; Nahapiet & Ghoshal, 1998; Spender, 1996)); I argue in this dissertation that organizational support for knowledge workers may also productively be framed in terms of the expertise branch of information processing theory (Ericsson, Krampe, & Tesch-Römer, 1993; Lord & Maher, 1990; H. A. Simon & Chase, 1973). Thus, I argue, that supporting knowledge workers by providing high-utility access to the knowledge required to perform their tasks (so that they can perform them with higher expertise) is an important endeavor for organizations seeking to benefit from their workers' collective knowledge. In this dissertation I therefore argue that – by extension though IT – mental capabilities are developed indirectly (in contrast to arguments that – by technical or specialized training – mental capabilities are directly developed).

One way organizations support knowledge workers' expertise is by undertaking knowledge management (KM) initiatives, often utilizing information technologies (ITs) to provide access to explicit knowledge embedded in document-access type systems (termed *codification*) or tacit knowledge contained within individuals who are linked to workers through personal-contact type systems (termed *personalization*) (Hansen, Nohria, & Tierney, 1999). Knowledge management systems (KMS – herein used to denote both singular and plural use of the term) enable knowledge workers to gain access to both types of knowledge and to therefore apply expertise that often would be otherwise unavailable, aiding knowledge workers in their work tasks and enhancing work output (Haas & Hansen, 2007). But more particularly, by utilizing KMS, knowledge workers are also able to better leverage this organizational knowledge, and further develop expertise through learning-by-doing as they use KMS knowledge (Ko & Dennis, 2011). The success of ITs such as KMS is thus also linked to its use (DeLone & McLean, 2003; Haas & Hansen, 2005; Ko & Dennis, 2011; Seddon, 1997).

In studying the KMS use – success link, prior research has mainly explored codification-based KMS use and personalization-based KMS use separately. This work can be classified into two streams: (1) studies that investigate outcomes from using a single type of KMS (i.e., codification-based KMS use) (e.g., Ko & Dennis, 2011); or (2) studies that investigate outcomes from using either type of KMS but that treat KMS use (and thus outcomes from use) separately (e.g., Haas & Hansen, 2007). For example, in investigating the use of a single type of KMS Ko and Dennis (2011) show how knowledge workers that use a codification-based KMS are able to improve work performance over time. And Haas and Hansen (2007), in investigating the use of either type of KMS, demonstrate that codification-based KMS use helps knowledge workers complete tasks more quickly while personalization-based KMS use helps workers to improve the quality of the work output. In this prior research, a clear link has been established between KMS use and outcomes from use. However, much of this research does not explicitly recognize that codified and personalized organizational KM initiatives are often undertaken together, and that as a result knowledge workers have a portfolio of ITs and KMS available to them as they seek knowledge to grow their expertise (Zimmer, Henry, & Butler, 2007). While other research in the KM literature recognizes this blending as an organizational reality (e.g., Gray & Meister, 2004, 2006; Massey & Montoya-Weiss, 2006; Zimmer et al., 2007), the central question for much of this work that recognizes this blending concerns what factors influence knowledge workers to utilize codification-based KMS versus personalization-based KMS (and vice versa) (i.e., the antecedents of KMS use). It does not, however, explain as well what influence KMS use has on outcomes (i.e., the consequences of KMS use). Furthermore, much of this other work still treats types of KMS use as separate phenomena. Therefore, given that knowledge workers not only have a choice of the type of KMS to use (codification-based or personalization-based), but that they often *utilize them together* (both), I suggest that what has previously been viewed to be independent (separate) phenomena – outcomes from using either codification-based KMS or personalization-based KMS – are in reality *inter*dependent phenomena: that outcomes from using one type of KMS are also dependent on using the other type of KMS, and I seek to test this assertion. For the IT managers, for example, who spend vast sums on IT systems, testing this assertion will help them to better understand how to plan their budgets: more machine power, more people power, or both?

KM research is only beginning to address a more-nuanced reality (e.g., Boh, 2008). In addition to KMS use interdependence, recent KM research has also begun to recognize the importance of its temporal nature: that it takes time for knowledge workers to derive benefits from KMS use (Gallivan, Eynon, & Rai, 2003; Ko & Dennis, 2011). This work underscores the importance of the individual learning that occurs over time, as knowledge workers utilize KMS: that it takes time to derive benefits from KMS use, because knowledge workers must internalize the knowledge and learn how to use it (Ko & Dennis, 2011; H. A. Simon, 1991).

Thus, in this research I propose to utilize a learning-based theory focused on the development of expertise (expert information processing theory – EIPT) (Ericsson et al., 1993; Lord & Maher, 1990; H. A. Simon & Chase, 1973) to investigate outcomes from the temporal use of interdependent codification-based KMS and personalization-based KMS. EIPT provides an appropriate theoretical lens because it accounts for the individual internalization of knowledge (and the time it takes to do so) in its theoretical explanation. I therefore explore the following research question: *In using KMS over time, to what extent does utilizing codified knowledge and personalized knowledge from KMS influence KMS success: which I define to be KMS utility as perceived by individuals engaged in support-centered knowledge work?*

I study this question in the technical support environment of a large organization in the industrial environmental heating and cooling industry. In this setting, knowledge workers utilize KMS in their problem solving work. I use data gathered from several sources within the organization: longitudinal KMS perception data, longitudinal KMS use data, and knowledge worker experience data. As these data span multiple levels (i.e., multiple time points within individuals), I analyze these data with Hierarchical Linear Modeling (HLM).

There are several contributions to knowledge which result from this research. First, this research contributes specifically to the KM domain by investigating how the use over time of *both* codified and personalized KMS knowledge complement one another and influence KMS success, thus extending prior work in this domain. Second, this research clarifies the conceptual structure underlying the use of KMS knowledge in problem-solving knowledge work to better-include the human element in the immediate nomological net of the IT artifact. Information Systems research has as a core tenet the investigation the IT artifact and its nomological net, which includes not only the technology but also the *technology-in-use*: the human element that thereby situates both technology ('machine') *and* individual ('mind') in a more comprehensive context (Benbasat & Zmud, 2003). This research thus provides one possible theoretical basis for the 'machine-mind' link in KMS use for problem-solving knowledge work, and suggests that IT artifacts – such as personalized and codified knowledge contained within KMS – can have a significant impact on human performance. Third, this research makes a methodological contribution to knowledge by explaining one possible approach – HLM – to the analysis of KMS use over time data in a unique setting: problem-solving knowledge work. Finally, this research provides insights on how knowledge worker experience may be conceptualized in regards to knowledge worker use of information technologies.

The remainder of this dissertation proceeds as follows. In Chapter 2 I begin by reviewing the IS success literature, of which KMS success is a subset. This literature is relevant to KMS success because it helps to inform this research on the important dependent and independent constructs and their possible associations that need to be considered in research on KMS success. In Chapter 3 I introduce the theoretical lens – Expert Information Processing Theory (EIPT) – and discuss how its theoretical explanation allows for the development of a research model and hypotheses that capture the nuances in KMS use (and subsequent outcomes from use) when both KMS codified and personalized knowledge are used. Chapter 4 sees the explanation of the methodology to be employed in my analysis, which includes a description of the research setting, data gathering methods, measurement approach, and data analysis technique employed. In Chapter 5 I then detail the results of my analysis, including the limitations of this research. I finally conclude in Chapter 6 with a summary of this dissertation research: the research problem and question, the principle findings of this work, and what they suggest in both the context of the KM literature and in the broader context of the IS literature. I include here possible questions for future research.

CHAPTER 2. BACKGROUND

Before building a theoretical model to explore how the use of different types of KMS influence KMS success, in this chapter I first review the prior literature on IS success (KMS being a subset of IS) because this literature can better inform our understanding of KMS success. In doing so I highlight several important concepts that are critical in examining – with an Expert Information Processing Theory (EIPT)-focused lens – the success of KMS used over time.

Information Systems (IS) Success

IS research has a rich history of studying IS success, with multiple research streams addressing the central question of how and why individuals adopt and use IT and what impacts result from doing so (e.g., F. D. Davis, 1989; DeLone & McLean, 1992; Goodhue & Thompson, 1995; Sabherwal, Jeyaraj, & Chowa, 2006; Seddon, 1997; Venkatesh, Morris, G. B. Davis, & F. D. Davis, 2003; Wixom & Todd, 2005). Past research on IS success has focused on various parts of this adoption-use-impact chain in conceptualizing IS success. This work suggests that IS success is a multidimensional construct (DeLone & McLean, 1992, 2003), where factors of success can be conceptualized and measured at various points along the chain (Doll & Torkzadeh, 1998). Table 2.1 contains a selection of relevant key literature on how IS success has been conceptualized.

An important body of work within this literature suggests that individuals' perceptions of IT are fundamental in conceptualizing IS success (e.g., F. D. Davis, 1989). The reasoning is that individuals more-often utilize IT when they believe that it helps

Table 2.1: Selected Literature Addressing IS Success

Source		Salient Quote(s)	Chronological Narrative
Ackoff	1967	"Contrary to the impression produced by the growing literature, few computerized management information systems have been put into operation. Of those I've seen that have been implemented, most have not matched expectations and some have been outright failures. I believe that these near- and far-misses could have been avoided if certain false (and usually implicit) assumptions on which many such systems have been erected had not been made." (p. B-147)	With the advent of information systems (IS) in organizational and managerial contexts, this work highlights that many IS are not meeting desired expectations, and that the failure to do so is likely due to common but erroneous assumptions made by IS designers. Thus, for IS success, this paper suggests ways IS designers can avoid these assumptions.
Lucas	1975	"The purpose of this paper is to explore the contributions of information systems to the organization. A descriptive model is presented which identifies 1) expected predictors of performance and the use of an information system and 2) the relationship between the use of a system and performance. The results of a study of sales force performance and the use of a sales information system … confirm the general relationships among classes of variables in the model, but specific relations among variables are complex and depend heavily on the environment of the organization." (p. 908)	Links use of an IS in an organization to organizational performance, thus suggesting that IS success involves understanding the 'use' to 'benefits-to-use' relationship.
Ein-Dor & Segev	1978	"This paper identifies the organizational context variables affecting the success and failure of MIS. The variables are categorized as uncontrollable, partially controllable and controlled, and a conceptual scheme is suggested. In addition, current information on these variables and the interactions between them is surveyed; propositions are stated concerning relationships between the variables and the success or failure of MIS." (p. 1064)	Proposed various organization context variables that may influence IS success.
Zmud	1979	"This analysis of the empirical literature regarding the influence of individual differences upon MIS success indicates rather clearly that individual differences do exert a major force in determining MIS success. It is just as apparent, however, that much remains unknown regarding the specific relationships involved and the relative importance of individual differences when contrasted with contextual factors." (p. 975)	Reviews prior work on how individual differences influence IS success, and suggests specific areas for future research.

Table 2.1: Selected Literature Addressing IS Success (continued)

Source		Salient Quote(s)	Chronological Narrative
Ives & Olson	1984	"User involvement in the design of computer-based information systems is enthusiastically endorsed in the prescriptive literature. However determining when and how much, or even if, user involvement is appropriate are questions that have received inadequate research attention. … In order to foster higher quality integrated research and to increase understanding of the user involvement-system success relationship, the authors present the following: a conceptual framework into which previous research has been mapped that can provide direction to future efforts; a review of existing measures of user involvement and system success; a set of variables that have been proposed as potentially impacting the relationship between user involvement and system success." (p. 586)	Reviews prior work on how user involvement in IS design influences IS success, and suggests a conceptual framework for further research on user involvement in IS design.
Davis, Bagozzi, & Warshaw	1989	"Computer systems cannot improve organizational performance if they aren't used. Unfortunately, resistance to end-user systems by managers and professionals is a widespread problem. To better predict, explain, and increase user acceptance, we need to better understand why people accept or reject computers. This research addresses the ability to predict peoples' computer acceptance from a measure of their intentions, and the ability to explain their intentions in terms of their attitudes, subjective norms, perceived usefulness, perceived ease of use, and related variables. … [The] results suggest the possibility of simple but powerful models of the determinants of user acceptance, with practical value for evaluating systems and guiding managerial interventions aimed at reducing the problem of underutilized computer technology." (p. 982)	Suggests that IS success can better be understood by looking at the use-performance relationship, and specifically what determines technology acceptance by IS users.
DeLone & McLean	1992	"A large number of studies have been conducted during the last decade and a half attempting to identify those factors that contribute to information systems success. However, the dependent variable in these studies—I/S success—has been an elusive one to define. Different researchers have addressed different aspects of success, making comparisons difficult and the prospect of building a cumulative tradition for I/S research similarly elusive. To organize this diverse research, as well as to present a more integrated view of the concept of I/S success, a comprehensive taxonomy is introduced. This taxonomy posits six major dimensions or categories of I/S success—SYSTEM QUALITY, INFORMATION QUALITY, USE, USER SATISFACTION, INDIVIDUAL IMPACT, and ORGANIZATIONAL IMPACT." (p. 60) (CAPS in original)	Seminal paper on IS success which suggests that success is a multi-dimensional construct.
Goodhue & Thompson	1995	"A key concern in Information Systems (IS) research has been to better understand the linkage between information systems and individual performance. … At the heart of the new model is the assertion that for an information technology to have a positive impact on individual performance, the technology: (1) must be utilized and (2) must be a good fit with the tasks it supports. … This research highlights the importance of the fit between technologies and users' tasks in achieving individual performance impacts from information technology." (p. 213)	Suggests there must be a fit between the IS used and the tasks that are supported by the IS. Also links system use with individual performance (one measure of IS success).

Table 2.1: Selected Literature Addressing IS Success (continued)

Source		Salient Quote(s)	Chronological Narrative
Yoon, Guimaraes, & O'Neal	1995	"As the widespread use and company dependency on expert systems (ES) increase, so does the need to assess their value and to ensure implementation success. This study identifies and empirically tests eight major variables proposed in the literature as determinants of ES success, in this case measured in terms of user satisfaction." (p. 83)	Identifies important determinants of the success of an expert IS as measured by user satisfaction.
Seddon	1997	"DeLone and McLean's (1992) comprehensive review of different information system success measures concludes with a model of 'temporal and causal' interdependencies between their six categories of IS Success. After working with this model for some years, it has become apparent that the inclusion of both variance and process interpretations in their model leads to so many potentially confusing meanings that the value of the model is diminished. Because of the confusion that this overloading of meanings can cause, this paper presents and justifies a respecified and slightly extended version of DeLone and McLean's model." (p. 240)	Provides a respecification of the DeLone & McLean (1992) model, which helps provide clarifications.
Igbaria & Tan	1997	"As more information technology (IT) is deployed in organizations, it is important to understand its impact on individual performance and organizational productivity. Most past research has concentrated on identifying determinants of computer acceptance. … This study seeks to investigate the implications and consequences of IT acceptance by examining the relationships between IT acceptance and its impact on the individual user. … The results suggest that user satisfaction is an important factor affecting system usage and that user satisfaction has the strongest direct effect on individual impact. The results also demonstrate the importance of system usage in mediating the relationship of user satisfaction on individual impact." (p. 113)	Supports notion that use of an IS is linked to successful outcomes from use.
Doll & Torkzadeh	1998	"System-use is a pivotal construct in the system-to-value chain that links upstream research on the causes of system success with downstream research on the organizational impacts of information technology." (p. 171)	Suggests that system use is central in the "system-to-value chain" of IS success.
Karahanna, Straub, & Chervany	1999	"…the study makes an important theoretical contribution toward articulating differences in the determinants of adoption and usage. The majority of MIS research in the belief/attitude tradition to date has focused on beliefs and attitudes related to usage of IT. Consequently, our understanding of beliefs, attitudes, and norms leading to IT adoption and how these are modified over time is limited. … [The] results represent an important first step toward a deeper understanding of the temporal evolution of beliefs, attitudes, norms, and behavior across different phases of the innovation process." (p. 203)	Suggests that temporality should be considered in IS success research.

Table 2.1: Selected Literature Addressing IS Success (continued)

Source		Salient Quote(s)	Chronological Narrative
DeLone & McLean	2003	"Considering the recent research studies that both validate and support our model as well as those that challenge it, we conclude that our original model and related conclusions still form a sound basis for IS success measurement even in the e-commerce environment. We believe that our proposed changes in the updated D&M IS Success Model are largely changes in degree, not in kind. The addition of 'service quality' and the collapsing of 'individual impacts' and 'organizational impact' into 'net benefits' still preserve the parsimonious nature of the model." (p. 26-27)	Reaffirms and updates model of IS success initially proposed by DeLone & McLean (1992).
Devaraj & Kohli	2003	"The relationship between investment in information technology (IT) and its effect on organizational performance continues to interest academics and practitioners. In many cases, due to the nature of the research design employed, this stream of research has been unable to identify the impact of individual technologies on organizational performance. This study posits that the driver of IT impact is not the investment in the technology, but the actual usage of the technology. … The data analysis provides evidence for the technology usage-performance link after controlling for various external factors. Technology usage was positively and significantly associated with measures of hospital revenue and quality, and this effect occurred after time lags." (p. 273)	Links IS usage with organizational performance, and suggests there may be lag effects in this relationship.
Venkatesh, Morris, Davis, & Davis	2003	"Information technology (IT) acceptance research has yielded many competing models, each with different sets of acceptance determinants. In this paper, we (1) review user acceptance literature and discuss eight prominent models, (2) empirically compare the eight models and their extensions, (3) formulate a unified model that integrates elements across the eight models, and (4) empirically validate the unified model." (p. 425) "… the Unified Theory of Acceptance and Use of Technology (UTAUT) … thus provides a useful tool for managers needing to assess the likelihood of success for new technology introductions and helps them understand the drivers of acceptance in order to proactively design interventions (including training, marketing, etc.) targeted at populations of users that may be less inclined to adopt and use new systems." (p. 425-426)	Compares and tests prior models of IS success, and from this comparison, formulates and tests a unified model that explains more variance than the prior models.

Table 2.1: Selected Literature Addressing IS Success (continued)

Source		Salient Quote(s)	Chronological Narrative
Wixom & Todd	2005	"In general, perceptions of information systems (IS) success have been investigated within two primary research streams—the user satisfaction literature and the technology acceptance literature. These two approaches have been developed in parallel and have not been reconciled or integrated. This paper develops an integrated research model that distinguishes beliefs and attitudes about the system (i.e., object-based beliefs and attitudes) from beliefs and attitudes about using the system (i.e., behavioral beliefs and attitudes) to build the theoretical logic that links the user satisfaction and technology acceptance literature. … The proposed model was supported, providing preliminary evidence that the two perspectives can and should be integrated." (p. 85)	Develops and tests a model that integrates parallel IS success research streams.
Wu & Wang	2006	"We proposed and empirically assessed a KMS success model. This was derived through an analysis of current practice of knowledge management and review of IS success literature. Five variables (system quality, knowledge or information quality, perceived KMS benefits, user satisfaction, and system use) were used as dependent variables in evaluating KMS success, and their interrelationships were suggested and empirically tested. The results provide an expanded understanding of the factors that measure KMS success…." (p. 728)	Applies an IS success model to knowledge management systems.
Sabherwal, Jeyaraj, & Chowa	2006	"… the observed empirical relationships among the constructs related to IS success might be due to the exclusion of other factors affecting them. This problem could be mitigated by examining IS success along with its potential determinants. Therefore, this paper addresses the following specific questions: (1) How do the various constructs reflecting IS success affect each other? (2) How do these IS success constructs depend on constructs characterizing the users and the context? To" (p. 1849)	Suggests that IS success is partially dependent on users and the context of use, which had been largely missing in prior models of IS success.
Kulkarni, Ravindran, & Freeze	2007	"We examine a knowledge management (KM) success model that incorporates the quality of available knowledge and KM systems built to share and reuse knowledge such as determinants of users' perception of usefulness and user satisfaction with an organization's KM practices." (p. 309)	Takes the DeLone and McLean (1992, 2003) IS success model and the Seddon (1997) reconceptualization to develop a model of knowledge management success.

them in their work. Thus perceptions have been argued to be a good indicator of whether ITs are actually being useful.

Perceptions of IT are used in several ways in the IS success literature. Some studies in this literature use perceptions as explanations for individuals' intentions-to-use/ use of IT (e.g., F. D. Davis, 1989; Wixom & Todd, 2005). In these studies, use of perceptions focuses on questions of IT adoption and acceptance. Other studies in the IS success literature utilize perceptions as evaluations of the IT being used (e.g., DeLone & McLean, 2003; Seddon, 1997). In this literature use of perceptions centers on questions concerning the influence of IT attributes on the utility or satisfaction with IT. While these uses are distinctively different, both are at some level related given the breadth with which IS success is conceptualized (i.e., along the adoption-use-impact chain).

Karahanna, Straub, and Chervany (1999) suggest a helpful link that enables us to better understand these different uses of perceptions: that that the links among perceptual uses are temporal; that is, using and evaluating IT happens over time. Their work suggests that in conceptualizing system success, time should also be considered. The implication of considering time in system success suggests that attention should as well be given to aspects of success influenced by time: the use of a system over time, and the experience of the individual users.

