BUILDING A FOUNDATION FOR KNOWLEDGE MANAGEMENT RESEARCH: DEVELOPING, VALIDATING, AND APPLYING THE KNOWLEDGE INTERNALIZATION CONSTRUCT

by

KAMPHOL WIPAWAYANGKOOL

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ABSTRACT

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CONSTRUCT

Kamphol Wipawayangkool, Ph.D.

The University of Texas at Arlington, 2011

Supervising Professor: James T. C. Teng

The notion of knowledge internalization (KI), albeit a critical link in Nonaka's (1994) organizational knowledge creation theory, has not been rigorously conceptualized and defined, let alone operationalized. To strengthen the foundation for knowledge management (KM) research, we attempt to fulfill the following research objectives in the three essays of this dissertation.

In the first essay, by drawing from Anderson (1983)'s ACT (adaptive control of thought) theory and Glaser et al. (1985)'s framework on the dimensions of cognitive skills, we develop the construct of KI and demonstrate its nomological validity by examining its role in knowledge sharing phenomenon through its relationships with knowledge self-efficacy, expert power, and intention to share knowledge.

In the second essay, we apply the KI construct and show that whether people will share their tacit knowledge, measured via expert power, depends on the degree of KI and the extent of a knowledge-based individual-task-technology fit*,* based on Goodhue and Thompson (1995)'s task and technology fit theory, of which knowledge self-efficacy, preference for

personalization KM strategy, accessibility of corresponding KM systems, and task variety, are conceptualized as the underlying components.

In the third essay, we profile knowledge workers in organizations using the dimensions of KI, and explore how each profile varies in terms of knowledge self-efficacy, expert power, knowledge sharing intention, and preference for KM strategy.

With the three essays, we contribute to KM research by demonstrating that KI is a crucial construct that can help clarify many unresolved issues in KM. To practice, we offer a reliable, easy-to-use, and domain-independent instrument that can be used in evaluating not only the effectiveness of knowledge workers in creating sustainable competitive advantage of organizations, but also success of organizational KM initiatives.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

Table Page

CHAPTER 1

KNOWLEDGE INTERNALIZATION: CONSTRUCT DEVELOPMENT AND EMPIRICAL EXAMINATION OF ITS ROLE IN KNOWLEDGE SHARING

1.1 Abstract

The concept of internalization, albeit a critical link in Nonaka (1994)'s organizational knowledge creation theory, has been understudied. Through several theories in cognitive psychology, this study defines knowledge internalization as *the process in which an individual relies on various cognitive mechanisms to transform his or her declarative knowledge into procedural knowledge***.** The objectives of the research are twofold. First, we aim to conceptualize, develop, and validate the construct of knowledge internalization by drawing from Anderson (1983)'s adaptive control of thought (ACT) theory and Glaser, Lesgold, and Lajoie (1985)'s framework on the dimensions of cognitive skills. Second, we examine the roles of the construct in knowledge sharing phenomenon through its relationships with expert power, knowledge self-efficacy, and intention to share knowledge.

Based on the results of both exploratory and confirmatory assessments, exhibiting satisfactory psychometric properties and validities, knowledge internalization is formulated as a second-order formative construct consisting of the following five dimensions: *organization and structure, mental models, efficiency, automaticity, and metacognition*. The path analysis reveals that the effect of knowledge internalization on intention to share knowledge is fully mediated by both expert power and knowledge self-efficacy. In addition, the effect of knowledge internalization on expert power is partially mediated by knowledge self-efficacy. This study contributes to research by demonstrating that knowledge internalization is a crucial construct that can help clarify numerous unresolved issues in KM. To practice, the validated instrument

can be used to evaluate KM effectiveness in organizations. To conclude the paper, limitations and future research directions are discussed.

1.2 Introduction and Motivations

Knowledge management (KM) has become an important research stream in information systems discipline (IS) (Alavi and Leidner, 2001; Argote, McEvily, and Reagans, 2003; Grover and Davenport, 2001; King, Marks, and McCoy, 2002). Of theoretical advances in the field, Nonaka (1994)'s organizational knowledge creation theory is arguably the most influential and widely adopted theory (e.g. Lee and Choi, 2003; Linderman et al., 2004; Becerra-Fernandez and Sabherwal, 2001). The theory posits that organizational knowledge is created through interactions between tacit and explicit knowledge in a spiral process of socialization, externalization, combination, and internalization (i.e. the SECI model). Tacit knowledge, residing in the brain, is rather personal and difficult to communicate, while explicit knowledge can be codified and transmittable in systematic documents. In socialization, tacit knowledge is exchanged through shared experience and communications among individuals. In externalization, tacit knowledge is converted or codified into explicit knowledge. In combination, explicit knowledge from different sources is systematically combined. In internalization, explicit knowledge is finally converted back to tacit knowledge in human minds through individuals' learning processes. We argue that the internalization particularly deserves a closer examination, because of the following reasons.

First, the internalization is a powerful means for acquiring tacit knowledge, which is known for being instrumental to sustainable competitive advantage (Ambrosini and Bowman, 2001; Grant, 1996; Lubit, 2001; Berman, Down, and Hill, 2002). Since the notion of the internalization is analogous to that of learning (Kakabadse, Kouzmin, and Kakabadse, 2001; Nonaka, 1994), it can be stated that how employees learn to acquire and manage their knowledge affects how organizations become and remain competitive. While tacit knowledge is the outcome of both internalization and socialization, the value of socialization critically depends on the effectiveness of the internalization. Because common experience is key in sharing tacit knowledge (Nonaka, 1994), exchanging knowledge among individuals whose experiences are limited due to constrained learning abilities would result in unproductive socialization. The influences of the internalization on externalization and combination also exist. The effectiveness of externalization would be limited, unless the effort comes from individuals whose knowledge has been effectively internalized. Furthermore, individuals with limited knowledge due to inferior internalization may be uncertain on how to combine knowledge from multiple sources. Thus, the internalization appears to be the critical link in the SECI model, because it determines the usefulness of the remaining processes (i.e. socialization, externalization, and combination) and in turn the effectiveness of organizational knowledge creation process. Figure 1.1 depicts the classic SECI model and our perspective on the internalization as a critical link.

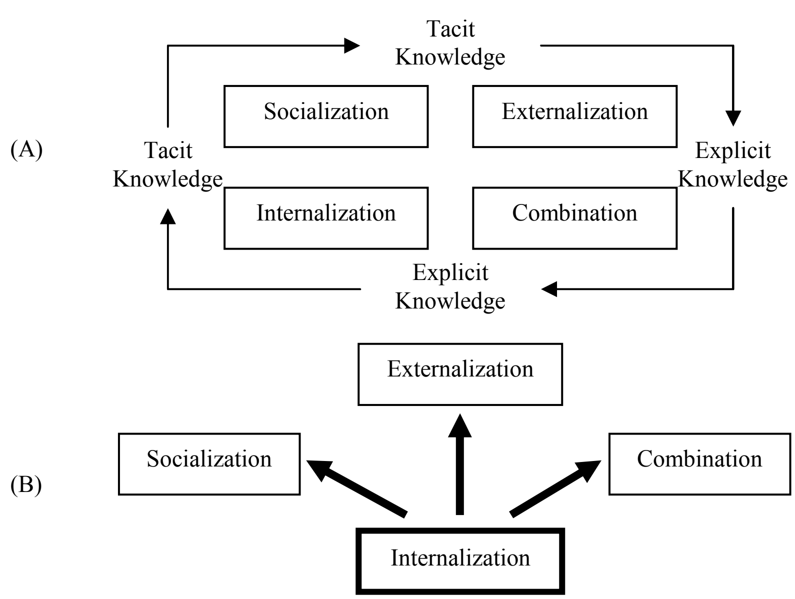

Figure 1.1 (A) the Nonaka (1994)'s SECI Model versus (B) Internalization as the Critical Link

The second reason researchers should pay more attention to the concept of internalization is related to how organizations gauge their success in KM initiatives. Although constructs such as intention to share knowledge (Bock et al., 2005) and performance in general (Edmondson et al., 2003) have been applied to evaluate the success of KM, we believe that, given the underlying influences of the internalization in the SECI model as previously discussed, the degree of the knowledge internalization should precede those constructs. Without effective internalization, it would be difficult to claim that KM indeed contributes to employees' knowledge sharing activities or improved performance. Therefore, to better justify the utility of KM practices in organizations, measuring individual knowledge internalization is also important.

Finally, research in the area of information technology (IT) usage has recently highlighted the underlying effects of the internalization in the context of continuing use. Ortiz de Guinea and Markus (2009) suggest that automatic or unconscious behaviors may be able to explain post-adoption phenomena more than planned behaviors can. To that end, Limayem, Hirt, and Cheung (2007) assume the influence of learning on habit in the context of IT usage by defining the habit as the extent to which people tend to use IS "*automatically because of learning*". Importantly, drawing from the memory perspective in cognitive psychology, Kim (2009) demonstrates that experiences that have been internalized into memories affect post-adoptive technology use. Taken together, these studies suggest that internalization plays an important role in creating automatic behaviors in the IT usage phenomena.

Despite its aforementioned importance in research, the concept of the internalization has received scant attention and never been systematically studied. Nonaka, Byosiere, Borucki, and Konno (1994) attempt to test the organizational knowledge creation theory by conceptualizing knowledge creation as a second-order construct comprising socialization, externalization, combination, and internalization. However, their internalization factor includes vaguely identified dimensions of real world knowledge acquisition (i.e. personal experience) and virtual world knowledge acquisition (i.e. simulation and experimentation), which are measured with items that were developed without much theoretical justification. Drawing from the same work of Nonaka et al. (1994), Lee and Choi (2003) similarly view the internalization as the degree of personal experience, simulation, and experimentation. Similarly, adopting yet the same Nonaka et al.'s work, Sabherwal and Becerra-Fernandez (2003) measure the internalization by using only three items related to the notions of on-the-job training, learning by doing, and learning by observation. We believe that for such an important construct, internalization needs to be especially grounded in well-established theories and its measurement systematically developed. Thus, to fill in such a gap in the literature, we aim to:

1. Develop and validate the construct of knowledge internalization by drawing from well-established theories, including Nonaka's (1994) organizational knowledge creation theory, Anderson (1983)'s adaptive control of thought (ACT) theory, and Glaser, Lesgold, and Lajoie (1985)'s framework on the dimensions of cognitive skills.

2. Test the nomological validity of the construct by examining the roles of the knowledge internalization in the knowledge sharing phenomenon, specifically through its predicted relations to expert power, knowledge self-efficacy, and intention to share knowledge.

1.3 Theoretical Foundations

1.3.1 Types of Knowledge

Among a number of classifications of knowledge existing in the literature, tacit versus explicit knowledge and declarative versus procedural knowledge are perhaps the two most well-known classification schemes (see Alavi and Leidner (2001) for more detail on other types). Tacit versus explicit knowledge is commonly used in information systems (IS) research, while declarative versus procedural knowledge is a key concept in cognitive psychology (e.g. Anderson, 1982; 1983).

Tacit knowledge "is deeply rooted in action, commitment, and involvement in a specific context" (Nonaka, 1994). Residing in experts' heads, tacit knowledge is highly personal and thus difficult to communicate. Polanyi (1966)'s famous statement "*we can know more than we can tell*" precisely captures the essence of tacit knowledge, because not all the knowledge in the brain can be told or even recognized. On the other hand, *explicit knowledge* can be "codified and is transmittable in formal and systematic formats such as archives, databases, and statistics" (Nonaka, 1994). Researchers acknowledge that tacit and explicit represent two endpoints of the continuum of knowledge (Nonaka, 2009).

Recognized as fundamental to cognitive psychologists (Anderson, 1983), the concept of declarative and procedural knowledge is also used by IS researchers (e.g. Arnold et al., 2006; Kim, 2009; Leonardi and Bailey, 2008). Some researchers view declarative knowledge as know-what, while procedural knowledge as know-how (Alavi and Leidner, 2001; Arnold et al., 2006). In relation to explicit and tacit knowledge, some researchers also believe that explicit knowledge is simply know-what and tacit knowledge is know-how (e.g. Sambamurthy and Subramani, 2005). However, such analogies limit our understanding of the interconnections among declarative, procedural, explicit, and tacit knowledge (Nickols, 2000). For example, if certain procedures (i.e. know-how) are codified in a formal document or knowledge repository, then it is ambiguous whether or not we should still consider it tacit knowledge.

To resolve this conceptual confusion, we define *declarative knowledge* as the part of knowledge that *can be* represented or described by communication media such as natural languages, schematics, mathematics, audios, and videos. As a result, our definition of declarative knowledge includes elements of both know-what and know-how as well as know-why. Our definition is thus consistent with that of Nickols (2000), in which declarative knowledge is not restricted only to know-what. In addition, we define declarative knowledge that is *actually* documented, represented, or described by communication media as *externalized declarative knowledge*. For example, food cookbooks (e.g. know-what and know-how) and academic theories (e.g. in the field of economics) in a textbook (e.g. know-what and know-why) are therefore externalized declarative knowledge.

We define *procedural knowledge* as *actionable* knowledge that has been internalized from a collection of declarative knowledge. It is actionable in a sense that only when practiced over time, declarative knowledge can become procedural knowledge. In other words, although an individual has learned basic facts and information (know-what), established methodologies (know-how), and theoretical principles (know-why), he or she must apply them before the knowledge can turn into procedural knowledge. For example, to become an experienced chef, one cannot simply read and even memorize declarative knowledge in a cookbook, but must persistently practice it.

In this study, our focal interest is *how* an individual transforms his or her declarative knowledge into procedural knowledge – that is, the *knowledge internalization* process. Before developing a formal definition of the knowledge internalization and its construct systematically, we need to turn to discuss several prominent theories pertinent to the concepts of learning and knowledge in cognitive psychology.

1.3.2 Adaptive Control of Thoughts Theory

Anderson (1983)'s Adaptive Control of Thoughts (ACT) theory is essentially about human learning and knowledge representation. The theory states that learning occurs in three stages: declarative, compilation, and procedural stage. In the *declarative* stage, an individual applies declarative knowledge to interpret problems, but his or her performance at this stage is heavily weighted by processing time and working memory load when recalling the knowledge. The *compilation* stage marks the changing point where the individual learns how to apply declarative knowledge with less consciousness. Inside the brain, accumulated declarative knowledge is gradually transformed into procedural form that is ready to be activated with less memory load. Finally, in the *procedural* stage, the individual can activate and apply compiled declarative knowledge to solve a problem or work on a task automatically or with minimum memory load. At this stage, the individual is also much cognizant of how to control or plan his or her problem solving endeavors in a more effective and efficient way.

The ACT theory indeed improves our understanding of the concept of knowledge internalization. Specifically, knowledge internalization occurs when an individual can improve his or her performance on a task by proceeding from declarative to compilation and finally to procedural stage. More precisely, it occurs when an individual can effectively apply accumulated declarative knowledge to solve a problem in a more automatic manner. Although the ACT theory provides an answer to *when* knowledge internalization occurs, another question remains. That is, in experiencing the three stages of learning, *how* can one actually internalize knowledge? Thus, to be discussed next are the dimensions of cognitive skills that essentially enable people to learn.

1.3.3 Dimensions of Cognitive Skills

Glaser et al. (1985)'s framework on cognitive skills includes the following six dimensions: organization and structure, problem representation, mental models, efficiency, automaticity, and metacognition. *Organization and structure* refers to the extent to which declarative knowledge becomes interconnected and structured. This cognitive skill is attained when an individual can proficiently access coherent chunks of declarative knowledge to perform a task. *Problem representation* refers to the extent to which underlying principles of a problem or task situation are recognized. This cognitive skill is achieved when an individual can perceive the underlying principles of a problem rather than the surface structure. *Mental models* refer to the extent to which operations of a system in a particular domain are understood and developed. With a mental model, an individual can envision or imagine how things work in a domain and use such visions to guide his or her performance. *Efficiency* refers to the extent to which developed skills, or procedural knowledge, are efficiently utilized. This cognitive skill occurs when an individual can reach to the solution of a problem efficiently with minimum efforts. *Automaticity* refers to the extent to which procedural knowledge is automatically exerted. This cognitive skill occurs when an individual can perform a task or solve a problem automatically without conscious cognitive efforts in retrieving declarative knowledge. Finally, *metacognition* refers to self-regulatory and self-management skills. It is defined as the extent to which performance is reflected and controlled in a useful and efficient manner. With this cognitive skill, an individual can plan his or her behaviors, monitor the outcomes of the actions, and adjust behaviors appropriately.

1.4 The Knowledge Internalization Construct

Glaser et al. (1985)'s dimensions of cognitive skills help us identify specific mechanisms an individual needs to achieve in order to transform declarative knowledge into procedural knowledge. Specifically, these cognitive skills collectively enable knowledge internalization. Therefore, while the ACT theory helps explain *when* knowledge internalization occurs in general, the dimensions of cognitive skills elucidate more precisely *how* knowledge internalization occurs. Based on the discussion in Royer, Cisero, and Carlo (1993)'s work, we integrate Anderson (1983)'s ACT theory and Glaser et al. (1985)'s dimensions of cognitive skills, and develop the theoretical foundation for the knowledge internalization construct (Figure 1.2).

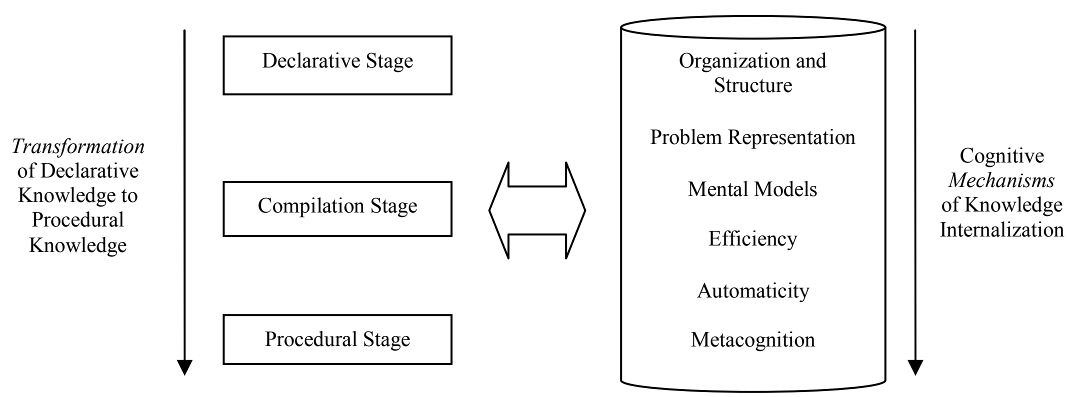

Figure 1.2 Theoretical Foundation of Knowledge Internalization

With the theoretical foundation and previous discussions, we at this point define knowledge internalization as *the process in which an individual relies on various cognitive mechanisms to transform his or her declarative knowledge into procedural knowledge.*

To determine whether a construct is reflective or formative, Jarvis, Mackenzie, and Podsakoff (2003) and Petter, Straub, and Rai (2007) recommend that prior to data collection phase, researchers *conceptually* analyze causal relationships between measures and constructs. We conceptualize knowledge internalization as a second-order formative construct comprising the abovementioned cognitive mechanisms, essentially because (1) the underlying cognitive mechanisms *enable or cause* the extent to which knowledge internalization occurs – *not vice versa*, (2) the cognitive mechanisms theoretically capture *different and non-interchangeable aspects* of knowledge internalization, and (3) removing one of the cognitive mechanisms will *alter* the conceptual domain of the knowledge internalization construct.

Importantly, although these cognitive mechanisms of the knowledge internalization appear to be both accumulative and hierarchical in nature (i.e. from declarative stage, to compilation, and to procedural stage), some mechanisms will be manifested more actively than others, because of the Polanyi's statement "*we can know more than we can tell.*" The statement implies that once a person becomes an expert and thus can perform a task in a more automatic manner, the person may not be able to recall some of the knowledge knowingly. Such a connotation of the knowledge internalization is also present in the phenomenon of automatic or habitual IT usage (Kim, 2009; Limayem et al., 2007; Ortiz de Guinea and Markus, 2009). That is, learning and experience acquired over time affect people's habitual IT usage. Therefore, it can be stated that automaticity is more presently active than organization and structure and problem representation in the case of experts (and vice versa for novices). Precisely, the accumulative nature of the mechanisms suggests that the organization and structure and problem representation in the experts' brains still remain higher than novices', while the hierarchical nature implies that the higher dimensions such as automaticity will be manifested more strongly. Figure 1.3 depicts the proposed construct of the knowledge internalization.

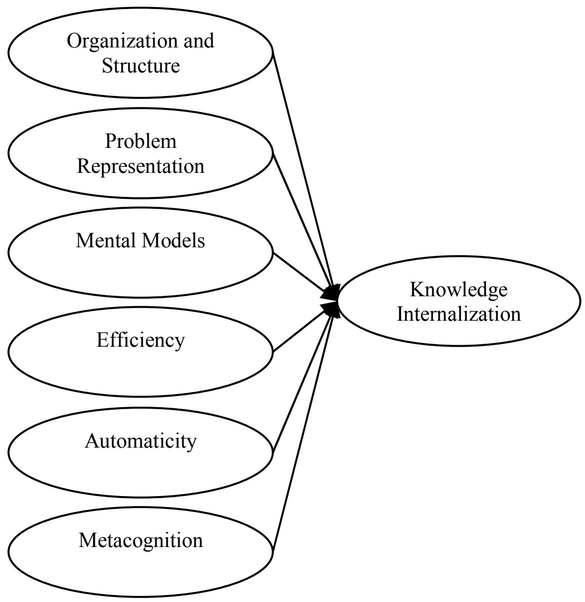

Figure 1.3 The Knowledge Internalization Construct

1.4.1 Knowledge Internalization and Tacit Knowledge

As discussed earlier, internalization is the means to acquiring tacit knowledge. However, the question “how so” still remains unanswered, arguably because tacit knowledge has always been ambiguous in the literature, thus making it uncertain how the notion of internalization can be related to that of tacit knowledge. In conjunction with the distinctions of declarative versus procedural knowledge, previously introduced to facilitate the discussions on the theoretical foundations of knowledge internalization, in this section we attempt to employ the proposed definition of knowledge internalization to enhance our understanding of the nature of tacit knowledge.

In addition to defining tacit knowledge as “deeply rooted in action, commitment, and involvement in a specific context”, Nonaka (1994) states further that tacit knowledge involves technical and cognitive dimensions. Technical dimension covers "concrete know-how, crafts, and skills that apply to specific contexts," while cognitive dimension centers on "*mental models*" which "includes schemata, paradigms, beliefs, and viewpoints that provide perspectives that help individuals to perceive and define their world." In order to gain deeper understanding of tacit knowledge, we need not only a general definition of tacit knowledge, but also especially well-defined definitions of its dimensions. Unfortunately, although used rather arbitrarily in a number of studies (e.g. Insch, McIntyre, and Dawley, 2008; Leonard and Insch, 2005), these definitions have never been theoretically justified. Specifically, how can only mental models be essential to the cognitive dimension of tacit knowledge? This issue needs some clarifications.

We argue that mental models are not the only mechanism in the cognitive dimension, primarily because of the elaboration of Glaser et al. (1985)'s framework on cognitive skills. In fact, any cognitive mechanism that is used to transform declarative knowledge into procedural knowledge, that is to ultimately acquire tacit knowledge, needs to be included. Therefore, we define the cognitive dimension of tacit knowledge as the underlying cognitive mechanisms used to create knowledge, comprising organization and structure, problem representation, mental models, efficiency, automaticity, and metacognition. In other words, we can state that the *cognitive dimension of tacit knowledge* refers to *all the cognitive mechanisms used during the knowledge internalization*. With this definition, we clarify how the cognitive dimension plays a role in making certain knowledge tacit. In addition, we provide a more thorough understanding of not only how knowledge internalization is the means to acquire tacit knowledge, but also how the two concepts are indeed intertwined.

1.5 Nomological Validity of the Knowledge Internalization Construct

Our second research objective is to examine the nomological validity of the knowledge internalization construct. To do so, we hypothesize that it will enhance an individual's knowledge self-efficacy and expert power in the organization, as depicted in Figure 1.4.

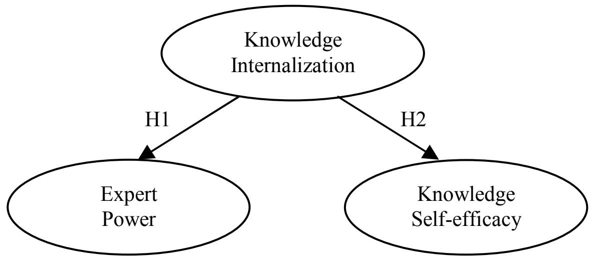

Figure 1.4 Testing Nomological Validity of the Knowledge Internalization Construct

1.5.1 Expert Power

In the literature about power in organizations, French and Raven (1959)'s bases of social power is probably the best known and most influential framework (Schriesheim, Hinkin, and Podsakoff, 1991). They assert that one can gain his or her authority via reward, coercive, legitimate, referent, and expert power. Of our focal interest, an individual's expert power refers to *the perception by other people that the individual possesses special knowledge or expertise* (Raven and French, 1958). Thus, a person's expert power will increase when his or her expertise is more and more sought after. To that end, one's expertise should be repeatedly requested by other people, only when the person is indeed knowledgeable, that is, possessing high degree of knowledge internalization. Consequently, we hypothesize that:

H1: Knowledge internalization is positively associated with expert power.

1.5.2 Knowledge Self-efficacy

Bandura (1982) defines self-efficacy as the perception about what people can do with the skills they possess. In particular, knowledge self-efficacy refers to *the confidence in one's ability to provide valuable knowledge* (Kankanhalli, Tan, and Wei, 2005). Thus, while our definition of expert power refers to how other people perceive one's expertise, knowledge self-efficacy purely reflects on his or her self-assessment of the confidence to be able to contribute valuable knowledge. Generally, the more knowledge acquired, the more confident one should be. Therefore, we hypothesize that:

H2: Knowledge internalization is positively associated with knowledge self-efficacy.

1.6 Knowledge Internalization in Knowledge Sharing

The SECI model suggests that organizational knowledge is created through interactions not only between tacit and explicit knowledge, but also among people (Nonaka, 1994). However, as it is known that people are rather reluctant to share their knowledge, knowledge sharing is thus a challenging and critical issue in KM research (e.g. Bock et al., 2005; Bock, Kankanhalli, and Sharma 2006; Kankanhalli et al., 2005; Ray et al., 2005; Thomas-Hunt, Ogden, and Neale, 2003; Wang and Noe, 2010; Wasko and Faraj, 2005). As the second objective of this research, we aim to demonstrate further the usefulness of our conceptualization of knowledge internalization in improving our understanding of knowledge sharing phenomenon. As a result, we extend the model for testing nomological validity by including the construct of intention to share knowledge. As shown in Figure 1.5, the extended research model includes expert power, knowledge self-efficacy, and intention to share knowledge. By testing this nomological network, we expect to contribute to the literature by demonstrating that knowledge internalization importantly affects individuals' intention to share knowledge possibly both directly and through certain mediators such as expert power and knowledge self-efficacy. The findings would reinforce one of our motivations of the study, that is, to show that knowledge internalization is the basis for other processes including knowledge sharing.

1.6.1 Intention to Share Knowledge

While much of the extant literature focuses on the benefits of shared knowledge in general (e.g. Ray, Muhanna, and Barney, 2005; Saraf, Langdon, and Gosain, 2007), our interest is in the studies about the antecedents of knowledge sharing particularly those related to expert power and knowledge self-efficacy. In the context of electronic discussion boards, where individuals exchange ideas based on their common interests, Wasko and Faraj (2005) found that the individuals with longer tenure in the field tend to share more knowledge, because they have more experience to share. To that end, we conjecture that the reason they have more experience is that they have the ability to not only acquire, but also apply knowledge effectively; that is, their level of knowledge internalization is likely to be high. Thus, we hypothesize that effective knowledge internalization can increase the chances people will share their knowledge:

H3: Knowledge internalization is positively associated with intention to share knowledge.

Researchers have also found that knowledge self-efficacy influences people's intention to share knowledge. Moreover, such relationship appears to be recursive. Kankanhalli et al. (2005) found that when feeling confident that their expertise is useful to the organization, individuals are more inclined to contribute their knowledge to the electronic knowledge repositories. Lee, Cheung, Lim, and Sia (2006) found that the lack of knowledge self-efficacy explains the reason that people do not want to share knowledge with others. As a result of sharing, they will feel even more confident (Constant, Kiesler, and Sproull, 1994). Thus, we suggest further that with high level of knowledge self-efficacy, an individual will share knowledge not only voluntarily but also when requested by others, thus eventually enhancing his or her expert power. Collectively, we hypothesize that:

H4: Knowledge self-efficacy is positively associated with intention to share knowledge.

H5: Knowledge self-efficacy is positively associated with influence expert power.

Another factor found to influence knowledge sharing is an individual's status of expertise perceived by others in the organization, namely expert power. Particularly, Thomas-Hunt et al. (2003) found that the individuals perceived as experts are more likely than those perceived as non-experts to accentuate the value of shared knowledge. In addition, Wasko and

Faraj (2005) found that individuals also share knowledge when they perceive that doing so will improve their professional reputation. Taken together, these findings suggest that expert power can motivate people to share knowledge. Thus, we hypothesize that:

H6: Expert power is positively associated with intention to share knowledge.

Additionally, the discussions on both the hypotheses for testing the predictive validity of knowledge internalization (H1-H2) and those related to intention to share knowledge (H3-H6) collectively result in the following three partial mediation effects. First, we hypothesize that the relationship between knowledge internalization and intention to share knowledge is partially mediated by expert power, because knowledge internalization is expected to increase expert power (H1) and both knowledge internalization (H3) and expert power (H6) can lead to higher intention to share knowledge. Second, we posit that the relationship between knowledge internalization and expert power is partially mediated by knowledge self-efficacy, due to the previous discussion, in which knowledge internalization can improve knowledge self-efficacy (H2) and in turn knowledge self-efficacy can lead to enhanced expert power (H5). Finally, we propose that the relationship between knowledge internalization and intention to share knowledge is partially mediated by knowledge self-efficacy, because knowledge internalization can improve knowledge self-efficacy (H2) and, subsequently knowledge self-efficacy can yield greater likelihood of intention to share knowledge (H4). Thus, the hypotheses are:

H7: *The relationship between knowledge internalization and intention to share knowledge is partially mediated by expert power.*

H8: *The relationship between knowledge internalization and expert power is partially mediated by knowledge self-efficacy.*

H9: *The relationship between knowledge internalization and intention to share knowledge is partially mediated by knowledge self-efficacy.*

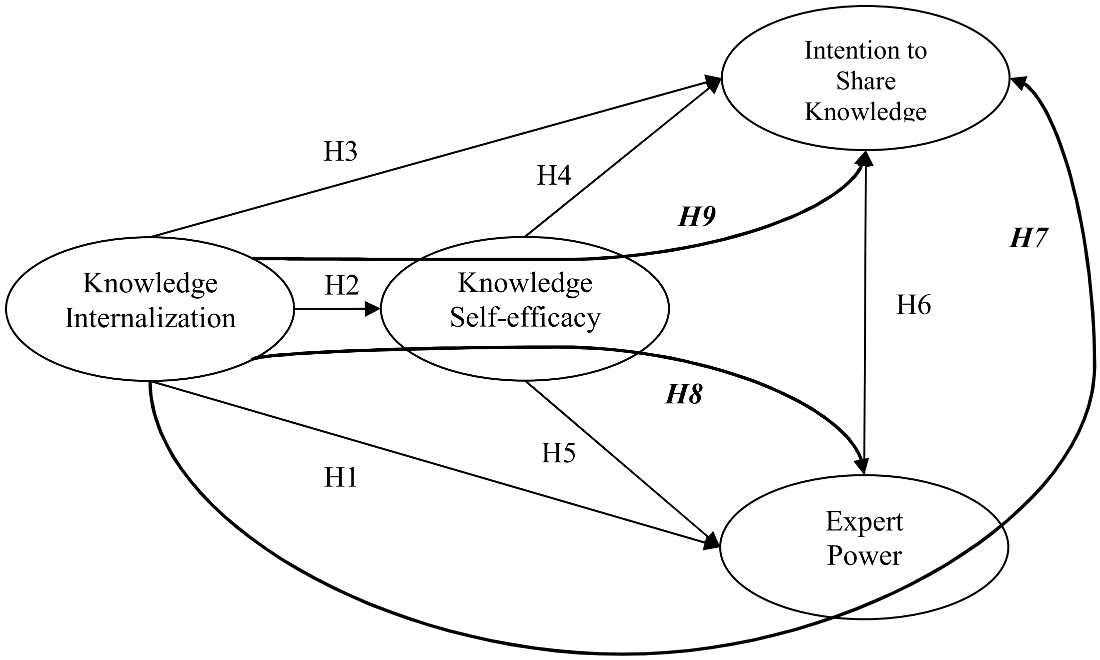

Figure 1.5 Research Model for Testing Extended Nomological Validity
Note. The curved arrows represent the mediation hypotheses.

1.6.2 Control Variables

To control for explanatory power of possible confounding factors, we added the following variables as our controls to the research model: gender, age, education, tenure in the current position, tenure with the current organization, tenure in the current profession, number of employees in the department, number of employees in the organization, and number of professional contacts. An individual's demographic characteristics such as gender, age, and education may influence to some degree the extent to which other people perceive his or her expertise, the extent to which he or she is confident of his or her own knowledge, and finally the extent to which he or she intends to share knowledge. Tenures in the current profession and current organization are also anticipated to impact the level of expert power perceived by other individuals in the organization. For example, the longer an individual stays in the current profession and with the organization, the more likely he or she would be perceived as an expert, thus leading to more knowledge sharing (Wasko and Faraj, 2005). Workplace-related factors such as department and organization size may also be relevant. While a smaller department can help an individual's expertise stand out more noticeably, a larger organization may decrease his or her intention to share knowledge, possibly due to minimal visibility of doing so. Finally, the individuals with more professional contacts developed throughout their careers may be more likely to be not only more confident of their knowledge, but also perceived as experts than those with fewer contacts.

1.7 Research Methodology

The framework for developing our measurement of knowledge internalization is based on several modified versions of Churchill (1979)'s framework such as the approaches adopted by Xia and Lee (2005), Lewis, Templeton, and Byrd (2005), and Malhotra and Grover (1998), as well as guidelines and practices recommended by Moore and Benbasat (1991) and Straub (1989). Overall, the phases of the framework are conceptual development and initial item creation, conceptual refinement and item modification, data collections, and data analysis and measurement validation (Xia and Lee, 2005).

1.7.1 Conceptual Development and Initial Item Creation

Since our endeavor is the first to attempt to systematically theorize the construct of knowledge internalization, an initial set of measurement items was not generated based on prior literature per se, but specifically based on our theoretical foundations – that is, the conceptual integration between Anderson (1983)'s ACT theory of human cognition and Glaser et al. (1985)'s categorization of dimensions of cognitive skills. To strive for satisfactorily initial face and content validity of the measure, multiple sessions with a distinguished scholar with over thirty years of academic experience were conducted to ensure that the items of the measure were appropriately derived and worded according to the theoretical foundation. As a result, a total of 25 items was generated. A seven-point Likert-type scale anchored from strongly disagree (1) to strongly agree (7) was used for all of the items.

1.7.2 Conceptual Refinement and Item Modification

The goal of this phase is to modify the initial items so that we could establish more satisfactory face and content validity as well as improving clarity and wording of the refined items. To accomplish such a goal, we first performed a sorting procedure which was an adaptation based on the works of Moore and Benbasat (1991) and Xia and Lee (2005). Second, after incorporating feedbacks from the sorting procedure, we conducted a pilot test to further improve the quality and validity of the items. The sorting procedure and pilot test are described in detail below.

1.7.3 Sorting Procedure

In this sorting procedure, our panel of judges included a rich combination of practitioners and researchers with a mixture of experience as follows: two practitioners/researchers, both accompanied with more than twenty years of industry experience in fields such as management, IT, finance, and operations management, one practitioner with over ten years of experience in IT, and two doctoral students with several years of experience in operations management and finance. We believed that such a diverse profile of the panel helped ensure that the measurement being developed in the study could be effectively used in a variety of contexts.

The judges were provided with sorting instructions as well as the definitions of each dimension of the construct (i.e. Organization and Structure, Problem Representation, Mental Models, Efficiency, Automaticity, and Metacognition). First, we asked each of the judges to read the definitions carefully and encouraged them to ask questions if anything was unclear. With some explanations and clarifications, all the judges agreed that the definitions were clear and they understood. Then, we presented a completely random list of the items on a computer screen to the judges and asked them to select which of the dimensions an item would belong to the most. During the procedure, the judges could also see all the definitions easily next to the labels of the dimensions on top of the screen. After the judges were finished, we discussed with them regarding each of the selections and their reasoning. On average, approximately five items out of the initial pool were misplaced by each of the judges, mainly due to certain words such as “easily”, “effortlessly”, “quickly”, and “rule-of-thumbs”. For example, three of the judges placed the items with the term “rule-of-thumbs” at least one or two dimensions higher than they should be (e.g. to Metacognition or Efficiency instead of Mental Models), because they felt that the term implied quite complicated and advanced ability. Similarly, when considering the items with the terms “easily” and “effortlessly”, all of the judges were somewhat indecisive, because they felt that the two terms could suggest a higher-level ability (e.g. to Efficiency or Automaticity instead of Problem Representation). In addition to refining the wording of the items as expected, we particularly incorporated the judges’ abovementioned feedbacks by completely removing the terms “rule-of-thumbs”, “quickly”, and “effortlessly” while keeping the term “easily” consistently used in all the associated items. We believed doing so helped eliminate the possible confounding interpretations.

1.7.4 Pilot Test

Next, we conducted a pilot test to improve further the quality and validity of the measurement. The survey was distributed in a graduate-level course in college of business administration at a public university in a large metropolitan area of the southwest US. A total of 31 students with an average of five years of experience in professions such as management (e.g. project managers and administrators) and IT (e.g. software engineers and analysts) participated in the study. The results of the Kaiser-Meyer-Olkin and Bartlett’s test were significant, indicating that the level of multicolinearlity in the data was sufficient to perform an exploratory factor analysis. Common factor analysis with oblique rotation was then conducted.

Based on the eigenvalues (>1.0), the scree plot (showing a break after the fourth factor), and a threshold value of 0.55, four factors (i.e. Mental Model, Efficiency, Automaticity, and Metacognition) overall emerged as theorized, with an exception that some items of Organization and Structure overloaded with some of Problem Representation. Despite these outcomes, we believed that they were not conclusive due to the following reasons. First, the sample size in the pilot test was so small that it is very unlikely to yield a stable structure of the factors. Second, our panel of the judges in the sorting procedure was rather insightful and experienced than the convenient student sample in the pilot test. Nonetheless, taking the results into consideration, we revisited the proposed definitions of the construct and carefully reworded all the items further, particularly those that merged into one factor. Finally, after consulting with our distinguished scholar in multiple sessions, we were content that this refined set of items was theoretically justified and ready for the actual study. The final set of items for the factors of the knowledge internalization construct is listed in Table 1.1.

Table 1.1 Items for the Knowledge Internalization Construct (after the pilot study)

Organization & Structure	
OS1	I can easily group relevant information into different categories.
OS2	I can easily tell how a piece of needed information is similar or different from another.
OS3	I can easily sort out required information in a systematic fashion.
OS4	I can easily see how a piece of relevant information fits with other pieces.
Problem Representation	
PR1	I can easily identify the reasons that cause these problems.
PR2	I can easily see how difficult situations are caused by certain factors.
PR3	I can easily explain to other people the basic cause-and-effect relationships involved.
PR4	I can easily recognize various cause-and-effect linkages in the problems.
Mental Models	
MM1	I can easily visualize the step-by-step process to solve them effectively under various situations.
MM2	I can easily envision possible solutions in vivid details given different circumstances.
MM3	I can easily imagine how certain solutions will work out under a variety of conditions.
MM4	I can clearly picture in my head how potential solutions would play out differently due to certain factors.

Table 1.1 – *Continued*

Efficiency	
EF1	I can solve them very effectively and proficiently.
EF2	I can resolve many difficulties with less time and effort.
EF3	I can obtain effective solutions with great ease and speed.
EF4	I am faster than most of my colleagues in solving them effectively.
Automaticity	
AU1	I can rely on my instinct for correct solutions without following step-by-step analytical procedures.
AU2	I can instantly figure out correct solutions without realizing exactly how.
AU3	My immediate intuitions without much thinking are usually correct.
AU4	I can jump to correct conclusions without consciously following prescribed procedures.
Metacognition	
MC1	I always act appropriately in difficult situations using what I learn from my past experiences.
MC2	I always control my actions carefully based on the lessons previously learned.
MC3	I always monitor both successes and failures of my decisions and adjust my actions effectively.
MC4	I always evaluate and learn from my actions so that I do not repeat the same mistakes.

Note: All items are preceded by the phrase: When I work on job-related problems:

1.7.5 Measurements of Other Constructs

Other constructs in the research model are measured using scales adapted from prior literature as described below. *Expert power* is measured with four items adapted from Schriesheim et al. (1991)'s study, in which the alpha coefficient exceeds 0.80, indicating satisfactory level of the reliability of the construct. *Knowledge self-efficacy* is measured with three items adapted from Kankanhalli et al. (2005)'s study, in which the alpha coefficient is 0.96, thus exhibiting rather high reliability. Finally, *intention to share knowledge* is measured with three items adapted from Bock et al. (2005)'s study, in which the composite reliability is 0.93, indicating high reliability. Seven-point Likert-type scales anchored from strongly disagree (1) to strongly agree (7) are used for all the items of the three constructs. The items for the three constructs are presented in Table 1.2.

Table 1.2 Items for Expert Power, Knowledge Self-efficacy, and Intention to Share Knowledge

Expert Power (adapted from Schriesheim et al., 1991)	
EP1	My coworkers often seek my solutions for job-related problems.
EP2	My coworkers often comment that my advice is sound.
EP3	My coworkers often seek my technical knowledge.
EP4	My coworkers often say that my technical suggestions are excellent.
Knowledge Self-efficacy (adapted from Kankanhalli et al., 2005)	
KS1	I have confidence in my ability to provide knowledge that others in my organization consider valuable.
KS2	I have the expertise needed to provide valuable knowledge for my organization.
KS3	I can provide more valuable knowledge than most other employees can.
Intention to Share Knowledge (adapted from Bock et al., 2005)	
IN1	I intend to share my experience and knowledge with my coworkers more frequently in the future.
IN2	I will try to share my expertise from my education or training with my coworkers in a more effective way.
IN3	I will always provide my experience and knowledge at the request of my coworkers.

1.7.6 Data Collection

Because our scale of knowledge internalization aims to help determine how knowledge workers in general learn to apply knowledge accumulated over time, our target respondents are professionals who deal with knowledge on a daily basis and have reasonable amount of industry experience. To fit this sampling frame, we conducted the study with the collaboration of the college of business administration at a public university in a large metropolitan area of the southwest US. Specifically, we administered the survey instrument to graduate students mainly in the professional cohort (team-based) format of master's degree of business administration program exclusively designed for full-time working professionals as well as the regular format. The survey was handed out to the students at the beginning of their classes and collected once they completed it (lasting about twenty minutes). A total of 266 questionnaires were returned out of expected 324, yielding the response rate of 82.1%. After screening for a noticeably high number of missing data, we eliminated 7 responses, thus resulting in a final sample size of 259.

The demographic characteristics of the final sample are provided in Table 1.3. Approximately 63 and 35 percent of the participants hold bachelor's degrees and master's degrees respectively. Among the professions identified in the questionnaire, engineers, IS/IT, and general management are the leading groups with around 16 percent each, while accountants, financial analysts, and marketing follow with roughly 8 percent each. The average tenure in the profession is about 7 years, while the average tenures in the current organization and in the current position are about 5 and 3 years respectively. Such demographics of the sample suggest that they are indeed knowledge workers who have substantial work experience. We therefore believed that the collected data is very appropriate for this study and is consistent with our targeted sampling frame.

Table 1.3 Demographic Characteristics of the Sample (n = 259)

Characteristics	Percent	Characteristics	Percent
Gender		*Industry*	
Male	69.8	Banking/Insurance/Financial Service	14.8
Female	30.2	Constructions/Architecture/Engineering	7.4
Age		Consulting/Business Service	4.3
21-30	58.4	Education	8.2
31-40	32.7	Government/Military	8.6
41-50	7.4	Healthcare	7.8
51-60	1.6	Hotel/Entertainment/Service Industry	4.7
Education		IT/Telecommunications	7.4
High school	0.4	Manufacturing	14.5
Associate	0.4	Other	22.3
Bachelor	63.4		
Master	34.6	Characteristics	Mean
Doctorate	1.2	Years on current position	3.3
Profession		Years with current organization	4.4
Accountant	8.1	Years in the profession	6.6
Engineer	16.2	No. of Employees in Department	665.9
Financial Analyst	6.6	No. of Employees in Organization	24866.3
General Management	16.6	No. of Professional Contacts	170.9
IS/IT	15.8		
Lawyer	0.4		

Table 1.3 – *Continued*

Marketing	7.7	
Medical/Physician/Nurse	1.5	
Public Relation	1.9	
Other	25.1	

1.8 Measurement Validation

The objective of this phase is to assess the validity of the knowledge internalization construct, particularly regarding the convergent and discriminant validity and the reliability of the construct. To ensure that the psychometric properties and validities of the measurement are evaluated as rigorously as possible, both exploratory and confirmatory assessments are sequentially employed (Lewis et al., 2005). All the steps are described below.

1.8.1 Exploratory Assessment

To perform an exploratory factor analysis (EFA), principal component analysis with varimax rotation was conducted (n = 259). Based on the eigenvalues (>1.0), the scree plot (showing a break after the fifth factor), and a threshold value of 0.65, five factors evidently emerged as opposed to six as theorized (see Table 1.4). The five factors explained about 71% of the variance in the data. We specifically selected 0.65 as the threshold for the following reasons. Lewis et al. (2005) recommend that researchers not only maximize a loading threshold to ensure greater correlation among the items in the corresponding factors, but also include as many items as possible. While the results strongly suggested that the four factors (i.e. Organization and Structure, Efficiency, Automaticity, and Metacognition) were the structure of the measures, Problem Representation and Mental Models appeared to merge into one factor. To maintain the content validity of the construct, using the value of 0.65 allowed as many as six items to be included; more importantly, three items (PR1, PR2, and PR4) were from Problem Representation and three items (MM2, MM3, and MM4) were from Mental Models as originally anticipated. Some researchers even suggested further that retaining insignificant items also helps sustain the content validity (Bollen and Lennox, 1991; Petter et al., 2007). Consequently, to be consistent with prior literature such as the works of Nonaka and his colleagues, we relabeled the factor simply as Mental Models. The following are the items included in the Mental Models:

- I can easily identify the reasons that cause these problems. (PR1)
- I can easily see how difficult situations are caused by certain factors. (PR2)
- I can easily recognize various cause-and-effect linkages in the problems. (PR4)
- I can easily envision possible solutions in vivid details given different circumstances. (MM2)
- I can easily imagine how certain solutions will work out under a variety of conditions. (MM3)
- I can clearly picture in my head how potential solutions would play out differently due to certain factors. (MM4)

High factor loading (> 0.65) of the items within their corresponding factors exhibited a relatively high level of convergent validity, while the distinctiveness of the factors (i.e. no cross-loading items) provided evidence of discriminant validity of the construct (Lewis et al., 2005). Each of the four factors contained four items, while the Mental Model factor embraced six items. Finally, all Cronbach’s alpha coefficients exceeded 0.8 (see Table 1.5), indicating satisfactory level of the reliability of all the scales (Nunnally, 1978).

Table 1.4 EFA Result of Principal Component Analysis with Varimax Rotation (n = 259)

	Mental Models	Organization & Structure	Automaticity	Metacognition	Efficiency
MM3	.762	.120	.159	.078	.277
PR1	.708	.315	.126	.039	.133
PR2	.701	.427	.172	.186	.046
PR4	.695	.399	.091	.116	.104
MM4	.689	.051	.168	.157	.394
MM2	.677	.112	.165	.086	.399
MM1	.627	.164	.163	.030	.422
PR3	.580	.385	.014	.244	.044
OS1	.244	.820	.093	.043	.161
OS2	.217	.796	.075	.133	.239
OS4	.345	.774	.065	.046	.194
OS3	.228	.745	.164	.106	.264
AU4	.162	.080	.881	.043	.092
AU3	.196	.122	.842	.018	.184
AU2	.145	.001	.839	.047	.134
AU1	.065	.155	.792	.065	.187
MC2	.109	.087	.056	.886	.066
MC3	.082	.095	-.008	.839	.156
MC1	.127	.044	.115	.821	.066
MC4	.106	.077	.006	.805	.137
EF3	.214	.201	.233	.165	.767
EF2	.232	.229	.211	.190	.743
EF1	.283	.268	.101	.205	.738
EF4	.352	.243	.213	.023	.672

Table 1.5 Descriptive Statistics and Reliability of the Constructs (n = 259)

Factor	Mean (SD)	No. of Items	Cronbach's Alpha
Organization and Structure	5.77 (.93)	4	0.90
Mental Models	5.36 (.87)	6	0.89
Efficiency	5.32 (.99)	4	0.89
Automaticity	4.62 (1.28)	4	0.89
Metacognition	5.76 (.92)	4	0.90

1.8.2 Confirmatory Assessment

For confirmatory factor analysis (CFA), we used SmartPLS 2.0 M3 (Ringle, Wende, and Will, 2005) to validate both measurement and structural models using the same data (n = 259) used in the exploratory assessment. Unlike a covariance-based structural equation modeling (SEM) approach used in LISREL, Partial Least Squares (PLS), a component-based SEM, was selected, mainly because it is able to handle formative latent constructs, which exist in our research model, more effectively (Petter et al., 2007). In addition, PLS is more flexible than LISREL in terms of both distribution assumptions (e.g. multivariate normality is not necessary) and sample size requirements (Chin, Marcolin, and Newsted, 2003). Typically, a sample of 100-200 is considered satisfactory (Lewis et al., 2005); therefore, our sample of 259 is sufficient.

Based on the EFA results and the theoretical framework, knowledge internalization is thus modeled as a formative construct – that is, formed by the following five dimensions: (1) Organization and Structure, (2) Mental Models, (3) Efficiency, (4) Automaticity, and (5) Metacognition. As previously theorized, these underlying cognitive mechanisms are the defining characteristics of the knowledge internalization construct. We now offer empirical evidence as follows. Specifically, due to its multidimensional nature, knowledge internalization is modeled as a second-order formative construct, with first-order reflective constructs (i.e. the five dimensions). Like Malhotra, Gosain, and El Sawy (2007), we created equally weighted average scores for each of the five dimensions based on its associated items. While it is debatable whether using average scores or using weighted composite scores is more appropriate, some researchers suggest that the estimates from the latter approach are rather data dependent, unreliable, and difficult to interpret (Hair et al., 1987), and that the results of both approaches are not different (Dillon and McDonald, 2001). The variance inflation factor statistics (VIF) of all the five factors were lower than 3.3 (ranging from 1.1 for Metacognition to 2.2 for Mental Model), indicating fairly low level of multicollinearity among the dimensions – that is, they are quite distinct between one another (Petter et al., 2007; Diamantopoulos and Signuaw, 2006). As this empirical result appears to support the theoretical justification, we therefore are certain that knowledge internalization construct should indeed be modeled as formative.

Next, we assessed convergent validity, discriminant validity, and reliability of the reflective constructs only (e.g. the five dimensions of knowledge internalization), since conventional approaches for reflective constructs are inappropriate for formative ones, and how to systematically validate them is still uncertain among researchers (Diamantopoulos and Winklhofer, 2001; Gefen and Straub, 2005; Petter, Straub, and Rai, 2007). To validate the psychometric properties of a construct in SmartPLS, both measurement and structural models technically have to be analyzed simultaneously. However, we would continue to evaluate the structural model, only if the CFA results of the measurement model were satisfactory. Due to the second-order nature of the knowledge internalization construct, we adopted the hierarchical construct modeling approach (Wetzels, Odekerken-Schroder, and van Oppen, 2009), which was favorably reviewed and recommended by Marcoulides, Chin, and Saunders (2009). Essentially, the items of a lower-order construct (e.g. Mental Model) were re-used by its higher-order construct (i.e. knowledge internalization); hence, the technique is also known as repeated indicators approach (Wetzels et al., 2009).

The CFA results (see Table 1.7) attested discriminant validity, convergent validity, and reliability of not only the knowledge internalization construct, but also all other reflective constructs in the research model as discussed below. All the items strongly loaded (> 0.7) on their corresponding factors, and there were no cross-loading items (most well below 0.6), demonstrating discriminant validity (Gefen and Straub, 2005). In addition, as can be seen in Table 1.6, the square root of the average variance extracted (AVE) of each of the reflective constructs was much larger than its correlation with all the other constructs, thus confirming evidence of discriminant validity. The *t*-statistics of all the items loading on their respective factors (approximately ranging from 24 to 65) were significant at the 0.001 level, therefore strongly exhibiting high degree of convergent validity (Gefen and Straub, 2005). Finally, both composite reliability indices and Cronbach's alpha coefficients of all the constructs exceeded 0.8, indicating satisfactory reliability (Nunnally, 1978). Taken together, these results not only corroborated our conceptualization of knowledge internalization, but also demonstrated the validity of the construct. Given these commendable measurement model results, we now turned to examine the structural model.