System Use Over Time

Research in IS advocates that one area in which IS constructs should be conceptualized is at the interface of the IT artifact and the individual user (i.e., 'machine' and 'mind') (Benbasat & Zmud, 2003). Prior research on IS success has suggested that the central factor in success is the extent of system use (Devaraj & Kohli, 2003; Doll &

Torkzadeh, 1998). Thus IS success is thought to occur at the interface of ‘machine’ and ‘mind’, or where systems are actually used by individuals. But what is actual use?

In IS research, system use has been conceptualized in different ways (Burton-Jones & Straub, 2006). Table 2.2 presents a chronology of the key literature on how system use has been conceptualized. For example, in the IS success literature, Seddon (1997) suggests that system use has been utilized in this literature in three ways: (1) as a variable that proxies for the benefits from use; (2) as the dependent variable in a variance model of future use; and (3) as an event in a process leading to individual or organizational impact (1997: 242–243). However, in a reconceptualization of the system use construct, Burton-Jones and Straub (2006), lacking a clear definition of system use from the literature, suggest that system use involves three elements – user, system, and task – and define it at the individual level as “an individual user’s employment of one or more features of a system to perform a task” (2006: 231). One implication of this definition, they suggest, is that much of the prior research which utilized system use was often referring to distinct constructs (e.g., information use) or was using it as a proxy for another construct (e.g., IT acceptance). For system-success research, this implication suggests that more clarity is needed when referring to system use.

The three elements of system use suggested by Burton-Jones and Straub (2006) – user, system, and task – provide a helpful basis for attempting such clarification. For IS success research, prior research has focused almost exclusively on the *system* part of system use (e.g., system characteristics, information quality). In doing so this research has focused mostly on the use of one IT. In practice, however, a portfolio of technologies

Table 2.2: Selected Literature Addressing System Use / System Use Over Time

Source		Salient Quote(s)	Chronological Narrative
Barkin & Dickson	1977	"The utilization, usage, or use of a system refers to the inclusion of system generated data by the decision-maker in their Human Information Processing system. The Human Information Processing (HIP) system is the cognitive system that has the capacity to organize, manipulate, and integrate data for decision making. An information system is therefore utilized if the output from the information system is organized and/or manipulated and/or integrated by the decision-making process." (p. 36)	Provides a definition of system use centered on human information processing, thus linking machine and mind via utilization of data/ information (contained in machines) by humans (contained in minds).
Robey	1979	"The basic problem may be succinctly stated: MIS can and does fail where user psychological reactions and organizational factors are ignored by system designers. … One notion receiving attention is that attitudes of MIS users are related to their actual use of a system. … This paper deals with this problem and addresses the relationship between user attitudes and behavior." (p. 527-528)	Links user attitudes with system use.
Trice & Treacy	1988	"The amount of use an individual, group, or organization makes of an information system is a key variable in MIS research. It is often used as an independent variable when studying or predicting the impacts that an information system has had on process, structure, and performance. … Utilization of a system has also been used as a dependent variable. It has been modeled as an outcome construct that can be influenced by the process of design and implementation and by characteristics of the information system, the task, the individual user and their interaction. … For such an important MIS variable as information system use, which has many readily obtainable measures, it is somewhat surprising that the field does not have generally accepted measurement instruments." (p. 33)	As system use becomes an increasingly important construct, research begins to examine how it is operationalized and measured.
Davis	1989	"Valid measurement scales for predicting user acceptance of computers are in short supply. Most subjective measures used in practice are unvalidated, and their relationship to system usage is unknown. The present research develops and validates new scales for two specific variables, perceived usefulness and perceived ease of use, which are hypothesized to be fundamental determinants of user acceptance. … The measures were refined and stream-lined, resulting in two six-item scales with reliabilities of.98 for usefulness and.94 for ease of use. … Perceived usefulness was significantly correlated with both self-reported current usage (r=.63, Study 1) and self-predicted future usage (r=.85, Study 2). Perceived ease of use was also significantly correlated with current usage (r=.45, Study 1) and future usage (r=.59, Study 2). In both studies, usefulness had a significantly greater correlation with usage behavior than did ease of use."	Develops and tests measures that link perceptions to system use.

Table 2.2: Selected Literature Addressing System Use / System Use Over Time (continued)

Source		Salient Quote(s)	Chronological Narrative
Thompson, Higgins, & Howell	1991	"…the purpose of the study described in this article is to conduct an initial test of a model of personal computer (PC) utilization using a subset of Triandis' (1980) theory of attitudes and behavior. This theory implies that the utilization of a PC by a knowledge worker in an optional use environment would be influenced by the individual's feelings (affect) toward using PCs, social norms in the work place concerning PC use, habits associated with computer usage, the individual's expected consequences of using a PC, and facilitating conditions in the environment conducive to PC use." (p. 126)	Suggests other attitudinal constructs that may influence the use of personal computer systems.
Szajna	1993	"While the utilization of an information system (IS) is widely regarded as an indicator of its success, effectiveness, or acceptance, past research has found inconsistent associations between usage and other measures of system success. … One area in particular has apparently been neglected: establishing the relevance of the way of measuring usage to the task or study. Data obtained from a laboratory experiment on user expectations illustrate the necessity of choosing a utilization measure that is relevant to the task involved. The data also indicate that behavioral and perceptual variables of IS evaluation ought to be considered separately when determining the level of IS success." (p. 147)	Choosing a task-relevant measure of system usage considered important. Likewise, that in examining IS success, behavioral and perceptual evaluations should likely be considered independently.
Thompson, Higgins, & Howell	1994	"For researchers, the implications are that prior experience with an information technology (IT) is an important factor to include when developing, testing, or applying models of IT adoption and use." (p. 168)	Suggests that experience may influence system use.
Straub, Limayem, & Karahanna-Evaristo	1995	"There is widespread agreement among researchers that system usage … is the primary variable through which IT affects white collar performance. Despite the number of studies targeted at explaining system usage, there are crucial differences in the way the variable has been conceptualized and operationalized. … The purpose of this paper is to address conceptual as well as methodological issues related to measuring system usage. … [Results] suggest that system usage should be factored into self-reported system usage and computer-recorded system usage. Contrary to expectations, these constructs do not appear to be strongly related to each other." (p. 561)	Provides better conceptualization and measurement of system use, and states that computer-recorded system use measures more-accurately measure actual system use.
Taylor & Todd	1995	"…the results from this study suggest that the augmented TAM can be applied to understand the behavior of both experienced and inexperienced users; however it is important to note that inexperienced users place a different emphasis on the determinants of intention and usage." (p. 566-567)	Likewise suggests that accounting for experience may be important, suggesting that experience may have a moderating influence on system use.

Table 2.2: Selected Literature Addressing System Use / System Use Over Time (continued)

Source		Salient Quote(s)	Chronological Narrative
Doll & Torkzadeh	1998	"The perception of a widening gap between the potential of information technology (that is, what it is capable of being and what it can ideally achieve) and its actual use has focused attention on the need for better measures of how extensively information technology is utilized in an organizational context. Building on a taxonomy of system-use and the rich descriptive literature provided by social scientists who focus on the impact of information technology on work, this paper makes an effort to develop new multidimensional measures of how extensively information technology is utilized in an organizational context for decision support, work integration, and customer service functions." (p. 171)	Recognizing the multidimensional nature of system use, this paper attempts to develop measures to capture this nature.
Kraut, Mukhopadhyay, Szczypula, Kiesler, & Scherlis	1999	"… one can predict a participant's current e-mail use from his or her use in the prior week much better than one can predict a participant's current Web use from his or her prior Web use." (p. 296)	Accounting for prior use (which implicates time) seems to be important when examining factors that influence system use.
Venkatesh, Morris, & Ackerman	2000	"Sustained technology usage behavior was driven by early usage behavior…." (p. 33)	Likewise suggests that accounting for prior system use (again implicating time) is important.
Agarwal & Karahanna	2000	"To eliminate the confounding of results based on specific individual characteristics, a respondent's web experience, PC experience, and gender were included in the analysis as controls." (p. 683)	Recognizes that there may be various conceptualizations of experience, and thus uses several operationalizations as a control in their model of system use.
Venkatesh, Speier, & Morris	2002	"…based on the strong evidence that prior behavior predicts future behavior, we expect that user perceptions (i.e., perceived usefulness, ease of use, and intrinsic motivation) measured at a later time will add no additional explanatory power in continued usage behavior beyond prior usage of the technology." (p. 304) "Finally, immediate use (USE12) was the sole significant predictor of continued usage (USE23) (.59, $p < .001$)—all other variables measured at t1 and t2 were non-significant predictors of USE23…." (p. 307)	Further support that prior system use (which again implicating time) is a significant determinant of continued system use.

Table 2.2: Selected Literature Addressing System Use / System Use Over Time (continued)

Source		Salient Quote(s)	Chronological Narrative
Haas & Hansen	2005	"…sales teams … derived different levels of value from obtaining and using electronic documents and advice from colleagues. Highly experienced teams were more likely than inexperienced teams to lose the sales bids if they utilized such knowledge. … There were situations, however, where teams performed better if they utilized the firm's knowledge resources. These results suggest that competitive performance depends not on how much firms know but on how they use what they know." (p. 1)	Links use of KMS knowledge to performance, and suggests that performance is dependent on how knowledge is used (thus also linking experience as having a moderating influence).
Jasperson, Carter, & Zmud	2005	"By its nature, the study of post-adoptive behavior situates an individual's use of an IT application within a stream of use experiences, some of which have already occurred and some of which have yet to occur. However, … the majority of previous studies tend to either examine IT application use immediately after adoption or otherwise do not account for a user's history in using a focal, much less a similar, IT application. In studies that have considered the direct impact of prior use on post-adoptive behaviors, as might be expected, researchers found prior use to be a significant antecedent of post-adoptive behavior." (p. 527)	Illustrates the need to (among other things) account for prior use in studies of the adoption and continued use of IS.
Burton-Jones & Straub	2006	"In this article, we present a systematic approach for reconceptualizing the system usage construct in particular nomological contexts. ... The structure of system usage is tripartite, comprising a user, system, and task, and researchers need to justify which elements of usage are most relevant for their study. In terms of function, researchers should choose measures for each element (i.e., user, system, and/or task) that tie closely to the other constructs in the researcher's nomological network." (p. 228)	Seminal reconceptualization of the system use construct, suggesting that system use is a multidimensional construct consisting of the user, system, and task.
Gray & Meister	2006	"Employees can source knowledge recorded in document form, through dyadic conversations, or in-group settings. We proposed and tested a theory to support the idea that employees' use of different classes of knowledge sourcing methods produced different kinds of performance outcomes. Our findings suggested that (1) different classes of knowledge sourcing methods are not as interchangeable as the KM literature might suggest, (2) technology-based methods are neither inherently superior nor inferior to traditional methods and (3) that group knowledge sourcing supports a wider range of performance outcomes than other methods." (p. 142)	Highlights that different knowledge sourcing methods – via KMS that link people to a document in machine, or to a conversation with another person(s) – influence performance differentially.
Burton-Jones & Gallivan	2007	"The objective of this paper is to contribute to a deeper understanding of system usage in organizations by examining its multilevel nature. …we draw on recent advances in multilevel theory to present system usage as a multilevel construct and provide an illustration for what it takes for researchers to study it as such." (p. 657)	Suggests that system usage is also a multilevel construct; that is, it can be examined at/ across multiple levels in organizations.

Table 2.2: Selected Literature Addressing System Use / System Use Over Time (continued)

Source		Salient Quote(s)	Chronological Narrative
Haas & Hansen	2007	"We develop a differentiated productivity model of knowledge sharing in organizations proposing that different types of knowledge have different benefits for task units. In a study of 182 sales teams in a management consulting company, we find that sharing codified knowledge in the form of electronic documents saved time during the task, but did not improve work quality or signal competence to clients. In contrast, sharing personal advice improved work quality and signaled competence, but did not save time. … These findings dispute the claim that different types of knowledge are substitutes for each other, and provide a micro-foundation for understanding why and how a firm's knowledge capabilities translate into performance of knowledge work." (p. 1133)	Provides further support that the use of codified and personalized KMS knowledge differentially influence performance.
Zimmer, Henry, & Butler	2007	"Although it has been argued that knowledge is an important organizational resource, little research has investigated where individuals go to search for information or knowledge. Prior work has investigated sources in isolation, but in an organizational setting, sources are encountered as an open portfolio instead of in isolation. … Building on prior work, this research looks at factors underlying the selection of sources that require direct interpersonal contact (relational sources) and those that do not (nonrelational sources) and explores factors that differentially affect the use of these types of sources." (p. 297)	Suggests that in using KMS, knowledge workers have a choice in where they source knowledge from.
Hsieh, Rai, & Xu	2011	"How can firms extract value from already-implemented information technologies (IT) that support the work processes of employees? One approach is to stimulate employees to engage in post-adoptive extended use, i.e., to learn and apply more of the available functions of the implemented technologies to support their work. Such learning behavior of extending functions in use is ingrained in a process by which users make sense of the technologies in the context of their work system. …our findings highlight the critical role of employees' sensemaking about the implemented technologies in promoting their extended use of IT and improving their work performance." (p. 2018)	Suggests that performance benefits from system use can come over time, due to learning that occurs in system use.
Ko & Dennis	2011	"Although many organizations are implementing knowledge management systems (KMS), there is little empirical evidence about whether KMS use can improve individual performance, and how time and experience influence the value derived from KMS use. Using hierarchical linear modeling (HLM) statistical analysis, we examined the impact of using a codification-based KMS on the sales performance of 2,154 sales representatives in a pharmaceutical firm over a 24-month period. We found that KMS had significant positive impacts on individual performance and that these performance benefits grew over time. Moreover, experience moderated the relationship between KMS use and individual performance." (p. 134)	Found that the use over time of a codification-based KMS is linked to individual performance, and that experience moderates this relationship.

Table 2.2: Selected Literature Addressing System Use / System Use Over Time (continued)

Source		Salient Quote(s)	Chronological Narrative
Wang, Meister, & Gray	2013	"Theory suggests that coworkers may influence individuals' technology use behaviors, but there is limited research in the technology diffusion literature that explicates how such social influence processes operate after initial adoption. We investigate how two key social influence mechanisms (identification and internalization) may explain the growth over time in individuals' use of knowledge management systems (KMS)—a technology that because of its publicly visible use provides a rich context for investigating social influence." (p. 299)	Suggests that there are social influences that may influence the use of KMS.

is often available to users, as is the case with KMS (Gray & Meister, 2004, 2006; Zimmer et al., 2007). Thus, in conceptualizing system success, the possibility of being able to use multiple systems should be considered.

Additionally, of the extensive literature that examines system use, only a handful of articles consider the role that prior system use plays on IS success (cf. Jasperson, Carter, & Zmud, 2005). Most of these works suggest that prior use influences continued use in non-trivial ways (e.g., Kraut, Mukhopadhyay, Szczypula, Kiesler, & Scherlis, 1999; Venkatesh, Morris, & Ackerman, 2000; Venkatesh, Speier, & Morris, 2002). These findings are both foreseen and documented by DeLone and McLean (1992, 2003), who state that "…'use' and 'user satisfaction' are closely interrelated. 'Use' must precede 'user satisfaction' in a *process* sense, but positive experience with 'use' will lead to greater 'user satisfaction' in a *causal* sense. Similarly, increased 'user satisfaction' will lead to increased 'intention to use,' and thus 'use'" (italics in original) (1992, 2003: 23). Thus, in considering individual factors that may impact system success, it seems that accounting for the temporality of system use is also relevant.

Experience

Prior research on IS success suggests that individual experience has an influence on IS success; and more particularly, that experience most likely has a moderating effect on other system success constructs (Taylor & Todd, 1995; Thompson, Higgins, & Howell, 1994). Where experience is considered explicitly in this research: i.e., is included in the research models (e.g., Sabherwal et al., 2006) versus as a control (e.g., Agarwal & Karahanna, 2000), the definition most-often used concerns individual work experience, and is mostly operationalized as a time dimension, such as how long an individual: (1)

has been employed in an organization (e.g., Haas, 2006), (2) has been employed in their current position (e.g., Ko & Dennis, 2011), or (3) has performed a specific task(s) (e.g., Haas & Hansen, 2007). However, other work within the IS success literature has operationalized experience as how long an individual: (4) has used a specific technology (e.g., Venkatesh et al., 2003). Most of this research, either implicitly or explicitly, utilizes experience as a signal for individual expertise level, although it should be noted that some research suggests that these concepts may be distinct (Bradley, Paul, & Seeman, 2006). These varied operationalizations of the experience construct suggest that experience may too be multidimensional. As mentioned though, one thing seems reasonably certain: that regardless of the operationalization, experience likely has a moderating effect.

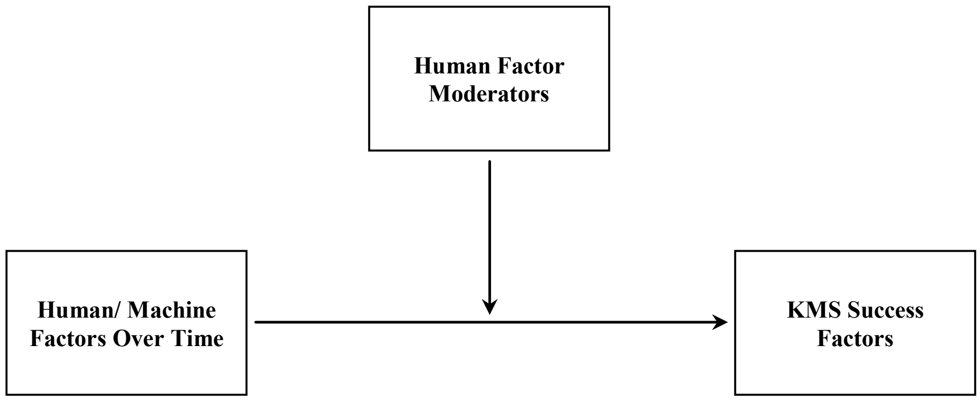
CHAPTER 3. THEORY & HYPOTHESES

From an analysis of the literature reviewed in the previous chapter, I obtain three important points that are applicable to investigating KMS success: (1) that the 'user' in system use has often been relegated to the theoretical sidelines in IS success research, but may play a central role in better-understanding system success; (2) that the 'systems' in system use have mostly only been considered as single technologies in IS success research, but that understanding systems as a portfolio of technologies, such as with KMS, may help in better-understanding system success; and (3) that the temporal nature of using and evaluating IS success has not been considered in sufficient theoretical depth, but may be an important part of better-understanding system success.

Helpfully, these points, while originating in IS success research, are applicable to research investigating KMS success because they suggest the kind of theory that would be appropriate to examine KMS success: theory that encompasses the users (knowledge workers), using systems (codification-based and personalization-based KMS), over time. Expert information processing theory (EIPT) provides such a theoretical lens. Based on an EIPT logic – that knowledge workers extend their capabilities through developing expertise over time by using KMS; that this increase in expertise has beneficial performance outcomes that influence individual perceptions of the KMS; and that individual characteristics can also influence perceptions – I suggest a general theoretical model of KMS success that links the human/ machine elements, human elements, and success elements, as shown in Figure 3.1.

In the remainder of this section I introduce relevant theory drawn from the EIPT theoretical viewpoint, specify a research model based on the general theoretical model,

Figure 3.1: General Theoretical Model



and present the testable hypotheses that follow from using specific, relevant concepts from the EIPT lens.

Expert Information Processing Theory (EIPT)

EIPT provides an appropriate lens to conceptualize how the machine/ mind interface relates to KMS success because it links individuals and their information environments – which importantly includes the information/ knowledge they use from systems – to performance outcomes through expertise development over time. From my literature review, it might be observed that there are three overlapping but related literatures that suggest the EIPT concepts relevant to answering my research question: human information processing, the expert information processing model, and expert scripts. Table 3.1 summarizes key works from the literature that form the foundation for the EIPT application in this dissertation.

EIPT has its roots in studies of human information processing (e.g., Newell & H. A. Simon, 1972; Shiffrin & Schneider, 1977). Within the field of cognitive psychology,

Table 3.1: Selected Literature Addressing Expert Information Processing Theory

Source		Salient Quote(s)	Chronological Narrative
		Information Processing	
Shannon & Weaver	1949	"The word *communication* will be used here in a very broad sense to include all of the procedures by which one mind may affect another. This, of course, involves not only written and oral speech, but also music, the pictorial arts, the theatre, the ballet, and in fact all human behavior." (italics in original) (p. 3)	Theory of information introduced. Communication (i.e., the exchange of information) influences human behavior.
Miller	1956	"First, the span of absolute judgment and the span of immediate memory impose severe limitations on the amount of information that we are able to receive, process, and remember. … Second, the process of recoding is a very important one in human psychology …. In particular, the kind of linguistic recoding that people do seems to me to be the very lifeblood of the thought processes." (p. 95)	Application of information theory to the mental processes (i.e., information processing) that help to manage stimuli (i.e., information environment).
Simon & Newell	1964	"Organizing a computer to perform complex tasks depends very much more upon the characteristics of the task environment than upon the "hardware"—the specific physical means for realizing the processing in the computer. Thus, all past and present digital computers perform basically the same kinds of symbol manipulations. … In programing [sic] a computer it is substantially irrelevant what physical processes and devices … accomplish the manipulations. A program, written in one of the symbolic programing languages … will produce the same symbolic output on a machine that uses electron tubes for processing and storing symbols, one that incorporates magnetic drums, one with a magnetic core memory, or one with completely transistorized circuitry. The program, the organization of symbol-manipulating processes, is what determines the transformation of input into output. … By the same token, since the thinking human being is also an information processor, it should be possible to study his processes and their organization independently of the details of the biological mechanisms—the "hardware"—that implement them. The output of the processes, the behavior of *Homo cogitans*, should reveal how the information processing is organized, without necessarily providing much information about the protoplasmic structures or biochemical processes that implement it. … There is a growing body of evidence that the elementary information processes used by the human brain in thinking are highly similar to a subset of the elementary information processes that are incorporated in the instruction codes of present-day computers. As a consequence it has been found possible to test information-processing theories of human thinking by formulating these theories as computer programs—organizations of the elementary information processes—and examining the outputs of computers so programed [sic]." (italics in original) (p. 281-282)	The computer model of information processing is helpful in conceptualizing human information processing, which leads to the notion that human thinking is more about the mental information processes than the underlying biological mechanisms, and the notion that human behavior should reveal how human information processing is organized.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Mandler	1967	"Organization variables have assumed a new importance in human psychology, particularly in the area of human memory. The present paper will be devoted to the illustration of three general principles: First, memory and organization are not only correlated, but organization is a necessary condition for memory. Second, the organization of, and hence memory for, verbal material is hierarchical, with words organization in successively higher-order categories. Third, the storage capacity within any one category or within any level of categories is limited." (p. 328)	There is organization underlying the mental processes of information processing, which is foundational in later schema-based (knowledge structures) work.
Neisser	1967	"It has been said that beauty is in the eye of the beholder. As a hypothesis about localization of function, the statement is not quite right—the brain and not the eye is surely the most important organ involved. Nevertheless it points clearly enough toward the central problem of cognition. Whether beautiful or ugly or just conveniently at hand, the world of experience is produced by the man who experiences it. … There certainly is a real world of trees and people and cars and even books, and it has a great deal to do with our experiences of these objects. However, we have not direct, *im*mediate access to the world, nor to any of its properties. Whatever we know about reality has been *mediated*, not only by the organs of sense but by complex systems which interpret and reinterpret sensory information." (italics in original) (p. 3)	Reality (i.e., information environment) is mediated by complex human information processing systems.
Norman	1969	"We view the human as a processor of information. In particular, we are concerned primarily with verbal, meaningful information in acoustical and visual form. The aim is to follow what happens to the information as it enters the human and is processed by the nervous system. The sense organs provide us with a picture of the physical world. Our problem is to interpret the sensory information and extract its psychological content. To do this we need to process the incoming signals and interpret them on the basis of our past experiences. Memory plays an active role in this process. It provides the information about the past necessary for proper understanding of the present. There must be temporary storage facilities to maintain the incoming information while it is being interpreted and it must be possible to add information about presently occurring events into permanent memory. We then make decisions and take actions on the information we have received." (p. 3-4)	Interpretation of information environment is dependent on past experience, for which memory plays an important role, providing the basis for future research.
Newell & Simon	1972	"…states the [information processing] theory in comprehensive form." (p. 14)	Information processing theory formalized, and subsequently linked to human problem solving.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Schneider & Shiffrin	1977	"A two-process theory of human information processing is proposed. … Automatic processing is activation of a learned sequence of elements in long-term memory that is initiated by appropriate inputs and then proceeds automatically—without subject control, without stressing the capacity limitations of the system, and without necessarily demanding attention. Controlled processing is a temporary activation of a sequence of elements that can be set up quickly and easily but requires attention, is capacity-limited (usually serial in nature), and is controlled by the subject." (p. 1) "Automatic sequences … are learned following the earlier use of controlled processing that links the same nodes in sequence. … Controlled processing is used to facilitate long-term learning of all kinds, including automatic processing." (p. 51-52)	Types of human information processing are explored and linked (i.e., automatic and controlled), which provides a foundation for learning-based theories to emerge.
Shiffrin & Schneider	1977	"The studies demonstrate the qualitative difference between two modes of information processing: automatic detection and controlled search … [and] trace the course of the learning of automatic detection, of categories, and of automatic-attention responses. … A general framework for human information processing is proposed. The framework emphasizes the roles of automatic and controlled processing." (p. 127)	Further clarifies how modes of information processing are linked and provides a basis for a general theory of human information processing.
Lachman, Lachman, & Butterfield	1979	"Information-processing psychology is fundamentally committed to the concept of representation: Everything you know is considered to be represented in your memory. How these representations are put to use is one of the central questions in many areas of cognitive psychology." (p. 8) "The information-processing approach has been in the forefront of a scientific revolution; it has provided psychologists with a fundamentally new way of thinking about people. …[It] focuses on normal and rational behavior, and view[s] the human being as an active seeker and user of information." (p. 10)	The concept of mental representations in memory plays an important part of human information processing.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Bourne, Dominowski, Loftus, & Healy	1986	”Cognitive psychologists face the enormous task of explaining phenomena … in systematic, scientific terms. The approach that seems to show the most promise of providing an explanation is based on the notion that human being are systems for processing information.” (p. 11) “The way people behave is dependent on the information available and a set of processes for operating on that information. The information a person has to work with at any moment comes from at least three sources: (1) current circumstances, which usually include some focal source of stimulation; (2) memory, which is defined as information about past experiences and about functional skills; and (3) feedback contingent upon action, that is, information that derives from sensing one’s own activity, and from the reactions of one’s social and physical environment to that activity.” (p. 12) “Information is processed over time. … it is convenient to think of information as passing through several [mental] stages, each with its own characteristics.” (p. 12)	Pinpoints several important sources of information available for processing, and highlights the temporal aspect of human information processing, which together further link information processing theory to explain human behavior.
Lord & Maher	1990	“A general taxonomic system of alternative information-processing models (rational, limited capacity, expert, and cybernetic) found in the management and psychological literatures is developed. … each model provides a different explanation of information processing in typical work situations … [and also] provides a different explanation of processing in several theoretical domains (attribution theory, decision making, performance appraisal).” (p. 9)	Specific models of information processing are developed to explain information processing in different practical and theoretical domains.
		Expert Information Processing	
Miller	1956	“… the concepts and measures provided by the theory of information … provides us with a yardstick for calibrating our stimulus materials and for measuring the performance of our subjects.” (p. 96)	Information processing theory can be a basis for understanding individual performance differences.
de Groot	1965	“The purpose of the investigations described in this study is first of all *to carry out an experimentally based psychological analysis of chess thinking*. Until now there have been no studies that have concerned themselves with a systematic description of the chess player’s characteristic attitudes and methods of thinking. Herein, however, lies the heart of the psychological problems involved in chess. Only from a knowledge of the normal thinking of the chessmaster can one understand special arts, such as ‘blind’ and/or simultaneous play. Only by analyzing the thought process can one arrive at a thorough insight into the demands the game makes on its practitioners. Only along this path can the question of chess aptitude be fully handled. A systematic empirical analysis of the chess player’s thinking therefore forms a sound basis for practically every psychological study in the field of chess.” (italics in original) (p. 13)	An initial connection made between human information processing and expert task performance (e.g., in chess).

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Chase & Simon	1973a	"This paper develops a technique for isolating and studying the perceptual structures that chess players perceive. Three chess players of varying strength — from master to novice — were confronted with two tasks: (1) A perception task, where the player reproduces a chess position in plain view, and (2) de Groot's (1965) short-term recall task, where the player reproduces a chess position after viewing it for 5 sec. The successive glances at the position in the perceptual task and long pauses in the memory task were used to segment the structures in the reconstruction protocol. The size and nature of these structures were then analyzed as a function of chess skill." (p. 55)	Underlying mental structures provide the basis for expert performance.
Chase & Simon	1973b	"… chess skill depends in large part upon a vast, organized long-term memory of specific information about chessboard patterns. Only chess-related tasks that tap this organization … are sensitive to chess skill. Although there clearly must be a set of specific aptitudes … that together comprise a talent for chess, individual differences in such aptitudes are largely overshadowed by immense individual differences in chess experience. Hence, the overriding factor in chess skill is practice. The organization of the Master's elaborate repertoire of information takes thousands of hours to build up, and the same is true of any skilled task …. That is why *practice* is the major independent variable in the acquisition of skill." (italics in original) (p. 278-279)	Specifies that greatly superior long-term memory for sequences of chess moves, which are developed through experience over time, underlie individual performance differences.
Simon & Chase	1973	"In the course of our story … we will see the important constraint that a limited capacity short-term memory imposes on problem solving in chess and how this limit can be bypassed by specific perceptual knowledge acquired through long experience, stored in long-term memory, and accessed by perceptual discrimination processes." (p. 394)	Indicates that how information is stored in memory also explains differences in performance.
Larkin, McDermott, Simon, & Simon	1980	"Although a sizable body of knowledge is prerequisite to expert skill, that knowledge must be indexed by large numbers of patterns that, on recognition, guide the expert in a fraction of a second to relevant parts of the knowledge store. The knowledge forms complex schemata that can guide a problem's interpretation and solution and that constitute a large part of what we call physical intuition." (p. 1336) "Experts solve complex problems considerably faster and more accurately than novices do. Those differences are commonplaces of everyday experience, yet only recently have we begun to understand what the expert does differently from the novice to account for this superiority." (p. 1335) "The most obvious difference between expert and novice is that the expert knows a great many things the novice does not know and can rapidly evoke the particular items relevant to the problem at hand." (p. 1336) "The principal explanation for these memory phenomena is the 'chunking' of familiar stimuli (2). (A chunk is any stimulus that has become familiar from previous repeated exposure and hence is recognizable as a single unit." (p. 1336)	Information stored in memory that becomes familiar is 'chunked' to allow for the rapid recall of relevant information in problem solving, providing another clue to individual performance differences.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Chase & Ericsson	1981	"… skilled memory is the rapid and efficient utilization of memory in some knowledge domain to perform a task at an expert level. Without the knowledge base, task performance by a novice is poor or nonexistent." (p. 141) "During the course of our analysis …, we have outlined three principles of skilled memory. The first principle—that skilled memory involves knowledge structures in semantic memory—is already well-documented in the literature. It is the second and third principles that we believe are important additional contributions to our understanding of skilled memory. These principles say that experts store and retrieve intermediate knowledge structures, and that they do it *fast*. The key to skilled memory performance, we believe, is in the ability to rapidly store and reaccess intermediate knowledge states. … This rapidly accessible intermediate knowledge structure in effect provides the expert with a large memory system that has the properties of short-term memory. The advantages are enormous. It frees up short-term memory for other processes. Direct accessibility reduces search, which costs time, takes up processing capacity, and dredges up interfering knowledge states. Finally, it allows the expert to organize and execute more complex mental operations than would otherwise be impossible with the small capacity of short-term memory." (p. 185)	Skilled memory based on intermediate knowledge structures may also explain expert performance.
Chi, Feltovich, & Glaser	1981	"The representation of physics problems in relation to the organization of physics knowledge is investigated in experts and novices. … Results from sorting tasks and protocols reveal that experts and novices begin their problem representations with specifiably different problem categories, and completion of the representations depends on the knowledge associated with the categories. For, the experts initially abstract physics principles to approach and solve a problem representation, whereas novices base their representation and approaches on the problem's literal features." (p. 121)	Differences in memory structures in experts and novices suggests that different strategies to problem solving are undertaken and thus lead to differences in performance, which highlights how the development of expertise can influence performance differences.
Chase & Ericsson	1982	"… exceptional memory performance has been attributed to the existence of a vast long-term knowledge base built up by the expert with years of practice. In game-playing domains this knowledge takes the form, in part, of patterns which serve as retrieval aids to desirable courses of action. … In other domains, hierarchical knowledge structures exist in the expert for the purpose of organizing knowledge." (p. 6) "…we have discovered three principles of memory skill that we believe characterize the cognitive processes underlying this memory skill: (a) subjects use meaningful associations with material in long-term memory, (b) subjects store the order of items in another long-term memory structure that we have called a 'retrieval structure,' and (c) subjects' encoding and retrieval operations speed up with practice." (p. 8)	In skilled memory tasks, prior experiences (i.e., associations in long-term memory) are used in developing, over time, knowledge structures that enhance performance, which reaffirms that knowledge structures, *and the time it takes to develop them*, are fundamental in explaining individual performance differences.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Glaser	1982	"Of particular interest here is the emphasis in recent cognitive research on the organization and structure of knowledge and on the processes of task performance. … This work suggests that the way information is stored in and retrieved from long-term memory can account in large part for differences in performance between experts and novices in various task domains. This view further suggests that a possible difference in cognitive functioning between individual with high and low aptitude is their ability to organize information in ways that make it readily accessible for transfer from old to new problems." (p. 298)	Reviews work on how the organization and structure of knowledge – between experts and novices – influences task performance, for both old and new tasks.
Schoenfeld & Herrmann	1982	"Students' perceptions of the structure of mathematical problems were examined before and after a month-long intensive course on mathematical problem solving. These perceptions were compared with experts' perceptions. Subjects sorted problems on the basis of similarity. Hierarchical clustering analysis of the sorting data indicated that novices perceive problems on the basis of 'surface structure' (i.e., words or objects described in the problem statement). After the course the students perceived problem relatedness more like the experts—according to principles or methods relevant for problem solution. Thus, criteria for problem perception shift as a person's knowledge bases become more richly structured." (p. 484)	Shows that for mathematical problems, as individuals gain expertise their knowledge-base becomes more richly structured, leading them to perceive problems more like experts.
Fiske, Kinder, & Larter	1983	"People draw heavily on accumulated experience to aid their understanding. The more experience they have, the more easily and thoroughly they can assimilate new information. … The basic point is this: expertise affects *how* old information is used to understand new information. " (italics in original) (p. 382) "Here we take the position that shared knowledge may be used differently by different people. Essentially, we are arguing for a distinction between content knowledge (schemata, prototypes, and the like) and process knowledge (strategies)." (p. 383) "The essential implication of the differences in knowledge content—amount and structure—is that not only do experts know more than novices, but also their knowledge is more tightly organized. Thus, despite the greater quantity of information available to them, they can handle it more efficiently. Specifically, tighter organization of information implies that experts can hold more in short-term memory. … Assuming a limited capacity for short-term memory or on-line processing, experts and novices place different strains on the system. Experts and novices encountering the same information … are using up differing amounts of on-line capacity. The extra capacity of experts potentially frees them to process additional relevant information, simply as a function of their greater organization of the same information content. Thus, differences in the organization of information allow differences in *strategies* for the use of that information." (italics in original) (p. 384)	Provides evidence to support the notion that experts and novices utilize information differently due to the differences in the organization of the knowledge structures.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Glaser	1984	"A guiding question for us in this work is, How does the organization of the knowledge base contribute to the observed thinking of experts and novices? Our assumption is that the relation between the structure of the knowledge base and problem-solving process is mediated through the quality of the representation of the problem. We define a problem representation as a cognitive structure corresponding to a problem that is constructed by a solver on the basis of domain-related knowledge and its organization. At the initial stage of problem analysis, the problem solver attempts to 'understand' the problem by constructing an initial problem representation. The quality, completeness, and coherence of this internal representation determine the efficiency and accuracy of further thinking. And these characteristics of the problem representation are determined by the knowledge available to the problem solver and the way the knowledge is organized." (p. 98) "In addition, the knowledge of experts includes knowledge about the application of what they know. For the expert, these aspects of knowledge comprise tightly connected schema. The novice's schema, on the other hand, may contain sufficient information about a problem situation but lack knowledge of related principles and their application. Our interpretation is that the problem-solving difficulty of novices can be attributed largely to the inadequacies of their knowledge bases and not to limitations in their processing capabilities such as the inability to use problem-solving heuristics. Novices show effective heuristics; however, the limitations of their thinking derive from their inability to infer further knowledge from the literal cues in the problem statement. In contrast, these inferences are necessarily generated in the context of the knowledge structure that the experts have acquired." (p. 99)	At the core of performance differences (e.g., in problem solving) are differences in the knowledge structures of experts versus novices, and not differences in processing capabilities across these groups. The quality of these representations are a function of existing knowledge structures and their organization.
Lord & Maher	1990	"The recognition that expertise supplements simplified information processing defines a set of models which are labeled expert information processing. The key assumption underlying these models is that people rely on already developed knowledge structures to supplement simplified means of processing information. However, these knowledge structures pertain only to a specific content domain." (p. 13)	The expert model of information processing is summarized in the management literature, suggesting the broader appeal of expert information processing research to different practical and theoretical domains.
Day & Lord	1992	"The results … indicated that experts tended to categorize the ill-structured problems significantly faster than novices, … had greater variance in the number of categories used and … incorporated more problem information [in a problem sorting task]." (p. 35)	Research on organizational decision-making empirically confirms prior conceptualizations and findings of expert information processing research.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Ericsson, Krampe, & Tesch-Römer	1993	"The theoretical framework … explains expert performance as the end result of individuals' prolonged efforts to improve performance while negotiating motivational and external constraints. In most domains of expertise, individuals begin in their childhood a regimen of effortful activities (deliberate practice) designed to optimize improvement. Individual differences, even among elite performers, are closely related to assessed amounts of deliberate practice. Many characteristics once believed to reflect innate talent are actually the result of intense practice extended for a minimum of 10 years." (p. 363)	Research on expertise moves from trying to understand expert/ novice differences to attempting to understand how expertise develops. Deliberate practice seems to play a central role.
Ericsson & Charness	1994	"… to attain exceptional levels of performance, subjects must … undergo a very long period of active learning, during which they refine and improve their skill, ideally under the supervision of a teacher or coach." (p. 737) "Our analysis has shown that the central mechanisms mediating the superior performance of experts are acquired; therefore acquisition of relevant knowledge and skills may be the major limiting factor in attaining expert performance." (p. 737)	Expert performance can be achieved through engaging in deliberate practice over an extended period of time, suggesting that studies of expertise need to account for this time element.
Ericsson & Kintsch	1995	"To account for the large demands on working memory during text comprehension and expert performance, the traditional models of working memory involving temporary storage must be extended to include working memory based on storage in long-term memory. In the proposed theoretical framework cognitive processes are viewed as a sequence of stable states representing end products of processing. In skilled activities, acquired memory skills allow these end products to be stored in long-term memory and kept directly accessible by means of retrieval cues in short-term memory, as proposed by skilled memory theory." (p. 211) "… reliance on acquired memory skills enables individuals to use [long-term memory] LTM as an efficient extension of [short-term working memory] ST-WM in particular domains and activities after sufficient practice and training." (p. 211) "… we show that mechanisms similar to those underlying a 10-fold increase in performance on tests of [short-term memory] STM are used by experts and skilled performers to expand their effective working memory capacity." (p. 211)	Revisits the mechanisms underlying working memory in expert performance, and suggests that the working memory capacity of experts is increased due to these mechanisms, thus linking performance to deep knowledge stored in long-term memory via retrieval cues between short- and long-term working memory.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Gobet & Simon	1998	"… this paper re-examines experimentally the finding of Chase and Simon (1973a) that the differences in ability of chess players at different skill levels to copy and to recall positions are attributable to the experts' storage of thousands of chunks (patterned clusters of pieces) in long-term memory. … We conclude that the two-second inter-chunk interval used to define chunk boundaries is robust, and that chunks have psychological reality, … and extend the chunking theory to take account of the evidence for large retrieval structures (templates) in long-term memory." (p. 225)	Links chunking theory to "templates" (i.e., knowledge structures) in long-term memory.
Ericsson	2003	"… the recent evidence from imaging brain activity during exceptional performance provides very strong support for the acquired nature of exceptional memory. It shows that the experts' reported encoding methods differ qualitatively from those of the controls and that the differential pattern of activation of brain regions during memorization can be explained by these strategy differences. This research provides compelling evidence that ordinary people can dramatically improve their memory performance with appropriate strategies and practice." (p. 235)	Provides support – via reviewing brain imaging studies – for the notion that expert performance is made and not born; i.e., that expertise is acquired via deliberate practice and is thus attainable by ordinary people.
Ericsson, Delaney, Weaver, & Mahadevan	2004	"After extensive laboratory testing of the famous memorist Rajan, Thompson, Cowan, and Frieman (1993) proposed that he was innately endowed with a superior memory capacity for digits and letters and thus violated the hypothesis that exceptional memory fully reflects acquired 'skilled memory.' We successfully replicated the empirical phenomena that led them to their conclusions. From additional analyses and new experiments, we found support for an alternative hypothesis, namely that Rajan's superior memory for digits was mediated by learned encoding techniques that he acquired during nearly a thousand hours of practice memorizing the mathematical constant π." (p. 191)	Provides further support that expert performance is made – via deliberate practice over a considerable amount of time – and not born.
Bradley, Paul, & Seeman	2006	"This paper reports the results of a study in which the tacit knowledge of domain experts was elicited, represented, and analyzed for validity. The subjects were a group of instructors and students at a USPS training school whose memory structures were analyzed for evidence of two common characteristics of expertise: holistic perception and use of abstract concepts. No evidence of either characteristic was found in the more experienced instructor group but, when the subjects were regrouped based on observed performance, the cognitive models of the high performers contained structural evidence of both characteristics. This finding led to the conclusion that experience alone is not an indicator of expertise. Other factors, such as the cognitive ability to correctly structure those experiences, must also be present." (p. 77)	Suggests that experience alone is not an indicator of expertise, and thus that expertise ought to be measured by observed performance versus measures of experience.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
		Expert Scripts/ Knowledge Structures	
Schank & Abelson	1977	"The form of memory organization upon which our arguments are based is the notion of episodic memory. An episodic view of memory claims that memory is organized around personal experiences or episodes rather than around abstract semantic categories." (p. 17) "An episodic memory … is organized around propositions linked together by their occurrence in the same event or time span. Objects are most commonly defined by their place in a sequence of propositions describing the events associated with an object for an individual" (p. 18) "Some episodes are reminiscent of others. As an economy measure in the storage of episodes, when enough of them are alike they are remembered in term of a standardized generalized episode which we call a script." (p. 19) "We recognize two classes of knowledge that people bring to bear during the understanding process: general knowledge and specific knowledge. General knowledge enables a person to understand and interpret another person's actions simply because the other person is a human being with certain standard needs who lives in a world which has certain standard methods of getting those needs fulfilled. … We use specific knowledge to interpret and participate in events we have been though many times. Specific detailed knowledge about a situation allows us to do less processing and wondering about frequently experience events. … The remainder of this chapter [on scripts] deals with the nature and form of such specific knowledge." (p. 37)	Discusses the idea of a script – a specific type of mental knowledge structure – developed over multiple iterations of similar experiences and that helps in reducing mental processing.
Graesser, Gordon, & Sawyer	1979	" The results suggested that discriminative accuracy is best explained by properties of a passage's representation rather than the amount of cognitive resources allocated at acquisition." (p. 319)	Tests script theory and shows that script performance can best be explained by the representation of the script versus the amount of mental processing allocated when the script was formed.
Abelson	1981	"There has been growing interest within several subfields of psychology in the schematic nature of mental representations of real-world objects and events. One simple form of schema is the script, embodying knowledge of stereotyped event sequences. This article traces applications of the script concept in artificial intelligence, cognitive psychology, and social psychology. … The suggested theoretic function of the script concept is to unify central notions in learning, developmental, clinical, social, and cognitive psychology."	Reviews script research and suggests that the function of the script concept helps to link schema-based (i.e., knowledge structure) research in learning, development, and behavior.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Gioia & Poole	1984	"A prototype script (a "protoscript") is a generic script appropriate to a class of situations (e.g., strategy meetings). Exposure to a new situation that shares some common elements with previous experiences cues a comparison-to-prototype process." (p. 450) "Scripts can be acquired by both direct and indirect means. Direct script acquisition includes interaction experience with other people, events, or situations. This experience tends to initiate a script development process." (p. 451) "Indirect script acquisition occurs by means of communication or media. Conversations with other people communicate expectations for appropriate behavior. Similarly, reading and watching the scripts portrayed in training films can provide good indications of behaviors fitting a number of common organizational situations." (P. 451) "Perhaps the progression toward automatic script processing is best represented as a continuum of script development …. It is anchored at one end by active, controlled cognitive processing (novel situations) and at the other by automatic processing (familiar situations)." (p. 451) "As repetitive situations or situations with partially stereotypical scenes occur, a protoscript begins to emerge. The protoscript serves as a basis for modifications that fit a current situation…. Finally, in complete or stereotypical situations, a schematized strong protoscript guides behavior that is performed automatically." (p. 453-454)	Abstract knowledge structures – developed through both repeated direct and indirect means – exist that aid in situation comprehension by comparing situational cues to prototypical situations, thus suggesting appropriate behavior.
Gioia & Manz	1985	"Vicarious learning and modeling are important processes in the acquisition, development, and alteration of behavior in organizations. The authors argue that a primary basis for vicarious learning is a cognitively held 'script' on the part of the observer of a model. A script is a procedural knowledge structure or schema for understanding and enacting behaviors. The close parallels are drawn between scripts and vicarious learning as vehicles for both understanding and influencing organizational behavior." (p. 527)	Links scripts with learning in an organizational setting.
Leddo & Abelson	1986	"We begin by constraining the type of knowledge structure within which explanations are to be sought – our examples come from scripted activities. Further, we … examine explanatory preferences among different possible plan failures, occurring at different points in the script. The reasons for this strategy are twofold: First, scripts have sequential structure, and choice of explanation may depend on sequence; … second, norms are available on various attributes of script actions, … and perhaps the explanatory priorities given to failures of different actions can be associated with these norms." (p. 107)	Outlines the structure of a script, which includes *sequences* and *norms*.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Read	1987	"People's primary attributional problem is to understand extended sequences of behavior. These sequences or episodes have four general components: the goal of the sequence, the plan into which the actions fit, the outcome of the plan, and the conditions that initiated the goal. People make extensive inferences to tie the individual events into a coherent, understandable scenario. Making such inferences depends on detailed knowledge. The result is a mental representation of the sequence that can be used as the basis for answers to requests for explanation." (p. 289) "The way in which a script is used in explanation depends heavily on whether we wish to explain the performance of the whole script (i.e., Why did he go to the restaurant?) or just a part of the script (i.e., Why did she look at the menu?)." (p. 290)	Links scripts to attribution theory; and suggests that scripts can be used as explanations for behavior and that the way a script it used for explanation is dependent on the desired explanation: the performance of the whole script or of part of the script.
Lord & Kernan	1987	"This paper focuses on the role cognitive scripts … play in generating purposive behaviors in organizations." (p. 265) "Although the argument presented here also relies heavily on an information processing perspective, the emphasis is on showing how cognitive systems guide the *output of purposeful behavior*." (italics in original) (p. 265) "… the goal-related content inherent in scripts provides organization and makes information meaningful; this, in turn, facilitates learning in initial stages of task performance. Once scripts are well-developed and learning is stabilized, consistent information related to a task can be encoded generically, while inconsistent or novel information can be encoded specifically and tagged into an existing script structure." (p. 273) "A second issue related to learning concerns changes in the content and structure of scripts as one becomes more experienced. Compared to novices, experts should have a greater repertoire of more thoroughly developed scripts for many work activities. Experts also may have more efficiently organized cognitive systems." (p. 273)	Ties the development (learning) and usage of scripts to the output of purposeful behavior in organizations, and hence to task performance. Also helps to understand how existing scripts are shaped by consistent and novel information.