Table 1.6 Descriptive Statistics, Reliability, and Discriminant Validity of the Constructs (n = 259)

Construct	Mean (SD)	No. of Items	Composite Reliability	Cronbach 's Alpha	AVE	OS	MM	EF	AU	MC	EP	KS	IN
OS	5.77 (.93)	4	0.93	0.90	0.77	0.88							
MM	5.36 (.87)	6	0.92	0.89	0.65	0.63	0.81						
EF	5.32 (.99)	4	0.92	0.89	0.75	0.55	0.65	0.87					
AU	4.62 (1.28)	4	0.93	0.89	0.76	0.29	0.39	0.45	0.87				
MC	5.76 (.92)	4	0.92	0.88	0.74	0.19	0.27	0.31	0.16	0.86			
EP	5.50 (1.07)	4	0.93	0.90	0.76	0.44	0.44	0.48	0.29	0.14	0.87		
KS	5.66 (.92)	3	0.90	0.84	0.76	0.48	0.44	0.49	0.33	0.21	0.64	0.87	
IN	5.85 (.96)	3	0.89	0.82	0.74	0.21	0.17	0.14	0.05	0.17	0.26	0.34	0.86

Notes. Square root of AVE is shown and highlighted along the diagonal. OS = Organization and Structure, MM = Mental Models, EF = Efficiency, AU = Automaticity, MC = Metacognition, EP = Expert Power, KS = Knowledge Self-efficacy, IN = Intention to Share Knowledge

Table 1.7 CFA Result (n = 259)

	AU	EF	EP	IN	KS	MC	MM	OS
AU1	0.833	0.391	0.226	0.078	0.282	0.142	0.323	0.284
AU2	0.848	0.354	0.241	0.050	0.269	0.123	0.314	0.181
AU3	0.899	0.445	0.297	0.084	0.318	0.118	0.408	0.297
AU4	0.899	0.354	0.239	0.044	0.268	0.126	0.339	0.239
EF1	0.324	0.855	0.423	0.178	0.429	0.349	0.575	0.518
EF2	0.399	0.892	0.383	0.155	0.398	0.317	0.550	0.453
EF3	0.416	0.876	0.367	0.168	0.362	0.298	0.532	0.444
EF4	0.404	0.832	0.473	0.144	0.481	0.192	0.588	0.485
EP1	0.236	0.419	0.875	0.301	0.609	0.164	0.353	0.377
EP2	0.241	0.389	0.832	0.303	0.527	0.247	0.351	0.385
EP3	0.248	0.429	0.889	0.326	0.567	0.072	0.392	0.388
EP4	0.289	0.423	0.891	0.263	0.550	0.126	0.409	0.377
IN1	0.082	0.124	0.283	0.837	0.303	0.158	0.151	0.124
IN2	0.067	0.187	0.329	0.920	0.383	0.167	0.194	0.232
IN3	0.046	0.164	0.266	0.811	0.378	0.171	0.146	0.217

Table 1.7 – *Continued*

KS1	0.314	0.466	0.612	0.432	0.875	0.282	0.402	0.469
KS2	0.222	0.393	0.559	0.362	0.904	0.196	0.372	0.427
KS3	0.323	0.398	0.510	0.278	0.833	0.100	0.344	0.334
MC1	0.173	0.269	0.161	0.147	0.187	0.836	0.279	0.202
MC2	0.129	0.275	0.110	0.152	0.147	0.895	0.273	0.224
MC3	0.094	0.312	0.169	0.152	0.244	0.865	0.264	0.224
MC4	0.104	0.295	0.157	0.213	0.209	0.836	0.255	0.208
MM2	0.352	0.569	0.311	0.094	0.284	0.245	0.791	0.471
MM3	0.337	0.509	0.293	0.121	0.292	0.230	0.837	0.480
MM4	0.349	0.570	0.299	0.138	0.342	0.303	0.792	0.439
PR1	0.294	0.493	0.425	0.196	0.357	0.178	0.807	0.508
PR2	0.329	0.491	0.322	0.197	0.382	0.308	0.825	0.594
PR4	0.274	0.515	0.440	0.182	0.424	0.241	0.787	0.544
OS1	0.241	0.439	0.400	0.215	0.441	0.178	0.526	0.881
OS2	0.234	0.494	0.387	0.175	0.405	0.263	0.524	0.877
OS3	0.310	0.510	0.372	0.185	0.432	0.243	0.553	0.865
OS4	0.233	0.483	0.376	0.224	0.393	0.192	0.598	0.884

Notes. OS = Organization and Structure, MM = Mental Models, EF = Efficiency, AU = Automaticity, MC = Metacognition, EP = Expert Power, KS = Knowledge Self-efficacy, IN = Intention to Share Knowledge

1.9 Structural Model Analysis and Results

To examine the significance of the paths in SmartPLS, bootstrapping procedure (n = 259 with 500 cases) was performed. We first tested for possible confounding effects of the control variables on all the three endogenous variables simultaneously (i.e. expert power, knowledge self-efficacy, and intention to share knowledge), and found only two significant relationships. Specifically, only gender (b = 0.112, t = 2.704, p < 0.01) and tenure in the current organization (b = 0.189, t = 4.318, p < 0.001) were significantly associated (based on two-tailed tests) with expert power. As a result, we retained only them in the research model and continued with our analysis.

Overall, knowledge internalization explained approximately 51% of the variance in expert power, 30% of the variance in knowledge self-efficacy, and 18% of the variance in intention to share knowledge. Knowledge internalization is found to be a significant predictor of both expert power (b = 0.26, p < 0.01) and knowledge self-efficacy (b = 0.546, p < 0.01).

Therefore, H1 and H2 are supported. However, the relationship between knowledge internalization and intention to share knowledge is insignificant (*b* = -0.014, *p* > 0.05); H3 is thus not supported. Knowledge self-efficacy is also a significant predictor of intention to share knowledge (*b* = 0.341, *p* < 0.01) and expert power (*b* = 0.483, *p* < 0.01), thus supporting H4 and H5 respectively. Finally, the relationship between expert power and intention to share knowledge is also significant (*b* = 0.129, *p* < 0.05), thus showing support for H6. The results of PLS path analysis are shown in Figure 1.6.

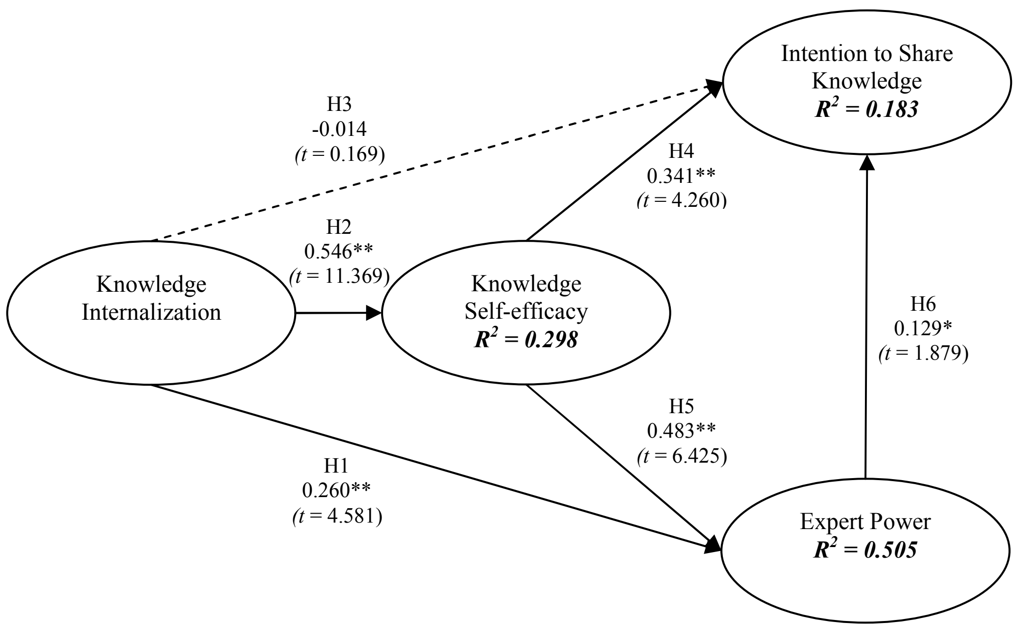

Figure 1.6 Results of Path Analysis
Notes. * *p* < 0.05, ** *p* < 0.001 in one-tailed tests. Dashed line represents insignificant path. The factors of the knowledge internalization and control variables are graphically excluded for clarity purpose.

Before we turn to examine the remaining hypotheses, it is noteworthy to revisit the aforementioned result of H3 (i.e. the relationship between knowledge internalization and intention to share knowledge). Unlike traditional regression, PLS allows us to test as many regression models as desired simultaneously. The derived statistical results of each path are thus adjusted by taking into account other paths in the same nomological network. In other words, the results pertain to the research model being tested only. Thus, the fact that H3 is found unsupported in this particular nomological network does not absolutely warrant us to conclude that there is no significant relationship between knowledge internalization and intention to share knowledge. On the contrary, by conducting a separate test including only the two constructs, we found that knowledge internalization is a significant predictor of intention to share knowledge (b = 0.240, t = 2.847, $p < 0.05$). Interestingly, when tested alone, knowledge internalization is also a significant predictor of expert power (b = 0.517, t = 10.957, $p < 0.001$), which is consistent with the PLS results that support H1. We will discuss these findings again after performing formal mediation analyses next.

1.9.1 Mediation Analysis

We have hypothesized that expert power will partially mediate the relationship between knowledge internalization and intention to share knowledge (H7), knowledge self-efficacy will partially mediate the relationship between knowledge internalization and expert power (H8), and knowledge self-efficacy will partially mediate the relationship between knowledge internalization and intention to share knowledge (H9). To test the significance of these mediated paths via the PLS technique, two additional procedures were conducted (Malhotra et al., 2007; Subramani, 2004). Specifically, they are (1) comparisons of nested models and (2) analyses of individual mediated paths. The two tests are complementary in that the former examines overall contribution of direct paths in addition to mediated paths to the fit of the model, while the latter particularly analyzes the significance of each individual mediated path (Malhotra et al., 2007; Subramani, 2004).

First, we evaluated the model fit by comparing the research model, which includes both the direct and mediated effects of knowledge internalization on the endogenous variables (hence, full model; partial mediation) to a competing model, which includes only the mediated effects without the direct paths. As shown in Table 1.8, the research model was able to predict 51% of the variance in expert power and 18% of the variance in intention to share knowledge, while the competing model predicted 46% and 18% respectively. The explanatory power in predicting intention to share knowledge of the two models was not different, indicating that the direct path from knowledge internalization and intention to share knowledge was not contributing to the model.

However, whether the explanatory power in predicting expert power (i.e. 51% vs. 46%) of the models would be significantly different further required a pseudo *F* test (Chin et al., 2003). The f^2 statistic was first calculated based on the difference in R^2 between the full model and the nested model (f^2 = (R^2 full model – R^2 nested model) / (1 – R^2 full model)). Then, the f^2 statistic was used to calculate a pseudo *F* statistic ($F = f^2$ * (n – k – 1) with 1, (n – k) degrees of freedom, where n is the sample size and k is the number of the constructs in the model). The result of the *F* test revealed that the R^2 difference was significantly different ($p < 0.01$). As a result, the analysis suggested that the direct path from knowledge internalization to expert power significantly explained additional variance in the full model.

Table 1.8 Comparisons of Nested Models

Direct Path	R^2 Full Model (Partial Mediation)	R^2 Nested Model (Full Mediation)	f^2 statistic	Pseudo-F (1, 248)
KI → EP	0.51	0.46	0.10	25.2**
KI → IN	0.18	0.18	0.00	0.00

Notes. ** $p < 0.01$, KI = Knowledge internalization, EP = Expert power, IN = Intention to share knowledge

Next, based on the PLS results, we examined the significance of individual mediated paths (H7-H9) using the path coefficients and standard errors of the direct paths among independent, mediating, and dependent variables (Hoyle and Kenny, 1999; Malhotra et al., 2007; Subramani, 2004). The path coefficient of a mediation effect is the product of path coefficients between the independent variable and the mediator and between the mediator and the dependent variable. The standard error of a mediated path is estimated as *sqrt* ($b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2$), where *a* is the path coefficient of the path from the independent variable to the mediator, b is the path coefficient of the path from the mediator to the dependent variable, and s_a and s_b are the standard deviations of *a* and *b*. The significance testing of the mediated paths is presented in Table 1.9. Based on the computed *z* statistics (see Table 1.9), the results showed limited support for the mediation effect in H7 ($0.05 < p < 0.10$), but strong support for the mediation effects in H8 ($p < 0.01$) and H9 ($p < 0.01$). Furthermore, because the path from knowledge internalization to intention to share knowledge is insignificant, and because the path from knowledge internalization to expert power is significant, it can be respectively concluded that the effects of knowledge internalization on intention to share knowledge are fully (as opposed to partially as hypothesized) mediated by expert power and by knowledge self-efficacy, and that the effect of knowledge internalization on expert power is partially mediated by knowledge self-efficacy (as hypothesized).

Table 1.9 Significance of Mediated Paths

Mediated Path	Path Coefficient	St. Error	*z* statistic	Mediation
H7: KI → EP → IN	0.034	0.0197	1.704*	Full
H8: KI → KS → EP	0.264	0.0472	5.588**	Partial
H9: KI → KS → IN	0.186	0.0468	3.975**	Full

Notes. * $p < 0.10$, ** $p < 0.01$, KI = Knowledge internalization, EP = Expert power, IN = Intention to share knowledge, KS = Knowledge self-efficacy

As previously mentioned, while the base relationship between knowledge internalization and intention to share knowledge (H3) is found to be insignificant in this particular nomological network, the relationship is actually significant when tested without including any other construct. Here, that conclusion is also confirmed by the findings of the full mediation effects (H7 and H9).

1.10 Common Method Variance

Since the collected data was self-reported and collected in one setting, the issue of common method variance (CMV) (i.e. variance attributable to the measurement method rather than the variable the measurement represents) may be raised (Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). To determine the extent to which the CMV may affect our research findings, several tests were conducted as follows. First, we performed the Harman's single-factor test by including all items from all of the constructs into a factor analysis to determine whether the majority of the variance in the research model can be accounted for by one general factor (Podsakoff et al., 2003). Principal component analysis without rotation yielded seven factors. The first factor explained about 34% of the variance. This certainly does not constitute a majority of the total variance, as a recent study by Malhotra et al. (2007) reported 40% as being not a majority of variance. Thus, the result of Harman's single-factor test indicates that the CMV is not likely a source of major concern.

Second, we evaluated the potential impact of the CMV by assuming and including a single unmeasured latent method factor as the source of the CMV to the research model (Herath and Rao, 2009; Podsakoff et al., 2003). The basic premise of this approach is that all the items will load on not only their respective constructs but also the CMV factor. To create the CMV factor using PLS, we adopted the method proposed by Liang, Saraf, Hu, and Xue (2007), in which each item was first transformed into a single-item construct of its own, and then the added CMV factor was directly linked to only these constructs (i.e. no links between the CMV factor and all other currently higher-order constructs such as the dimensions of the knowledge internalization construct and the knowledge self-efficacy construct). We determined the effects of the CMV factor by comparing structural parameters both with and without the CMV factor in the research model (Herath and Rao, 2009; Podsakoff et al., 2003). In both scenarios, we found that factor loadings appeared to be similarly consistent, that all path coefficients were similar in magnitude, and that the significance of the *t* statistics remained the same. Taken together, these results suggested that the research findings are unlikely to be affected by the CMV.

1.11 Discussion

The first objective of this study is to conceptualize the notion of knowledge internalization and develop its measurement. Based on the results of the scale development process, knowledge internalization was demonstrated to be a second-order formative construct, and can be now specifically described as ***the process, in which an individual transforms his or her declarative knowledge into procedural knowledge via such cognitive mechanisms as organization and structure, mental models, efficiency, automaticity, and metacognition***. It should be noted that rather than six dimensions initially derived from Glaser et al.'s framework, five dimensions are revealed in the factor analyses. Specifically, Problem Representation and Mental Models merged into one factor. We believe that due to certain level of abstractness of the two dimensions, our respondents may consider them the same. In addition, the two dimensions may actually be more highly correlated in practice than in theory. For example, one can see that to be able to represent a problem correctly (e.g. identifying reasons or factors that cause the problem of interest), certain extent of mental models may also have to be activated (e.g. imagining how factors are related in a few scenarios). Future research may employ a different research methodology such as a laboratory experiment, to see whether the difference between the two factors exists.

Regarding the second objective of the study, which is to examine the role of knowledge internalization in knowledge sharing phenomenon, we found that higher level of knowledge internalization leads to higher level of both expert power and knowledge self-efficacy, but interestingly, does not lead to intention to share knowledge within this nomological network. This finding suggests that knowledge workers, who can actually apply their procedural knowledge to solve problems, not only will feel more confident toward their knowledge and skills, but also perceive that their expertise is recognized and sought after by their colleagues. However, the mere fact that they can effectively internalize knowledge does not directly suggest they will share knowledge.

In addition to the effects of knowledge internalization, we found that knowledge self-efficacy is associated with both expert power and intention to share knowledge. Additionally, expert power will increase people's intention to share knowledge. These findings suggest that in conjunction with knowledge internalization, expert power and knowledge self-efficacy are somehow essential in determining whether knowledge workers will share knowledge. Indeed, we found that both expert power and knowledge self-efficacy fully mediate the effect of knowledge internalization on intention to share knowledge. The mediating effect of knowledge self-efficacy is found to be somewhat stronger than that of expert power. Knowledge self-efficacy is also found to mediate the effect of knowledge internalization on expert power.

Collectively, these findings support our belief that knowledge internalization indeed precedes other knowledge-related processes including knowledge sharing. Specifically, while it does not automatically make people want to share knowledge, it leads to people feeling more confident and more recognized; in turn, they will then intend to share the knowledge. In sum, taking the two mediators into account, effective knowledge internalization will increase the intention to share knowledge.

1.12 Theoretical Implications

This study significantly contributes to the literature with the following topics: the concept and the construct of knowledge internalization, the relationship between knowledge internalization and knowledge sharing, and the conceptual amalgamation among tacit, explicit, declarative, and procedural knowledge.

The first and main theoretical contribution of this study is the conceptualization and measurement of knowledge internalization. The extant literature suggests that the influence of knowledge internalization underlying in various phenomena is critical and needs to be explicitly addressed. In the field of KM, first of all, it is not only that, despite the popularity and significant contributions of Nonaka's organizational knowledge creation theory, the details of the SECI process are rather lacking, but particularly the internalization, which appears to be instrumental to the effectiveness of the remaining processes in organizations, has never been theoretically explored in depth. Second, research in the IT use phenomena also implies that people's knowledge internalization creates their automatic behaviors, which in turn affect their IT usage.

Despite its crucial role in the aforementioned research streams, the concept has never been formally established, therefore limiting not only our understandings of the phenomena, but also theoretical advancement in the field. To the best of our knowledge, this study is the first both to systematically conceptualize the knowledge internalization by drawing from several prominent theories and to develop and validate its construct. The conceptualization helps illuminate exactly when and how knowledge workers internalize knowledge, that is, the internalization occurs when they can convert their declarative knowledge to procedural knowledge via a combination of cognitive mechanisms. Researchers can adopt the scale to investigate further its prospective role not only in KM and IT usage as mentioned, but also some other relevant phenomena such as information security management. For example, as people factors can eventually triumph technical infrastructure, people's level of security awareness is important and known in the field to be instrumental to the effectiveness of information security management in organizations (Kruger and Kearney, 2006; Siponen, 2000; Thompson and von Solms, 1998). Drawing from the theory of learning outcomes (Kraiger Ford, and Salas, 1993), Wipawayangkool (2009) propose that an individual's security awareness is a multidimensional construct comprising cognitive, affective, and behavioral dimensions. Particularly related to knowledge internalization is the behavioral dimension, which is defined as skills *actionable* in *automatic* and secure manners. We thus speculate that the level of people's security awareness may be improved significantly, once they start internalizing knowledge about information security.

The next contribution is the findings of the role of knowledge internalization in knowledge sharing phenomenon. We essentially found, among others, that knowledge internalization will not influence the intention to share knowledge directly, but particularly through knowledge self-efficacy and expert power. By including the construct of knowledge internalization, this study expands the nomological network of knowledge sharing phenomenon. While previous research found that both intrinsic (e.g. general attitudes, self-efficacy, and enjoyment) and extrinsic factors (e.g. subjective norms and organizational climate) can explain people's knowledge sharing behaviors (Bock et al., 2005; Kankanhalli et al., 2005; Ray et al., 2005), paradoxically, factors specifically tied to knowledge have not been explored much. In addition, in their recent review paper, Wang and Noe (2010) suggest that more studies to analyze knowledge sharing from a power perspective are needed. As a result, this study fills in such gaps in the literature by testing a nomological network that includes knowledge internalization and expert power.

Finally, although research suggests that tacit knowledge can sustain organizational competitive advantage, how knowledge workers apply their knowledge to solve problems, so that so-called tacit knowledge could be achieved, has always been uncertain. Two key reasons include how knowledge workers actually create tacit knowledge has been akin to a black box, and that tacit knowledge itself is ambiguous. This study resolves the first issue by suggesting that people's knowledge internalization is the means to ultimately produce tacit knowledge. In the process of conceptualizing the knowledge internalization, we also shed some light on the second issue, that is, the fuzzy nature of tacit knowledge by theoretically integrating four well-known types of knowledge, namely, explicit, tacit, declarative, and procedural knowledge.

1.13 Practical Implications

Effective KM practices can help organizations sustain their competitive advantage. However, such a statement can be rather vague in practice, unless managers precisely know what knowledge to manage. Different manifestations of knowledge such as explicit, tacit, declarative, and procedural possess different values and benefits to organizations. Rather than declarative knowledge, which can be made explicit, tacit and procedural knowledge, which reside in experts' heads and thus are difficult to communicate and imitate, have been found to be instrumental to sustainable competitive advantage. Therefore, to fully reap the benefits from the KM initiatives and achieve sustainable competitive advantage, it is critical that organizations are able to assess the extent to which the employees possess tacit and procedural knowledge. Such a knowledge-oriented assessment is importantly needed, because general performance, often used to measure the effectiveness of organizational KM, is not necessarily affected by knowledge and expertise and thus can be misrepresentative of the KM success.

This study presents a rigorously validated survey instrument that is directly tied to the notion of knowledge. Unlike many sophisticated techniques (see Royer et al., 1993) which can be cumbersome to administer and interpret, our easy-to-use and domain independent measurement can be adopted not only to assess the employees' overall knowledge and ability across domains, but also to classify them further (e.g. to find experts or mentors) based on the cognitive skills of the knowledge internalization. That is, the measurement can help organizations evaluate not only to what extent their employees have acquired knowledge, but also to what extent they can actually apply such knowledge to perform a task or solve a job-related problem in a more effective and automatic manner. Specifically, the measurement allows managers to gauge how well employees can potentially, based on their accumulated declarative knowledge, create procedural and eventually tacit knowledge, so that organizational competitive advantage could be sustained.

1.14 Limitations and Future Research Directions

Upmost care is exercised in this study to strengthen the validity and generalizability of the findings. Nevertheless, our findings need to be interpreted in the context of certain limitations of the study. First, we have found that the effect of knowledge internalization on knowledge sharing intention is fully mediated by both knowledge self-efficacy and expert power. While this finding contributes yet another important layer to research in knowledge sharing phenomenon, we did not examine further than the sharing intention. Like Bassellier and Benbasat (2004) and Bassellier, Benbasat, and Reich (2003), we believe that intentions are not necessarily an inferior dependent variable compared with actual behaviors, because, consistent with Ajzen (1991)'s theory of planned behavior, intentions eventually affect actual actions in an expected manner in most scenarios. In fact, Chennmaneni (2006) found that knowledge sharing intention leads to actual sharing behaviors. Nonetheless, a direction for future researchers can explore is, by building on this study, to investigate whether the effects of not only knowledge internalization but also knowledge self-efficacy and expert power on some constructs related to actual knowledge sharing behaviors exist.

Second, we have provided richness to the concept of knowledge internalization. Specifically, we found that organization and structure, mental models, efficiency, automaticity, and metacognition are the essence of the internalization process. To the best of our knowledge, this study is the first to provide such details to the construct and to develop its measurement systematically. We have also established its role in a nomological network in knowledge sharing. Nonetheless, we did not explore the decomposed model of the network, that is, the effects of each cognitive mechanism in knowledge sharing. We suggest that a future study can be based on this limitation, and doing so may provide more granulated understanding on the role of different types of cognitive mechanism in knowledge sharing and knowledge management.

Third, while our conceptualization of knowledge internalization refers to the cognitive conversion from declarative to procedural knowledge and eventually to tacit knowledge, we did not examine how easy or difficult for people with different degrees of knowledge internalization to share their knowledge. We thus recommend that researchers determine further whether the effect of knowledge internalization on knowledge sharing depends on sharing mechanisms. For example, can personal approaches or less-structured technology assist people with high degrees of knowledge internalization to share their knowledge, more than systematic approaches or more-structured technology can? Thus, it is important that organizations determine a set of KM-related factors (e.g. KM strategy and KM systems) that correspond with varying degree of knowledge internalization, so that different work environment can be provided for different groups of knowledge workers to facilitate their knowledge sharing.

Forth, we consider knowledge internalization a critical process that can determine the value of the remaining processes in the SECI model (i.e. socialization, externalization, and combination) (Nonaka, 1994). We have found that knowledge internalization is associated with knowledge sharing in several important ways. Nonetheless, while knowledge sharing is certainly a fundamental objective of organizational KM initiatives, other processes, particularly those in the SECI model also deserve researchers' attention. To continue the direction of this study and for richness of the construct, we recommend that future researchers first explore each of those processes independently by grounding it with well-established theories, and then investigate its role in an appropriate nomological network. Consequently, in the future, an attempt to integrate all the four systematically developed constructs can be conducted. If these directions are to be adopted, researchers can then learn full-scale effects of the SECI spiral process at individual level in organizational KM initiatives.

Finally, since our data is collected via self-reported survey instrument, the issue of the CMV can always be raised. As previously shown, our analyses suggest that the influence of the CMV on the findings is unlikely. Some prior empirical studies even suggested or found that third-party measures are not any superior to self-reporting measures (Heneman, 1974; Teigland and Wasko, 2003; Wexley et al., 1980). Nonetheless, to enhance rigor of a study, a potential future work is to triangulate with the use of supervisor-rating measures or any other research method such as design experiments.

1.15 Conclusion

Appearing as a critical link in the SECI model of the organizational knowledge creation theory (Nonaka, 1994) and as an important underlying factor in research streams such as automatic systems usage behaviors, the concept of knowledge internalization has never been theoretically justified as much as it deserves and its measurement has never been systematically developed. Drawing from the ACT theory (Anderson, 1983) and framework on the dimensions of cognitive skills (Glaser et. al, 1985), this study defines knowledge internalization as the process in which an individual relies on various cognitive mechanisms to transform his or her declarative knowledge into procedural knowledge.

Through our rigorous and systematic approach, knowledge internalization emerges as a formative construct with organization and structure, mental models, efficiency, automaticity, and metacognition as its underlying dimensions. Our measurement of the knowledge internalization construct exhibits satisfactory psychometric properties and validities in both exploratory and confirmatory analysis phases. In relation to knowledge sharing intention, the path analysis reveals that the effect of knowledge internalization on intention to share knowledge is fully mediated by not only expert power but also knowledge self-efficacy. Additionally, the effect of knowledge internalization on expert power is partially mediated by knowledge self-efficacy. These findings suggest that knowledge workers are likely to share knowledge, when they are confident of their expertise and/or when they feel their expertise is appreciated and recognized. These findings expand our understanding of knowledge sharing phenomenon. In addition, in the process of conceptualizing the construct of knowledge internalization, this study also helps clarify how explicit, tacit, declarative, and procedural knowledge are related among one another, an area that has long been fuzzy in the literature. For practice, the findings also imply that to improve the value and effectiveness of organizational KM initiatives, people's knowledge internalization should be considered one of the top priority issues, as the quality of shared knowledge depends on it. The developed survey instrument can be used as an initial diagnostic tool to evaluate knowledge workers in organizations to search for areas of improvement. In conclusion, knowledge internalization is a critical and powerful means knowledge workers can exert to help improve the value of organizational KM initiatives and perhaps facilitate organizations in sustaining their competitive advantage.