Table 3.1: Selected Literature Addressing Expert Information Processing Theory (continued)

Source		Salient Quote(s)	Chronological Narrative
Mooney	1990	“Abstract knowledge of typical plans, generally called *plan schemata* or *scripts*, have been shown to play an important role in cognitive tasks. … However, the issue of how plan schemata are learned has not received much attention. To the extent that the learning issue has been addressed, it has generally been assumed that plan schemata are learned by induction across numerous experiences…. This article concerns the acquisition of plan schemata from specific observed instances by means of *explanation-based learning* (EBL). … EBL is capable of learning a general plan schema from a single observed instance by building and generalizing an explanation for how the observed plan achieves its goal. The ability of EBL to use existing knowledge to acquire a schema from a single instance distinguishes it from *similarity-based learning* methods which induce concepts from numerous examples and counter-examples. … In particular, this article describes how EBL of plan schemata from observation can improve the performance of *plan recognition*, the task of explaining the observed actions of others.” (italics in original) (p. 483-484)	Suggests that acquiring scripts by observation through using existing knowledge can influence task performance in explaining the observed actions of others.
Acton, Johnson, & Goldsmith	1994	“Network representations of student knowledge are usually evaluated by comparing them to an expert ‘referent’ structure. This study compared referent structures produced by the instructor, other experts, averaged experts, and an average based on the best students in the class. The referents were compared in their ability to predict exam performance in 2 college level computer programming courses and to differentiate among levels of expertise. Results showed that in terms of these criteria, (a) instructor-based referents were no better than other experts; (b) there was substantial variability among experts; and (c) structures derived from both averaged experts and averaged best students provided valid referents, but the expert-based referent was superior.” (p. 303)	Further support that knowledge structures between experts and novices differ.
Day, Arthur & Gettman	2001	“As individuals develop expertise in a domain, their knowledge structures converge toward a true representation of that domain. … Assuming that experts' organization and comprehension of domain knowledge are a close approximation of the true representation of that domain, then similarity to an established expert structure can be considered an indicator of skill development.” (p. 1023)	Suggests the development of knowledge structures implies that learning (skill acquisition) has occurred.

scholars have developed theory to relate individuals to their information environments through mental structures and processes that explain how information is acquired, stored, and retrieved from individual memory (Neisser, 1967). An important concept that emerges from this work is the notion that human action jointly influences and is influenced by the information environment via information processing. This notion provides the basis for the development of different models of information processing that attempt to explain differences in human action. In the IS management setting, one of these models focuses on individual performance differences: the *expert* model (Lord & Maher, 1990).

Based on the aforementioned foundational work, we can draw the notion that the expert information processing model attempts to explain individual performance differences based on how individuals store and retrieve information from long-term memory. This model suggests, for example, that experts do so differently than novices, and that the difference lies in the highly ordered knowledge structures that experts utilize to achieve exceptional performance in a specific domain, knowledge structures that have not yet developed in novices (Glaser, 1984). These knowledge structures are organized around context-relevant scripts, or expert scripts (Abelson, 1976; Schank & Abelson, 1977).

Expert scripts are highly developed, highly organized knowledge structures – "mental representations of the causally-connected actions, props, and participants that are involved in common activities" (Galambos, Abelson, & Black, 1986: 19) – that individuals acquire over an extended period of deliberate practice (Ericsson et al., 1993; H. A. Simon & Chase, 1973), and which permit expert performance by an individual in a specific domain (Glaser, 1984). Expert scripts have two key parts: (1) a *sequential structure* of ordered actions; and (2) *norms* that guide these actions (Leddo & Abelson, 1986: 107). An expert script specifies, in steps, the actions an expert takes (the sequence), and how and in what situations these actions should be performed (the norms). The sequence part of expert scripts are learned fairly quickly; it is the norms that take time to develop (Gioia & Poole, 1984). However, the time it takes to acquire the norms give rise to deep domain-specific knowledge. Expert scripts are thus a fundamental explanation for expertise and its development: as expert scripts are acquired, expertise becomes more-fully developed (Glaser, 1984).

From the EIPT literature surveyed, I have therefore drawn three premises, or key assertions found within that literature, that summarize the use of the EIPT lens in this dissertation research, as follows:

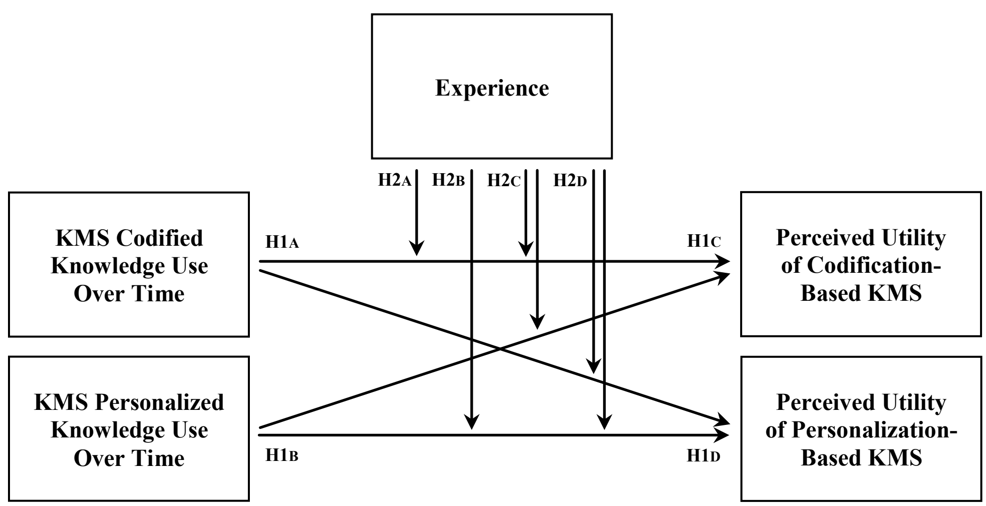
1. Because expertise is cognitive and relies upon ordered knowledge in a mind (Glaser, 1984), then to obtain expertise, an individual needs deliberate practice over an extended period of time to develop the requisite problem solving processes and knowledge base in that mind (Ericsson et al., 1993; H. A. Simon & Chase, 1973).
2. Because expertise is cognitive and relies upon ordered knowledge in a mind (Glaser, 1984), this ordered knowledge is divided in the mind into two qualitatively different elements: sequence (steps) and norms (standards) (Leddo & Abelson, 1986). Sequences can be learned fairly quickly, but the norms take time to develop (Gioia & Poole, 1984).

3. Because expertise is cognitive and relies upon ordered knowledge in a mind, expertise permits individuals to draw on deep knowledge versus surface features (Chi, Feltovich, & Glaser, 1981; Glaser, 1984; Schoenfeld & Herrmann, 1982). The acquisition of the norms over time is what gives rise to the deep knowledge (Gioia & Poole, 1984).

A Research Model

In order to investigate how utilizing knowledge over time from both codification-based KMS and personalization-based KMS influences system success, I developed a research model that specifies the KMS success factors, human/ machine factors over time, and a human factor moderator, and their hypothesized relationships based on a concepts from EIPT (Figure 3.2).

Figure 3.2: Research Model



KMS Success Factors – The Perceived Utility of KMS

As noted previously, perceptions of IT are one way in which system success is determined (e.g., F. D. Davis, 1989; Robey, 1979). Furthermore, perceptions have been used as either explanations for individuals' adoption and IT acceptance (e.g., F. D. Davis, 1989; Wixom & Todd, 2005), or as evaluations of utility/ satisfaction with the IT in use (e.g., DeLone & McLean, 2003; Seddon, 1997). In this research I utilize the latter usage of perceptions of IT. Since I study the use of two types of KMS – codification-based KMS and personalization-based KMS – the two factors representing KMS success are the *perceived utility of codification-based KMS* and the *perceived utility of personalization-based KMS*.

Human/ Machine Factors Over Time – KMS Knowledge Use Over Time

According to the definition of system use discussed previously, human/ machine factors require specifying the user, system(s), and task (Burton-Jones & Straub, 2006). Accordingly, in my research model I focus on *knowledge workers* who utilize *knowledge management systems (KMS)* to extend their mental capabilities to perform a *problem solving task* with higher expertise. I focus on these users, systems, and task for several reasons. First, focusing on knowledge workers provides a context where system use is voluntary: knowledge workers can choose whether to utilize KMS or not, choose which KMS to use, and choose how much to use them, in their problem solving task. Second, focusing on KMS provides a context where multiple systems providing access to different kinds of knowledge (e.g., Alavi & Leidner, 2001; Nonaka, 1994) are available to knowledge workers to find the requisite knowledge: codification-based KMS and personalization-based KMS (Hansen et al., 1999). Codification-based KMS provide access to knowledge that has been made explicit, whereas personalization-based KMS provide access to knowledge that is tacit (Nonaka, 1994; Polanyi, 1966). Third, focusing on a task where system use is not a part of the task (i.e., problem solving), but is one step removed from the task provides a context where system use over time is highlighted because the benefits from use do not immediately appear (Ko & Dennis, 2011: 136). Thus, the human/ machine factors selected for the research model are *KMS codified knowledge use over time*, and *KMS personalized knowledge use over time*. Note, however, that because codification-based KMS often contain codified knowledge of various types (e.g., problem solving documents, product manuals, product bulletins, etc.), as a boundary condition I make a distinction between the use of all codified knowledge potentially available in a codification-based KMS, and that codified knowledge which is task-specific. Hence, given the nature of the task, *KMS codified knowledge use over time* refers to the use, over time, of that codified knowledge which is problem-solving-task oriented only.

According to EIPT and as summarized in Premise 1, because expertise is cognitive and relies upon ordered knowledge in a mind (Glaser, 1984), in order to obtain expertise in a specific domain it takes an extended period of time of deliberate practice to acquire the requisite problem solving processes and knowledge base (Ericsson et al., 1993; H. A. Simon & Chase, 1973).

For knowledge workers engaged in technical support problem solving, their expertise is developed by becoming better-informed in learning-by-doing (deliberate practice) over time. The interplay of problem solving and expertise development is facilitated by KMS; for, until expertise has more-fully developed, knowledge workers need to rely upon external help – such as KMS – for knowledge needed to solve problems. However, because developing expertise continually involves internalizing and mentally ordering the requisite knowledge gained through learning-by-doing over time, being able to utilize the knowledge from KMS, and derive the benefits from this knowledge will take time, suggesting that perceived KMS success will increase over time as the knowledge from the KMS is used. Hence, as baseline hypotheses,

HYPOTHESIS 1 (H1-general hypothesis): *Perceived KMS success from the use of KMS knowledge increases over time.*

HYPOTHESIS 1A (H1A): *The perceived utility of codification-based KMS from the use of KMS codified knowledge increases over time.*

HYPOTHESIS 1B (H1B): *The perceived utility of personalization-based KMS from the use of KMS personalized knowledge increases over time.*

These hypotheses, if supported, should both confirm prior research (in the case of H1A; see Ko & Dennis, 2011), and extend this work to include the success implications of personalized knowledge use over time (in the case of H1B). The EIPT lens is clear about the observed relationships we would expect here. However, the basic time-focused learning-based argument used here and in prior KMS success theory does not sufficiently explain what we might expect when both kinds of knowledge are used from both types of KMS, as is often the case in knowledge work. Helpfully, the EIPT lens also provides a more nuanced learning perspective and informs us in this regard, providing the mechanisms upon which learning and expertise is developed, and giving us a theoretical foundation upon which we may further hypothesize the expected cross-relationships (as shown in Figure 3.2) between knowledge use over time of both kinds of KMS knowledge and KMS success.

According to EIPT and as summarized in Premise 2, because expertise is cognitive and relies upon ordered knowledge in a mind (Glaser, 1984), this ordered knowledge in the mind is divided into two qualitatively different elements: sequence (steps) and norms (standards) (Leddo & Abelson, 1986). Sequences can be learned fairly quickly, but the norms take time to develop (Gioia & Poole, 1984).

The terms *sequence* and *norms* are those used within the EIPT literature to refer to each part of an expert script (i.e., the mental knowledge structures acquired over time as expertise develops). In technical support problem solving parlance, however, terms such as *solution steps* and *solution guidelines*, representing sequence and norms, respectively, are more applicable to this domain and will thus be used when referencing this domain.

In using knowledge from a KMS, according to Premise 2 the influence that using this knowledge will have on KMS success depends on the type of KMS knowledge used: whether codified or personalized. The reason for this relates to: (1) the propensity for KMS codified knowledge use versus KMS personalized knowledge use to provide more solution steps-related knowledge versus solution guideline-related knowledge, respectively; and (2) the fact that the order with which steps and guidelines are acquired/internalized matters. Let us explore this line of reasoning in more depth.

To begin let us look more closely at KMS codified knowledge use. Codification involves making explicit that which is tacit (Nonaka, 1994), and entails cataloging knowledge and storing the result in a KMS, such as a document repository, for later use by knowledge workers. Hansen and colleagues term this a people-to-document approach (Hansen et al., 1999).

For knowledge workers engaged in technical support problem solving, KMS codified knowledge documents are structured in a way to facilitate do-it-yourself search of catalogued knowledge, providing an efficient, clear, and precise set of actions to follow in solving a problem, with each document specifying the actions to take to solve a specific problem. The reasoning behind this economical structure relates to a document's purpose: to enable knowledge workers to quickly and easily follow the suggested actions so that problems can be solved quickly (Gray & Durcikova, 2006). Because of this, documents do not contain a lot of extra information, such as why specific actions are suggested, why they are suggested in a specific order, and so on. To be economical, documents leave out information that may be applicable for an appropriate application of actions, making assumptions about, for example, the problem situations and the users trying to perform the actions (e.g., that users have the requisite knowledge to follow and appropriately apply the actions). In this sense, documents have a propensity towards being rich in *solution step*-related knowledge: the specific actions that must be taken to solve problems. Knowledge workers who thus utilize KMS codified knowledge documents in their problem solving work predominantly gain access to solution step-rich knowledge, which allows them to more-quickly solve problems and through learning-by-doing internalize this knowledge as sequences in expert scripts.

For KMS personalized knowledge use, personalization involves the giving and receiving of expert advice, insight, help, and support, directly between two or more people via some communication channel. Hansen and colleagues term this a person-to-person approach (Hansen et al., 1999).

For knowledge workers engaged in technical support problem solving, KMS personalized knowledge use provides the knowledge worker with a considerable amount of knowledge from other experts. These interactions allow knowledge workers to engage in dialogue with others, who help in diagnosing and suggesting an appropriate course of action to solve the problem at hand (Orr, 1996). In these interactions, knowledge workers can describe the problem circumstances, what has been tried thus far, and what the result has been. They are also able to ask problem-clarifying questions, and likewise receive immediate feedback. At the very least, KMS personalized knowledge use allows them to get the problem solving help they need. But more importantly, this interaction also allows them to attach meaning to an inherently ambiguous problem situation which they cannot make sense of without expert help. This is important given the need to develop skill-based guidance and focus in their problem solving activities. By better understanding and comprehending the problems they face and the suitable actions that are suggested, when faced with the same or similar problems in the future, they will better be able to act without help from others. In a sense, KMS personalized knowledge use helps to establish the *solution guidelines* associated with problems and their suggested solution steps: the guidelines that specify when to follow a set of actions and why these actions are taken. Knowledge workers who thus utilize KMS personalized knowledge in their problem solving work gain access to solution guideline-rich knowledge and through learning-by-doing internalize this knowledge as norms in expert scripts.[1] This allows them to better-apply the correct solution steps to the problems they encounter.

[1] This is not to say that the KMS personalized knowledge use is devoid of solution step knowledge; it just has a greater propensity towards containing solution guideline-rich knowledge due to the personal contact

According to this EIPT logic as applied to knowledge work in technical support problem solving, *both kinds* of knowledge available from each type of KMS (respectively) are needed to develop the requisite problem solving processes and knowledge base upon which expert performance operates. Thus, knowledge workers who use both KMS codified knowledge and KMS personalized knowledge in developing these problem solving processes and knowledge base will likely view both types of KMS more favorably, leading them to exhibit a higher perceived utility of each. The reasoning is that using both better-enables knowledge workers to jointly acquire and internalize the solution steps and solution guidelines, respectively, needed to develop the requisite problem solving expertise. And furthermore, like H1A and H1B and according to premise 1, these perceptions are likely to increase over time. Consequently,

> HYPOTHESIS 1C (H1C): *The perceived utility of codification-based KMS from the use of both KMS codified knowledge and KMS personalized knowledge increases over time.*

> HYPOTHESIS 1D (H1D): *The perceived utility of personalization-based KMS from the use of both KMS codified knowledge and KMS personalized knowledge increases over time.*

A Human Factor Moderator – The Role of Knowledge Worker Experience

As discussed previously, individual users' experience has been shown to have a moderating influence on system success. Thus, individual user experience is included as a moderator in the research model.

Premise 2 also has an explanation for the influence of experience on KMS knowledge used and perceived KMS success. The implication of this premise is that

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(Glaser, 1984; Orr, 1996). The reverse is also the case with KMS codified knowledge use, it having the propensity towards containing greater solution step-rich knowledge.

knowledge worker experience will influence to what extent knowledge workers place value on a given type of KMS vis-à-vis the other type of KMS, based on the following rationale. Because solution steps (i.e., sequences) can be learned fairly quickly, whereas the solution guidelines (i.e., norms) take more time to develop (Gioia & Poole, 1984), it is expected that knowledge workers with less-experience will find using codification-based knowledge more helpful vis-à-vis personalization-based knowledge, given that they are still acquiring and internalizing the solution steps needed for problem solving and are thus less focused on acquiring the guidelines that underscore solution use. Consequently, less-experienced knowledge workers will likely exhibit a higher perceived utility of codification-based KMS than more-experienced knowledge workers. On the other hand, more-experienced knowledge workers have put in more time acquiring and internalizing the solution steps, and are thus more focused on understanding the solution guidelines for the already-internalized steps. Thus, more-experienced knowledge workers will likely exhibit a higher perceived utility of personalization-based KMS than less-experienced knowledge workers. Hence,

> HYPOTHESIS 2 (H2-general hypothesis): *Experience will moderate the relationship between KMS knowledge use over time and perceived KMS success.*

> HYPOTHESIS 2A (H2A): *Experience will moderate the relationship between KMS codified knowledge use over time and the perceived utility of codification-based KMS such that less-experienced knowledge workers will exhibit a higher perceived utility of codification-based KMS than more-experienced workers.*

> HYPOTHESIS 2B (H2B): *Experience will moderate the relationship between KMS personalized knowledge use over time and the perceived utility of personalization-based KMS such that more-experienced*

knowledge workers will exhibit a higher perceived utility of personalization-based KMS than less-experienced workers.

The above rationale is also applicable to hypothesizing the moderating influence of experience on the cross-relationships. It is therefore expected that, given the focus on acquiring solution steps, less-experienced knowledge workers would exhibit a higher perceived utility of codification-based KMS when both types of knowledge are used, whereas more-experienced knowledge workers, given their focus on acquiring solution guidelines, would exhibit a higher perceived utility of personalization-based KMS when both types of knowledge are used. Thus,

HYPOTHESIS 2C (H2C): *Experience will moderate the relationship between the use of both KMS codified knowledge and KMS personalized knowledge over time and the perceived utility of codification-based KMS such that less-experienced knowledge workers will exhibit a higher perceived utility of codification-based KMS than more-experienced workers.*

HYPOTHESIS 2D (H2D): *Experience will moderate the relationship between the use of both KMS codified knowledge and KMS personalized knowledge over time and the perceived utility of personalization-based KMS such that more-experienced knowledge workers will exhibit a higher perceived utility of personalization-based KMS than less-experienced workers.*

CHAPTER 4. METHODS

The technical support environment provides an excellent setting to study the utilization of KMS knowledge because KM is central to the problem solving work undertaken in this environment (Das, 2003). In this setting, both types of KMS knowledge are used. And further, in this environment KMS utilization can be easily identified through system use logs, which helps in gathering data on KMS knowledge used. The remainder of this chapter will address the methods I use for this research: the proposed setting, data gathering, measurement, and data analysis methods I use to test the hypotheses specified.

Research Setting

The research setting entails the technical support group for a company in the industrial environmental heating and cooling industry. In this setting, technical problem solving support for the company's overall product portfolio is provided to field support technicians (those individuals using the KMS) located at various field offices throughout the United States. Field support technicians in turn provide on-site technical problem solving support for these products to clients of the company: the organizations and institutions with installed company products.

Data Gathering

The data to test the proposed relationships between KMS knowledge used over time and perceived KMS success come from several sources generated within the company and as such are secondary rather than primary data. Two and a half years of semi-annual perceived KMS success data (July 2008 to December 2010), and three and a half years of KMS use data (July 2007 to December 2010) were available from the company, and in this respect the data are longitudinal. Complete perceptions and use data from 336 field support technicians who used both types of KMS are available, an approximately 15% response rate. These sources and the data from each will be discussed in more detail below.

Perceived KMS success data come from semi-annual surveys administered to field support representatives by the company's KM group. The semi-annual surveys are conducted to understand field support technicians' perceptions of different KM efforts provided by the company. Included in the surveys are questions that relate to the perceived utility of the company's online document repository and the perceived utility of their call system.

Data with respect to KMS knowledge used over time come from various systems utilized when field support technicians obtain technical support. Prior research suggests that system use data that are computer-recorded are generally preferred to those that are self-reported (Straub, Limayem, & Karahanna-Evaristo, 1995). As such, for the operationalization of KMS codified knowledge used over time, system use logs of field support technicians searching for support documentation in the company's online document repository system were obtained. And for KMS personalized knowledge used over time, tickets created by technical support representatives in the company's incident management system when field support technicians contact the call center were acquired.

The data for field support technician experience was obtained from the KM group in the company, which provided some information about the population of field support technicians in question.

Measurement

The variables of interest are measured in several ways appropriate to the data in question, as illustrated in Table 4.1.

Perceived Utility of KMS

The dependent (outcome) variables – *perceived utility of codification-based KMS* and *perceived utility of personalization-based KMS* – are measured via self-reported online questionnaires. For each KMS type, a two-item, Likert-type scale developed by the KM group in the company was used. While Likert-type items are generally considered ordinal, when item responses are aggregated they can operate as though interval scaled (Nunnally, 1978), which then permits the use of inferential statistics. This approach is consistent with past research which has measured perceptions in the system success literature (e.g., F. D. Davis, 1989).

Knowledge Use Over Time

Measures for the independent (predictor) variables – *KMS codified knowledge use over time only*, *KMS personalized knowledge use over time only*, and *both KMS codified knowledge and KMS personalized knowledge use over time* – are measured via system use logs which detail a field support technician's interactions with the KMS. For each of these measures the general approach used herein is to count the number of times a certain kind of knowledge is used, for each semi-annual period from July 2007 to December 2010 and for each field support technician, respectively. Thus, *KMS codified knowledge use over time only* is measured by counting the number of problem solving documents displayed to a technician when the technician searches the document repository only, for each semi-annual period. *KMS personalized knowledge use over time only* is measured by

Table 4.1: Variables and Measurement

Variables		Measurement
		Perceived Utility of KMS Outcome Variables
DV	Perceived Utility of Codification-Based KMS	Semi-annual survey-based measure consisting of the sum of 5-point Likert-type responses to two items*: 1. Overall, how satisfied are you with [Name of codification-based KMS]? 2. How likely are you to recommend [Name of codification-based KMS] to others (if the subject comes up)?
DV	Perceived Utility of Personalization-Based KMS	Semi-annual survey-based measure consisting of the sum of 5-point Likert-type responses to two items*: 1. Overall, how satisfied are you with the phone system? 2. How likely are you to recommend [Phone # of personalization-based KMS] to others (if the subject comes up)?
		KMS Knowledge Use Predictor Variables
IV	KMS Codified Knowledge Use Over Time Only	System log-based measure from the document repository system consisting of semi-annual counts of problem-solving documents displayed to each field support technician only, per technician
IV	KMS Personalized Knowledge Use Over Time Only	System log-based measure from the incident management system consisting of semi-annual counts of call center tickets created for each field support technician only, per technician.
IV	Both KMS Codified Knowledge & KMS Personalized Knowledge Use Over Time	System log-based measure from both the incident management system and the document repository system consisting of the semi-annual counts where both call center tickets were created for and problem-solving documents were displayed to each field support technician, per technician.
		Moderator and Control Variables
Moderator	Technician Experience	Field Support Technician job title, segregated into five differing experience levels by the head of the KM group in the company.
Control	Time	A measure consisting of the different semi-annual periods in the study between July 2008 and December 2010, where time = 0 at the beginning of the study.
Control	Document Findability Over Time	Semi-annual survey-based measure consisting of a 5-point *non*-Likert-type response to one item*: 1. When using [Name of codification-based KMS], what percent of the time are you able to find your answer?
Control	KMS Non-Problem-Solving Codified Knowledge Use Over Time Only	System log-based measure from the document repository system consisting of semi-annual counts of non-problem-solving documents displayed to each field support technician only, per technician.
Control	Both KMS Personalized Knowledge & KMS Non-Problem-Solving Codified Knowledge Use Over Time	System log-based measure from both the incident management system and the document repository system consisting of the semi-annual counts where both call center tickets were created for and non-problem-solving documents were displayed to each field support technician, per technician.
Control	Total Technicians	A count of the number of other field support technicians in a given field service office available to a technician.

* Information that could identify the company were removed from this (these) item(s).

counting the number of call center tickets created for a technician when the technician calls the technical support call center only, for each semi-annual period. And *both KMS codified knowledge and KMS personalized knowledge use over time* is measured by counting when both a problem solving document is displayed and a call center ticket is created for a technician, for each semi-annual period. The data measured in this way, as counts, are considered ratio scaled, which also allows the use of inferential statistics (Nunnally, 1978; Trochim, 2001).

As has been established previously, prior research suggests that it takes time for problem solving expertise to develop, and that the benefits from KMS knowledge use do not immediately appear (Ko & Dennis, 2011). This finding is supported by a fundamental tenet of the EIPT lens, where the development of expertise happens over an extended period of time (see Premise 1). Taken together, this time-based expertise development argument suggests that there may be lag effects that occur regarding when the benefits from using knowledge from a KMS might appear, even more so than Ko and Dennis (2011) had supposed. As such, for each of my knowledge use variables I measure use at both 0-6 months and at 6-12 months prior to the administration of the semi-annual survey. The outcome from doing so will be discussed in more detail in the next chapter.

Experience

Because of the limitations imposed by the company on collecting personal information about field support technicians, I use technician job titles as a proxy for *technician experience*. These titles were segregated into five differing experience levels by the head of the KM group in the company. While measuring experience in this way is not ideal, I am limited to the data gathering possibilities and data available to me.

Controls

The classic threats to internal validity tend to be respondent characteristics, mortality, location, instrumentation, testing, history, maturation, respondent attitude, regression to the mean, and implementer bias (Fraenkel & Wallen, 1990; Trochim, 2001). In survey-based research, and specifically in the instrumentation process, Fraenkel and Wallen (1990) suggest specifically that location, history, and instrumentation threats can arise. While the nature of this research setting and data gathering efforts make it impossible to control for all of these threats, certain threats – instrumentation, testing, respondent characteristics, maturation, history, and location – are minimized through either the research design and data gathering efforts or through the addition of control variables (as shown in Table 4.1).

The nature of the research design and data gathering efforts helps to manage threats to internal validity due to instrumentation and testing. Instrumentation threats can often arise in longitudinal studies where surveys are administered at multiple time points, and specifically when changes in the testing instrument or its items are introduced (Trochim, 2001). In this research this threat is minimized because the same survey method and questions were used across each semi-annual survey. Also note that in this research some of the variables are measured via system use logs, which also negates instrumentation as a threat. Testing threats are also managed by the research design and data gathering efforts in that because the surveys were conducted on a semi-annual basis, a long enough period of time had elapsed between survey collection points such that a pretest-posttest testing bias is unlikely to have been introduced.

In an effort to manage threats to internal validity from respondent characteristics, maturation, history, and location, I include several variables as controls. For the threat due to respondent characteristics and maturation I include as a control the findability of repository documents over time (i.e., the extent to which, in aggregate over time, field support technicians can locate helpful documentation). *Document findability over time* helps to mitigate these threats because it accounts for, over time, some potential variability in technicians that may be due to their ability to effectively find the desired codified knowledge (and hence it is thus distinct from the subsequent use of this knowledge). *Document findability over time* was included as single-item response on the semi-annual surveys.

For similar reasons, I also include as controls the following to further help to mitigate threats due to respondent characteristics and maturation: (1) *KMS non-problem-solving codified knowledge use over time*; and (2) *both KMS personalized knowledge and KMS non-problem-solving codified knowledge use over time*. As mentioned previously, because codification-based KMS often also include documents that are not problem-solving related, I include these measures as controls to account for potential variability that may be present due to a technician's accessing of these other kinds of codified knowledge over time. These variables are measured in a similar way as to the independent variables listed previously, as counts, but instead as counts of the number of non-problem-solving documents displayed to a technician only, for each semi-annual period; or as the counts of both the number of call center tickets created and the number of non-problem-solving documents displayed to a technician, for each semi-annual period, respectively.

In addition, in an effort to manage threats from history, I include as a control each semi-annual period – referred to as *time* – to account for any global changes or events (e.g., the introduction of a new product line, the addition documents to the repository, the addition of more-knowledgeable call-center technical support representatives, etc.) that may have occurred during data gathering that, if not controlled for, could lead to an alternative explanation of my findings. And finally, location threats are minimized by including as a control the number of other field support technicians – referred to as *total technicians* – that may be available to a technician (i.e., those other technicians that work out of the same office location).

Data Analysis

Because the data used in this analysis are multilevel: i.e., KMS knowledge use over time and perception data are nested within individual field support technicians, Hierarchical Linear Modeling (HLM) (Raudenbush & Bryk, 2002) is appropriate for use in the data analysis. Due to the hierarchical structure of the data, traditional regression techniques are not appropriate for multilevel research designs whereas HLM is suitable for such designs (Hofmann, 1997; Raudenbush & Bryk, 2002). Further, the appropriateness of HLM for studying KMS knowledge use and its effects has previously been demonstrated by Ko and Dennis (2011) under similar circumstances. Accordingly, I first discuss the fundamentals of modeling with HLM, and then outline how I employ HLM for the analysis conducted in this research.

HLM Fundamentals

The purpose of modeling with HLM is to produce a series of models that, as a whole, address the research question and include all necessary predictors (variables)[2] and no unnecessary ones (Singer & Willett, 2003: 104–105). This purpose is accomplished through a multi-part process involving initial model specification – where the likely predictors to be modeled are determined and the hierarchies set – followed by iterations of model modification (re-specification) and comparison. In the next few paragraphs I outline the fundamentals of this multi-part process I used in this dissertation research.

Initial Model Specification. In HLM, model building is guided by the research question and relies upon both theory and statistical evidence. Initial model specification is largely theory-driven, where the theory suggests what relevant relationship between constructs should be modeled and thus what predictors should likely be included. However, statistical evidence (via preliminary analysis) can also guide initial model specification by suggesting in what ways the predictors should be modeled (i.e., as fixed, random, or nonrandomly varying) or whether they should be modeled at all (Raudenbush & Bryk, 2002; Singer & Willett, 2003). In this same way statistical evidence (via intermediate analysis) also influences further modifications made to the model. Hence, in modeling with HLM there is give-and-take between theory and statistical evidence regarding what predictors should be included and how they should be included, with the end-goal of being able to produce a set of models that are correctly specified and fit the data well, but that are also parsimonious.

[2] In HLM parlance, variables included in a model are termed *predictors*, and includes any independent variables, moderators, and controls.

As discussed previously, HLM is designed to deal with the multi-level structure of hierarchical data sets, such as with students nested within classrooms, measurement occasions nested within individuals (as in the data set in this research), and even more-complex, higher-order hierarchies (e.g., with 3+ levels). The reason for this is that in the HLM equation there are multiple error terms included, one (or more) for each level[3] (Snijders & Bosker, 2012: 42). Modeling thus occurs at multiple levels, the number of which is established at the outset and is determined by the research question, by the number of hierarchies available in the data set, and by statistical evidence. Predictors can be added at each level, ensuring that (in the case of modeling change over time) both time-variant predictors (at level 1) and time-invariant predictors (at level 2) can be modeled.

In HLM, a predictor may have multiple parameters, especially if modeling the predictor as having both fixed and random parts (Raudenbush & Bryk, 2002). A predictor's fixed part is often termed the *fixed effect*, while the random part of a predictor is termed the *variance component*. Each of a model's parameters are estimated using the maximum likelihood (ML) method by "maximizing numerically the log-likelihood function, the logarithm of the joint likelihood of observing all the sample data actually observed" (Singer & Willett, 2003: 116). After a model's parameters have been estimated they can each separately be evaluated by using single parameter hypothesis tests against the null hypothesis that, controlling for all other parameters in the model, a parameter's population value is equal to 0 (H_0: $\gamma = 0$ for fixed effects; H_0: $\sigma^2 = 0$ for variance components) versus the two-sided alternative that it is not (H_1: $\gamma \neq 0$ and H_1: $\sigma^2 \neq 0$,

[3] In the traditional multiple regression equation there is only one error term modeled.

respectively). For both fixed effects and variance components the *z*-statistic is computed (Singer & Willett, 2003: 71–74). While single parameter tests are useful for determining whether a parameter significantly adds to the model or not, for variance components these tests are sensitive to departures of normality (Singer & Willett, 2003: 73). Further, single parameter tests do not allow for comparisons to be made across models. Fortunately, a superior method to both testing hypotheses about variance components and comparing models exists in deviance-based tests (Singer & Willett, 2003: 73). These tests are further discussed below.

Comparing Model Fit. From the ML estimation process, the deviance statistic for the model is also produced (calculated from the sample log-likelihood), and is regarded as "a measure of the lack of fit between model and data" (Snijders & Bosker, 2012: 97). While the value of a deviance statistic cannot be directly interpreted, it is useful in comparing models to each other (if certain conditions are met) (Singer & Willett, 2003: 118; Snijders & Bosker, 2012: 97). Because model building in HLM takes place over multiple iterations, where in each iteration a prior model is in some meaningful way extended, such as by adding, retaining, or removing predictors (Singer & Willett, 2003: 105), there needs to be a way to compare models to see which model better fits the data. Deviance-based tests based on full maximum likelihood (FML) estimation (versus restricted maximum likelihood, or RML, estimation)[4] fulfill this role.

[4] In ML estimation there are two methods of estimation: full maximum likelihood (FML) and restricted maximum likelihood (RML). Singer and Willett state the following about each: "Under FML, we maximize the likelihood of the sample data; under RML, we maximize the likelihood of the sample *residuals*. As a result, an FML deviance statistic describes the fit of the entire model (both fixed and random effects), but a RML deviance statistic describes the fit of only its stochastic portion of the model (because, during estimation, its fixed effects are assumed 'known')" (*italics* in original) (2003: 118). Because of this difference in estimation, when conducting deviance-based tests to compare models where the fixed parts of

Models can be compared in various ways, with deviance-based tests being the most common. Deviance-based tests compare the difference between the deviance statistics of two models, and can be conducted to compare models that meet the following criteria: (1) the same data set must be used across models; and (2) one model must be nested within the other model (Singer & Willett, 2003: 118). Importantly, the difference between the models' deviance statistics can then be used as a test statistic against the null hypothesis that there is no difference between the models. This test statistic has a χ^2 distribution with degrees of freedom (*d.f.*) equal to the difference in the number of constraints (i.e., fixed and random parameters) imposed by each model. A test statistic with a significant χ^2 value suggests the extended model better fits the data than the prior model, and should thus be utilized (Singer & Willett, 2003: 118–119; Snijders & Bosker, 2012: 97).