CHAPTER 2

KNOWLEDGE INTERNALIZATION AND KNOWLEDGE-BASED INDIVIDUAL-TASK-TECHNOLOGY FIT IN TACIT KNOWLEDGE SHARING

2.1 Abstract

A critical objective of organizational knowledge management (KM) initiatives is to foster tacit knowledge sharing among knowledge workers, since it is instrumental in sustaining competitive advantage of organizations. However, due to a variety of factors, people not only are reluctant to share, but may not be able to do so. This study proposes that whether people will share their tacit knowledge depends on (1) the extent to which people internalize knowledge into their brains and (2) the degree of a fit among certain task, technology, and individual factors. First, drawing from Anderson (1983)'s Adaptive Control of Thought (ACT) theory and Glaser et al. (1985)'s cognitive skills, we develop and define ***Knowledge Internalization*** as the process in which an individual relies on various cognitive mechanisms to transform his or her declarative knowledge into procedural knowledge. Second, based on Goodhue and Thompson (1995)'s Task and Technology Fit framework, we propose a notion of ***Knowledge-based Individual-Task-Technology Fit (KITTF)*** by including knowledge self-efficacy, preference for personalization KM strategy, accessibility of corresponding KM systems, and task variety as the underlying components. We hypothesize that expert power, a proxy for tacit knowledge sharing, depends on both knowledge internalization and the KITTF.

The results of the path analysis on a survey of 259 knowledge workers overall support the modeling of both knowledge internalization and the KITTF, and confirm that they are significant predictors of expert power. This study contributes by not only providing rich conceptualizations of the two crucial constructs but also establishing their roles in knowledge sharing phenomenon. To improve effectiveness of organizational KM, managers should assess

knowledge workers' knowledge internalization to seek areas of improvement and consider the components of the KITTF as they collectively affect tacit knowledge sharing in organizations.

2.2 Introduction and Motivations

In today's knowledge-driven economy, knowledge management (KM) has become more critical to organizations than ever (Alavi and Leidner, 2001; Argote, McEvily, and Reagans, 2003; Grover and Davenport, 2001; King, Marks, and McCoy, 2002; Massey and Montaya-Weiss, 2006). To be able to manage knowledge effectively, organizations first need to acknowledge different types of knowledge such as the well-known explicit versus tacit knowledge (Alavi and Leidner, 2001; Nonaka, 1994). Unlike explicit knowledge, tacit knowledge, residing in the brain, is rich in context and is much more difficult to communicate or codify using systematic media such as documents (Nonaka, 1994). Since the characteristics of tacit knowledge such as rareness and inimitability make it strategically central to sustainable competitive advantage of organizations (Ambrosini and Bowman, 2001; Grant, 1996; Lubit, 2001; Berman, Down, and Hill, 2002), organizations need to be able to manage and exploit tacit knowledge which is embedded deeply within knowledge workers effectively (Grant, 1996; Spender, 1996). Therefore, one of the most important objectives of any KM initiatives should be to foster tacit knowledge sharing among knowledge workers (Grant, 1996; Wang, Ahmed, and Rafiq, 2008). Nonetheless, both research and practice show that, depending on a variety of both intrinsic and extrinsic factors, people are rather reluctant to share what they know (Bock et al., 2005; Kankanhalli et al., 2005; Ray et al., 2005; Thomas-Hunt, Ogden, and Neale, 2003; Wang and Noe, 2010; Wasko and Faraj, 2005).

In their recent review of literature on knowledge sharing in several disciplines including information systems and management, Wang and Noe (2010) found that factors in areas such as organizational context (e.g. management support), team and interpersonal characteristics (e.g. diversity), cultural characteristics (e.g. national cultures), motivational factors (e.g. trust and attitudes), and individual characteristics (e.g. personality) influence both knowledge sharing perceptions and actual sharing behaviors. For organizations to fully reap the benefits of KM, it is crucial to not only identify influential factors, but also learn the effects of how they may be related among themselves (Wang and Noe, 2010). For example, while a person's knowledge self-efficacy can increase the likelihood of sharing knowledge (Kankanhalli et al., 2005), the person may disregard his or her sharing intention, because the available technology support for KM, or KM systems (KMS) (Alavi and Leidner, 1999; Alavi and Leidner, 2001) may not suit either the task characteristics (Gebauer and Ginsburg, 2009; Lin and Huang, 2008; Song and Teng, 2006) or the personal preferences in handling knowledge (Gebauer and Ginsburg, 2009; Gray and Durcikova, 2006; Song and Teng, 2006). Thus, in the context of knowledge sharing, the collective effect of factors such as self-efficacy, task characteristics, personal preferences, and technology support, may provide better explanation for the phenomenon and, as a result, deserve more attention from researchers.

Since the nature of tacit knowledge is different from that of explicit knowledge, factors that foster knowledge workers' intention or behaviors in sharing their tacit knowledge should also be different from those associated with sharing explicit knowledge. Because tacit knowledge exists in the brain, the more deeply the knowledge is embedded within a person, the more tacit knowledge the person will have to offer, yet, at the same time, the more difficult the person will be able to express and share it (Ambrosini and Bowman, 2001; Swap, Leonard, Shields, Abrams, 2001). Thus, a suitable set of KM strategy and KMS that especially support tacit knowledge sharing should be provided (Bloodgood and Salisbury, 2001; Hansen, Nohria, and Tierney, 1999). To the best of our knowledge, extant literature has never systematically offered a theoretically justified construct to help assess the effectiveness of how knowledge is internalized into the brains of individuals. We believe this lack of the construct for measuring individuals' degree of knowledge internalization has significantly hindered our understanding of the effects of factors that can impact tacit knowledge sharing.

Based on the aforementioned observations, this study aims to examine whether ***(1) the extent to which people internalize knowledge into their brains and (2) the degree of a fit among certain task, technology, and individual factors will affect their tacit knowledge sharing behaviors***. To respond to such an objective of the study, we develop two constructs as follows. First, drawing from Anderson (1983)'s Adaptive Control of Thought (ACT) theory and Glaser et al. (1985)'s cognitive skills, we develop the concept of ***Knowledge Internalization*** as the process in which an individual relies on various cognitive mechanisms to transform his or her declarative knowledge into procedural knowledge. Second, based on Goodhue and Thompson (1995)'s Task and Technology Fit framework, we propose a notion of ***Knowledge-based Individual-Task-Technology Fit (KITTF),*** by incorporating knowledge self-efficacy and preference for personalization KM strategy as individual factors, availability of appropriate KMS as a technology factor, and task variety as a task factor. We hypothesize that both knowledge internalization and the KITTF have a positive impact on expert power considered a proxy for tacit knowledge sharing behaviors in this study. Rather than employing constructs such as sharing intention, using expert power as a proxy for tacit knowledge sharing is more accurate and in line with Goodhue and Thompson (1995)'s framework (Cane and McCarthy, 2009), because it implies that tacit knowledge, which has been widely viewed as a significant source of special expertise (Bassellier, Reich, and Benbasat 2001; Geisler, 2009; Hedlund et al., 2003; Reuber, Dyke, and Fischer, 1990; Ryan and O'Connor, 2009; Tan and Libby, 1997), has actually been shared with other people.

The remainder of the paper is organized as follows. First, we discuss the concept of expert power and argue that it can be used as a proxy for tacit knowledge sharing. First, we develop the conceptualization of knowledge internalization by drawing from Anderson (1983)'s Adaptive Control of Thought (ACT) theory and Glaser et al. (1985)'s cognitive skills. Second, we present the knowledge-based individual-task-technology fit (KITTF) construct based on Goodhue and Thompson (1995)'s Task-Technology Fit (TTF) framework by proposing that knowledge self-efficacy, preference for personalization KM strategy, availability of KMS for personalization KM strategy, and task variety are the underlying components of the fit. Then, we discuss research methodology, analyses, and results. Finally, we conclude the paper with discussions, implications for both researchers and practitioners, and limitations and future research directions.

2.3 Expert Power

French and Raven (1959)'s bases of social power are arguably the most influential framework in the literature about power in organizations, (Schriesheim, Hinkin, and Podsakoff, 1991). Despite its renowned status in the power literature, Wang and Noe (2010)'s review suggests that more knowledge sharing studies based on a power perspective are still needed. The power theory posits that an individual can achieve authority via reward, coercive, legitimate, referent, and expert power. We choose to study the role of expert power in particular, because its notion appears to be most relevant to the context of KM. Indeed, an individual's expert power refers to ***the perception by other people that the individual possesses special knowledge or expertise*** (Raven and French, 1958). Many researchers have associated "special knowledge or expertise" with tacit knowledge. For example, Ryan and O'Connor (2009) found that instead of explicit knowledge, tacit knowledge that is based on team members' expertise can predict effectiveness in software development teams. Similarly, Geisler (2009) found that while explicit knowledge in the form of concrete procedures has failed, it is experts' tacit knowledge that saves emergency patients' lives. Hedlund et al. (2003) found that it is tacit knowledge that can explain individual differences in leadership effectiveness in military. Attempting to define expertise in entrepreneurship, Reuber, Dyke, and Fischer (1990) resort to using the notion of tacit knowledge. Tan and Libby (1997) found that tacit knowledge is a significant determinant of audit expertise. Finally, Bassellier, Reich, and Benbasat (2001) suggest that experience can be viewed as a proxy for tacit knowledge. Taken together, these studies suggest that an individual's expert power stems from his or her tacit knowledge.

Using expert power as a proxy for tacit knowledge sharing is appropriate, since the notion of expert power is predicated on knowledge sharing, and people generally consult experts for knowledge that is not readily available from codified sources. Doing so is also aligned with Goodhue and Thompson (1995)'s framework, since it suggests that performance is influenced by actual behaviors, not intentions (Cane and McCarthy, 2009). The definition of expert power implies that actual sharing behaviors have indeed occurred, because a person's expert power is very likely to increase, when his or her expertise is often sought after. After all, people should frequently request a person's expertise, only when the person is truly knowledgeable, that is, possessing high degree of tacit knowledge.

2.4 Knowledge Internalization

2.4.1 Background

In Nonaka (1994)'s organizational knowledge creation theory, organizational knowledge is created through continuous interactions between tacit and explicit knowledge in socialization, externalization, combination, and internalization processes (SECI). Tacit knowledge is exchanged through common experiences and communications among individuals in socialization. Tacit knowledge is then converted or codified into explicit knowledge in externalization. Explicit knowledge from different sources is then systematically combined in combination. Explicit knowledge is finally converted back to tacit knowledge in people's minds through their learning processes in internalization. Thus, it can be inferred that the internalization is a learning process that can generate tacit knowledge.

Even though tacit knowledge is the product of both internalization and socialization, the effectiveness of internalization can critically determine the value of socialization. Because shared experience is crucial when sharing tacit knowledge (Nonaka, 1994), exchanging knowledge among less experienced individuals due to constrained learning abilities would result in rather unproductive socialization. The influence of internalization on externalization and combination also exist. The value of externalization would be rather limited, unless the effort comes from individuals whose knowledge has been internalized effectively. Furthermore, individuals with inhibited ability due to inferior internalization may be uncertain on how to combine knowledge from multiple sources. Thus, we suggest that knowledge internalization is such a critical link in the SECI process that ultimately affects the effectiveness of organizational knowledge creation process.

Despite its importance, the notion of internalization has received little attention and never been systematically studied. Nonaka, Byosiere, Borucki, and Konno (1994) attempt to test the organizational knowledge creation theory by conceptualizing knowledge creation as a second-order construct with socialization, externalization, combination, and internalization as its underlying factors. However, their notion of internalization was not grounded in any theory and the measurement arbitrarily included real world knowledge acquisition via personal experience and virtual world knowledge acquisition via simulation and experimentation. Drawing from the same work of Nonaka et al. (1994), Lee and Choi (2003) similarly view the internalization as the degree of personal experience, simulation, and experimentation. Similarly, adopting yet the same work, Sabherwal and Becerra-Fernandez (2003) measure the internalization by using merely three items related to the notions of on-the-job training, learning by doing, and learning by observation. For such an imperative construct, we believe that stronger and richer theoretical justification is needed, so that its measurement could be meticulously developed.

2.4.2 Theoretical Foundations

Based on the discussion in Royer, Cisero, and Carlo (1993)'s work, we integrate Anderson (1983)'s Adaptive Control of Thoughts (ACT) theory and Glaser et al. (1985)'s framework on cognitive skills and use this conceptual integration as the theoretical foundation for developing the construct of knowledge internalization. Because the concepts of declarative and procedural knowledge are essential in the ACT theory, we first need to discuss how they are related to tacit and explicit knowledge. Some researchers believe that declarative knowledge refers to know-what while procedural knowledge to know-how (Alavi and Leidner, 2001; Arnold et al., 2006). Similarly, some researchers believe that explicit knowledge is simply know-what and tacit knowledge is know-how (e.g. Sambamurthy and Subramani, 2005). However, such comparisons prevent us from truly comprehending the connections among declarative, procedural, explicit, and tacit knowledge (Nickols, 2000). For example, if certain procedures (i.e. know-how) are codified in a formal document or knowledge repository system, then it is ambiguous as to whether we should still consider it tacit knowledge.

To resolve this ambiguity, we define *declarative knowledge* as the part of knowledge that *can be* represented or described by communication media such as natural languages, schematics, mathematics, audios, and videos. As a result, our definition of declarative knowledge includes elements of both know-what and know-how as well as know-why. Our definition is consistent with that of Nickols (2000), in which declarative knowledge is not restricted to know-what. In addition, declarative knowledge that is *actually* documented, represented, or described by communication media is referred as externalized declarative knowledge. For example, food cookbooks (e.g. know-what and know-how) and even economics theories in a textbook (e.g. know-what and know-why) are considered externalized declarative knowledge. Therefore, we view declarative knowledge as the "*non-sticky*" part of tacit knowledge, while externalized declarative knowledge definitely as explicit knowledge. Next, we define *procedural knowledge* as a*ctionable* knowledge that has been internalized from a collection of declarative knowledge. It is actionable in a sense that only when repeatedly practiced, declarative knowledge can turn into procedural knowledge. For example, although an individual has learned declarative knowledge such as basic facts and information (know-what), established methodologies (know-how), or even theoretical principles (know-why), he or she must practice them before the knowledge can turn into procedural knowledge. Therefore, procedural knowledge is the "*sticky*" part of tacit knowledge that is, if possible, rather difficult to externalize.

We are interested in *how* an individual transforms his or her declarative knowledge into procedural knowledge, that is, the knowledge internalization process. Simply put, the knowledge internalization is the process that can produce tacit knowledge that is rare, virtually inimitable, and valuable to organizations. Before defining knowledge internalization formally, we now need to turn to discuss the theoretical foundation for the construct, that is the integration of Anderson (1983)'s ACT theory and Glaser et al. (1985)'s framework on cognitive skills.

The core idea of the ACT theory is about knowledge representation and human learning. The theory posits that learning occurs in declarative, compilation, and procedural stages. In the *declarative* stage, an individual applies declarative knowledge to interpret problems, but his or her performance at this stage is heavily weighted by processing time and working memory load when recalling the knowledge. The *compilation* stage marks the pivotal point, where the individual learns how to apply declarative knowledge with less consciousness. Inside the brain, accumulated declarative knowledge is gradually transformed into procedural form that is ready to be activated with less memory load. Finally, in the *procedural* stage, the individual can activate and apply compiled declarative knowledge to solve a problem or work on a task automatically or with minimum memory load. At this stage, the individual is also aware of how to control or plan his or her problem solving endeavors in a more effective and efficient way. The ACT theory improves our understanding of the concept of knowledge internalization. That is, knowledge internalization occurs when an individual can improve his or her performance on a task by proceeding from declarative to compilation and finally to procedural stage. More precisely, it occurs when an individual can effectively apply accumulated declarative knowledge to solve a problem in a more automatic manner. Although the ACT theory provides an answer to *when* knowledge internalization occurs, another question remains.

That is, in progressing through the three stages of learning, *how* can one actually internalize knowledge? Discussed next are the dimensions of cognitive skills that primarily enable an individual to learn.

Glaser et al. (1985)'s framework on cognitive skills includes the following dimensions: *Organization and structure* refers to the extent to which declarative knowledge becomes interconnected and structured. This cognitive skill is attained when an individual can proficiently access coherent chunks of declarative knowledge to perform a task. *Problem representation* refers to the extent to which underlying principles of a problem or task situation are recognized. This cognitive skill is achieved when an individual can perceive the underlying principles of a problem rather than the surface structure. *Mental models* refer to the extent to which operations of a system in a particular domain are understood and developed. With a mental model, an individual can envision or imagine how things work in a domain and use such visions to guide his or her performance. *Efficiency* refers to the extent to which developed skills, or procedural knowledge, are efficiently utilized. This cognitive skill occurs when an individual can reach to the solution of a problem efficiently with minimum efforts. *Automaticity* refers to the extent to which procedural knowledge is automatically exerted. This cognitive skill is achieved when an individual can perform a task or solve a problem automatically without conscious cognitive efforts in retrieving declarative knowledge. Finally, *metacognition* refers to self-regulatory and self-management skills. It is defined as the extent to which performance is reflected and controlled in a useful and efficient manner. With this cognitive skill, an individual can plan his or her behaviors, monitor the outcomes of the actions, and adjust behaviors appropriately.

These cognitive skills help us identify the specific mechanisms an individual needs to achieve in order to transform declarative knowledge into procedural knowledge. Specifically, these cognitive skills together enable knowledge internalization. Therefore, while the ACT theory helps explain *when* knowledge internalization occurs in general, these cognitive skills elucidate *how* knowledge internalization occurs. Figure 2.1 illustrates the theoretical foundation of the knowledge internalization construct.

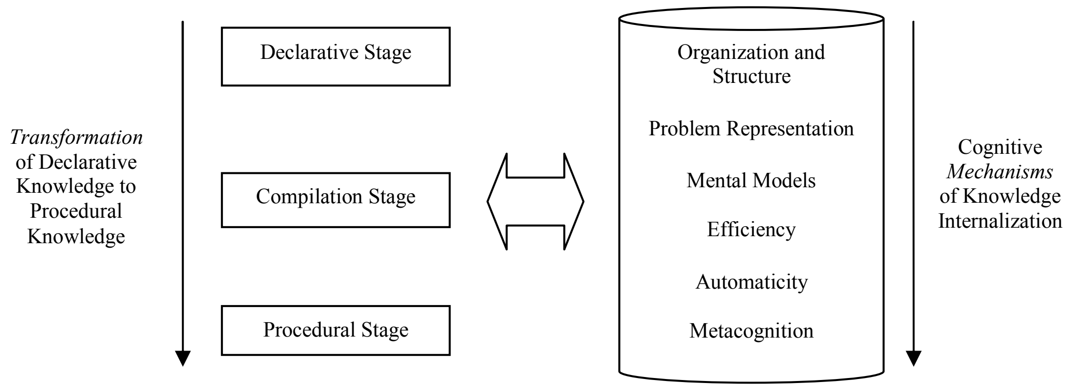

Figure 2.1 Theoretical Foundation of Knowledge Internalization

2.4.3 Definition

From previous discussions and the theoretical foundation, we finally define knowledge internalization as ***the process in which an individual relies on various cognitive mechanisms to transform his or her declarative knowledge into procedural knowledge***. According to Jarvis, Mackenzie, and Podsakoff (2003) and Petter, Straub, and Rai (2007), we conceptualize knowledge internalization as a second-order formative construct consisting of the abovementioned cognitive mechanisms, because of the following reasons. First, the underlying cognitive mechanisms *enable or cause* the extent to which knowledge internalization occurs – *not vice versa*. Second, the cognitive mechanisms theoretically capture *different and non-interchangeable aspects* of knowledge internalization. Finally, removing one of the cognitive mechanisms will *alter* the conceptual domain of the knowledge internalization construct.

2.4.4 Impact of Knowledge Internalization on Expert Power

Since knowledge internalization refers to the individual learning process that ultimately produces tacit knowledge, and tacit knowledge can reflect expert power, we infer further that the greater extent to which a person internalizes knowledge, the greater extent to which the person will have tacit knowledge to share, and thus the greater extent to which the person will be perceived as an expert by other people. Therefore, we hypothesize that knowledge internalization is positively associated with expert power, a proxy for measuring tacit knowledge sharing.

Hypothesis 1: Knowledge internalization is positively associated with expert power.

2.5 Knowledge-based Individual-Task-Technology Fit

In this section, we discuss how knowledge self-efficacy, preference for personalization KM strategy, availability of KMS for personalization KM strategy, and task variety are the underlying factors of our conceptualization of the knowledge-based individual-task-technology fit (KITTF), the fit that can ultimately further enhance tacit knowledge sharing.

2.5.1 Individual-Task-Technology Framework

To improve our understanding of the relationship between IS and individual performance, Goodhue and Thompson (1995) introduce the technology-to-performance chain model, in which its premise is that an information technology will positively impact individual performance, when the technology used fits both the task it supports and the user's needs. They particularly emphasize the effect of the fit among individual, task, technology characteristics on individual performance impacts. Included in the model, the construct of the task-technology fit (TTF), or to be precise, the individual-task-technology fit (ITTF) (Goodhue and Thompson, 1995, p. 218), refers to the correspondence or synergy among task, technology, and individual factors. Despite such a definition, Goodhue and Thompson (1995)'s original study did not empirically examine the role of individuals. Although somewhat included in another study by Goodhue (1995), the operationalization of the individual characteristic can certainly be improved, since it uses a mere single item to determine if the users are computer literate. Much of the extant research also not only has neglected the role of individual factors in the TTF (exceptions include Lee, Cheng, and Cheng (2007) and Lin and Huang (2008)'s study). In Cane and McCarthy (2009)'s meta-analysis study of the TTF research, it is noticeable that individual factors are studied much less than task and technology. Perhaps, this lack of factoring the influence of individuals into the TTF is a reason the TTF acronym is commonly known instead of the ITTF. This gap in the literature results in limited empirical evidence for the effect of individual factors in relation to the notion of the fit. This study aims to fill in the gap by including knowledge self-efficacy and preference for KM strategy as KM-based individual factors.

The TTF framework provides an ideal theoretical platform for our study for the following reasons. First, positing that the correspondence among individual, task, and technology factors positively impacts performance, the TTF offers a theoretical lens to examine the impact of the fit contributed by multiple relevant factors in those areas on knowledge sharing behaviors simultaneously. In fact, Marcolin, Compeau, Munro, and Huff (2000) suggest that among other theories, the TTF is most appropriate for studying the role of individual abilities in performance. Figure 2.2 depicts the principle of the TTF framework.

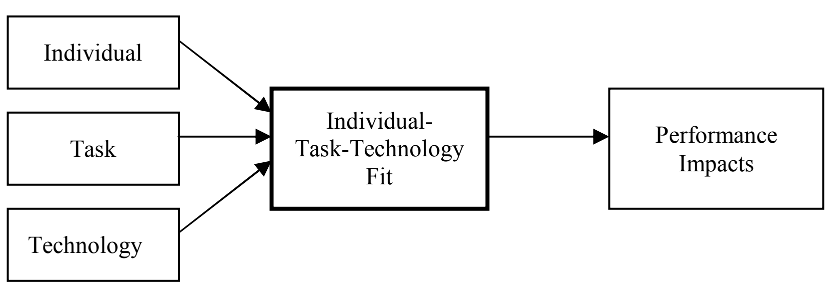

Figure 2.2 The Principle of the Individual-Task-Technology Fit Framework (adapted from Goodhue and Thompson, 1995)

2.5.2 Knowledge Self-efficacy

Bandura (1982) defines self-efficacy as self perception about what people can do with their skills. Specific in the context of KM, knowledge self-efficacy refers to ***the confidence in one's ability to provide valuable knowledge*** (Kankanhalli, Tan, and Wei, 2005). Thus, while expert power reflects other people's perception of one's expertise, knowledge self-efficacy indicates his or her self-confidence in contributing valuable knowledge.

Wasko and Faraj (2005) found that individuals with more experience in their fields tend to share more knowledge. To that end, we interpret that having more experience first leads to feeling more confident of one's knowledge and finally to sharing more knowledge. Specifically, being experienced implies that they have indeed mastered some tacit knowledge, suggesting that they are confident of their knowledge. As a result, they are likely to share what they know. Indeed, Kankanhalli et al. (2005) found that people are more willing to contribute their knowledge, when people are confident that their expertise is useful to the organization. Conversely, Lee, Cheung, Lim, and Sia (2006) found that the lack of knowledge self-efficacy is a reason people do not want to share knowledge with others. Based on these studies, we thus posit that people with higher degree of knowledge self-efficacy will share their tacit knowledge more often.

2.5.3 Preference for Personalization KM Strategy

KM strategies can be classified into personalization and codification (Hansen et al., 1999). Some researchers also refer to them as human-oriented versus system-oriented KM styles (e.g. Choi and Lee, 2002, 2003; Maier and Remus, 2003). While codification focuses on people-to-documents approach, personalization emphasizes person-to-person interactions (Hansen et al., 1999). Consequently, the objective of codification strategy is to reuse explicit knowledge; thus, it concerns more about providing computer systems for codifying and storing knowledge. On the other hand, the goal of personalization strategy is to facilitate exchange of tacit knowledge through socializations and collaborations among knowledge workers (Hansen et al., 1999). We define preference for personalization KM strategy as ***the extent to which an individual prefers person-to-person approaches in sharing knowledge to solve problems***.

Song, Nerur, and Teng (2007) found that high degree of personalization KM strategy practiced through social interactions among knowledge workers improves effectiveness of KM in their work units. They suggest further that when knowledge workers in the same unit with so much common experience among one another, conceivably indicating high degree of shared tacit knowledge flowing in the unit, engage in personalization KM strategy, KM in their units will be more effective. Indeed, personalization strategy can help experts share their tacit knowledge with others, because they tend to have difficulty externalizing their tacit knowledge (e.g. documenting or explaining their solutions for the problems) (Ambrosini and Bowman, 2001; Rintala and Kuronen, 2006). Swap et al. (2001) learn that because experts are most likely to come up with the solution for a problem simply by recognizing its pattern, and because they may not be able to formally articulate their complex thought process to other people, socialization modes such as informal mentoring and storytelling are more effective mechanisms in relaying their knowledge. Therefore, to facilitate tacit knowledge sharing among knowledge workers in organizations, personalization KM strategy should be emphasized and practiced.

2.5.4 Availability of KMS for Personalization KM Strategy

Information technology has always been a crucial enabler of organizational KM (Gold, Malhotra, and Segars, 2001; Lee and Choi, 2003). Information systems used to support KM in organizations are called KM systems (KMS) (Alavi and Leidner, 1999; Alavi and Leidner, 2001). Although definitely required for codification strategy, certain KMS may not be ideal for codification, yet can perfectly support personalization strategy. We define the availability of KMS for personalization KM strategy as ***the extent to which information systems that facilitate direct communications or direct knowledge sharing among people are available for uses***.

Certain KMS such as knowledge-based systems and electronic knowledge repositories are suitable for codification strategy, because they facilitate both codifying and reuse of explicit knowledge (Bloodgood and Salisbury, 2001; Hansen et al., 1999; Markus, 2001). On the other hand, KMS such as email, groupware, video conferences, electronic directories, and social network systems that facilitate or allow direct communications among parties (i.e. people-to-people) are more aligned with personalization strategy, as they can allow people to create networks to exchange their tacit knowledge directly (Bloodgood and Salisbury, 2001; Hansen et al., 1999).

Research has found that mental perceptions can dictate people's choices of technology they prefer to use. Massey and Montaya-Weiss (2006) suggest that the extent to which individuals engage in multiple tasks simultaneously determines how they perceive the usefulness of media, and in turn such a perception influences how they select and use the media. Chakraborty, Hu, and Cui (2008) found that cognitive styles affect people's perceptions in terms of ease of use and usefulness of a technology. Taylor (2004) found that people with analytic cognitive style prefer using tools such as knowledge repository (i.e. a KMS for codification strategy), while people with intuitive cognitive style prefer tools such as email and groupware (i.e. KMS for personalization strategy). Therefore, it is expected that people, whose mental perceptions echo personalization as their preferred choice of KM strategy for sharing their tacit knowledge, would be even more willing and ready to do so, if they can easily access and use KMS particularly appropriate for the personalization strategy.

2.5.5 Task Variety

Researchers found that task characteristics significantly influence people's choice of KM strategies, and in turn, such a relationship affects the effectiveness of KM in organizations (Song and Teng, 2006). Task variety can be used to represent the characteristic of a task (Perrow, 1967). Task variety refers to ***the frequency of unexpected and novel events that***

occur when one performs a task or solves a problem (Daft and Macintosh, 1981). High degree of task variety can obstruct people's ability to analyze or see through the nature of the problem at hand or foresee potential issues that may arise in advance (Daft and Macintosh, 1981), thus giving a cue to people that tacit knowledge from more experienced people is most likely to be helpful in clarifying the uncertainty of the task (Song and Teng, 2006). Therefore, it is expected that high degree of task variety will lead to more tacit knowledge sharing.

2.5.6 Collective Impact of the KITTF on Expert Power

As mentioned, the study aims to investigate the impact of the fit collectively contributed by certain knowledge-based factors on tacit knowledge sharing. We define the KITTF as ***the collective pattern of fitting together a set of factors facilitating tacit knowledge sharing, including knowledge-based individual factors, and factors for the supporting technology and task environment.***

In addition to grounding the notion of the KITTF in the TTF theory, in which certain individual, task, and technology can form a fit that will improve individual performance, existing relevant research has been suggesting that individuals' abilities play an important role in how they perceive which KM strategy and KMS are appropriate to support knowledge sharing in order to solve the tasks at hand. Daft, Lengel, and Trevino (1987) found that high performing managers are more aware of the relationship between ambiguity of messages and richness of supporting media than low performing managers are. They particularly found that high performing managers understand that written communication is best for routine or structured communications, and face-to-face communication is needed for ad-hoc or unstructured communications. Jarvenpaa and Staples (2000) also found that task characteristics affect individual use of collaborative media to share information among each other. Song and Teng (2006) found that to respond to the variety of the task, knowledge workers prefer engaging in personalization KM strategy, as direct collaborations with other people may help clarify the situation of the task more effectively and efficiently than searching for relevant information in the systems and making sense out of them on their own. Results of these studies appear to suggest that the presence of individual abilities, KM strategy, available KMS, and task at hand in work environment could together enhance tacit knowledge sharing among people.

Therefore, based on the above discussion and the definition of the KITTF, we believe that knowledge workers with high degree of knowledge self-efficacy will share their tacit knowledge by using personalization KM strategy, and are expected to do so even more not only when appropriate KMS for personalization strategy are available, but also when the degree of task variety is especially high. In short, the effect of the KITTF on tacit knowledge sharing is expected to be much stronger than that of each factor alone. Thus, we hypothesize that, through the KITTF, these four factors will collectively have a positive impact on tacit knowledge sharing behaviors measured through expert power. Figure 2.3 depicts the research model.

Hypothesis 2: The KITTF is positively associated with expert power.

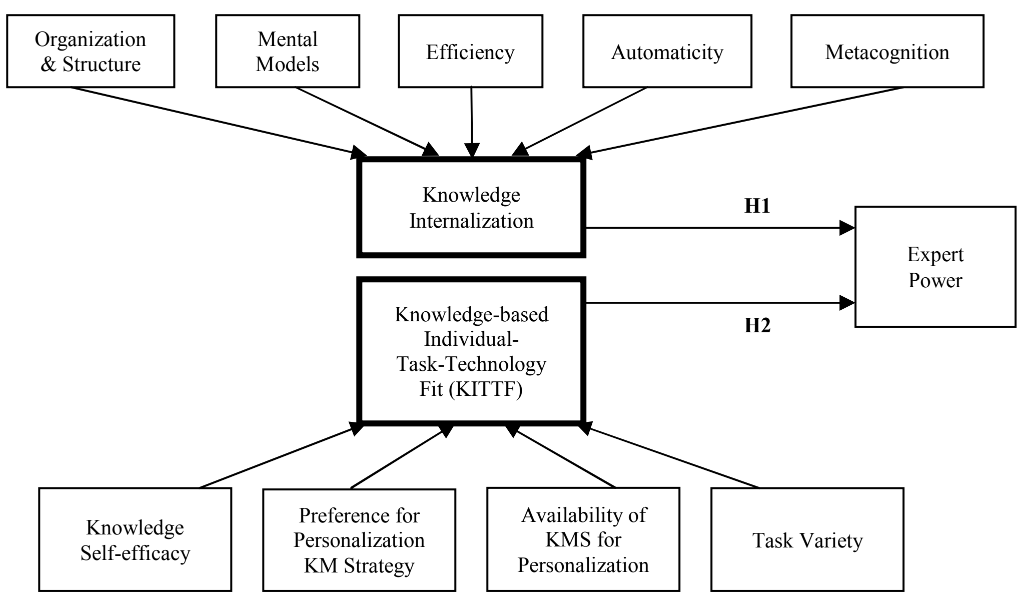

Figure 2.3 Research Model

2.6 Methodology

2.6.1 Data Collection and Sample Characteristics

To fit the context of KM in this study, knowledge workers, or professionals with reasonable amount of industry experience, are our desired respondents. The survey instrument is administered to MBA students mainly in the professional cohort format specially created for full-time working professionals as well as the regular format at a public university in a metropolitan area of the southwest US. The survey was handed out and collected in the same class period. A total of 266 out of expected 324 questionnaires were returned, providing a response rate of 82.1%. Due to a high number of missing data, 7 responses were eliminated, resulting in a useable sample size of 259.

Table 2.1 presents the demographic characteristics of the final sample. While a majority of the subjects holds bachelor's degrees (63%), quite many hold master's degrees (35%). Engineers, IS/IT, and general management make up nearly half of the sample (about a total of 48%), while accountants, financial analysts, and marketing represent a moderate portion of the sample (approximately a total of 24%). The average years in the profession are about 7 years. The average years in the current organization are almost 5, and the average years in the current position are about 3 years. These characteristics show that our sample indeed represents knowledge workers with substantial work experience, and is thus appropriate for the study.

Table 2.1 Demographic Characteristics of the Sample (n = 259)

Characteristics	Percent	Characteristics	Percent
Gender		*Industry*	
Male	69.8	Banking/Insurance/Financial Service	14.8
Female	30.2	Constructions/Architecture/Engineering	7.4
Age		Consulting/Business Service	4.3
21-30	58.4	Education	8.2
31-40	32.7	Government/Military	8.6
41-50	7.4	Healthcare	7.8
51-60	1.6	Hotel/Entertainment/Service Industry	4.7
Education		IT/Telecommunications	7.4
High school	0.4	Manufacturing	14.5
Associate	0.4	Other	22.3
Bachelor	63.4		
Master	34.6	Characteristics	Mean
Doctorate	1.2	Years on current position	3.3
Profession		Years with current organization	4.4
Accountant	8.1	Years in the profession	6.6
Engineer	16.2	No. of Employees in Department	665.9
Financial Analyst	6.6	No. of Employees in Organization	24866.3
General Management	16.6	No. of Professional Contacts	170.9
IS/IT	15.8		
Lawyer	0.4		
Marketing	7.7		
Medical/Physician/Nurse	1.5		
Public Relation	1.9		
Other	25.1		

2.6.2 Scale Development for Knowledge Internalization Construct

To develop the scale for the knowledge internalization construct, we followed modified versions of Churchill (1979)'s framework and guidelines provided by researchers such as Xia and Lee (2005), Lewis, Templeton, and Byrd (2005), Malhotra and Grover (1998), Moore and Benbasat (1991), and Straub (1989). First, to ascertain content validity of the measure, multiple sessions with a scholar with over thirty years of academic experience were conducted to ensure that the words of the items were in line with the theory. A total of 25 items was generated, all of which uses seven-point Likert-type scales (1 = strongly disagree; 7 = strongly agree). Next, to ensure face validity, we performed a sorting procedure as follows. The judges for the procedure include two practitioners/researchers who have over twenty years of experience in fields such as management and IT, one practitioner with over ten years of experience in IT, and two doctoral students with several years of experience in management and finance. Sorting instructions and the definitions of the dimensions of the construct were shown to the judges. Then, with a completely random list of the items presented on a computer screen, the judges were asked to choose which dimension an item should fall under the most. Other than refining the wording of the items per the judges' feedback, we did not find any major problems.

Next, we conducted a pilot test by distributing the survey in a graduate-level course in college of business administration at a public university in a metropolitan area of the southwest US. A total of 31 participants with an average of five years of experience in management and IT completed the survey. With this data, the significant results of the Kaiser-Meyer-Olkin and Bartlett's test indicated that the level of multicolinearlity in the data was sufficient to perform an exploratory factor analysis. Then, common factor analysis with oblique rotation was conducted. Based on the eigenvalues (>1.0), the scree plot (showing a break after the fourth factor), and a threshold value of 0.55, Mental Model, Efficiency, Automaticity, and Metacognition emerged as expected. An exception was that some items of Organization and Structure cross-loaded with some of Problem Representation. We then revisited the proposed definitions of the construct and carefully reworded all the items as necessary. Finally, we were content that this refined set of items was ready for the actual study. The final set of items for the factors of the knowledge internalization construct is listed in Table 2.2.

Table 2.2 Items for the Knowledge Internalization Construct (after the pilot study)

Organization & Structure	
OS1	I can easily group relevant information into different categories.
OS2	I can easily tell how a piece of needed information is similar or different from another.
OS3	I can easily sort out required information in a systematic fashion.
OS4	I can easily see how a piece of relevant information fits with other pieces.
Problem Representation	
PR1	I can easily identify the reasons that cause these problems.
PR2	I can easily see how difficult situations are caused by certain factors.
PR3	I can easily explain to other people the basic cause-and-effect relationships involved.
PR4	I can easily recognize various cause-and-effect linkages in the problems.
Mental Models	
MM1	I can easily visualize the step-by-step process to solve them effectively under various situations.
MM2	I can easily envision possible solutions in vivid details given different circumstances.
MM3	I can easily imagine how certain solutions will work out under a variety of conditions.
MM4	I can clearly picture in my head how potential solutions would play out differently due to certain factors.
Efficiency	
EF1	I can solve them very effectively and proficiently.
EF2	I can resolve many difficulties with less time and effort.
EF3	I can obtain effective solutions with great ease and speed.
EF4	I am faster than most of my colleagues in solving them effectively.
Automaticity	
AU1	I can rely on my instinct for correct solutions without following step-by-step analytical procedures.
AU2	I can instantly figure out correct solutions without realizing exactly how.
AU3	My immediate intuitions without much thinking are usually correct.
AU4	I can jump to correct conclusions without consciously following prescribed procedures.
Metacognition	
MC1	I always act appropriately in difficult situations using what I learn from my past experiences.
MC2	I always control my actions carefully based on the lessons previously learned.
MC3	I always monitor both successes and failures of my decisions and adjust my actions effectively.
MC4	I always evaluate and learn from my actions so that I do not repeat the same mistakes.

Note. All items are preceded by the phrase: When I work on job-related problems:

2.6.3 Operationalizations of Other Constructs

Other constructs are measured using scales adapted from prior literature, which have been previously tested and demonstrated satisfactory degree of reliability and validities. *Expert* *power* is measured with four items adapted from Schriesheim et al. (1991)'s study, in which the alpha coefficient of the construct exceeds 0.80. *Knowledge self-efficacy* is measured with three items adapted from Kankanhalli et al. (2005)'s study, in which the alpha coefficient is 0.96. *Preference for personalization KM strategy* is measured with four items adapted from Song and Teng (2006)'s study, in which the composite reliability is 0.91. *Availability of KMS for personalization KM strategy* is measured with four items adapted from Chennamaneni (2006)'s study, in which the composite reliability is 0.97. *Task variety* is measured with four items adapted from Daft and Macintosh (1981)'s study, in which the alpha coefficient is 0.91. Seven-point Likert-type scales anchored from strongly disagree (1) to strongly agree (7) are used for all the items of the constructs. The items for these constructs are presented in Table 2.3.

Table 2.3 Items for All Other Constructs

Expert Power (adapted from Schriesheim et al., 1991)	
EP1	My coworkers often seek my solutions for job-related problems.
EP2	My coworkers often comment that my advice is sound.
EP3	My coworkers often seek my technical knowledge.
EP4	My coworkers often say that my technical suggestions are excellent.
Knowledge Self-efficacy (adapted from Kankanhalli et al., 2005)	
KS1	I have confidence in my ability to provide knowledge that others in my organization consider valuable.
KS2	I have the expertise needed to provide valuable knowledge for my organization.
KS3	I can provide more valuable knowledge than most other employees can.
Preference for Personalization KM Strategy (adapted from Song and Teng, 2006)	
PE1	I prefer to make face-to-face social interactions to exchange knowledge.
PE2	I prefer to engage in informal dialogues and formal meetings to share and transfer knowledge.
PE3	I prefer to use meetings and discussion via brainstorming and debate, etc. to generate new knowledge.
PE4	I prefer to use knowledge from accumulated experience to solve problems.
Availability of KMS for Personalization KM Strategy (adapted from Chennamaneni, 2006)	
KMS1	I can easily access e-mail/groupware to exchange needed knowledge directly with my coworkers.
KMS2	I can easily access teleconferencing/videoconferencing to exchange needed knowledge with my coworkers.
KMS3	I can easily access online chat/instant messaging to exchange needed knowledge with my co-workers.
KMS4	I can easily access electronic directories on experts/social networking systems to locate the people I need to contact personally to obtain needed knowledge.

Table 2.3 – *Continued*

Task Variety (adapted from Daft and Macintosh, 1981)	
VA1	There is variety in the events that cause the work.
VA2	Work decisions are dissimilar from one day to the next.
VA3	Takes a lot of experience and training to know what to do when a problem arises.
VA4	Tasks require an extensive and demanding search for a solution.

2.6.4 Operationalization of the KITTF

Following Jarvis, Mackenzie, and Podsakoff (2003) and Petter, Straub, and Rai (2007), we operationalize the KITTF as a second-order formative construct and its underlying four factors as first-order reflective constructs, because they not only *cause* the KITTF to manifest in work environment (*not vice versa*), but also capture *different and non-interchangeable aspects* of the fit. In addition, without any of these factors, the intended conceptualization of the KITTF will *change*.

2.6.5 Control Variables

Control variables in this study include gender, age, education, years in the current position, years with the current organization, years in the current profession, number of employees in the department, number of employees in the organization, and number of professional contacts. Demographic variables such as gender, age, and education may influence how people perceive a person's expertise. Years in the current profession and current organization are also anticipated to impact the level of expert power perceived by other people. For example, the longer a person is in the current profession and with the organization, the more the person may be perceived as a knowledgeable person who likes to share knowledge (Wasko and Faraj, 2005). Size of department and organization may also be pertinent. For example, while a smaller department or organization can help an individual's expertise shine, a larger one may do the opposite. Finally, people who have built more professional contacts may be more likely to be perceived as experts than those with fewer contacts.

2.7 Validation of Measurement Model

We perform both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), so that the psychometric properties and validities of the knowledge internalization construct will be evaluated as rigorously as possible (Lewis et al., 2005). All the other constructs, including the KITTF as suggested by Venkatraman (1989), will be validated with CFA.

2.7.1 Exploratory Factor Analysis

Principal component analysis with varimax rotation was conducted (n = 259). Based on the eigenvalues (>1.0), the scree plot (showing a break after the fifth factor), and a threshold value of 0.65, five factors evidently emerged as opposed to six as theorized (see Table 2.4). The five factors explained about 71% of the variance in the data. We selected 0.65 as the threshold for the following reasons. Lewis et al. (2005) recommend that researchers not only maximize a loading threshold to ensure greater correlation among the items in the corresponding factors, but also include as many items as possible. The results revealed that while Organization and Structure, Efficiency, Automaticity, and Metacognition were the structure of the items, Problem Representation and Mental Models merged into one factor. To maintain the content validity of the construct, using the value of 0.65 allowed us to include the same number of items from both Problem Representation (PR1, PR2, and PR4) and Mental Models (MM2, MM3, and MM4). To be consistent with prior literature such as the works of Nonaka and his colleagues, we relabeled this factor simply as Mental Models. High factor loading (> 0.65) of the items within their corresponding factors exhibited a high level of convergent validity, while the distinctiveness of the factors (i.e. no cross-loading items) provided evidence of discriminant validity of the construct (Lewis et al., 2005). Except for the Mental Model factor consisting of 6 items, the remaining four factors included 4 items. Finally, all Cronbach's alpha coefficients exceeded 0.8 (see Table 2.4), indicating satisfactory level of the reliability of all the scales (Nunnally, 1978).

Table 2.4 EFA Results, Descriptive Statistics, and Reliability of the Underlying Factors of the Knowledge Internalization Construct (n = 259)

	Mental Models	Organization & Structure	Automaticity	Metacognition	Efficiency	Descriptive statistics & Reliability
MM3	.762	.120	.159	.078	.277	Mean = 5.36 SD = 0.87 Cronbach's Alpha = 0.89
PR1	.708	.315	.126	.039	.133	
PR2	.701	.427	.172	.186	.046	
PR4	.695	.399	.091	.116	.104	
MM4	.689	.051	.168	.157	.394	
MM2	.677	.112	.165	.086	.399	
MM1	.627	.164	.163	.030	.422	
PR3	.580	.385	.014	.244	.044	
OS1	.244	.820	.093	.043	.161	Mean = 5.77 SD = 0.93 Cronbach's Alpha = 0.90
OS2	.217	.796	.075	.133	.239	
OS4	.345	.774	.065	.046	.194	
OS3	.228	.745	.164	.106	.264	
AU4	.162	.080	.881	.043	.092	Mean = 4.62 SD = 1.28 Cronbach's Alpha = 0.89
AU3	.196	.122	.842	.018	.184	
AU2	.145	.001	.839	.047	.134	
AU1	.065	.155	.792	.065	.187	
MC2	.109	.087	.056	.886	.066	Mean = 5.76 SD = 0.92 Cronbach's Alpha = 0.90
MC3	.082	.095	-.008	.839	.156	
MC1	.127	.044	.115	.821	.066	
MC4	.106	.077	.006	.805	.137	
EF3	.214	.201	.233	.165	.767	Mean = 5.32 SD = 0.99 Cronbach's Alpha = 0.89
EF2	.232	.229	.211	.190	.743	
EF1	.283	.268	.101	.205	.738	
EF4	.352	.243	.213	.023	.672	

2.7.2 Confirmatory Factor Analysis

SmartPLS 2.0 M3 (Ringle, Wende, and Will, 2005) is employed to validate both measurement and structural models with the same data used in the EFA. Partial Least Squares

(PLS), a component-based structural equation modeling (SEM) technique, is selected primarily because it handles formative latent constructs (i.e. knowledge internalization and the KITTF) more effectively than a covariance-based SEM approach used in LISREL can (Petter et al., 2007). PLS is also more flexible than LISREL, in that multivariate normality is not necessary and sample size requirements are less stringent (Chin, Marcolin, and Newsted, 2003). A sample of 100-200 is commonly considered reasonable (Lewis et al., 2005). Thus, our sample of 259 is sufficient.

Given the EFA results, knowledge internalization is viewed as a formative construct, formed by Organization and Structure, Mental Models, Efficiency, Automaticity, and Metacognition. In viewing these cognitive mechanisms as the defining characteristics of the knowledge internalization construct, we now present empirical evidence as follows. Knowledge internalization is modeled as a second-order formative construct, with five first-order reflective constructs (i.e. the five cognitive mechanisms). Like Malhotra, Gosain, and El Sawy (2007), we created equally weighted average scores for each of the five dimensions based on its respective items. We used average scores instead of weighted composite scores, because it is suggested that the estimates from the latter approach are rather data dependent, unreliable, and difficult to interpret (Hair et al., 1987), and that the results of both approaches are not different after all (Dillon and McDonald, 2001). The variance inflation factor statistics (VIF) of all the five factors were lower than 3.3 (ranging from 1.1 for Metacognition to 2.2 for Mental Model), indicating very low level of multicollinearity among the dimensions. These low VIF values substantiated that they are quite distinct among one another (Petter et al., 2007; Diamantopoulos and Signuaw, 2006). Since this empirical result supports the conceptual justification, we are now certain that knowledge internalization is a formative construct.

Similarly, the VIF values of all the four factors of the KITTF construct (ranging from 1.05 for Task Variety to 1.1 for Knowledge Internalization) indicated very low level of multicollinearity among the factors, suggesting that each factor contributes unique influence to the fit (Petter et al., 2007; Diamantopoulos and Signuaw, 2006). Thus, as proposed, the KITTF should indeed be modeled as a formative construct.

Next, we assessed convergent validity, discriminant validity, and reliability of the reflective constructs only (that is, every construct except for that of knowledge internalization and the KITTF), since conventional approaches for reflective constructs are inappropriate for formative ones, and how to validate them is still uncertain among researchers (Diamantopoulos and Winklhofer, 2001; Gefen and Straub, 2005; Petter, Straub, and Rai, 2007). Due to the second-order nature of both the knowledge internalization and the KITTF constructs, we adopted the hierarchical construct modeling approach (Wetzels, Odekerken-Schroder, and van Oppen, 2009), a method favorably reviewed and recommended by Marcoulides, Chin, and Saunders (2009). Essentially, the items of a lower-order construct (i.e. the five cognitive mechanisms, knowledge self-efficacy, preference for personalization KM strategy, availability of KMS for personalization strategy, and task variety) were re-used by its higher-order construct (i.e. knowledge internalization and the KITTF). Thus, this technique is also known as repeated indicators approach (Wetzels et al., 2009).

The CFA results (see Table 2.6) attested discriminant validity, convergent validity, and reliability of all the constructs as discussed below. Except for two items of the task variety (0.65 and 0.66) and one item of the preference for personalization KM strategy (0.67), all the items strongly loaded (> 0.7) on their respective factors, and there were no cross-loading items, demonstrating discriminant validity (Gefen and Straub, 2005). Since the task variety scale has long been well established in the literature (Daft and Macintosh, 1981), and the loadings of those two items are actually almost 0.7, we believe that the scale exhibited the discriminant validity. In addition, the square root value of the average variance extracted (AVE) of each of the reflective constructs was much larger than its correlation with all the other constructs, thus confirming evidence of discriminant validity. The *t*-statistics of all the items loading on their own factors (ranging from 3.82 to 66.55) were significant at the 0.001 level, exhibiting high degree of convergent validity (Gefen and Straub, 2005). Finally, the composite reliability values of all the constructs exceeded 0.8, indicating satisfactory reliability (Nunnally, 1978). Taken together, these empirical results not only demonstrate convergent validity, discriminant validity, and reliability of all the constructs, but also support the conceptualizations of both knowledge internalization and the KITTF. The psychometric properties of the measurement are presented in Table 2.5. The CFA results are provided in Table 2.6.

Table 2.5 Descriptive Statistics, Reliability, and Correlations of the Constructs (n = 259)

Construct	Mean (SD)	CR	AU	EF	EP	KMS	KS	MC	MM	OS	PE	VA
AU	4.62 (1.28)	0.93	0.87									
EF	5.32 (.99)	0.92	0.45	0.86								
EP	5.50 (1.07)	0.93	0.29	0.48	0.87							
KMS	5.06 (1.38)	0.84	0.05	0.09	0.14	0.75						
KS	5.66 (.92)	0.90	0.33	0.48	0.65	0.04	0.87					
MC	5.76 (.92)	0.92	0.15	0.34	0.17	0.13	0.23	0.86				
MM	5.36 (.87)	0.92	0.40	0.65	0.43	0.16	0.43	0.31	0.81			
OS	5.77 (.93)	0.93	0.29	0.55	0.44	0.09	0.48	0.25	0.63	0.88		
PE	5.72 (.88)	0.83	0.21	0.24	0.25	0.08	0.26	0.29	0.23	0.27	0.74	
VA	5.10 (1.05)	0.81	0.03	0.12	0.32	0.18	0.12	0.05	0.12	0.20	0.16	0.71

Notes. CR = Composite Reliability. Square roots of AVE values are highlighted along the diagonal. OS = Organization and Structure, MM = Mental Models, EF = Efficiency, AU = Automaticity, MC = Metacognition, EP = Expert Power, KMS = Availability of KMS for Personalization KM Strategy, KS = Knowledge Self-efficacy, PE = Preference for Personalization KM strategy, VA = Task Variety.

Table 2.6 CFA Result (n = 259)

	AU	EF	EP	KMS	KS	MC	MM	OS	PE	VA
AU1	0.83	0.39	0.23	-0.01	0.28	0.14	0.32	0.28	0.16	0.01
AU2	0.85	0.35	0.24	0.06	0.27	0.12	0.31	0.18	0.14	-0.04
AU3	0.90	0.44	0.30	0.09	0.32	0.12	0.41	0.30	0.22	0.07
AU4	0.90	0.35	0.24	0.04	0.27	0.13	0.34	0.24	0.20	0.04

Table 2.6 - *Continued*

EF1	0.32	0.86	0.42	0.03	0.43	0.35	0.57	0.52	0.19	0.05
EF2	0.40	0.89	0.38	0.07	0.40	0.32	0.55	0.45	0.23	0.12
EF3	0.42	0.88	0.37	0.06	0.36	0.30	0.53	0.44	0.17	0.15
EF4	0.40	0.83	0.47	0.13	0.48	0.19	0.59	0.49	0.25	0.09
EP1	0.24	0.42	0.87	0.10	0.61	0.16	0.35	0.38	0.15	0.28
EP2	0.24	0.39	0.83	0.13	0.53	0.25	0.35	0.38	0.29	0.26
EP3	0.25	0.43	0.89	0.12	0.57	0.07	0.39	0.39	0.20	0.29
EP4	0.29	0.42	0.89	0.15	0.55	0.13	0.41	0.38	0.27	0.28
KMS1	0.02	0.08	0.15	0.70	0.08	0.10	0.07	0.08	0.02	0.16
KMS2	0.01	0.09	0.13	0.79	0.04	0.13	0.15	0.10	0.06	0.18
KMS3	0.01	0.05	0.07	0.76	0.02	0.03	0.14	0.06	0.07	0.03
KMS4	0.12	0.03	0.08	0.75	-0.03	0.12	0.10	0.01	0.11	0.16
KS1	0.31	0.47	0.61	0.02	0.87	0.28	0.40	0.47	0.27	0.10
KS2	0.22	0.39	0.56	0.03	0.90	0.20	0.37	0.43	0.22	0.10
KS3	0.32	0.40	0.51	0.07	0.84	0.10	0.34	0.33	0.17	0.11
MC1	0.17	0.27	0.16	0.11	0.19	0.84	0.28	0.20	0.23	0.08
MC2	0.13	0.27	0.11	0.11	0.15	0.90	0.27	0.22	0.25	0.04
MC3	0.09	0.31	0.17	0.09	0.24	0.86	0.26	0.22	0.26	0.03
MC4	0.10	0.29	0.16	0.14	0.21	0.83	0.26	0.21	0.23	0.00
MM2	0.35	0.57	0.31	0.14	0.28	0.24	0.79	0.47	0.21	0.05
MM3	0.34	0.51	0.29	0.12	0.29	0.23	0.84	0.48	0.16	0.10
MM4	0.35	0.57	0.30	0.09	0.34	0.30	0.79	0.44	0.25	0.06
PR1	0.29	0.49	0.42	0.13	0.36	0.18	0.81	0.51	0.15	0.15
PR2	0.33	0.49	0.32	0.13	0.38	0.31	0.82	0.59	0.21	0.08
PR4	0.27	0.51	0.44	0.13	0.42	0.24	0.79	0.54	0.15	0.14
OS1	0.24	0.44	0.40	0.03	0.44	0.18	0.53	0.88	0.22	0.15
OS2	0.23	0.49	0.39	0.08	0.40	0.26	0.52	0.88	0.25	0.18
OS3	0.31	0.51	0.37	0.10	0.43	0.24	0.55	0.87	0.21	0.16
OS4	0.23	0.48	0.38	0.09	0.39	0.19	0.60	0.88	0.26	0.22
PE1	0.13	0.13	0.04	-0.04	0.11	0.23	0.08	0.13	0.74	0.02
PE2	0.16	0.14	0.22	0.03	0.22	0.19	0.17	0.19	0.77	0.05
PE3	0.05	0.07	0.18	0.20	0.07	0.11	0.17	0.10	0.67	0.14
PE4	0.23	0.29	0.26	0.07	0.29	0.27	0.23	0.30	0.80	0.20
VA1	0.01	0.03	0.19	0.12	0.15	0.10	0.07	0.18	0.13	0.66
VA2	0.03	0.10	0.27	0.13	0.10	-0.06	0.11	0.11	0.08	0.74
VA3	0.04	0.16	0.29	0.10	0.08	0.07	0.08	0.17	0.15	0.80
VA4	-0.01	0.02	0.11	0.22	-0.03	-0.02	0.07	0.09	0.05	0.65

Notes. OS = Organization and Structure, MM = Mental Models, EF = Efficiency, AU = Automaticity, MC = Metacognition, EP = Expert Power, KMS = Availability of KMS for Personalization KM Strategy, KS = Knowledge Self-efficacy, PE = Preference for Personalization KM strategy, VA = Task Variety.