Another way to compare models, which is a variation of the deviance-based, is based on additional information from the models run. These tests, termed the Akaike Information Criterion (AIC; Akaike, 1973) and the Bayesian Information Criterion (BIC; Schwarz, 1978), use the deviance statistics, but also add a penalty to each based on the number of parameters modeled (AIC and BIC) and based on the sample size (BIC only), making it possible to compare models that are non-nested (but still use the same data) (Singer & Willett, 2003: 120–121).

Models can also be compared by analyzing the change in the variance components of the models. Specifically, by analyzing the decline in the residual variance

the models have changed, FML must be used. RML may be used in comparing models where only the random part has changed (and thus the fixed parts are identical).

– or "that portion of the outcome variation *unexplained* by a model's predictors" (*italics* in original) (Singer & Willett, 2003: 103) – when predictors are added to the model, a Pseudo-R^2 statistic can be calculated for each level in the model, which gauges the proportional reduction in residual variance (Singer & Willett, 2003: 103). Several different Pseudo-R^2 calculations have been proposed by statisticians (Singer & Willett, 2003: 103–104; Snijders & Bosker, 2012: 111–113).

Deviance-based tests are not only useful for testing models that differ in their predictors, but can also be specifically used to determine whether a predictor should be modeled as having both fixed and random parts, or whether the random part can be removed entirely (Singer & Willett, 2003: 120; Snijders & Bosker, 2012: 102). As model complexity increases, so do the data requirements: a more complex model requires additional data to fit the model. Singer and Willett suggest that with "three (and sometimes fewer) measurement occasions per person, we often lack sufficient data to estimate additional variance components" (2003: 169). Deviance-based tests use RML estimation to determine whether modeling a predictor without its variance component is justified.

So to both summarize thus far and highlight the general steps to model building with HLM, modeling starts with initial model specification and then proceeds over multiple iterations of model modification (re-specification) and comparison, with the end-goal of being able to produce a set of models that are correctly specified and fit the data well, but that are also parsimonious. At the outset, both the research question and underlying theory base are used to develop the initial model specification, but may also include preliminary analysis to determine, for example, how the predictors should be modeled (e.g., without their random parts) (Raudenbush & Bryk, 2002: 112; Snijders & Bosker, 2012: 102).

Iterative HLM Process. Once the initial model is specified – that is, once the likely parameters that will be modeled have been determined and the hierarchies are known – the general approach to modeling change over time in HLM proceeds with fitting two unconditional models to the data (Singer & Willett, 2003: 92). Unconditional models do not contain (and are thus not conditioned by) any substantive predictors. The first of these models is the *unconditional means model*, and includes only the intercept and error terms, while the second of these models is the *unconditional growth model*, and includes the addition of the time component. According to Singer and Willett, these models "partition and quantify the outcome variation in two important ways: first, across people without regard to time (the unconditional means model), and second, across both people *and* time (the unconditional growth model)" (*italics* in original) (2003: 92). Fitting these models helps to establish a baseline upon which other more complex models can be compared. In addition, fitting these models helps to establish: "(1) whether there is systematic variation in [the] outcome that is worth exploring; and (2) *where* that variation resides (within or between people)" (*italics* in original) (Singer & Willett, 2003: 92).

Once the outcome variation has been partitioned and quantified, additional model building can then proceed iteratively, as was discussed above. Often predictors at level 1 (i.e., time-variant predictors at the measurement occasions level) are added first, followed by predictors at level 2 (i.e., time-invariant predictors at the individual level), and so on (for hierarchies greater than two) (Raudenbush & Bryk, 2002: 256). Once a suitable model has been identified via model comparison, hypotheses tests on the models parameters can then be conducted and interpreted.

HLM Analysis Approach

Modeling KMS knowledge use over time on the perceived utility of different types of KMS requires that I model two different sets of models: those for the perceived utility of codification-based KMS, and those for the perceived utility of personalization-based KMS. However, while each of these sets of models will be modeled separately, the general approach to modeling them is the same. Therefore, I first discuss the initial model specification, including the predictors to be modeled and at what level they are modeled. I then outline the models I iteratively develop to answer my research question and subsequent hypotheses.

Based on preliminary analysis, in this research I model two-level HLM models: measurement occasions (at level 1) nested within individuals (at level 2). While the data set used does contain a third hierarchy (i.e., office/ location) and thus would support running three-level HLM models, the amount of data needed to do so is not sufficient in this data set. Further, neither theoretical grounds nor substantive predictors exist for doing so; and, running three-level HLM models would substantially increase model complexity and thus likely deviate from producing a succinct set of parsimonious models.

At the lowest level (level 1) are the perception of KMS utility outcome data, the KMS knowledge use predictors, and the time-variant controls for each semi-annual period and for each field support technician in the data set. Because some of the surveys are not taken by each technician every semi-annual period, the level 1 model is unbalanced. However, this is largely unproblematic in HLM and is one reason why HLM is so versatile (Snijders & Bosker, 2012: 247). At the second level (level 2) are the individual field support technician data, and includes the experience moderator for each technician and the number of other technicians available to each technician at his/her location.

In the data set there are only a total of five possible measurement occasions for each technician, and as previously discussed, the survey was not always taken by every technician in each semi-annual period. Hence, statistical guidelines suggest that for unbalanced data with a low number of measurement occasions for each individual (such as in this data set), the predictors at level 1 should be modeled as fixed – that is, each with no variance component (i.e., the predictors at level 1 are not allowed to vary randomly at level 2) – because there is not sufficient data to model otherwise (Singer & Willett, 2003: 151, 169). However, in doing due diligence, I nonetheless conducted additional preliminary analyses based on deviance-based tests using RML estimation to verify these statistical guidelines, and my preliminary findings confirm that the predictors at level 1 should be modeled as fixed. The implication of doing so is that there are only two variance components in the model, one at each level, and thus as an ancillary benefit, as each model is run, the interpretation of the proportional reduction in residual variance (Pseudo-R^2) at each level is more straightforward.

Based on this initial model specification I then begin the iterative model building process. I follow the suggestion of Raudenbush & Bryk by first modeling at level 1 before moving to the level 2 model (2002: 256). I first estimate the unconditional means model, followed by the unconditional growth model, which includes the addition of the *time* predictor. As suggested previously, these models help to partition the variance across technicians and across both technicians and time, such that I may explore if and where there may be systematic variation in the outcome that is worth examining further (Singer & Willett, 2003: 92). I then add the time-variant predictors at level 1, which includes the level 1 controls: *document findability over time*, *KMS non-problem-solving codified knowledge use over time only*, and *both KMS personalized knowledge and KMS non-problem-solving codified knowledge use over time*. I then add the independent variables: *KMS codified knowledge use over time only*, *KMS personalized knowledge use over time only*, and *both KMS codified knowledge and KMS personalized knowledge use over time*. I then turn to the level 2 (time-invariant) predictors, and add (only to the significant independent variables from the prior model, so as to preserve statistical power) the *total technicians* predictor as a control, followed by the *technician experience* predictor as a moderator (again only to the significant independent variables from the prior model, so as to preserve statistical power).

CHAPTER 5. RESULTS

The descriptive statistics and correlation matrix, and the results of the HLM modeling for both the perceived utility of codification-based KMS and the perceived utility of personalization-based KMS are documented in Tables 5.1, 5.2, and 5.3, respectively. Note that non-significant controls at both level 1 and level 2 were dropped from the models and are thus not reported in these tables. In the remainder of this chapter I will first discuss the results from model building with HLM, followed by a discussion of the tests I conducted for the hypothesized relationships, and finally by a discussion of additional results of tests I conducted for several non-hypothesized relationships.

Model Building

As discussed in the last chapter, model building with HLM is a step-by-step process. In this section I review the results of this process for the models for both the perceived utility of codification-based KMS and the perceived utility of personalization-based KMS.

The first of the models that were fit to the data were the unconditional means models, which, as discussed previously, are not conditioned by any predictor variables and thus can partition the variance within and between individuals (see Models 1_C and 1_P in Tables 5.2 and 5.3, respectively). This partitioning is accomplished via the intraclass correlation coefficient (ICC), a statistic which “describes the proportion of the total outcome variation that lies ‘between’ people” (Singer & Willett, 2003: 96). For Model 1_C the ICC of 0.5490 indicates that just over half of the total variation in the perceived utility of codification-based KMS is attributed to differences among field support technicians (and thus just less than half can be attributed to within-technician differences), suggesting

Table 5.1: Descriptive Statistics and Correlation Matrix

Variable	Mean	Std.	1	2	3	4	5	6	7	8	9	10
1. Perceived Utility of Codification-Based KMS	7.10	1.83										
2. Perceived Utility of Personalization-Based KMS	8.43	1.30	0.31**									
3. KMS Codified Knowledge Use OT Only (0-6m prior)	11.80	25.02	0.11**	-0.11**								
4. KMS Codified Knowledge Use OT Only (6-12m prior)	12.20	32.43	0.09*	-0.14**	0.77**							
5. KMS Personalized Knowledge Use OT Only (0-6m prior)	10.54	12.09	-0.12**	0.06	-0.03	-0.02						
6. KMS Personalized Knowledge Use OT Only (6-12m prior)	9.87	12.26	-0.08*	0.09*	-0.01	-0.04	0.78**					
7. Both KMS CK & KMS PK Use Over Time (0-6m prior)	3.54	10.74	0.10**	0.03	0.41**	0.30**	0.34**	0.45**				
8. Both KMS CK & KMS PK Use Over Time (6-12m prior)	3.21	10.11	0.11**	0.04	0.36**	0.33**	0.32**	0.35**	0.80**			
9. Time	1.62	1.31	0.07*	0.06	-0.04	-0.00	-0.03	-0.09*	-0.07*	-0.03		
10. Document Findability OT	3.40	0.87	0.70**	0.22**	0.13**	0.10**	-0.08*	-0.07*	0.08*	0.07	0.05	
11. Technician Experience	3.66	0.91	0.03	-.0.03	-0.02	-0.03	-0.18**	-0.16**	-0.16**	-0.17**	-0.03	-0.02

** $p < 0.01$; * $p < 0.05$. CK = Codified Knowledge; PK = Personalized Knowledge; OT = Over Time

Table 5.2: HLM Results – Perceived Utility of Codification-based KMS

	Model 1_C		Model 2_C		Model 3_C		Model 4_C		Model 5_C	
	Baselines for Comparison				Modeling at Level 1				Modeling at Level 2	
	Unconditional Means Model		Unconditional Growth Model		Model 2_C + Document Findability OT		Model 3_C + Knowledge Use		Model 4_C + Technician Experience	
	Coefficient	*z*	Coefficient	*z*	Coefficient	*z*	Coefficient	*z*	Coefficient	*z*
Fixed Effects										
Intercept, Time, & Document Findability Over Time Models:										
Intercept (β_0):										
Intercept (γ_{00})	7.1248	80.74***	6.9700	63.70***	2.3822	10.77***	2.4791	11.12***	2.4773	11.06***
Time (β_1):										
Intercept (γ_{10})			0.0887	2.19*	0.0581	1.71†	0.0618	1.78†	0.0617	1.78†
Document Findability Over Time (β_2):										
Intercept (γ_{20})					1.3565	22.38***	1.3421	21.95***	1.3425	21.90***
Knowledge Use Models – Hypothesized Relationships:										
KMS Codified Knowledge Use Over Time Only (0-6m prior) (β_3):										
Intercept (γ_{30})							-0.0003	-0.09	-0.0005	-0.15
KMS Codified Knowledge Use Over Time Only (6-12m prior) (β_4):										
Intercept (γ_{40})							-0.0004	-0.20	-0.0004	-0.23
Both KMS CK and KMS PK Use Over Time (0-6m prior) (β_5):										
Intercept (γ_{50})							0.0014	0.275	0.0021	0.41
Both KMS CK and KMS PK Use Over Time (6-12m prior) (β_6):										
Intercept (γ_{60})							0.0165	3.134**	0.0130	1.58
Technician Experience (γ_{61})									0.0013	0.45
Knowledge Use Models – Non-Hypothesized Relationships:										
KMS Personalized Knowledge Use Over Time Only (0-6m prior) (β_7):										
Intercept (γ_{70})							-0.0142	-2.864**	-0.0131	-0.83
Technician Experience (γ_{71})									-0.0003	-0.07
KMS Personalized Knowledge Use Over Time Only (6-12m prior) (β_8):										
Intercept (γ_{80})							0.0045	0.883	0.0043	0.85
Variance Components										
σ_ϵ^2 (Level 1)	1.4975	14.14***	1.4857	14.14***	1.2161	14.35***	1.2034	14.36***	1.2038	14.36***
σ_0^2 (Level 2)	1.8277	8.84***	1.8198	8.85***	0.5035	5.48***	0.4795	5.36***	0.4786	5.35***
Model Fit and Pseudo-R^2				χ^2		χ^2		χ^2		χ^2
Deviance	2785.53		2780.59	4.94*	2423.37	357.22***	2409.97	13.40*	2409.88	0.09
AIC	2791.53		2788.59		2433.37		2431.97		2435.88	
BIC	2794.26		2792.23		2437.91		2441.96		2447.69	
Level 1 Pseudo-R^2 (within person)			0.59%		48.29%		49.39%		49.40%	
Level 2 Pseudo-R^2 (between person)			0.54%		55.53%		56.69%		56.72%	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$. CK = Codified Knowledge; PK = Personalized Knowledge; OT = Over Time

Table 5.3: HLM Results – Perceived Utility of Personalization-based KMS

	Model 1_P		**Model 2_P**		**Model 3_P**		**Model 4_P**		**Model 5_P**	
	Baselines for Comparison				Modeling at Level 1				Modeling at Level 2	
	Unconditional Means Model		Unconditional Growth Model		Model 2_P + Document Findability OT		Model 3_P + Knowledge Use		Model 4_P + Technician Experience	
	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z
Fixed Effects										
Intercept, Time, & Document Findability OT Models:										
Intercept (β_0):										
Intercept (γ_{00})	8.4313	139.99***	8.3176	106.65***	7.5844	40.13***	7.4566	37.53***	7.4657	37.11***
Time (β_1):										
Intercept (γ_{10})			0.0653	2.21*	0.0593	1.97*	0.0687	2.29*	0.0687	2.28*
Document Findability Over Time (β_2):										
Intercept (γ_{20})					0.2176	4.17***	0.2378	4.58***	0.2379	4.57***
Knowledge Use Models – Hypothesized Relationships:										
KMS Personalized Knowledge Use Over Time Only (6-12m prior) (β_3):										
Intercept (γ_{30})							0.0095	2.26*	0.0097	0.90
Technician Experience (γ_{31})									0.0000	0.00
Both KMS CK and KMS PK Use Over Time (6-12m prior) (β_4):										
Intercept (γ_{40})							0.0101	2.15*	0.0164	1.89†
Technician Experience (γ_{41})									-0.0041	-0.66
Knowledge Use Models – Non-Hypothesized Relationships:										
KMS Codified Knowledge Use Over Time Only (6-12m prior) (β_5):										
Intercept (γ_{50})							-0.0054	-4.16***	-0.0030	-0.28
Technician Experience (γ_{51})									-0.0007	-0.20
Variance Components										
σ_ϵ^2 (Level 1)	0.8398	14.18***	0.8294	14.18***	0.8277	14.19***	0.8211	14.20***	0.8224	14.20***
σ_0^2 (Level 2)	0.7818	8.04***	0.7873	8.10***	0.7365	7.90***	0.6833	7.70***	0.6787	7.67***
Model Fit and Pseudo-R^2				χ^2		χ^2		χ^2		χ^2
Deviance	2302.33		2297.42	4.91*	2282.08	15.34***	2262.18	19.89***	2261.62	0.57
AIC	2308.33		2305.42		2292.08		2278.18		2283.62	
BIC	2311.06		2309.05		2296.62		2285.45		2293.61	
Level 1 Pseudo-R^2 (within person)			0.31%		3.54%		7.23%		7.43%	
Level 2 Pseudo-R^2 (between person)			0.03%		4.15%		8.69%		9.00%	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$. CK = Codified Knowledge; PK = Personalized Knowledge; OT = Over Time that the use of HLM is appropriate (versus regular OLS regression) (Snijders & Bosker, 2012). Similarly, the ICC for Model 1_P is 0.4821, indicating that just under half of the total variation in the perceived utility of personalization-based KMS is attributed to differences among technicians (and thus just over than half can be attributed to within-technician differences), and likewise suggesting that the use of HLM is appropriate.

With an ICC of 0.5490 and 0.4821 for Models 1_C and 1_P, respectively, it is evident that there is systematic outcome variation worth exploring, both within and between technician, and thus that HLM model building can continue. These preliminary findings are confirmed by examining the single-parameter hypothesis tests for both variance components – σ_ε^2 and σ_0^2 – for each model, which are both significantly different from zero for Model 1_C ($\sigma_\varepsilon^2 = 1.4975$, $p < 0.001$; $\sigma_0^2 = 1.8277$, $p < 0.001$), and for Model 1_P ($\sigma_\varepsilon^2 = 0.8398$, $p < 0.001$; $\sigma_0^2 = 0.7818$, $p < 0.001$).

I next fit the unconditional growth models, which adds the *time* predictor to both models and thus partitions outcome variation across both individuals and time in these models (see Models 2_C and 2_P in Tables 5.2 and 5.3, respectively). The coefficient for *time* for both Models 2_C and 2_P are positive, and the single-parameter hypothesis test for the fixed effect estimate is significantly different from zero for Model 2_C ($\gamma_{10} = 0.0887$, $p < 0.05$), and for Model 2_P ($\gamma_{10} = 0.0653$, $p < 0.05$), suggesting that the perceived utility of both codification-based and personalization-based KMS are increasing over time, respectively. In addition, the change in the model fit (deviance) statistics between Models 2_C and 1_C ($\chi^2 = 4.94$, *d.f.* = 1, $p < 0.05$), and between Models 2_P and 1_P ($\chi^2 = 4.91$, *d.f.* = 1, $p < 0.05$), were also statistically significant. Taken together, these results suggest that modeling change over time is warranted. Furthermore, for Models 2_C and 2_P the single-parameter hypothesis tests for the variance components for both models are significantly different from zero for Model 2_C ($\sigma_\varepsilon^2 = 1.4857$, $p < 0.001$; $\sigma_0^2 = 1.8198$, $p < 0.001$) and for Model 2_P ($\sigma_\varepsilon^2 = 0.8294$, $p < 0.001$; $\sigma_0^2 = 0.7873$, $p < 0.001$). These latter results suggest that there is additional outcome variation that can be explained at both levels. Specifically, in terms of the level 1 variance component (σ_ε^2) for both models, these results suggest that additional time-variant predictors – such as KMS knowledge use over time – can be added to the models to help to explain some of this remaining within-technician variation.

In the next models I added the time-variant controls (see Models 3_C and 3_P in Tables 5.2 and 5.3, respectively). As indicated previously, several of the coefficients for these predictors were not significantly different than zero, including the coefficients for the *KMS non-problem-solving codified knowledge use over time* predictor and for the *both KMS personalized knowledge and KMS non-problem-solving codified knowledge use over time* predictor for either the 0-6 months or 6-12 months periods. These predictors were thus removed from the models. The coefficient for the other level 1 control, *document findability over time*, was positive and statistically significant for Model 3_C ($\gamma_{20} = 1.3565$, $p < 0.001$), and for Model 3_P ($\gamma_{20} = 0.2176$, $p < 0.001$), and was thus retained in these models. The change in model fit statistics between Models 3_C and 2_C ($\chi^2 = 357.22$, $d.f. = 1$, $p < 0.001$), and between Models 3_P and 2_P ($\chi^2 = 15.34$, $d.f. = 1$, $p < 0.001$), were also statistically significant when *document findability over time* was included in each model, indicating that Models 3_C and 3_P both fit the data better than prior models.

After adding the level 1 control variables, I then added the independent variables to the models, which also operate at level 1: *KMS codified knowledge use over time only*, *KMS personalized knowledge use over time only*, and *both KMS codified knowledge and KMS personalized knowledge use over time* (see Models 4_C and 4_P in Tables 5.2 and 5.3, respectively). As discussed in the previous chapter, I intended to include in the models measures of knowledge use at both 0-6 months and 6-12 months prior to the administration of the semi-annual survey to account for the potential time it would take for the benefits from using knowledge from a KMS to appear, as is suggested by both EIPT theory and by prior findings (cf. Ko & Dennis, 2011). However, preliminary analysis suggested that for the personalization-based models, only KMS knowledge use at 6-12 months prior should be included (as depicted in Model 4_P in Table 5.3). Hence, while in the codification-based models knowledge use at both 0-6 months and 6-12 months prior are included, in the personalization-based models only knowledge use at 6-12 months prior is included.

The change in model fit statistics between Models 4_C and 3_C ($\chi^2 = 13.40$, $d.f. = 6$, $p < 0.05$), and between Models 4_P and 3_P ($\chi^2 = 19.89$, $d.f. = 3$, $p < 0.001$), were statistically significant. In addition, the level 1 Pseudo-R^2 for Models 4_C and 4_P increase by 1.10% and 3.69%, respectively.[5] These preliminary findings suggest that additional outcome variation is being explained by the addition of the KMS knowledge use predictors; or in other words, some of the difference in the perceived utility of KMS is due to the addition of these time-variant predictors. The single-parameter hypothesis tests for each of the fixed effects coefficients will be discussed further in the next section.

[5] The equation for Pseudo R^2 used here was formulated by Snijders and Bosker (2012).

In the next set of models I moved to model building at level 2, and added the *total technicians* control to the level 2 equations for the significant level 1 independent variables, so as to preserve statistical power. However, after adding this control both the change in model fit statistics and the single-parameter hypothesis tests for both the codification-based model and for the personalization-based model were not significantly different than zero, and hence I did not include this control in model building or in either of the models depicted in Tables 5.2 and 5.3, respectively.

As such, the next models that are documented in Tables 5.2 and 5.3 are where *technician experience* is added as a moderator to the level 2 equations for the significant level 1 independent variables, again so as to preserve statistical power. However, like with the *total technicians* control, the change in model fit statistics between Models 5_C and 4_C ($\chi^2 = 0.09$, $d.f. = 2$, $p > 0.500$), and between Models 5_P and 4_P ($\chi^2 = 0.57$, $d.f. = 3$, $p > 0.500$) were not statistically significant, suggesting that these models did not fit the data better than Models 4_C and 4_P, respectively. The single-parameter hypothesis tests for these parameter estimates will be discussed in the next section.

The final HLM equations that were produced from the iterative model building process are depicted in Table 5.4. While Models 4_C and 4_P each fit the data better than Models 5_C and 5_P, respectively, I have included in the equations depicted in Table 5.4 the *technician experience* moderator, both to illustrate the different HLM levels but also to link these equations to the results documented in Tables 5.2 and 5.3, respectively. An examination of the level 1 and level 2 residuals – to inspect the distributional assumptions of normality for the residuals – showed that the residuals, as plotted, are approximately linear and suggests that the residual normality assumptions are tenable. In examining the

Table 5.4: HLM Equations – Models 5_C and 5_P

	Perceived Utility of Codification-based KMS (Model 5_C)	Perceived Utility of Personalization-based KMS (Model 5_P)
Level 1 Model	$PU_C = \beta_0 +$ β_1 *time* + β_2 *Document Findability OT* + β_3 *KMS CK Use OT Only (0-6m)* + β_4 *KMS CK Use OT Only (6-12m)* + β_5 *Both KMS PK & KMS CK Use OT (0-6m)* + β_6 *Both KMS PK & KMS CK Use OT (6-12m)* + β_7 *KMS PK Use OT Only (0-6m)* + β_8 *KMS PK Use OT Only (6-12m)* + r_{ti}	$PU_P = \beta_0 +$ β_1 *time* + β_2 *Document Findability OT* + β_3 *KMS PK Use OT Only (6-12m)* + β_4 *Both KMS PK & KMS CK Use OT (6-12m)* + β_5 *KMS CK Use OT Only (6-12m)* + r_{ti}
Level 2 Model	$\beta_0 = \gamma_{00} + u_{0i}$ $\beta_1 = \gamma_{10}$ $\beta_2 = \gamma_{20}$ $\beta_3 = \gamma_{30}$ $\beta_4 = \gamma_{40}$ $\beta_5 = \gamma_{50}$ $\beta_6 = \gamma_{60} + \gamma_{61}$ *technician experience* $\beta_7 = \gamma_{70} + \gamma_{71}$ *technician experience* $\beta_8 = \gamma_{80}$	$\beta_0 = \gamma_{00} + u_{0i}$ $\beta_1 = \gamma_{10}$ $\beta_2 = \gamma_{20}$ $\beta_3 = \gamma_{30} + \gamma_{31}$ *technician experience* $\beta_4 = \gamma_{40} + \gamma_{41}$ *technician experience* $\beta_5 = \gamma_{50} + \gamma_{51}$ *technician experience*
Mixed Model	$PU_C = \gamma_{00} +$ γ_{10} *time* + γ_{20} *Document Findability OT* + γ_{30} *KMS CK Use OT Only (0-6m)* + γ_{40} *KMS CK Use OT Only (6-12m)* + γ_{50} *Both KMS PK & KMS CK Use OT (0-6m)* + γ_{60} *Both KMS PK & KMS CK Use OT (6-12m)* + γ_{61} *Both KMS PK & KMS CK Use OT (6-12m)* * *technician experience* + γ_{70} *KMS PK Use OT Only (0-6m)* + γ_{71} *KMS PK Use OT Only (0-6m)* * *technician experience* + γ_{80} *KMS PK Use OT Only (6-12m)* + $u_{0i} + r_{ti}$	$PU_P = \gamma_{00} +$ γ_{10} *time* + γ_{20} *Document Findability OT* + γ_{30} *KMS PK Use OT Only (6-12m)* + γ_{31} *KMS PK Use OT Only (6-12m)* * *technician experience* + γ_{40} *Both KMS PK & KMS CK Use OT (6-12m)* + γ_{41} *Both KMS PK & KMS CK Use OT (6-12m)* * *technician experience* + γ_{50} *KMS CK Use OT Only (6-12m)* + γ_{51} *KMS CK Use OT Only (6-12m)* * *technician experience* + $u_{0i} + r_{ti}$

PU = Perceived Utility; CK = Codified Knowledge; PK = Personalized Knowledge; OT = Over Time normality of the dependent (outcome) variables, however, it appears that the dependent variables are somewhat non-normal, and thus I used robust standard errors in the analysis to help to correct for this non-normality (Snijders & Bosker, 2012).

Hypothesized Relationships

In this section I detail the results of the single-parameter hypothesis tests I conducted to test the hypotheses in this research, both for my primary hypotheses (H1A–H1D) and for my secondary hypotheses (H2A–H2D). I first discuss the results for the main effects of KMS knowledge use on the perceived utility of KMS (H1A–H1D), followed by detailing the results of the moderating effects of technician experience (H2A–H2D).

Main Effects

The results from the model building process detailed above suggest that Models 4_C and 4_P fit the data better than the prior models (respectively) and can thus be used to test the hypotheses outlined in this research. After controlling for the influence of *document findability over time*, the single-parameter hypothesis tests for the fixed effects estimates for these models show mixed results. For the effect of *KMS codified knowledge use over time only* in Model 4_C, the fixed effects estimates for both the 0-6 months period (γ_{30} = -0.0003, $p > 0.500$), and the 6-12 months period (γ_{40} = -0.0004, $p > 0.500$), are not significantly different than zero. H1A is thus not supported.

These results are somewhat surprising given that the findings in prior research suggest otherwise (Ko & Dennis, 2011). However, a potential explanation for these results are that the *document findability over time* control accounts for the majority of the variance in the *KMS codified knowledge use over time only* predictors, such that there is likely little variance left in these predictors to reveal any relationships between these predictors and the *perceived utility of codification-based KMS*, due to the variance already being partialed out by *document findability over time*. In the prior research, the ability to effectively find, over time, codified knowledge from a KMS was not included as a control. However, the results in this research suggest that document findability over time is a very strong indicator of the perceived utility of codification-based KMS. When this control was added in Model 3_C, the level 1 Pseudo-R^2 increased by 47.70%, and likewise, as indicated previously, the fixed effects estimate for this control was positive and very significant (γ_{20} = 1.3565, $p < 0.001$). Hence, it seems (in this data set at least) that being able to effectively find documents to use from a KMS is a necessary and important part – in terms of the perceived utility of codification-based KMS – of actually using KMS codified knowledge.

For the effect of using KMS personalized knowledge in Model 4_P, the single-parameter hypothesis test indicates that there is a significant positive relationship between *KMS personalized knowledge use over time only* and the *perceived utility of personalization-based KMS* for the 6-12 months period (γ_{30} = 0.0095, $p < 0.05$). In practical terms, this finding suggests that for each additional use of KMS personalized knowledge in the prior 6-12 months by technicians, there will be a small but significant increase in their perceived utility of personalization-based KMS. This finding therefore supports H1B.

In terms of the hypothesized cross-relationships (as depicted in Figure 3.2), in Model 4_C the results indicate that there is a significant positive relationship between *both KMS codified knowledge and KMS personalized knowledge over time* and the *perceived* *utility of codification-based KMS* for the 6-12 months period ($\gamma_{60} = 0.0165$, $p < 0.01$), but not for the 0-6 months period ($\gamma_{50} = 0.0014$, $p > 0.500$). These results support H1C, at least for the 6-12 months period. Similarly, in Model 4_P the results from the single-parameter hypothesis test indicate that there is a significant positive relationship between *both KMS codified knowledge and KMS personalized knowledge use over time* and the *perceived utility of personalization-based KMS* ($\gamma_{40} = 0.0101$, $p < 0.05$). Thus, H1D is also supported. Taken together, these findings in practice suggest that the additional use of both kinds of KMS knowledge over time by technicians lead to small but significant increases in their perceptions of KMS utility, and thus that the use of both kinds of KMS knowledge over time is important to them, at least in terms of their perceptions of KMS utility.

Experience Moderator

As discussed previously, the results for the change in model fit statistics when *technician experience* was added in Models 5_C and 5_P, respectively, were not significant, suggesting these models did not fit the data better than Models 4_C and 4_P, respectively. The single-parameter hypothesis tests for the fixed effects estimates are likewise non-significant. In Model 5_C the non-significant estimate of the interaction between *technician experience* and *both KMS codified knowledge and KMS personalized knowledge use over time* for the 6-12 months period ($\gamma_{61} = 0.0013$, $p > 0.500$) indicates that H2C is not supported. Likewise, as discussed previously, because the estimates for *KMS codified knowledge use over time only* in Model 4_C were not significantly different than zero (and thus did not support H1A), I could not test for the moderating influence of *technician experience* in Model 5_C, and thus I cannot find support for H2A.

For Model 5_P, the non-significant estimate for the interaction between *technician experience* and *KMS personalized knowledge use over time only* for the 6-12 months period ($\gamma_{31} < 0.0000$, $p > 0.500$) suggests that H2B is not supported. Similarly, the non-significant estimate for the interaction between *technician experience* and *both KMS codified knowledge and KMS personalized knowledge use over time* for the 6-12 months period ($\gamma_{41} = -0.0041$, $p > 0.500$) indicates that H2D is also not supported.

These results are surprising, given how consistent experience has been as a moderator in both the IS success and KM literatures (e.g., F. D. Davis, Bagozzi, & Warshaw, 1989; Haas & Hansen, 2005; Ko & Dennis, 2011; Taylor & Todd, 1995; Venkatesh et al., 2003). One possible explanation for this finding is that there really is no moderating relationship to be found; but given that the relevant literature is replete with findings suggesting otherwise, this possibility is remote. The more likely explanation given the data availability limitations in this study previously noted; is that my measure as operationally defined is a relatively weak proxy for knowledge worker experience, hence making it difficult to test for the moderating effects of experience, where experience was only measured as an artifact of job-title level. I tend to think the latter explanation is more likely, given the nature of my experience measure (i.e., a grouping of job titles into five differing experience "levels"). And in fact, prior work by Bradley et al. (2006) would support this notion, that measuring experience based on job position is potentially problematic.

So what is a better measure of experience? As noted in Chapter 2, the IS success and KM literatures are not consistent when it comes to measuring experience. One reason for this, it seems, is the lack of theoretical frameworks upon which to guide how experience might be conceptualized, modeled, and subsequently measured, especially as it relates to the use over time of knowledge from IT-based systems. It therefore seems that developing such frameworks – to aid in understanding how different conceptualizations of experience likely differentially moderate the outcome from the use over time of KMS knowledge – is potentially needed and may be warranted.

Non-Hypothesized Relationships

As illustrated in Figure 3.2, there were several non-hypothesized cross-relationships that were also included in the HLM models: (1) the potential relationship between KMS *codified* knowledge use over time on the perceived utility of *personalization*-based KMS; and (2) the possible relationship between KMS *personalized* knowledge use over time on the perceived utility of *codification*-based KMS. These relationships were included in the HLM models to account for any potential variability that might be due to these specific cross-relationships, even though these relationships were not hypothesized *a priori*. Because of this possibility, I therefore report the results of including these relationships in the HLM models.

A indicated in Model 4_C, the fixed effects estimate of *KMS personalized knowledge use over time only* was negative and statistically significant for the 0-6 months period ($\gamma_{70} = -0.0142$, $p < 0.01$), but positive and non-significant for the 6-12 months period ($\gamma_{80} = 0.0045$, $p = 0.378$). Likewise, in Model 4_P the fixed effects estimate for *KMS codified knowledge use over time only* was negative and statistically significant for the 6-12 months period ($\gamma_{50} = -0.0054$, $p < 0.001$). Taken together, these results suggest that something more is occurring in the interplay of codified and personalized knowledge use over time and the perceived utility of codification-based and personalization-based

KMS. The possible implications of these results will be discussed in more detail in the next chapter.

Limitations

This dissertation research includes several limitations, which are primarily, it seems, due to the nature of the data set (i.e., secondary data) and the limitations imposed by the company on collecting additional data (e.g., personnel data). For example, the results of the HLM analysis for both codification-based and personalization-based models indicates that additional outcome variation could be explained at both hierarchical levels in each sets of models – i.e., the single-parameter hypothesis tests for the variance components are significantly different from zero for Model 4_C (σ_ε^2 = 1.2034, p < 0.001; σ_0^2 = 0.4795, p < 0.001) and for Model 4_P (σ_ε^2 = 0.8221, p < 0.001; σ_0^2 = 0.6833, p < 0.001) – yet additional data could not be collected to help to potentially explain additional variation. Furthermore, some of the data that was available did not seem to adequately measure the construct in question, as was the case with the technician experience measure. Future research could explore in more depth how additional time-variant and time-invariant factors could impact KMS success.

In addition, because of the data limitations in this research, there were a low number of measurement occasions per field support technician (with a total possible maximum of five), and the measurement occasions were also low in granularity (i.e., measurement occasions were semi-annual periods compared to months, weeks, etc.). While this first limitation necessitated that I model each of the predictors as fixed rather than randomly varying across technicians, the latter limitation, for the purposes of this research, did not seem to be too problematic given the theory that was instantiated, wherein it takes a significant amount of time for expertise to be developed and thus human capability to be extended. Nonetheless, because of these limitations, more-complex growth models (e.g., non-linear) could not be modeled that would, for example, help to gauge the extent to which KMS use extends expertise differentially over time, and hopefully be able to answer – with additional theory to support it – why the results of KMS knowledge use over time from variable time points could be different, as was observed in this research. Follow-up research with additional (and more granular) measurement occasions could thus prove useful.

Further, there were measurement limitations regarding this study's outcomes – perceived utility of both types of KMS – in that the survey that was used only included four survey items that could be used to gauge perceived KMS utility, two for each type of KMS. The consequence of this limitation was the possibility that perceptions of KMS utility were not fully captured in this operationalization. Future research could thus explore the dimensions of these perceptions in greater detail.

Finally, because of the nature of the data set used (i.e., secondary data with relatively few observations), endogeneity concerns – that there are possible unmeasured construct(s) that exist that might influence both technicians decisions to use KMS and their perceptions that KMS are useful – cannot be addressed in this research. Follow-up research could help to address this endogeneity possibility.

In the next chapter I try to take a step back; and to consider the implications of this research in the larger sense. Thus, I try to set the development of the 'mind-machine' interface within a helpful context; and by this consideration, to enable possibilities for further exploration within this context.

CHAPTER 6. DISCUSSION & CONCLUSIONS

Since the dawn of the information age, there has been the hope that information technology would do for knowledge work what industrial technology has done for physical work (Bell, 1976). The essential question that underlies this hope concerns the extent to which personalized knowledge can be codified into knowledge management systems (KMS) (where human thinking can be extended by machines) in ways that, over time, liberate the mind from the mental operations that (a) the mind is not too good at, and (b) is often considered to be drudgery (Huber, 1984). The utility of KMS over time is thus central. I have therefore examined the research question: *In using KMS over time, to what extent does utilizing codified knowledge and personalized knowledge from KMS influence KMS success: which I define to be KMS utility as perceived by individuals engaged in support-centered knowledge work?* As noted in the Results chapter, tests were performed to address both my primary and my secondary objectives. In the following paragraphs I shall discuss the implications for each.

Primary Objective

The primary objective of this research was to explore the relationship between using KMS knowledge – both personalized <u>and</u> codified – over time, and KMS success. In this research I have defined KMS success to be the perceived utility of KMS. The three sub-objectives that flow from this primary objective are: (1) to explore the relationship between codified knowledge use over time and the perceived utility of codification-based KMS (to examine prior findings (cf. Ko & Dennis, 2011) on the use over time of codification-based KMS, but in a task setting that extends testing from "selling products" (the primary setting of the prior research) to "solving problems"; (2)

to explore the relationship between personalized knowledge use over time and the perceived utility of personalization-based KMS (to extend the research to the use over time of personalization-based KMS); and (3) to explore the relationships between both codified and personalized knowledge use over time, and the perceived utility of both codification-based and personalization-based KMS, respectively (to further extend the examination to the concurrent use over time of both types of KMS).

As hypothesized, I found that using personalized and codified knowledge over time, which have previously been assumed to be independent phenomena, are more likely to be interdependent. That is, using KMS knowledge over time was, in my testing, found to be related to the perceived utility of KMS in the majority of these relationships. However, in the relationship between codified knowledge use over time and the perceived utility of codification-based KMS, no significant relationship was observed. As a whole, these findings suggest that for KMS success (as perceived by the user), it is important both for researchers and for KMS design-users to not just focus on the temporal, independent nature of KMS knowledge use, but also to focus on the temporal, *inter*dependent nature of KMS knowledge use. In building off of this research, additional work could thus focus on questions regarding to what extent concurrent personalized and codified knowledge use potentially influences other KMS success constructs (other than perceived KMS utility) in both the problem-solving task domain and in other task environments, and how and to what extent personalized and codified knowledge use extends human capabilities in these environments.

Several other ancillary implications also emerge from these findings. First, as highlighted in the previous chapter, it was observed that the ability to find KMS codified knowledge to use is a significant positive determinant of the perceived utility of KMS, so much so, it seems, that there was little additional variance left to be explained in the perceived utility of codification-based KMS from actually using KMS codified knowledge. This finding suggests that additional work is needed in teasing out the relationship between finding and using KMS codified knowledge, and how this possible relationship influences KMS success.

Second, as a consequence of differentiating between task-specific (i.e., problem solving) versus non-task-specific documents, the findings herein suggest that not all KMS codified knowledge is created equally; that is, that the *content* of KMS codified knowledge matters. In the models of the perceived utility of both codification-based and personalization-based KMS, measures of the use over time of KMS non-problem-solving codified knowledge were not significant determinants of perceived KMS utility (i.e., as discussed previously, this control was dropped from the models because both the change in model fit statistics and single-parameter hypothesis tests were not significant). In the perceived utility of codification-based KMS models, this finding, like above, could be explained by the significance of document findability; that is, the non-significance of KMS non-problem-solving codified knowledge use over time could be due to a technician's ability to find relevant documentation over time. However, the same explanation would be tenuous in the perceived utility of personalization-based models, where KMS codified knowledge use over time was significant yet these measures of non-task-specific KMS codified knowledge use over time were not. Hence, future research could address questions regarding to what extent different kinds of KMS codified knowledge content differentially influences KMS success.

Finally, as highlighted in the previous chapter, there were two non-hypothesized cross-relationships that were significant negative determinants of perceived KMS utility. One possible explanation for these findings are that KMS users have a specific type of KMS they are more comfortable with, and hence the additional use over time of, for example, codified knowledge from codification-based KMS (more comfortable) might negatively influence perceptions of personalization-based KMS (less comfortable), and vice versa. Additional work thus is needed to better-understand the underlying mechanisms involved in these non-hypothesized cross-relationships.

Secondary Objective

The secondary objective of this research was to test the potential moderating effect of knowledge worker experience on each of the above relationships. This testing was important because prior research has found that specifically in the case of codified knowledge use, experience moderates the 'use' to the 'benefits from use' relationship. It therefore seemed prudent to examine this finding within the problem solving (vs. product sales) context. Unexpectedly, as previously explained, I found no significant moderating relationship.

Taken as a whole, the results of my hypothesis tests, while generally supporting theory, raise additional questions which I discuss in the following paragraphs. Specifically, if personalized knowledge use and codified knowledge use are interdependent; if experience ought to matter (moderate) the use and benefits from use relationship; and if we as a society expect that IT ought to effectually extend human capability; then are there relationships that might exist in using KMS (especially with a better conceptualization and operationalization of experience of a moderator) that can shed light on these additional questions? In the spirit of further exploration, I conducted a few *post hoc* tests that specifically address this question.