2.8 Structural Model Analysis and Results

Bootstrapping procedure in SmartPLS was performed (n = 259 with 500 cases) to examine the significance of the paths hypothesized in the research model. First, analyzing potential confounding effects of the control variables, we found that only gender ($b = 0.11$, $t = 2.54$, $p < 0.05$) and years in the current organization ($b = 0.17$, $t = 4.66$, $p < 0.001$) are significantly associated (based on two-tailed tests) with expert power. As a result, keeping only these two controls, we then proceeded with the analysis.

The path analysis reveals that the proposed research model consisting of knowledge internalization and the KITTF jointly explains 50% of the variance in expert power. As theorized, all the five cognitive mechanisms are significantly associated with knowledge internalization: organization and structure ($b = 0.28$, $p < 0.001$), mental models ($b = 0.39$, $p < 0.001$), efficiency ($b = 0.29$, $p < 0.001$), automaticity ($b = 0.20$, $p < 0.001$), and metacognition ($b = 0.15$, $p < 0.001$). Also as expected, all the four knowledge-based components significantly create the formation of the KITTF construct: knowledge self-efficacy ($b = 0.64$, $p < 0.001$), preference for personalization KM strategy ($b = 0.39$, $p < 0.001$), availability of KMS for personalization KM strategy ($b = 0.24$, $p < 0.005$), and task variety ($b = 0.33$, $p < 0.001$). Finally, as hypothesized, both knowledge internalization ($b = 0.26$, $p < 0.001$) and the KITTF ($b = 0.48$, $p < 0.001$) are found to be significant predictors of expert power as anticipated, thus confirming both H1 and H2. The results of PLS path analysis are shown in Figure 2.4.

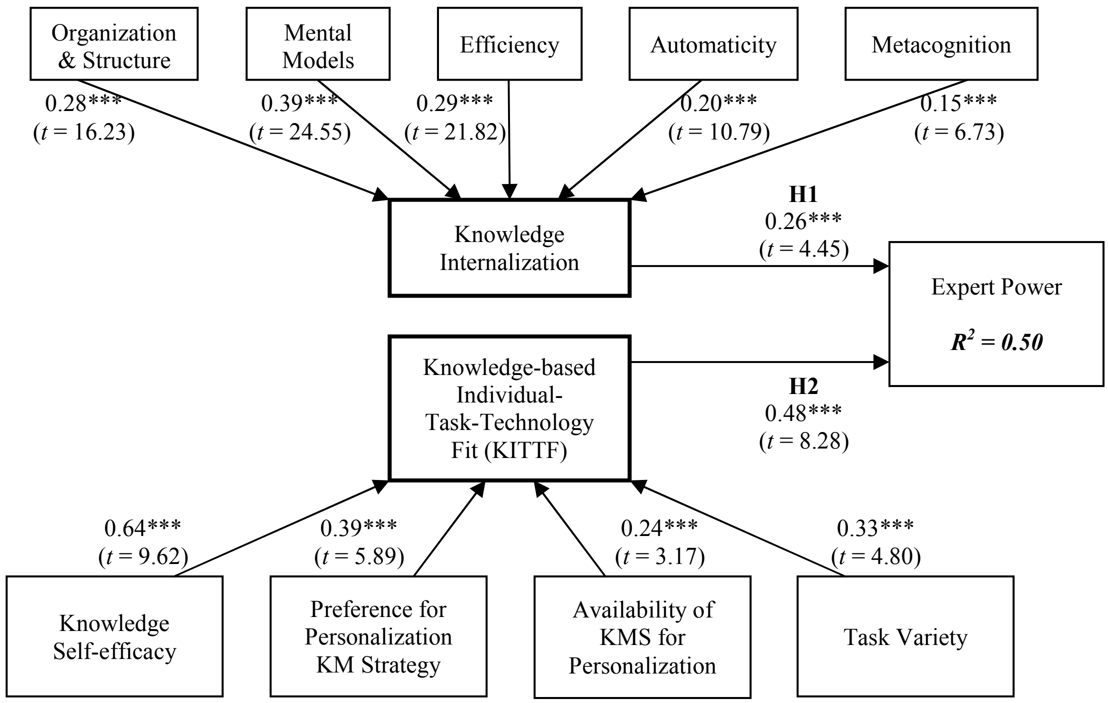

Figure 2.4 Results of Path Analysis

Notes. *** $p < 0.001$ in one-tailed tests. The items and control variables are graphically excluded for clarity purpose.

2.9 Common Method Variance

Because all the data was self-reported and collected in the same setting, we need to examine whether our findings are biased by common method variance, that is, variance attributable to the measurement method rather than the variable the measurement represents (Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). First, we conducted the Harman's single-factor test by including all items from all of the constructs into a factor analysis to determine whether the majority of the variance in the research model can be accounted for by one general factor (Podsakoff et al., 2003). Based on the results of principal component analysis without rotation, the first factor explained only about 27% of the total variance. We thus believe that common method variance does not bias our research findings.

Next, following Herath and Rao (2009) and Podsakoff et al. (2003), we evaluated the impact of common method variance by assuming and including an unmeasured latent method factor as the source of common method variance to the model. The basic premise of this approach is that all the items will load on not only their respective constructs but also the common method variance factor. To do so using PLS, we adopted Liang, Saraf, Hu, and Xue (2007)'s method, in which each item was first transformed into a single-item construct of its own, and then the added common method variance factor was directly linked to only these constructs. The effects of the common method variance factor can be assessed by comparing structural parameters both with and without the common method variance factor (Herath and Rao, 2009; Podsakoff et al., 2003); we found that factor loadings appeared to be similarly consistent, that all path coefficients were similar in magnitude, and that the significance of the *t* statistics remained the same. Thus, these findings suggest that common method variance does not affect the findings.

2.10 Discussions

Our observations are that people not only are reluctant to share what they know, but also may have certain difficulty in doing so. Hence, our research question is: Do the extent to which people internalize knowledge into their brains and the degree of the fit contributed by certain KM-based factors influence people's tacit knowledge sharing behaviors? To answer these questions, we have developed the constructs of knowledge internalization and the KITTF by drawing from well-established theories in cognitive psychology (Anderson, 1983) and information systems (Goodhue and Thompson, 1995). We have proposed that both are significant predictors of expert power, a proxy for tacit knowledge sharing behaviors.

Based on the results, the cognitive mechanisms of knowledge internalization appear to be organization and structure, mental models, efficiency, automaticity, and metacognition. The results confirm that knowledge internalization is a formative construct, indicating these cognitive mechanisms are indeed distinct from one another and cause the internalization to occur. Nonetheless, instead of six factors according to the theoretical foundation, five factors emerge. That is, problem representation and mental models merged into one factor. We believe that the theoretical differences between these two dimensions are not evident to the participants, and they may actually be more highly correlated in practice. For example, for an individual to represent a problem correctly (e.g. identifying reasons or factors underlying the problem), some of the mental models may have to be activated simultaneously (e.g. imagining how factors are related in a number of scenarios). Future researchers may use a different research methodology such as a laboratory experiment to study whether the difference between the two factors can be established.

The results also confirm that knowledge self-efficacy, preference for personalization KM strategy, availability of KMS for personalization KM strategy, and task variety are indeed different and non-interchangeable components that collectively contribute to the formative nature of the KITTF construct. Based on the notion of the fit, the results also appear to support our underlying reasoning of the KITTF. That is, the four factors together produce a collective force that is stronger than that of each factor alone. Specifically, knowledge workers with high degree of knowledge self-efficacy will share their tacit knowledge among one another through personalization strategy, and will do so even more not only when the KMS that can enhance those approaches are available for use, but also when the task at hand has much variety.

Finally, it is important to note the high explanatory power of both knowledge internalization and the KITTF (R square = 0.50), as they are found to be significant predictors of tacit knowledge sharing behaviors, measured via expert power (H1 and H2). Importantly, this finding provides the answer to the research question, that is, both the extent to which people internalize knowledge deep into their brains and the degree to which certain KM-based factors fit among one another have a positive impact on tacit knowledge sharing behaviors. Specifically, it is found that people with high degree of knowledge internalization do share their tacit knowledge, suggesting that due to their advanced cognitive skills, they have much more tacit knowledge to share. In addition, it is confirmed that the degree of the fit contributed by influential factors such as knowledge self-efficacy, personal preference for KM strategy, availability of KMS for the strategy, and the variety of the task possesses a positive impact on people's tacit knowledge sharing behaviors.

2.11 Theoretical Implications

This study contributes significantly to research by offering novel conceptualizations of the two constructs, namely knowledge internalization and the KITTF, and establishing their important roles in knowledge sharing phenomenon.

Despite its crucial role underlying in the SECI model of Nonaka (1994)'s organizational knowledge creation theory, which has been widely adopted in the literature, the concept of internalization has never been explored in depth, thus hindering both our understanding of the phenomenon and theoretical advancement of the field. This study is the first to conceptualize the knowledge internalization by grounding it in several renowned cognitive psychology theories. Our conceptualization informs when and how knowledge workers internalize knowledge, that is, the internalization occurs when they can create procedural knowledge using various cognitive mechanisms. As another contribution, the developed scale can be adopted or adapted to investigate its prospective roles further not only in KM, but also some other research streams such as those related to the concepts of automaticity and procedural knowledge. For example, recent literature in the area of IT usage has emphasized the role of the internalization in the context of continuing use. Ortiz de Guinea and Markus (2009) suggest that automatic behaviors may be able to explain post-adoption phenomena more than planned behaviors can. Kim (2009) demonstrates that experiences internalized into memories indeed affect post-adoptive technology use.

We also shed light on the nature of tacit knowledge by discussing how explicit, tacit, declarative, and procedural knowledge are related among one another. Although tacit knowledge is known to be instrumental to sustainable organizational competitive advantage, both how knowledge workers create tacit knowledge and tacit knowledge itself has been ambiguous. Specifically, this study suggests that knowledge internalization is build upon the cognitive mechanisms that transforms accumulated declarative knowledge, or absorbed explicit knowledge, to procedural knowledge or tacit knowledge.

Another important contribution is the finding of the role of knowledge internalization in knowledge sharing phenomenon. Specifically, we found that knowledge internalization positively impacts tacit knowledge sharing behaviors. While the extant research found that a number of both internal and external factors can explain knowledge sharing behaviors (Bock et al., 2005; Kankanhalli et al., 2005; Ray et al., 2005), factors specifically tied to the nature of tacit knowledge have not been explored much. With the construct of knowledge internalization included in the research model, this study yields an insightful nomological network of knowledge sharing phenomenon, particularly of tacit knowledge, to the field. In addition, since Wang and Noe (2010) found that knowledge sharing studies from a power perspective is lacking, this study to some degree fill in such a gap by using expert power as a proxy for tacit knowledge sharing behaviors.

Another important contribution of this study stems from the conceptualization of the KITTF construct. While individual effects of influential factors on knowledge sharing perceptions and behaviors have been much explored, how those factors may exert their effects collectively has never been examined. By integrating multiple knowledge-based factors such as knowledge self-efficacy, availability of KMS for personalization, and task variety, this study offers a cohesive explanation of how they can possess a collective impact on tacit knowledge sharing behaviors. In addition, in relation to Goodhue and Thompson (1995)'s TTF theory (or precisely, ITTF), by including the concepts of self-efficacy and personal preference for KM strategy, this study places the emphasis back on the role of individual factors, a direction that has been virtually overlooked in the extant TTF research.

2.12 Practical Implications

With the research findings, this study provides useful implications and recommendations for practitioners as follows. First, as tacit knowledge is associated with organizational sustainable competitive advantage, managers should be able to assess the extent to which their knowledge workers possess tacit knowledge, so that areas of improvement can be found and reinforced with appropriate actions or management practices. Unlike many sophisticated and costly techniques in psychology (see Royer et al. (1993) for a comprehensive list), this study offers a reliable, easy-to-use, and, even more importantly, domain-independent survey instrument that can be used as a diagnostic tool to help organizations accomplish such a goal. Specifically, managers can easily use the instrument to assess the likelihood the employees can produce tacit knowledge for the organization across domains, and if not, to identify which area needs reinforcement. For example, if it is found that many employees' scores on the organization and structure cognitive skill are much higher than the automaticity skill, then managers should provide rather hands-on and interactive trainings than lecture-based or book-oriented ones. Then, an evaluation to assess whether they can actually apply the accumulated knowledge should be followed up. Doing so will help ensure that the employees can create tacit knowledge, and that organizational competitive advantage could be achieved.

In addition to examining knowledge workers themselves, managers need to consider the fit among individual, task, and technology factors in their work environment. Influential factors such as knowledge self-efficacy, personal preference for KM strategy, availability of KMS for the preferred strategy, and the nature of the tasks are found to have a collective impact on whether knowledge workers will share their tacit knowledge among one another. Collectively, we suggest that confident and knowledgeable people are more likely to prefer direct personal communications to share their tacit knowledge, and they will do so even more often if certain tools and technologies appropriate for human-oriented communications are available, and if there is great amount of variety in the task. Thus, to facilitate tacit knowledge sharing, managers should not only evaluate the variety of the assigned tasks so that the degree of personalization strategy can be practiced appropriately, but also provide KMS that facilitates direct communications among parties such as video conferencing and real-time or instant messaging systems.

2.13 Limitations and Future Research Directions

Limitations of the study are discussed so that the research findings can be interpreted appropriately and to present multiple directions future researchers can build upon. First, since data for both independent and dependent variables is self-reported, the issue of common method variance is always relevant and needs to be addressed. Based on the results of the analyses, we found that the influence of common method variance on our findings is unlikely. In fact, previous studies even suggest that self-reporting measures are actually not any inferior to third-party measures (Heneman, 1974; Teigland and Wasko, 2003; Wexley et al., 1980). Nevertheless, a potential future work is to triangulate with the use of objective measures or any other research method such as design experiments.

Second, this study aims to improve our understanding of tacit knowledge sharing. Indeed, we found that both knowledge internalization and the KITTF affect tacit knowledge sharing behaviors. Although we strongly believe that expert power is a legitimate proxy for tacit knowledge sharing behaviors as suggested by ample previous literature, and doing so also contributes to power-based literature, using multifaceted or objective scales that indicate actual tacit knowledge sharing behaviors may be attempted by future researchers.

Third, this study is the first to provide a granulated conceptualization to the construct of knowledge internalization and its systematically validated measurement. While we found that knowledge internalization overall affects tacit knowledge sharing behaviors, we did not investigate the effects of different levels of knowledge internalization or individual effects of its cognitive mechanisms. Thus, a future research direction is to examine how different levels of knowledge internalization or each of the cognitive mechanisms may possess different effects on knowledge sharing perceptions, behaviors, or even sharing mechanisms. For example, we suspect that people with high degree of organization and structure and low degree of automaticity, albeit may not have a vast collection of procedural knowledge, may be able to externalize basic declarative knowledge more fluently than people with higher degree of organization and structure and even higher degree of automaticity can. As a result, they might prefer codification over personalization KM strategy. Thus, it is especially important that knowledge-driven organizations are able to identify appropriate KM strategy and KMS that correspond with different levels of knowledge internalization, so that appropriate work environment can be provided for different groups of knowledge workers to support their knowledge sharing.

Finally, by the same token, several future directions can be adopted based on the conceptualization of the KITTF. We have found that to establish work environment that is conducive to tacit knowledge sharing, factors such as personal preference for managing knowledge, availability of appropriate KMS, and the nature of the task need to be considered collectively. Nonetheless, we did not claim that the four factors of the KITTF are the only factors that can form a fit among individual, task, and technology. In fact, we recommend that future researchers look into a combination of other factors (e.g. attitudinal and managerial ones) that may be able to represent not only a fit of other aspects of tacit knowledge sharing, but also a fit that can facilitate explicit knowledge sharing.

2.14 Conclusion

Because tacit knowledge, embedded deeply within employees' brains, is instrumental to an organization's sustainable competitive advantage, organizations need to find ways to facilitate tacit knowledge sharing among knowledge workers. People not only can be reluctant to share their knowledge, but also may not be able to do so due to a variety of factors. This study suggests that the extent to which people internalize knowledge and the degree of the fit contributed by certain KM-based factors influence tacit knowledge sharing behaviors. We have conceptualized two constructs, namely knowledge internalization and the knowledge-based individual-task-technology fit (KITTF). Based on Anderson (1983)'s ACT theory and Glaser et al. (1985)'s framework for cognitive skills, knowledge internalization refers to the process an individual relies on various cognitive mechanisms to transform declarative knowledge into procedural knowledge and ultimately tacit knowledge. Based on Goodhue and Thompson (1995)'s Task and Technology Fit framework, the KITTF refers to the extent to which certain knowledge-based individual, task, and technology factors align with the collective pattern of the factors. We have hypothesized that both knowledge internalization and the KITTF have a positive impact on tacit knowledge sharing behaviors measured through expert power.

Data collected from 259 knowledge workers supports the formative structure of both knowledge internalization and the KITTF constructs. Specifically, we found that organization and structure, mental models, efficiency, automaticity, and metacognition cognitive mechanisms uniquely and significantly contribute to the knowledge internalization construct. For the KITTF construct, we found that knowledge self-efficacy, preference for personalization KM strategy, KMS for the personalization strategy, and task variety are significant components of the fit. Importantly, as hypothesized, both knowledge internalization and the KITTF are found to be significant predictors of tacit knowledge sharing behaviors.

To the research community, this study contributes by providing rich conceptualizations of the two important constructs and establishing their effects in knowledge sharing phenomenon, particularly regarding tacit knowledge. To practice, this study suggests that organizations can use the developed survey instrument to assess knowledge workers' knowledge internalization to seek areas of improvement. Organizations should also consider various knowledge-based factors such as those of the KITTF, so that suitable work environment can be provided to support tacit knowledge sharing among knowledge workers.

CHAPTER 3

PROFILING KNOWLEDGE WORKERS VIA KNOWLEDGE INTERNALIZATION

3.1 Abstract

To fully take advantage of existing knowledge, especially tacit knowledge by transferring it from experts to novices, organizations need to understand how factors influencing knowledge sharing may vary in both parties. Thus, we need to use a theoretically justified construct that is specifically tied to how novices can become experts to classify workers' expertise. Given the lack of such a construct in knowledge sharing literature, we develop and validate the construct of knowledge internalization by drawing from Anderson (1983)'s adaptive control of thought (ACT) theory and Glaser et al. (1985)'s dimensions of cognitive skills. We then apply the construct to develop several profiles of knowledge workers. Further, we demonstrate that each profile not only possesses different degrees of knowledge self-efficacy, expert power, and knowledge sharing intention, but prefers different knowledge sharing strategies.

Based on the cognitive mechanisms of knowledge internalization (i.e. organizations and structure, mental models, efficiency, automaticity, and metacognition), a cluster analysis with data from 295 knowledge workers shows three clusters. Based on the three learning stages in the ACT theory, we label them as *Novices*, *Practitioners*, and *Experts*. We find that knowledge self-efficacy and expert power are highest in experts, lower in practitioners, and lowest in novices, and that sharing intention of both experts and practitioners is higher than that of novices. Interestingly, it is found that while both experts and practitioners are fonder of personalization strategy than of codification, the difference of preference for codification strategy between practitioners and novices is greater than that between experts and novices,

and that novices are not as eager to adopt personalization and codification strategy as experts and practitioners are respectively. Theoretical and practical implications are discussed.

3.2 Introduction and Motivations

Knowledge is such a critical strategic asset that, if managed effectively, can not only produce but sustain competitive advantage, especially for knowledge-driven organizations. Many renowned theorists in the field of knowledge management (KM), such as Grant (1996), Nonaka (1994), and Spender (1996), have shed light on the nature of knowledge and advanced the field by highlighting the significant role of individuals in KM. Through knowledge-based view of the firm (KBV), Grant (1996) and Spender (1996) contend that strategically valuable knowledge does not exist independently as concrete objects like many other organizational resources, but originally resides within individuals who possess special knowledge and abilities. Their central ideas thus revolve around the integrations of individuals' special knowledge in organizations. In Nonaka (1994)'s organizational knowledge creation theory, organizational knowledge is created through interactions between tacit and explicit knowledge in a spiral process of socialization, externalization, combination, and internalization (SECI). In contrast to explicit knowledge, tacit knowledge, residing in the brain, is rather elusive, rich in context, and thus difficult to share (Alavi and Leidner, 2001; Nonaka, 1994). Tacit knowledge is first exchanged via socialization among individuals. Tacit knowledge is then externalized into explicit knowledge in forms such as formal documents. Explicit knowledge from a variety of sources is then combined into a repository of explicit knowledge such as databases. Converting explicit knowledge back into tacit knowledge through internalization, individuals then possess tacit knowledge which will be exchanged in socialization all over again. Similar to the KBV, the SECI spiral process underlines the important role of knowledgeable individuals in organizational KM. That is, they are the origin of organizational knowledge, particularly tacit knowledge, which has been considered the key to sustainable competitive advantage of organizations (Ambrosini and

Bowman, 2001; Grant, 1996; Lubit, 2001; Berman, Down, and Hill, 2002). More importantly, both theories imply that for organizations to gain any further benefits from KM, knowledge sharing among knowledge workers must first occur.

Knowledge sharing is a challenging topic for KM researchers. Many studies have shown that a large number of extrinsic and intrinsic factors can determine whether people will share their knowledge (e.g. Bock et al., 2005; Kankanhalli et al., 2005; Ray et al., 2005; Thomas-Hunt, Ogden, and Neale, 2003; Wasko and Faraj, 2005). Reviewing seventy-nine studies on knowledge sharing at individual level in disciplines such as information systems and management, Wang and Noe (2010) found that factors influencing both knowledge sharing perceptions and behaviors can be classified into environmental factors (e.g. organizational and cultural characteristics), motivational factors (e.g. attitudes and trust), and individual characteristics (e.g. education and experience). They found that while the roles of environmental and motivational factors have been much investigated, those of individual characteristics are rather understudied (e.g. Constant, Kiesler, and Sproull, 1994; Jarvenpaa and Staples, 2000; Wasko and Faraj, 2005).

In addition to identifying predictors of knowledge sharing, it is even more critical to understand how they may possess different effects among different groups of knowledge workers such as more and less knowledgeable individuals. For example, although knowledge self-efficacy can generally determine the likelihood of sharing (Lee, Cheung, Lim, and Sia, 2006; Kankanhalli et al., 2005), the impact may be different between experts and novices. In addition, experts may abandon their sharing intention, because organizational knowledge sharing strategy (e.g. system-oriented or codification) does not match with their personal preference for sharing strategy (e.g. human-oriented or personalization) (Hansen, Nohria, and Tierney, 1999; Song and Teng, 2006; Swap, Leonard, Shields, Abrams, 2001). Thus, to be able to fully take advantage of existing knowledge by establishing how to transfer it, especially tacit knowledge, from experts to novices effectively (Hinds, Patterson, and Pfeffer, 2001; Rintala and

Kuronen, 2006), organizations first need to learn how factors that can influence knowledge sharing may vary between experts and novices. Based on both the studies included in Wang and Noe (2010)'s review and our own literature search, we found that very few studies (e.g. Hinds et al., 2001; Rintala and Kuronen, 2006; Shim and Roth, 2008; Swap et al., 2001) have empirically explored the nature of knowledge sharing between experts and novices. We believe that such a gap in the literature would hinder theoretical advance in the field.

The relationship between expertise and knowledge sharing are found to be mixed in the existing literature (Wang and Noe, 2010). Particularly, Constant, Kiesler, and Sproull, (1996) found that expertise measured by a self-reported scale anchored from novice (1) to expert (10) is associated with knowledge sharing, but Wasko and Faraj (2005) found that self-rated expertise measured via items anchored from novice (1) to expert (5) is not. In addition to factors such as different research settings, we believe that such discrepancy is due to the measurement used for the expertise. Granted that self-reported scales are suggested to be not any inferior than third-party scales (Heneman, 1974; Teigland and Wasko, 2003; Wexley et al., 1980), to better classify whether people belong in either novice or expert group so that we can better understand their knowledge sharing behaviors, a more theoretically justified construct that is directly tied to how novices can become experts is needed.

Tacit knowledge has been recognized as a determinant of expertise. Ryan and O'Connor (2009) found that tacit knowledge which is based on team members' expertise determines effectiveness in software development teams. Geisler (2009) found that rather than explicit knowledge such as procedures, it is experts' tacit knowledge that saves emergency patients' lives. Hedlund et al. (2003) found that tacit knowledge explains individual differences in leadership effectiveness in the military. Tan and Libby (1997) found that tacit knowledge is a significant source of audit expertise. Bassellier, Reich, and Benbasat (2001) consider experience a proxy for tacit knowledge. Based on the SECI process (Nonaka, 1996), while both internalization and socialization produce tacit knowledge, the value of socialization simply depends on the effectiveness of internalization of the individuals, because unless knowledge exchanged in socialization comes from those with effective internalization, the socialization is apt to be futile. Thus, considering that an individual's internalization is the process that ultimately creates tacit knowledge, we believe that the degree of knowledge internalization can be used to classify whether an individual is an expert or a novice.

To the best of our knowledge, the notion of internalization has been neither rigorously theorized nor operationalized as it deserves. Conceptualizing organizational knowledge creation as a second-order construct consisting of socialization, externalization, combination, and internalization, Nonaka, Byosiere, Borucki, and Konno (1994)'s internalization scale was not grounded in any theory, and the scale capriciously included real world and virtual world knowledge acquisitions as its factors. Nonetheless, a few studies have drawn from their study (e.g. Lee and Choi, 2003 and Sabherwal and Becerra-Fernandez, 2003). We believe that given its enormous implications for further research as discussed, the concept of internalization needs to be strongly justified using well-established theories.

In this study, by drawing from Anderson (1983)'s Adaptive Control of Thought (ACT) theory and Glaser et al. (1985)'s framework on cognitive skills, we systematically develop the notion of knowledge internalization and define it as ***the process in which an individual relies on various cognitive mechanisms to transform his or her declarative knowledge into procedural knowledge***. To fill in several gaps in literature as discussed, the objectives of this study are twofold: ***First, we identify distinct profiles of knowledge workers using the cognitive mechanisms of knowledge internalization. Second, we explore how factors influencing knowledge sharing, including knowledge self-efficacy, expert power, sharing intention, and preference for knowledge sharing strategy, vary among the profiles.***

The remainder of the paper is organized as follows. First, we develop the conceptualization of knowledge internalization and discuss how its cognitive mechanisms can be used to classify the levels of knowledge workers' expertise. Then, we discuss how knowledge self-efficacy, expert power, sharing intention, and preference for sharing strategy are expected to manifest differently among different groups of knowledge workers. Then, we discuss research methodology, analyses, and results. Finally, we discuss theoretical and practical implications, limitations, and future research directions.

3.3 Knowledge Internalization

As discussed, we propose that knowledge internalization can be used to differentiate more knowledgeable from less knowledgeable individuals. That is, we suggest that an individual's ability to produce tacit knowledge can be an indication of his or her level of expertise. To probe into such a process, we draw from several theories in cognitive psychology. Specifically, based on a discussion in Royer, Cisero, and Carlo (1993)'s review study, we draw from Anderson (1983)'s ACT theory and Glaser et al. (1985)'s cognitive skills to develop the notion of knowledge internalization. Because the concept of declarative versus procedural knowledge is the foundation of the ACT theory, we first need to discuss their nature and how they are related to tacit knowledge.

3.3.1 Tacit Knowledge in Relation to Declarative and Procedural Knowledge

Researchers has typically viewed declarative knowledge as know-what and procedural knowledge as merely know-how (e.g. Alavi and Leidner, 2001; Arnold et al., 2006). Similarly, some researchers believe that explicit knowledge is know-what and tacit knowledge is know-how (e.g. Sambamurthy and Subramani, 2005). Separately, these views may seem to be reasonably valid. However, when attempting to integrate such different types of knowledge, one may find that such simple comparisons have importantly limited our understanding of the true similarities and differences among declarative, procedural, explicit, and tacit knowledge (Nickols, 2000). For example, if certain know-how (i.e. procedures) is codified in a formal document or knowledge repository system, then it is no longer clear as to whether the same know-how should still be considered tacit knowledge let alone procedural knowledge.

We attempt to resolve this uncertainty first by defining *declarative knowledge* as the part of knowledge that *can be* represented or described by communication media such as natural languages, mathematics, audios, and videos. As a result, consistent with that of Nickols (2000), in which declarative knowledge is not restricted to know-what, our definition is richer in that it includes elements of not only know-what and know-how but even know-why. In addition, once *actually* documented or represented by communication media, such knowledge is referred as externalized declarative knowledge. Food cookbooks (e.g. know-what and know-how) and even economics theories in a textbook (e.g. know-what and know-why) are examples of externalized declarative knowledge. Thus, in relation to tacit and explicit knowledge, declarative knowledge refers to the part of tacit knowledge that *can be* represented or described by communication media (i.e. “non-sticky”), while externalized declarative knowledge should definitely be viewed as explicit knowledge.

For *procedural knowledge,* we define it as a*ctionable* knowledge that has been internalized from a collection of declarative knowledge. It is actionable in a sense that only when repeatedly practiced, declarative knowledge can turn into procedural knowledge. For example, although an individual has learned declarative knowledge such as basic facts and information (know-what), established methodologies (know-how), or even theoretical principles (know-why), he or she must practice them before the knowledge can turn into procedural knowledge. Therefore, as rather complementary to declarative knowledge, procedural knowledge is the “sticky” part of tacit knowledge that is extremely and costly to externalize, if at all possible.

Our focal interest is *how* an individual transforms his or her declarative knowledge into procedural knowledge, that is, the knowledge internalization process. Simply put, the knowledge internalization is the process that can produce tacit knowledge *that is very rare, inimitable, and valuable to organizations*. Now that declarative and procedural knowledge have been linked to tacit knowledge, we can discuss the theoretical foundation for the construct, that is the integration of Anderson (1983)'s ACT theory and Glaser et al. (1985)'s cognitive skills.

3.3.2 Three Learning Stages and Associated Cognitive Mechanisms

First of all, Anderson (1983)'s ACT theory is about human learning and knowledge representation. The theory states that learning occurs in declarative, compilation, and procedural stages. At *declarative* stage, an individual applies declarative knowledge to interpret problems, but his or her performance is heavily weighted by processing time and working memory load when retrieving such knowledge. The *compilation* stage indicates the changing point where the same individual now learns how to apply declarative knowledge with less consciousness. In the process, declarative knowledge that has been accumulated is progressively transformed into procedural form that is ready to be activated with less memory load. Finally, at the *procedural* stage, the same individual can now apply a collection of compiled declarative knowledge, that is, procedural knowledge, to solve a problem or work on a task automatically or with minimum memory load. At this stage, the same individual is also aware of how to control or plan his or her problem solving endeavors in a more effective and efficient way. With these three learning stages, the ACT theory provides a foundation to the concept of knowledge internalization; that is, knowledge internalization occurs when an individual can improve his or her performance of performing a task or solving a problem by progressing from declarative to compilation and to procedural stage. More precisely, it occurs when an individual can apply accumulated declarative knowledge to perform a task or solve a problem in an automatic manner. While the ACT theory improves our understanding of *when* knowledge internalization occurs, *how* one can actually internalize knowledge is the next issue we explore.

Based on Glaser et al. (1985), the following six cognitive skills enable one to learn: First, *organization and structure* refers to the extent to which declarative knowledge becomes interconnected and structured. This cognitive skill enables an individual to proficiently access coherent chunks of declarative knowledge to perform a task. *Problem representation* refers to the extent to which underlying principles of a problem or task situation are recognized. This cognitive skill allows an individual to recognize deep principles or related factors of a problem rather than the simple ones. *Mental models* refer to the extent to which operations of a system in a particular domain are understood and developed. Mental models permit an individual to be able to visualize or imagine how things work in a domain in a number of scenarios and to use such visions to support his or her problem-solving endeavor. *Efficiency* refers to the extent to which developed skills, or procedural knowledge, are efficiently utilized. This cognitive skill allows an individual to reach to the solution of a problem efficiently with minimum efforts. *Automaticity* refers to the extent to which procedural knowledge is automatically exerted. This cognitive skill importantly enables an individual to perform a task or solve a problem automatically without conscious cognitive efforts. Finally, *metacognition* refers to self-regulatory and self-management skills. Referring to the extent to which performance is reflected and controlled in a useful and efficient manner, metacognition not only raises an individual's awareness of his or her own ability, but also helps the individual plan his or her behaviors, monitor the outcomes of the efforts, and adjust behaviors appropriately.

These cognitive skills help us identify the specific mechanisms an individual needs to use to transform declarative knowledge (i.e. non-sticky tacit knowledge) further into procedural knowledge (i.e. sticky tacit knowledge). Thus, while the ACT theory helps explain *when* knowledge internalization occurs, these cognitive skills specifically point out *how* it occurs. In essence, knowledge internalization refers to *the process in which an individual relies on various cognitive mechanisms to transform his or her declarative knowledge into procedural knowledge*. In relation to how knowledge internalization can be used to differentiate knowledge workers' expertise, it can be logically deduced that a novice will have significantly less degree of knowledge internalization than an expert has. To become an expert, a novice needs to not only experience the three learning stages, but simultaneously attempt to achieve and exert the aforementioned six cognitive mechanisms so that his or her declarative knowledge will ultimately be converted into procedural knowledge (i.e. tacit knowledge that is very rare and inimitable). Figure 3.1 illustrates the nature of the knowledge internalization.

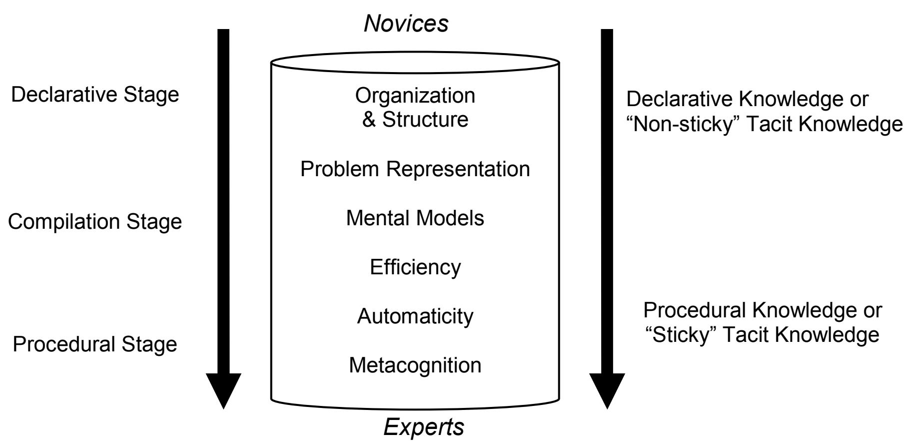

Figure 3.1 Nature of Knowledge Internalization

3.4 Factors Influencing Knowledge Sharing

In this section, we discuss how knowledge self-efficacy, expert power, knowledge sharing intention, preference for knowledge sharing strategy are influential in knowledge sharing, and how they are likely to manifest differently in different groups of knowledge workers such as between more knowledgeable and less knowledgeable.

3.4.1 Knowledge Self-efficacy and Knowledge Sharing Intention

Self-efficacy refers to self perception about what people can do with their skills (Bandura, 1982). Based on the concept of self-efficacy, researchers have specifically defined knowledge self-efficacy as the confidence in one's ability to provide valuable knowledge (Kankanhalli, Tan, and Wei, 2005). Knowledge self-efficacy has been found to be rather influential to both knowledge sharing intention and actual behaviors. Kankanhalli et al. (2005) found that people will contribute their knowledge to the knowledge repositories of organization, if they are confident that their expertise is useful to the organization. Cho, Chen, and Chung (2010) found that knowledge self-efficacy has a significant impact on knowledge sharing intentions in the context of Wikipedia. Lin (2007) found that knowledge self-efficacy influences both people's sharing attitudes and intentions. Lee et al. (2006) found that the lack of knowledge self-efficacy is a reason people do not want to share knowledge with others. Based on these studies, we expect that more knowledgeable workers will have not only higher knowledge self-efficacy but also higher sharing intention than less knowledgeable workers.

3.4.2 Expert Power and Knowledge Sharing Intention

French and Raven (1959)'s social power theory is widely regarded as one of the most influential in the literature about power in organizations (Schriesheim, Hinkin, and Podsakoff, 1991). Despite its potential to knowledge sharing phenomenon, knowledge sharing studies based on a power perspective are very scarce (Wang and Noe, 2010). The power theory posits that an individual can achieve authority via reward, coercive, legitimate, referent, and expert power. We are particularly interested in the role of expert power, because it appears to be most relevant to the context of knowledge sharing. An individual's expert power refers to the perception by other people that the individual possesses special knowledge or expertise (Raven and French, 1958). Therefore, while knowledge self-efficacy indicates self perception in one's ability to contribute knowledge, expert power is other people's perception of one's expertise. Indeed, Liao (2008) found that out of other bases of power, expert power is the most associated with knowledge sharing behaviors. Liao (2008) found that managers' expert power has a significant positive effect on employees' knowledge sharing behaviors, because more knowledgeable managers can create trusting climate of knowledge sharing among one another for the employees. Thus, we believe that more knowledgeable workers will have not only higher expert power but also higher sharing intention than less knowledgeable workers.

3.4.3 Preference for Knowledge Sharing Strategy

Strategies for managing knowledge can be classified into personalization and codification (Hansen et al., 1999). They are also known as human-oriented versus system-oriented styles (Choi and Lee, 2002, 2003; Maier and Remus, 2003). Personalization emphasizes person-to-person interactions, while codification focuses on people-to-documents approach, (Hansen et al., 1999). The purpose of personalization strategy is to facilitate tacit knowledge sharing through socializations and informal communications among knowledge workers, while the goal of codification strategy is to share and reuse explicit knowledge that has been codified and stored into a computer system (Boh, 2008; Hansen et al., 1999). In this paper, we define preference for personalization strategy as the extent to which an individual prefers person-to-person approaches in sharing knowledge to solve problems, and preference for codification strategy as the extent to which an individual prefers people-to-document approaches in sharing knowledge to solve problems.

While several contextual issues (e.g. reward, duration of collaboration, nature of industry and practice of organizations) exist regarding how organizations should adopt only one strategy or combine both strategies to enhance their KM practices (e.g. Boh, 2008; Hansen et al., 1999; Kankanhalli, Tanudidjaja, Sutanto, and Tan, 2003; Liu, Ray, Whinston, 2009), we believe that it is also important organizations first consider their employees' intrinsic needs and preferences; after all, they are the source of knowledge. Matching the strategy with workers' ability and preferences has been shown to improve effectiveness of KM in organizations. Song, Nerur, and Teng (2007) found that high degree of personalization strategy, that is, socialization among knowledge workers who particularly share much work experience leads to improvement of KM in the work units. Hansen (2002) essentially found that when exchanging tacit knowledge, the closer and more direct people can interact among one another, the more knowledge will be shared and the faster the project will be completed. Such a relationship is especially prominent in the case of experts. Personalization strategy can enable experts to share their tacit knowledge with others in a more effective manner, because experts are known to have difficulty externalizing or even articulating their tacit knowledge (Ambrosini and Bowman, 2001). Indeed, Swap et al. (2001) found that because experts tend to reach the solution for a problem simply by recognizing its pattern, and because they may not be able to formally explain their complex mental process to other people, let alone codify it into knowledge repositories, personalization approaches such as informal mentoring and storytelling can help convey their knowledge more effectively. Thus, it is more likely that more knowledgeable workers will prefer personalization strategy over codification than less knowledgeable workers do.

3.5 Methodology

3.5.1 Data Collection and Sample Characteristics

Given the context of the study, the target respondents are knowledge workers with reasonable amount of work experience. The survey instrument is administered to MBA students in the professional cohort program exclusively created for full-time working professionals as well as the regular format at a public university in a metropolitan area of the southwest US. The survey was distributed and collected back in the same class period. A total of 266 out of expected 324 questionnaires were returned (i.e. a response rate of 82.1%). Seven responses were eliminated due to too much missing data, resulting in a final sample size of 259. Table 1 presents the demographic characteristics of the sample. Almost all the subjects hold either bachelor's degrees (63%) or master's degrees (35%). Engineers, IS/IT, and general management make up nearly half of the sample (about a total of 48%), while accountants, financial analysts, and marketing represent a moderate portion of the sample (approximately a total of 24%). The average years in the profession, in the current organization, and in the current position are approximately 7, 5, and 3 years respectively. These characteristics demonstrate that the subjects are indeed knowledge workers with substantial work experience.

Table 3.1 Demographic Characteristics of the Sample (n = 259)

Characteristics	Percent	Characteristics	Percent
Gender		*Industry*	
Male	69.8	Banking/Insurance/Financial Service	14.8
Female	30.2	Constructions/Architecture/Engineering	7.4
Age		Consulting/Business Service	4.3
21-30	58.4	Education	8.2
31-40	32.7	Government/Military	8.6
41-50	7.4	Healthcare	7.8
51-60	1.6	Hotel/Entertainment/Service Industry	4.7
Education		IT/Telecommunications	7.4
High school	0.4	Manufacturing	14.5
Associate	0.4	Other	22.3
Bachelor	63.4		
Master	34.6	Characteristics	Mean
Doctorate	1.2	Years on current position	3.3
Profession		Years with current organization	4.4
Accountant	8.1	Years in the profession	6.6
Engineer	16.2	No. of Employees in Department	665.9
Financial Analyst	6.6	No. of Employees in Organization	24866.3
General Management	16.6	No. of Professional Contacts	170.9
IS/IT	15.8		
Lawyer	0.4		
Marketing	7.7		
Medical/Physician/Nurse	1.5		
Public Relation	1.9		
Other	25.1		

3.5.2 Scale Development for Knowledge Internalization Construct

We rigorously adhered to practices and recommendations by many researchers (e.g. Churchill, 1979; Lewis, Templeton, and Byrd, 2005; Malhotra and Grover, 1998, Moore and Benbasat, 1991, and Xia and Lee, 2005) for developing the measurement for the knowledge internalization construct. First, we established content validity of the measure by having a researcher who has more than thirty years of academic experience help substantiate the theoretical underpinning of each scale. Twenty-five Likert-type scales anchored from strongly disagree (1) to strongly agree (7) were generated. Next, we ensured face validity of the measure using a sorting exercise, in which the judges are two practitioners/researchers who have over twenty years of experience in management and IT, one practitioner with over ten years of experience in IT, and two doctoral students with several years of experience in management and finance. Provided with the sorting instructions, definitions of the dimensions of the construct, and a randomized list of the actual items, the judges then selected the dimension they believed is most appropriate for each item. Based on their feedbacks, no major problems were found.

Next, we conducted a pilot study by administering the survey in a graduate-level course in college of business administration at a public university in a metropolitan area of the southwest US. The participants included 31 valid responses, all of whom had an average of five years of experience in management and IT. With this sample, the significant results of the Kaiser-Meyer-Olkin and Bartlett’s test showed that the level of multicolinearlity in the data was enough to perform an exploratory factor analysis. Common factor analysis with oblique rotation was conducted. Based on the eigenvalues (>1.0), the scree plot (showing a break after the fourth factor), and a threshold value of 0.55, Mental Model, Efficiency, Automaticity, and Metacognition appeared as anticipated. However, several items of Organization and Structure were found to cross-load with those of Problem Representation. As a result, after refining all the items as necessary, we believed that they were ready to be used in the actual study (see Table 3.2).

Table 3.2 Items for the Knowledge Internalization Construct (after the pilot study)

Organization & Structure	
OS1	I can easily group relevant information into different categories.
OS2	I can easily tell how a piece of needed information is similar or different from another.
OS3	I can easily sort out required information in a systematic fashion.
OS4	I can easily see how a piece of relevant information fits with other pieces.
Problem Representation	
PR1	I can easily identify the reasons that cause these problems.
PR2	I can easily see how difficult situations are caused by certain factors.
PR3	I can easily explain to other people the basic cause-and-effect relationships involved.
PR4	I can easily recognize various cause-and-effect linkages in the problems.
Mental Models	
MM1	I can easily visualize the step-by-step process to solve them effectively under various situations.
MM2	I can easily envision possible solutions in vivid details given different circumstances.
MM3	I can easily imagine how certain solutions will work out under a variety of conditions.
MM4	I can clearly picture in my head how potential solutions would play out differently due to certain factors.
Efficiency	
EF1	I can solve them very effectively and proficiently.
EF2	I can resolve many difficulties with less time and effort.
EF3	I can obtain effective solutions with great ease and speed.
EF4	I am faster than most of my colleagues in solving them effectively.
Automaticity	
AU1	I can rely on my instinct for correct solutions without following step-by-step analytical procedures.
AU2	I can instantly figure out correct solutions without realizing exactly how.
AU3	My immediate intuitions without much thinking are usually correct.
AU4	I can jump to correct conclusions without consciously following prescribed procedures.
Metacognition	
MC1	I always act appropriately in difficult situations using what I learn from my past experiences.
MC2	I always control my actions carefully based on the lessons previously learned.
MC3	I always monitor both successes and failures of my decisions and adjust my actions effectively.
MC4	I always evaluate and learn from my actions so that I do not repeat the same mistakes.

Note. All items are preceded by the phrase: “When I work on job-related problems:”

3.5.3 Scales of Other Constructs

The scales of other constructs in the study are adapted from previous literature, in which their reliability and validities have been well substantiated. *Knowledge self-efficacy* is measured with three items adapted from Kankanhalli et al. (2005), in which the alpha coefficient is 0.96. *Expert power* is measured with four items adapted from Schriesheim et al. (1991), in which the alpha coefficient of the construct exceeds 0.80. *Knowledge sharing intention* is measured with three items adapted from Bock et al. (2005), in which the composite reliability is 0.93. Finally, *preference for personalization strategy* and *preference for codification strategy* are each measured with four items adapted from Song and Teng (2006), in which the composite reliability is 0.91 and 0.92 respectively. Using Seven-point Likert-type scales anchored from strongly disagree (1) to strongly agree (7), all the items of the constructs are shown in Table 3.3.

Table 3.3 Items for All Other Constructs

Knowledge Self-efficacy (adapted from Kankanhalli et al., 2005)	
KS1	I have confidence in my ability to provide knowledge that others in my organization consider valuable.
KS2	I have the expertise needed to provide valuable knowledge for my organization.
KS3	I can provide more valuable knowledge than most other employees can.
Expert Power (adapted from Schriesheim et al., 1991)	
EP1	My coworkers often seek my solutions for job-related problems.
EP2	My coworkers often comment that my advice is sound.
EP3	My coworkers often seek my technical knowledge.
EP4	My coworkers often say that my technical suggestions are excellent.
Knowledge Sharing Intention (adapted from Bock et al., 2005)	
IN1	I intend to share my experience and knowledge with my coworkers more frequently in the future.
IN2	I will try to share my expertise from my education or training with my coworkers in a more effective way.
IN3	I will always provide my experience and knowledge at the request of my coworkers.
Preference for Personalization Strategy (adapted from Song and Teng, 2006)	
PE1	I prefer to make face-to-face social interactions to exchange knowledge.
PE2	I prefer to engage in informal dialogues and formal meetings to share and transfer knowledge.
PE3	I prefer to use meetings and discussion via brainstorming and debate, etc. to generate new knowledge.
PE4	I prefer to use knowledge from accumulated experience to solve problems.
Preference for Codification Strategy (adapted from Song and Teng, 2006)	
CO1	I prefer to use formal documents to capture and describe knowledge.
CO2	I prefer to record knowledge formally whenever it is created (e.g. from projects and meetings).
CO3	I prefer to use formal documents to share and transfer knowledge.
CO4	I prefer to use knowledge and procedures from formal documents to solve problems.

3.6 Assessment of Measurement Properties

To evaluate the psychometric properties and validities of the knowledge internalization construct as rigorously as possible, we first performed exploratory factor analysis (EFA) and then confirmatory factor analysis (CFA) (Lewis et al., 2005). All the other constructs are validated with CFA. For EFA, we conducted principal component analysis with varimax rotation (n = 259). Based on the eigenvalues (>1.0), the scree plot (showing a break after the fifth factor), and a threshold value of 0.65, five factors emerged as opposed to six as theorized (see Table 4). The five factors explained approximately 71% of the variance. We selected 0.65 as the threshold, because to ensure greater correlation among the items in the corresponding factors, Lewis et al. (2005) recommend that researchers maximize a loading threshold so that as many intended items can be included as possible. The results showed that Organization and Structure, Efficiency, Automaticity, and Metacognition were the structure of the items, but Problem Representation and Mental Models combined into one factor. To maintain the content validity of the construct, using 0.65 allowed us to equally include three items of both Problem Representation (PR1, PR2, and PR4) and Mental Models (MM2, MM3, and MM4). To be consistent with prior literature mainly the works of Nonaka and his colleagues, we named this factor simply as Mental Models. High factor loading (> 0.65) of the items within their own factors exhibited a high level of convergent validity, while the uniqueness of the factors (i.e. no cross-loading items) provided evidence of discriminant validity of the construct (Lewis et al., 2005). The Mental Model factor consisted of 6 items, while the other four factors included 4 items. Finally, all the scales demonstrated satisfactory level of the reliability, as all Cronbach's alpha coefficients exceeded 0.8 (see Table 3.4) (Nunnally, 1978).

Table 3.4 EFA Results, Descriptive Statistics, and Reliability of the Underlying Factors of the Knowledge Internalization Construct (n = 259)

	Mental Models	Organization & Structure	Automaticity	Metacognition	Efficiency	Descriptive statistics & Reliability
MM3	.762	.120	.159	.078	.277	Mean = 5.36 SD = 0.87 Cronbach's Alpha = 0.89
PR1	.708	.315	.126	.039	.133	
PR2	.701	.427	.172	.186	.046	
PR4	.695	.399	.091	.116	.104	
MM4	.689	.051	.168	.157	.394	
MM2	.677	.112	.165	.086	.399	
MM1	.627	.164	.163	.030	.422	
PR3	.580	.385	.014	.244	.044	
OS1	.244	.820	.093	.043	.161	Mean = 5.77 SD = 0.93 Cronbach's Alpha = 0.90
OS2	.217	.796	.075	.133	.239	
OS4	.345	.774	.065	.046	.194	
OS3	.228	.745	.164	.106	.264	
AU4	.162	.080	.881	.043	.092	Mean = 4.62 SD = 1.28 Cronbach's Alpha = 0.89
AU3	.196	.122	.842	.018	.184	
AU2	.145	.001	.839	.047	.134	
AU1	.065	.155	.792	.065	.187	
MC2	.109	.087	.056	.886	.066	Mean = 5.76 SD = 0.92 Cronbach's Alpha = 0.90
MC3	.082	.095	-.008	.839	.156	
MC1	.127	.044	.115	.821	.066	
MC4	.106	.077	.006	.805	.137	
EF3	.214	.201	.233	.165	.767	Mean = 5.32 SD = 0.99 Cronbach's Alpha = 0.89
EF2	.232	.229	.211	.190	.743	
EF1	.283	.268	.101	.205	.738	
EF4	.352	.243	.213	.023	.672	

For CFA, we used SmartPLS 2.0 M3 (Ringle, Wende, and Will, 2005), which is based on Partial Least Squares (PLS), a component-based structural equation modeling (SEM) technique, because both multivariate normal distribution assumptions and sample size requirements are less stringent than LISREL, a covariance-based SEM (Chin, Marcolin, and Newsted, 2003). The CFA results showed evidence of discriminant validity, convergent validity, and reliability of all the constructs. Except for one item of preference for personalization strategy

(0.61), all the items strongly loaded (> 0.7) on their respective factors, and there were no cross-loading items, thus demonstrating discriminant validity (Gefen and Straub, 2005). In addition, the square root value of the average variance extracted (AVE) of each of the reflective constructs was much larger than its correlation with all the other constructs, thus confirming evidence of discriminant validity. The *t*-statistics of all the items loading on their own factors (ranging from 3.42 to 66.27) were significant at the 0.001 level, indicating high degree of convergent validity (Gefen and Straub, 2005). Finally, the composite reliability values of all the constructs exceeded 0.8, indicating satisfactory reliability (Nunnally, 1978). In essence, these results demonstrate convergent validity, discriminant validity, and reliability of all the constructs. The psychometric properties of the measurement are presented in Table 3.5. The CFA results are provided in Table 3.6.