Post Hoc Analysis

Accordingly, given the various different types of experience measures that have been used in the IS success and KM literatures that I could draw upon (as discussed in Chapter 2), I conducted additional (*post hoc*) analyses by instead including a different measure of experience: how long (in months) a field support technician had been using the KMS, as measured by when a technician's use first appears in the system logs of the KMS. As when modeling with the prior experience measure, this new measure is only added as a level 2 predictor on the significant level 1 knowledge use over time predictors that were previously observed (see Models 4_C and 4_P in Tables 5.2 and 5.3, respectively), so as to preserve statistical power. Including this new measure as a proxy for experience is consistent with research in the IS success literature. I note that substituting this new measure for the prior experience measure is not equivalent: they operationalize two conceptually different constructs, the former operationalizing *technical* experience, while the latter operationalizing *technological* experience.

The results of the *post hoc* analysis, both in regards to model fit and in regards to the single-parameter hypothesis tests for the KMS use over time predictors, show an improvement in explanatory potential. A comparison of these results to the results of my prior experience measure are presented in Tables 6.1 (for the codification-based models) and 6.2 (for the personalization-based models). While the change in model fit statistics for Models 6_C and 6_P when compared to the more-simple (nested) Models 4_C and 4_P, respectively, are only moderately significant for Model 6_C ($\chi^2 = 4.65$, $d.f. = 2$, $p < 0.10$)

Table 6.1: *Post Hoc* Analysis Results – Perceived Utility of Codification-based KMS

	Model 4_C		Model 5_C		Model 6_C	
	Baseline Comparison		Prior Exp. Measure		Updated Exp. Measure	
	Model 3_C + Knowledge Use		Model 4_C + Technical Experience		Model 4_C + Technological Experience	
	Coefficient	*z*	Coefficient	*z*	Coefficient	*z*
Fixed Effects						
Intercept, Time, & Document Findability Over Time Models:						
Intercept (β_0):						
Intercept (γ_{00})	2.4791	11.12^{***}	2.4773	11.06^{***}	2.5073	11.28^{***}
Time (β_1):						
Intercept (γ_{10})	0.0618	$1.78^{\dagger}$	0.0617	$1.78^{\dagger}$	0.0623	$1.79^{\dagger}$
Document Findability Over Time (β_2):						
Intercept (γ_{20})	1.3421	21.95^{***}	1.3425	21.90^{***}	1.3335	21.95^{***}
Knowledge Use Models – Hypothesized Relationships:						
KMS Codified Knowledge Use OT Only (0-6m prior) (β_3):						
Intercept (γ_{30})	-0.0003	-0.09	-0.0005	-0.15	-0.0003	-0.11
KMS Codified Knowledge Use OT Only (6-12m prior) (β_4):						
Intercept (γ_{40})	-0.0004	-0.20	-0.0004	-0.23	-0.0005	-0.25
Both KMS CK and KMS PK Use OT (0-6m prior) (β_5):						
Intercept (γ_{50})	0.0014	0.275	0.0021	0.41	0.0035	0.66
Both KMS CK and KMS PK Use OT (6-12m prior) (β_6):						
Intercept (γ_{60})	0.0165	3.134^{**}	0.0130	1.58	0.0252	0.69
Technician Experience (γ_{61})			0.0013	0.45	-0.0002	-0.25
Knowledge Use Models – Non-Hypothesized Relationships:						
KMS Personalized Knowledge Use OT Only (0-6m prior) (β_7):						
Intercept (γ_{70})	-0.0142	-2.864^{**}	-0.0131	-0.83	-0.0657	-2.65^{**}
Technician Experience (γ_{71})			-0.0003	-0.07	0.0009	2.17^{*}
KMS Personalized Knowledge Use OT Only (6-12m prior) (β_8):						
Intercept (γ_{80})	0.0045	0.883	0.0043	0.85	0.0039	0.76
Variance Components						
σ_ϵ^2 (Level 1)	1.2034	14.36^{***}	1.2038	14.36^{***}	1.1956	14.36^{***}
σ_0^2 (Level 2)	0.4795	5.36^{***}	0.4786	5.35^{***}	0.4768	5.36^{***}
Model Fit and Pseudo-R^2		χ^2		χ^2		χ^2
Deviance	2409.97	13.40^{*}	2409.88	0.09	2405.32	$4.65^{\dagger}$
AIC	2431.97		2435.88		2431.32	
BIC	2441.96		2447.69		2443.13	
Level 1 Pseudo-R^2 (within person)	49.39%		49.40%		49.70%	
Level 2 Pseudo-R^2 (between person)	56.69%		56.72%		56.96%	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$. CK = Codified Knowledge; PK = Personalized Knowledge; OT = Over Time; Exp. = Experience

Table 6.2: *Post Hoc* Analysis Results – Perceived Utility of Personalization-based KMS

	Model 4_P		**Model 5_P**		**Model 6_P**	
	Baseline Comparison		Prior Exp. Measure		Updated Exp. Measure	
	Model 3_P + Knowledge Use		Model 4_P + Technical Experience		Model 4_P + Technological Experience	
	Coefficient	*z*	Coefficient	*z*	Coefficient	*z*
Fixed Effects						
Intercept, Time, & Document Findability Over Time Models:						
Intercept (β_0):						
Intercept (γ_{00})	7.4566	37.53***	7.4657	37.11***	7.4546	37.65***
Time (β_1):						
Intercept (γ_{10})	0.0687	2.29*	0.0687	2.28*	0.0710	2.35*
Document Findability Over Time (β_2):						
Intercept (γ_{20})	0.2378	4.58***	0.2379	4.57***	0.2359	4.58***
Knowledge Use Models – Hypothesized Relationships:						
KMS Personalized Knowledge Use OT Only (6-12m prior) (β_3):						
Intercept (γ_{30})	0.0095	2.26*	0.0097	0.90	0.0397	0.20
Technician Experience (γ_{31})			0.0000	0.00	-0.0008	0.37
Both KMS CK and KMS PK Use OT (6-12m prior) (β_4):						
Intercept (γ_{40})	0.0101	2.15*	0.0164	1.89†	-0.0670	-2.45*
Technician Experience (γ_{41})			-0.0041	-0.66	0.0013	2.88**
Knowledge Use Models – Non-Hypothesized Relationships:						
KMS Codified Knowledge Use OT Only (6-12m prior) (β_5):						
Intercept (γ_{50})	-0.0054	-4.16***	-0.0030	-0.28	0.0397	1.90†
Technician Experience (γ_{51})			-0.0007	-0.20	-0.0008	-2.15*
Variance Components						
σ_ϵ^2 (Level 1)	0.8211	14.20***	0.8224	14.20***	0.8181	14.21***
σ_0^2 (Level 2)	0.6833	7.70***	0.6787	7.67***	0.6730	7.66***
Model Fit and Pseudo-R^2		χ^2		χ^2		χ^2
Deviance	2262.18	19.89***	2261.62	0.57	2257.09	5.09
AIC	2278.18		2283.62		2279.09	
BIC	2285.45		2293.61		2289.08	
Level 1 Pseudo-R^2 (within person)	7.23%		7.43%		8.05%	
Level 2 Pseudo-R^2 (between person)	8.69%		9.00%		9.65%	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$. CK = Codified Knowledge; PK = Personalized Knowledge; OT = Over Time; Exp. = Experience or approaching moderate significance for Model 6_P ($\chi^2 = 5.095$, *d.f.* = 3, $p = 0.16$), when compared to Models 5_C and 5_P, respectively, the models using the new experience measure each fit the data better, as evidence by the further reduction in both AIC and BIC statistics.[6] In the case of the change in BIC statistics for both sets of model comparisons, respectively ($\Delta BIC_C = 4.56$; $\Delta BIC_P = 4.53$), the approximate *p*-values corresponding to the differences are both $p < 0.01$ (Raftery, 1995). As such, it would appear that the new experience measure vis-à-vis the prior experience measure better fits the data. This finding is supported by the results of single-parameter hypothesis tests that were conducted.

In comparing both experience measures, there is also a difference in the results of the single-parameter hypothesis tests for the moderating relationships. For the updated measure, several of these parameters which were previously not statistically significant (in Models 5_C and 5_P) are now significant. Interestingly, of the three now-significant moderating effects, only one is for a relationship previously hypothesized – both KMS codified knowledge and KMS personalized knowledge use over time on the perceived utility of personalization-based KMS – while two of them are for relationships where there was no *a priori* theoretical explanation: KMS personalized knowledge use over time on the perceived utility of codification-based KMS, and KMS codified knowledge use over time on the perceived utility of personalize-based KMS. These results support the finding that this new experience measure better fits the data and that experience does, it seems, moderate the relationship between KMS knowledge use over time and the

[6] AIC and BIC can be used to compare non-nested models in this way as long as the same data set is used (Singer & Willett, 2003: 122).

perceived utility of KMS, in most cases. However, given that this new experience measure operationalizes a different experience construct, as previously noted, what might this finding imply? Further discussion and *post hoc* theorizing may provide additional insight into possible implications.

Implications of Post Hoc Tests

At this point in the *post hoc* analysis, it is becoming apparent that current theory may not fully exist to explain some of these findings. In particular, there seems to be a potential for the confounding of technical experience (i.e., the initial experience measure), with experience in using KMS technology (i.e., the new experience measure). This tentative observation leads me to wonder if a typology might be possible that relates these two constructs in such a way that theoretical assertions as to the outcome conditions might be imputed as to how, for example, knowledge workers might make preference selections for the type(s) of KMS to use in their tasks, and in particular, how strong such preferences might be. I define *technical experience* to be a knowledge worker's level of task expertise (e.g., Bradley et al., 2006; Haas, 2006; Ko & Dennis, 2011), whereas I define *technological experience* to be a knowledge worker's level of IT-use-related expertise (e.g., Morris & Venkatesh, 2000; Szajna, 1996; Thompson et al., 1994; Venkatesh et al., 2003). The former comes directly from a knowledge worker's deliberate practice in their primary work tasks (such as technical problem solving), while the latter can be formed from the ancillary use of ITs for these tasks.

On one axis (say x) we can place technical experience. Although such experience is likely to vary along a continuum, for purposes of a typology, a dichotomous (yes/no) setup is helpful for illustration purposes. The same might follow for the placement of

Figure 6.1: KMS Preference Selection Strength Conditions

		Technical Experience: Y	Technical Experience: N
Technological Experience	Y	1. Weak Preference (Both)	2. Strong Preference (Codified)
	N	3. Weak Preference (Personalized)	4. Strong Preference (Personalized)

technological experience: again for purposes of a typology, a dichotomous (yes/no) setup is also helpful for illustration purposes. Thus, where the dependent construct is "knowledge worker KMS preference selection strength" a likely theoretical typology might appear as illustrated in Figure 6.1.

Given that technical experience and technological experience are distinct constructs, I would expect that each type of experience would differentially provide the arguments for the differences that might be observed in both KMS preference selection (technological experience) and preference strength (technical experience). For KMS preference selection, I would expect that technological experience would operate on preference selection based on how technologically demanding using KMS are, due to the nature of codification-based and personalization-based KMS, where codification-based systems are more technologically demanding because they are fully technology-based and thus likely require more technological know-how to use effectively, while personalization-based systems are less technologically demanding because they still have a human element and thus likely require less technological know-how to use effectively.

Hence, I would expect differences in preferences to exist based on the technological experience of the knowledge worker.

Conversely, for KMS preference selection strength, I would expect technical experience to operate on preference strength based on the extent to which knowledge workers need to rely upon personalized and codified knowledge from KMS to perform with higher expertise in their work tasks. The argument used herein is similar to that used previously when detailing the logic for the expected moderating relationships of experience, where technical experience here is akin to the initial experience construct and operationalized measure used in hypothesizing and testing the moderating relationships (see H2A – H2D). I would thus expect that knowledge workers with more technical experience would likely need to rely less upon KMS than knowledge workers with less technical experience.

From these lines of reasoning, we can now explore the possible outcome conditions that are imputed as to how knowledge workers might make KMS preference selections and how strong such preferences might be.

Box 1. Both Technological and Technical Experience. Knowledge workers with both technical experience and technological experience are individuals who have developed both work-task expertise and KMS-use-related expertise in these work tasks. In expert information processing theory (EIPT) parlance, such knowledge workers would have already largely developed the knowledge structures – the sequences (solution steps) and associated norms (solution guidelines) – in both the work tasks and in using KMS to source knowledge for these tasks, respectively. For KMS preference selection, already having knowledge structures as to how to use the KMS (technological experience) would likely mean that there would be no general preference for using codification-based versus personalization-based KMS, since the technological demands to using KMS, especially codification-based KMS, would be minimized due to knowledge workers already having developed these knowledge structures. I would expect, then, that knowledge workers would have a general preference for using both codification-based KMS and personalization-based KMS.

Likewise, for preference selection strength, already having knowledge structures as to how to complete work tasks (technical experience) would likely mean that knowledge workers would need to rely less upon knowledge from KMS to perform their work tasks with higher expertise, and thus we might expect that such knowledge workers would have a relatively weak preference for using KMS.

Therefore, as outlined in Box 1, I would expect that knowledge workers would have a general preference for both types of KMS, and that this preference would be rather weak.

Box 2. Technological Experience, but No Technical Experience. In instances where knowledge workers have technological experience, but no technical experience, we might expect that such workers would have a preference for using codification-based KMS, since the technological demands to using such systems would be minimized due to the knowledge workers having already developed the knowledge structures as to how to use KMS (technological experience). Further, I would expect that this preference would be rather strong, given that the knowledge workers would have developed few of the knowledge structures as to how to complete work tasks (technical experience) and would thus likely need to rely more upon knowledge from KMS to perform tasks with higher expertise. Hence, as outlined in Box 2, I would expect that knowledge workers would have a strong preference for using codification-based KMS.

Box 3. No Technological Experience, but Technical Experience. When a knowledge worker has no technological experience, but does have technical experience, I would likely expect that such workers would have a preference to using personalization-based KMS, since they would have developed few of the knowledge structures as to how to use codification-based KMS (technological experience). I would also expect that this preference would be rather weak, given that the knowledge workers would have already developed many of the knowledge structures needed to effectively complete work tasks (technical experience) without relying upon knowledge from KMS. Consequently, as outlined in Box 3, I would expect that knowledge workers would have a weak preference for using personalization-based KMS.

Box 4. Neither Technological nor Technical Experience. Where knowledge workers have no technological experience nor technical experience, having developed few, if any, of the knowledge structures as to how to complete work tasks effectively (technical experience) and how to use codification-based KMS (technological experience) to help them perform tasks with higher expertise, we might expect these workers to have a strong preference to using personalization-based KMS (as outlined in Box 4), due to their being both technical and technological novices, and thus needing to rely upon personalization-based KMS to help them to perform with higher expertise in their work tasks.

There is some support for these arguments in the results of the *post hoc* analysis. While I cannot discern between differing levels of technical experience in this analysis due to the initial measure of (technical) experience being, it seems, a weak operationalization, the results of the *post hoc* analysis suggests that as technological experience decreases, any additional use over time of personalized knowledge 0-6 months prior decreases the perceived utility of codification-based KMS, as illustrated in Model 6_C in Table 6.1 (γ_{71} = 0.0009, $p < 0.05$). Conversely, the *post hoc* analysis suggests that when technological experience increases, any additional use over time of codified knowledge 6-12 months prior decreases the perceived utility of personalization-based KMS, as illustrated in Model 6_P in Table 6.2 (γ_{51} = -0.0008, $p < 0.05$). These findings suggest that codification-based KMS may be preferred when technological experience is high (Box 2), whereas personalization-based KMS may be preferred when technological experience is low (Boxes 3 and 4).

Further, any additional use over time of both codified and personalized knowledge 6-12 months prior leads to an increase of the perceived utility of personalization-based KMS when technological experience increases, as illustrated in Model 6_P in Table 6.2 (γ_{41} = 0.0013, $p < 0.01$). This finding suggests that there is the possibility for having both types of KMS be preferred, as suggested may be likely in Box 1.

While these *post hoc* findings seem promising, and while this exercise in creating a typology based on technical experience and technological experience has been informative, this *post hoc* analysis and theorizing brings up some important questions for future research in the knowledge management domain. For example, I recognize, as previously noted, that technical experience and technological experience are really not likely to be dichotomous, but rather each likely vary along a continuum. This possibility then suggests that knowledge workers likely differ on both the technical experience continuum and on the technological experience continuum. Given this possibility, how might progressing from being a technical novice to a technical expert, and likewise from being a technological novice to a technological expert, differentially change the nature of knowledge worker behaviors in regards to KMS use, preferences, etc.? Further, how does the development of technological experience influence the development of technical experience, and vise versa? Additionally, what might be the performance differential in, for example, the quality and/ or quantity of work output between knowledge workers at various points on both experience continua? Likewise, to what extent do technical and technological experts still rely upon codified and personalized knowledge in work tasks vis-à-vis technical and technological novices? And how might an understanding of technical experience and technological experience influence the knowledge management initiatives undertaken by companies, such that no matter where a knowledge worker is on these experience continua, specialized resources will be available to help knowledge workers perform tasks with higher expertise? These and the additional questions discussed below can be the focus of future research.

Conclusions

"There are no great men, only great challenges that ordinary men are forced by circumstances to meet."

- William F. Halsey

"Since most of us spend our lives doing ordinary tasks, the most important thing is to carry them out extraordinarily well."

- Henry David Thoreau

“At the same time [artifacts] are adapted to man’s goals and purposes. They are what they are in order to satisfy man’s desire to fly or to eat well. As man’s aims change, so too do his artifacts—and vice versa.”

- Herbert A. Simon

We face significant challenges in the world, challenges that necessitate the creation and use of tools (or *artifacts*, in Simon’s (1981) vocabulary) that help us to face these challenges by extending human capabilities so as to, as Thoreau notes, carry out our tasks extraordinarily well. Whereas in the 18^{th}, 19^{th}, and early part of the 20^{th} Centuries the challenges primarily concerned physical-world issues, and the subsequent tools we created were primarily designed to help to overcome our own physical limitations so that we could extend our reach, the challenges we now face, in an information world, primarily concern knowledge-based problems, and are primarily a function of limitations in mental processing and storage (H. A. Simon, 1991). More specifically, because there are bounds to our rationality – that is, we cannot know everything, and even if we knew everything we could not process it all – we are today, in the information and knowledge-based terms of the 21^{st} Century, as limited as we were in the physical-based terms of the last few centuries without the tools needed to extend human capabilities. Helpfully, as the quote by Simon above notes, as our aims change, so too do the tools we create to achieve these aims, and vice versa.

So what are these tools? Over the last approximately 40 years the field of expertise and the field of information technology (IT) have coexisted. The field of expertise has mainly been focused on understanding the nature and development of expert human performance (cf. Ericsson, 2005), while the field of information technology has largely focused on the study of the IT artifact (cf. Benbasat & Zmud, 2003). It has only been more recently, however, that overlaps in these fields have been recognized as important (Davenport & Klahr, 1998). Specifically, in recognizing that that which is tacit may be made explicit and vice versa (Nonaka, 1994) via IT (Davenport & Klahr, 1998), we find that within ITs, or more specifically within knowledge management (KM) ITs, we may find the tools necessary to extend human capabilities via personalized and codified knowledge such that individuals may perform with greater expertise. The examination of these KM-based tools on human performance thus significantly matters to our field, because to the extent that we are able to develop extensions of our minds using ITs (as "scaffolding"; cf. Clark, 1997, 2008), we are then able to better-manage an environment that would otherwise be relatively unmanageable. And the extent to which we are as effective at extending our knowledge space as we have been at extending our physical space, we will have done something worthwhile.

So in this research I examined to what extent is personalized and codified knowledge utilized over time, and is it effective to human beings who are trying to deal with knowledge problems. As detailed previously, I utilized expert information processing theory to guide the development of my hypotheses, and the results of the analysis suggest that personalized and codified knowledge were satisfactory to knowledge workers who were expecting to extend their capabilities.

In addition, via *post hoc* analysis and theorizing, I also examined the extent to which being technologically comfortable in using codification-based KMS might influence individual perceptions of the KMS and vice versa, and found that those knowledge workers who have more technological experience in using codification-based KMS to extend their minds are satisfied with it, while those workers that are less technologically savvy with using codification-based KMS to extend their minds are not and would rather use personalization-based KMS. While this finding would seem to be rather prosaic, the implication of this finding is that to the extent that a knowledge worker can use codification-based KMS, it can be a tool by which human capabilities are extended.

Thus, some additional key questions that future research can address include: To what extent can IT extend IQ? And to what extent can IT be a substitute for IQ? That is, to what extent are human cognitions becoming increasingly distributed in ITs (e.g., Clark, 1997, 2008; Smith & Conrey, 2009; Smith & Semin, 2004), such that ITs – via codified and personalized knowledge – really are becoming a substitute for IQ, even in experts? This dissertation research thus refreshes the expertise research stream by including the tools – information technologies – that can help individuals to perform with higher expertise. Herein is the frontier: the place where expertise and information technology research can go.

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