Table 3.5 Descriptive Statistics, Reliability, and Correlations of the Constructs (n = 259)

Construct	Mean (SD)	CR	AU	CO	EF	EP	IN	KS	MC	MM	OS	PE
AU	4.62 (1.28)	0.93	0.87									
CO	4.61 (1.27)	0.92	-0.10	0.87								
EF	5.32 (.99)	0.92	0.44	0.03	0.86							
EP	5.50 (1.07)	0.93	0.29	0.07	0.47	0.87						
IN	5.85 (.96)	0.89	0.07	0.12	0.19	0.34	0.85					
KS	5.66 (.92)	0.90	0.33	0.13	0.48	0.65	0.42	0.87				
MC	5.76 (.92)	0.92	0.14	0.18	0.34	0.17	0.19	0.24	0.86			
MM	5.36 (.87)	0.92	0.40	0.10	0.65	0.45	0.20	0.44	0.30	0.81		
OS	5.77 (.93)	0.93	0.29	0.06	0.55	0.44	0.23	0.48	0.25	0.63	0.88	
PE	5.72 (.88)	0.82	0.22	-0.06	0.25	0.26	0.22	0.27	0.30	0.23	0.28	0.74

Notes. CR = Composite Reliability. Square roots of AVE values are highlighted along the diagonal. OS = Organization and Structure, MM = Mental Models, EF = Efficiency, AU = Automaticity, MC = Metacognition, EP = Expert Power, KS = Knowledge Self-efficacy, IN = Knowledge Sharing Intention, PE = Preference for Personalization, CO = Preference for Codification.

Table 3.6 CFA Result (n = 259)

	AU	CO	EF	EP	IN	KS	MC	MM	OS	PE
AU1	0.82	-0.11	0.39	0.23	0.08	0.28	0.14	0.32	0.28	0.17
AU2	0.83	-0.16	0.35	0.24	0.05	0.27	0.12	0.31	0.18	0.14
AU3	0.91	-0.08	0.44	0.30	0.08	0.32	0.11	0.40	0.30	0.23
AU4	0.91	-0.04	0.35	0.24	0.04	0.27	0.12	0.33	0.24	0.21
CO1	-0.15	0.86	0.00	0.06	0.11	0.12	0.15	0.09	0.03	-0.09
CO2	-0.09	0.87	0.02	0.03	0.06	0.14	0.16	0.01	0.06	-0.01
CO3	-0.05	0.92	0.05	0.08	0.11	0.13	0.19	0.14	0.07	-0.05
CO4	-0.06	0.82	0.01	0.05	0.16	0.03	0.10	0.11	0.04	-0.07
EF1	0.32	0.07	0.86	0.42	0.18	0.43	0.35	0.57	0.52	0.20
EF2	0.40	0.01	0.89	0.38	0.16	0.40	0.31	0.55	0.45	0.24
EF3	0.42	0.02	0.88	0.37	0.17	0.36	0.30	0.53	0.44	0.18
EF4	0.40	-0.02	0.82	0.47	0.15	0.48	0.20	0.59	0.49	0.26
EP1	0.24	0.06	0.42	0.86	0.30	0.61	0.17	0.37	0.38	0.15
EP2	0.25	0.10	0.39	0.83	0.30	0.53	0.25	0.36	0.38	0.29
EP3	0.24	0.03	0.43	0.89	0.33	0.57	0.07	0.41	0.39	0.20
EP4	0.29	0.05	0.42	0.90	0.26	0.55	0.13	0.42	0.38	0.27
IN1	0.08	0.15	0.12	0.28	0.81	0.30	0.16	0.15	0.12	0.12
IN2	0.07	0.16	0.19	0.33	0.92	0.38	0.17	0.20	0.23	0.20
IN3	0.05	0.01	0.16	0.27	0.83	0.38	0.17	0.15	0.22	0.22
KS1	0.32	0.07	0.46	0.61	0.43	0.88	0.28	0.41	0.47	0.28
KS2	0.22	0.13	0.39	0.56	0.37	0.91	0.20	0.38	0.43	0.24
KS3	0.32	0.16	0.39	0.51	0.28	0.82	0.10	0.35	0.33	0.18
MC1	0.17	0.14	0.27	0.16	0.14	0.19	0.82	0.27	0.20	0.24
MC2	0.13	0.13	0.28	0.11	0.15	0.15	0.88	0.27	0.22	0.25
MC3	0.09	0.18	0.32	0.17	0.15	0.25	0.89	0.26	0.22	0.27
MC4	0.10	0.15	0.30	0.16	0.22	0.21	0.85	0.25	0.21	0.24
PR1	0.30	0.08	0.49	0.43	0.19	0.36	0.18	0.83	0.51	0.15
PR2	0.33	0.09	0.49	0.32	0.20	0.38	0.31	0.83	0.59	0.21
PR4	0.28	0.05	0.51	0.44	0.19	0.42	0.24	0.82	0.54	0.15
MM2	0.35	0.07	0.57	0.31	0.09	0.28	0.24	0.77	0.47	0.21
MM3	0.34	0.09	0.51	0.29	0.12	0.29	0.23	0.81	0.48	0.16
MM4	0.35	0.12	0.57	0.30	0.14	0.34	0.30	0.77	0.44	0.25
OS1	0.24	0.08	0.44	0.40	0.22	0.44	0.18	0.53	0.89	0.23
OS2	0.24	0.03	0.49	0.39	0.18	0.41	0.26	0.53	0.88	0.26
OS3	0.31	0.04	0.51	0.37	0.19	0.43	0.24	0.55	0.86	0.22
OS4	0.24	0.05	0.48	0.38	0.23	0.39	0.19	0.60	0.88	0.27

Table 3.6 – *Continued*

PE1	0.13	-0.03	0.13	0.05	0.06	0.11	0.23	0.08	0.13	0.73
PE2	0.16	-0.10	0.14	0.22	0.20	0.22	0.19	0.17	0.19	0.76
PE3	0.05	-0.05	0.07	0.18	0.10	0.07	0.11	0.16	0.10	0.61
PE4	0.23	-0.01	0.29	0.27	0.22	0.29	0.28	0.22	0.30	0.83

Notes. OS = Organization and Structure, MM = Mental Models, EF = Efficiency, AU = Automaticity, MC = Metacognition, EP = Expert Power, KS = Knowledge Self-efficacy, IN = Knowledge Sharing Intention, PE = Preference for Personalization, CO = Preference for Codification.

3.7 Analyses and Results

3.7.1 Profiling Knowledge Workers

To respond to the first objective of the study which is to profile knowledge workers, we performed cluster analysis using the cognitive mechanisms of knowledge internalization as described below. In spite of its exploratory nature, cluster analysis, a statistical technique that can be used to classify or seek groups among cases or observations, has been used in a number of IS studies. For example, Segars and Grover (1999) use cluster analysis to identify different approaches to strategic information systems planning. Wallace, Keil, and Rai (2004) use it to learn how numerous aspects of project risks such as user, team, and requirements manifest in low, medium, and high degree of project risks.

To increase validity of cluster solutions, Hair et al. (1992) and Ketchen and Shook (1996) recommend that researchers first use hierarchical clustering to identify the number of clusters in the data, and then use nonhierarchical clustering to evaluate that number by pre-specifying it into the clustering algorithm (e.g. *K*-means). Simply put, hierarchical clustering is to find the number, while nonhierarchical is to classify the observations according to that number, so that researchers can then theoretically examine the clusters. Following Ketchen and Shook (1996)'s recommendations, we first performed hierarchical clustering and analyzed the results by both examining the agglomeration coefficients (i.e. "a value at which various cases merge to form a cluster") and visually inspecting the dendogram (i.e. "a graph of the order that observations join clusters and the similarity of observations joined"). Based on the agglomeration coefficients (showing relatively large two jumps) and the dendogram (showing that the observations joined under distinctly large three areas), three clusters emerged. In conjunction to those techniques, Hair et al. (1992) and Ketchen and Shook (1996) suggest that a priori theory can also be used to determine the number of clusters. Thus, based on the three learning stages in the ACT theory, we decided to proceed with three clusters. Then, using the cognitive mechanisms of knowledge internalization, we performed nonhierarchical clustering through *K*-means with three clusters. Table 3.7 shows the cluster means of the three clusters according to the cognitive mechanisms.

Table 3.7 Cluster Means for the Cognitive Mechanisms of Knowledge Internalization

Cognitive Mechanisms of Knowledge Internalization	Cluster 1 (*Novice*) (n = 89)	Cluster 2 (*Practitioner*) (n = 75)	Cluster 3 (*Expert*) (n = 94)
Organization & Structure (OS)	4.94	6.01	6.34
Mental Models (MM)	4.61	5.50	5.96
Efficiency (EF)	4.38	5.62	5.97
Automaticity (AU)	3.99	3.82	5.87
Metacognition (MC)	5.19	6.14	6.01

Within each cluster, the number of the observations appears to be fairly comparable (i.e. 89, 75, and 94). Based on the overall differences in the means of each cognitive mechanism across the three clusters, it is logical to label them as Novice, Practitioner, and Expert respectively. We label the second cluster as Practitioner, because according to Oxford dictionary, a practitioner is "a person *actively engaged* in a profession", thus to some extent implying that the person is still actively trying to become an expert in his or her profession.

Of the first three cognitive mechanisms (i.e. organization & structure, mental models, and efficiency), the mean clearly increases from the novice to practitioner and to expert cluster with an interesting pattern, that is, the mean difference between the practitioner and expert clusters is much smaller (less than 0.5) than that between the novice and practitioner clusters (about 1). Interestingly, the means of automaticity of the novice and practitioner clusters are similarly low (nearly 4), while the mean of the expert cluster is noticeably much higher (almost 6). Finally, while the means of metacognition of the practitioner and expert clusters are similarly high (about 6), the mean of the novice cluster is evidently lower (about 5).

To substantiate the cluster solution and our observations above, we performed a series of Analysis of Variance (ANOVA) to determine whether the mean differences of all the cognitive mechanisms across the clusters are significant. Overall ANOVA test showed that all the mean differences are significant ($p = 0.000$). Further pairwise multiple comparisons using Bonferroni procedure indicated that all the pairwise mean differences are significant ($p < 0.05$), except that the mean difference of automaticity between practitioners and novices are not significant ($p > 0.05$), and that the mean difference of metacognition between experts and practitioners are not significant ($p > 0.05$). Thus, this result confirms the distinctions among the clusters as generated by cluster analysis. For better visualization, the differences among the three clusters of knowledge workers are depicted with the star chart in Figure 3.2, in which only the means of the novice and expert clusters are displayed to highlight the differences. As discussed, it is clear in the chart that automaticity mechanism differentiates experts from the others the most.

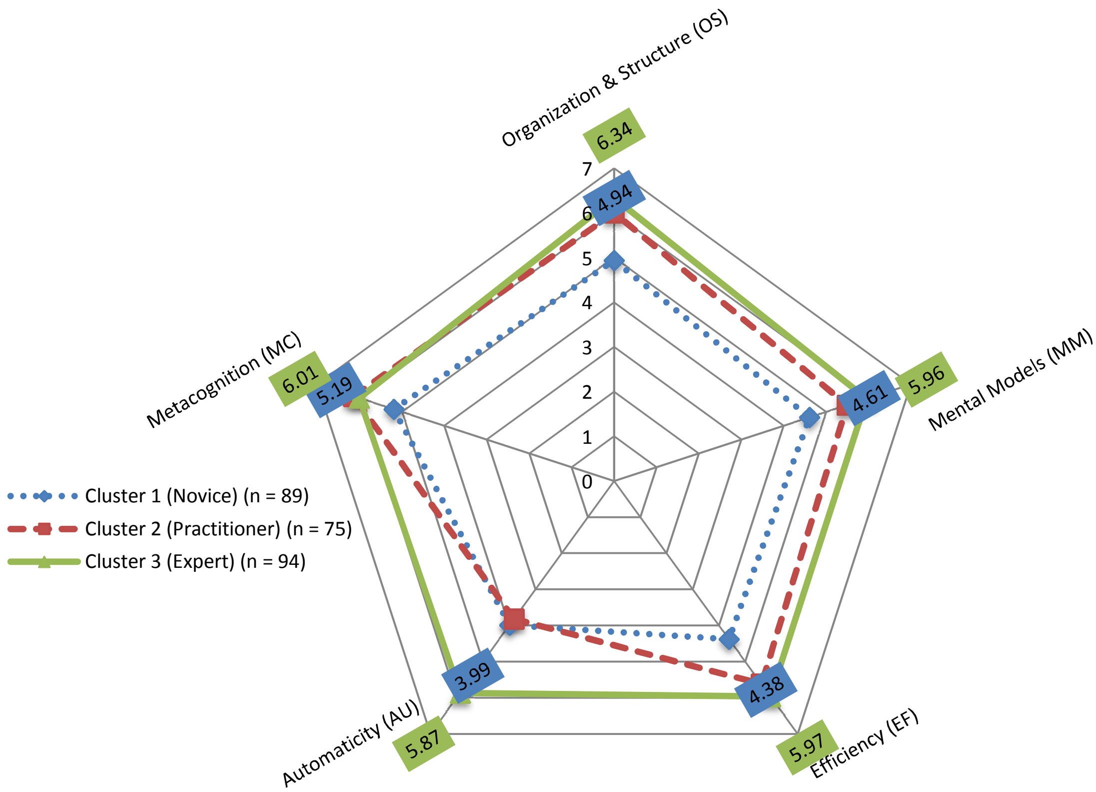

Figure 3.2 Profiles of Knowledge Workers
Note. To highlight the differences, only the means of expert and novice clusters are displayed.

3.7.2 Exploring Factors Influencing Knowledge Sharing across the Three Profiles

The second objective of this study is to explore how factors that are known to influence knowledge sharing manifest differently among the three profiles of knowledge workers. Specifically, we are interested in (1) whether the degrees of both knowledge self-efficacy (i.e. self perception) and expert power (i.e. perception of other people) will corroborate the different levels of expertise of the three profiles indicated by the cognitive mechanisms of knowledge internalization, (2) how knowledge sharing intention differs among the profiles, and more importantly, (3) which knowledge sharing strategy (i.e. personalization and codification) knowledge workers in each of the profiles prefer. Table 3.8 shows the means of these factors across the three clusters.

Table 3.8 Cluster Means for Factors Influencing Knowledge Sharing

Cluster	Knowledge Self-efficacy	Expert Power	Sharing Intention	Preference for Personalization	Preference for Codification
Expert	6.10	6.04	6.01	5.92	4.60
Practitioner	5.78	5.57	6.06	5.75	4.90
Novice	5.11	4.88	5.53	5.46	4.38

Before examining the three questions above, we first performed Multivariate Analysis of Variance (MANOVA) to determine whether the means of knowledge self-efficacy, expert power, sharing intention, preference for personalization strategy, and preference for codification strategy among the clusters are significantly different. The overall MANOVA analysis (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root) suggests that the mean differences of all the aforementioned factors across the clusters are significant ($p < 0.05$). Table 3.9 presents the overall MANOVA results. To investigate the three questions which basically are pairwise multiple comparisons, we performed a post-hoc test using Bonferroni procedure. The results of the multiple comparisons are presented in Table 3.10.

Table 3.9 Overall MANOVA Results (* Significance Level of 0.05)

Factor	Type III Sum of Squares	df	Mean Square	*F*	*p*
Expert Power	61.02	2	30.51	33.09*	0.000
Knowledge Self-efficacy	44.61	2	22.31	33.45*	0.000
Sharing Intention	14.75	2	7.37	8.42*	0.000
Preference for Codification	11.18	2	5.59	3.60*	0.029
Preference for Personalization	9.77	2	4.89	6.53*	0.002

Table 3.10 Results of Multiple Comparisons (* Significance Level of 0.05)

Factor	Cluster (I)	Cluster (J)	Mean Difference (I-J)	Std. Error	*p*
Expert Power	Expert	Novice	1.15*	0.14	0.00
	Expert	Practitioner	0.46*	0.15	0.00
	Practitioner	Novice	0.69*	0.15	0.00
Knowledge Self-efficacy	Expert	Novice	0.97*	0.12	0.00
	Expert	Practitioner	0.31*	0.13	0.04
	Practitioner	Novice	0.67*	0.13	0.00
Sharing Intention	Expert	Novice	0.48*	0.14	0.00
	Expert	Practitioner	-0.05	0.15	1.00
	Practitioner	Novice	0.53*	0.15	0.00
Preference for Codification	Expert	Novice	0.19	0.18	0.89
	Expert	Practitioner	-0.33	0.19	0.27
	Practitioner	Novice	0.52*	0.20	0.02
Preference for Personalization	Expert	Novice	0.46*	0.13	0.00
	Expert	Practitioner	0.16	0.13	0.68
	Practitioner	Novice	0.30	0.14	0.09

For the first question, the results clearly show that the significant pairwise mean differences of both knowledge self-efficacy and expert power indeed correspond with the three profiles of the knowledge workers' expertise contributed by the cognitive mechanisms of knowledge internalization; that is, the degrees of both knowledge self-efficacy and expert power are significantly highest in experts, lower in practitioners, and lowest in novices. In addition, the mean differences of the two factors between the pairs appear to be rather consistent, thus, exhibiting systematic differences among experts, practitioners, and novices. For the second question, the results indicate that both experts and practitioners, possessing equivalent degree of sharing intention, have significantly higher degree of sharing intention than novices do.

For the third question, the outcomes are particularly revealing. The only significant mean difference of preference for codification strategy is between practitioners and novices, suggesting that while practitioners prefer codification strategy significantly more than novices do, experts do not prefer the strategy any more than the others do. Similarly, the only significant mean difference of preference for personalization strategy is between experts and novices, indicating that experts prefer personalization strategy significantly more than novices do, while practitioners do not prefer the strategy any more than the others do. Collectively, these findings suggest (1) that while both experts and practitioners are fonder of personalization strategy than of codification, the difference of preference for codification strategy between practitioners and novices is greater than that between experts and novices, and (2) that novices are not as eager to adopt personalization and codification strategy as experts and practitioners are respectively. The variations of these factors across the three clusters are illustrated with the star chart in Figure 3. Graphically speaking, it can be seen that codification strategy is the only area, in which the mean of practitioners is higher than that of experts.

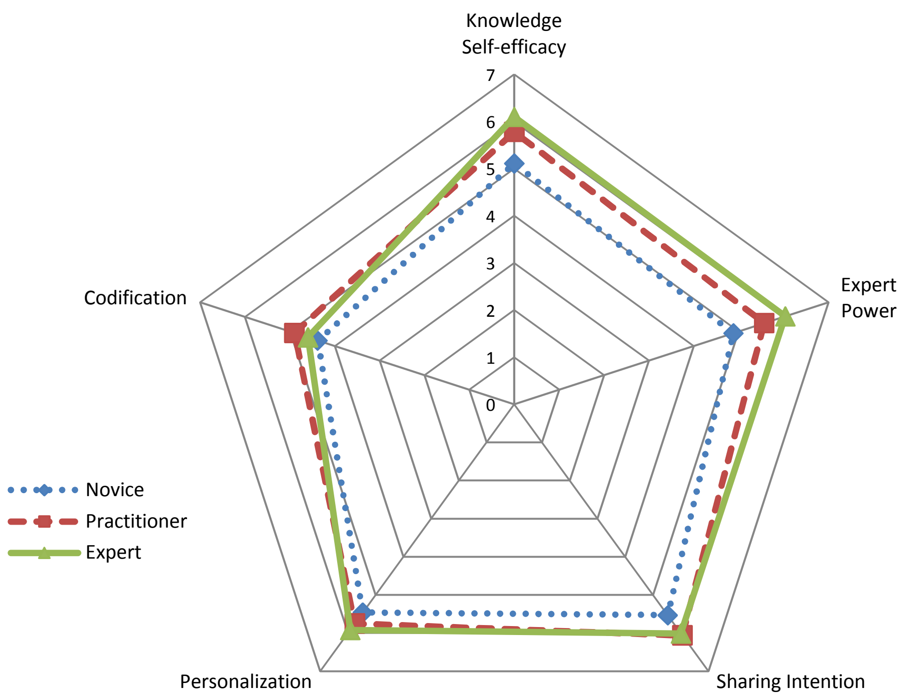

Figure 3.3 Variations of Factors Influencing Knowledge Sharing Across the Clusters

3.8 Discussions

The scarcity of empirical studies specifically focusing on knowledge sharing between experts and novices not only has to some degree limited theoretical advance in the field, but also has resulted in the lack of a well-elaborated construct that can be used to reliably classify knowledge workers based on their levels of expertise. To improve our understanding of the phenomenon, in this study, by drawing from renowned theories in cognitive psychology, we have developed the notion of knowledge internalization by defining it as a process in which an individual uses a variety of cognitive mechanisms to transform declarative knowledge (i.e. non-sticky tacit knowledge) into procedural knowledge (i.e. sticky tacit knowledge). The factor analyses show that those cognitive mechanisms are organization and structure, mental models, efficiency, automaticity, and metacognition. Rather than six mechanisms according to Glaser et al. (1985)'s theory, problem representation and mental models appear to merge in the view of our participants. In addition to the abstractness of their items, we believe that these two mechanisms may be highly correlated in practice; that is, to identify underlying reasons or factors of the problem (i.e. problem representation), individuals may also have to visualize how they are related in a number of scenarios (i.e. mental models). Future researchers may use a different research methodology such as an experiment to test whether the two factors are different.

Based on the cognitive mechanisms of knowledge internalization, knowledge workers can be classified into three groups, labeled as novices, practitioners, and experts. This finding is aligned with the ACT theory (Anderson, 1983), in which to ultimately create procedural knowledge, an individual will undergo three learning stages, that is, declarative, compilation, and procedural stages. Only when arriving at the procedural stage, an individual starts to have potential to become an expert. The results show that the degrees of organization and structure, mental models, and efficiency mechanisms, which are relatively fundamental to the declarative and compilation stages, are highest in experts, moderately high in practitioners, and much lower in novices, therefore suggesting that these cognitive mechanisms are accumulative in nature as they continuously internalize knowledge. Within the differences of these three mechanisms, an interesting pattern emerges, that is, the gap between practitioners and novices is larger than the gap between experts and practitioners, thus suggesting that it may be more challenging for an individual to advance from the declarative to compilation than from compilation to procedural stage.

Interestingly, automaticity is found to be the mechanism that distinguishes experts from the others the most; that is, even practitioners have the same degree of automaticity as novices do. This suggests that unless an individual can perform a task or solve a problem in an automatic manner, the individual is not yet an expert, given that the same individual has been progressing from early stages of learning. In conjunction with the systematic differences of the first three mechanisms across the groups, this exclusive finding about the automatic quality in experts suggests that these four mechanisms are not only accumulative, but also hierarchical in nature. This is yet another corroboration of the theoretical foundation of knowledge internalization, that is, the integration between the learning stages in the ACT theory (Anderson, 1983) and the associated cognitive skills (Glaser et al., 1985). Finally, both experts and practitioners exhibit equal degree of metacognition, which is still significantly higher than novices do. As a result, this suggests that metacognition can be significantly attained, when an individual's knowledge internalization has reached the level of practitioners as indicated by the first three mechanisms. Thus, metacognition deviates slightly from the hierarchy of these cognitive mechanisms in the theory, in that it appears to be the successor of the first three mechanisms, and as a result, places automaticity as the highest mechanism an individual can achieve.

In essence, we found that experts have the most procedural knowledge as distinctively contributed by automaticity mechanism. In addition, while automaticity is certainly not the strength of both practitioners and novices, practitioners still possess more of not only declarative but procedural knowledge than novices do as indicated by the difference of their organization and structure, mental models, and efficiency mechanisms. Finally, both experts and practitioners are more aware of their expertise and are able to use the outcomes of their actions to adapt their future behaviors accordingly than novices are. It is also important to point out that the hierarchy of these mechanisms is found to be slightly different from that in the theory, that is, organization and structure, mental models, efficiency, metacognition, and automaticity.

For the second research objective, we have investigated how the factors influencing knowledge sharing manifest differently among the three groups. First, consistent with the overall differences of the cognitive mechanisms of knowledge internalization across the groups, we found that followed by practitioners and novices respectively, experts are most confident of their own knowledge and most knowledgeable as perceived by other people in organizations. Next, we found that practitioners intend to share knowledge as much as experts do, but significantly more than novices do. This suggests that for an individual to like sharing knowledge, a vast amount of procedural knowledge is not necessary, as long as the amount of declarative knowledge is high and sufficiently compiled.

Finally, we found that while both experts and practitioners prefer personalization strategy over codification, practitioners prefer codification a little more than experts do. In addition, novices do not prefer either strategy as much as experts and practitioners do. Thus, these findings overall suggest that the higher degree of knowledge internalization, the higher degree of preference for personalization strategy, and the less degree of preference for codification strategy. Specifically, this can be interpreted that a vast collection of procedural knowledge (i.e. sticky tacit knowledge) can obstruct experts' ability to codify knowledge, thus making them prefer people-to-people approach. On the contrary, a moderately large amount of declarative knowledge (i.e. non-sticky tacit knowledge) coupled with a fair amount of procedural knowledge appears not to significantly hinder practitioners' ability to externalize knowledge, thus making them overall comfortable with both strategies.

3.9 Theoretical Implications

With the objectives of the study, we contribute to the literature by offering a theoretically justified construct of knowledge internalization, by providing the profiles of knowledge workers' expertise, and by finding the variations of multiple factors influencing knowledge sharing of each of the profiles.

Given that the overall goal of this study is to improve our understanding of knowledge sharing between more and less knowledgeable knowledge workers, a construct that can be used to reliably measure expertise is needed. We believe that the scales used for expertise in the extant literature may have contributed to the inconsistent finding between expertise and knowledge sharing (e.g. Constant et al., 1996; Wasko and Faraj, 2005). According to Nonaka (1996)'s theory, the concept of knowledge internalization is an individual process to create tacit knowledge, and tacit knowledge has been known to be a source of expertise (e.g. Bassellier, Reich, and Benbasat, 2001), thus making it an ideal concept for classifying knowledge workers' expertise. Despite its crucial role in the theory, knowledge internalization has never been explored and justified in depth. This study is the first to conceptualize the knowledge internalization by grounding it in prominent cognitive psychology theories (Anderson, 1983; Glaser et al., 1985). Our conceptualization informs that knowledge internalization occurs when individuals can create procedural knowledge (i.e. sticky, rare, and inimitable form of tacit knowledge) using various cognitive mechanisms. In the process, we also clarify the nature of tacit knowledge by suggesting that declarative and procedural knowledge are actually different forms of tacit knowledge (i.e. non-sticky and sticky). While research has considered tacit knowledge the key to sustainable competitive advantage (e.g. Ambrosini and Bowman, 2001; Grant, 1996; Lubit, 2001; Berman, Down, and Hill, 2002), both how knowledge workers create tacit knowledge and tacit knowledge itself has been rather unclear. Specifically, this study suggests that knowledge internalization is build upon the cognitive mechanisms that transforms accumulated declarative knowledge, or absorbed explicit knowledge, to procedural knowledge, which is the ultimate form of tacit knowledge.

Next, we used the cognitive mechanism of knowledge internalization to classify knowledge workers' expertise, so we can learn how factors that can impact their knowledge sharing manifest in different groups. Rather than expert-novice classification typically used by researchers (e.g. Nah and Benbasat, 2004; Schenk, Vitalari, and Davis, 1998), our analyses meaningfully indicate that practitioners are another distinct group of knowledge workers. Practitioners share some interesting similarities and differences with both novices and experts. Practitioners are similar to novices, in that both cannot perform a task or solve problems in the automatic manner experts can. Nonetheless, practitioners are similar to experts, in that both are more responsive to the consequences of their actions and possess a larger collection of declarative knowledge than novices do. In relation to their preference for sharing strategy, as a result, practitioners appear to be comfortable with both personalization and codification strategies, while experts appear to strongly prefer personalization. In short, we believe that the findings of the differences of both the cognitive mechanisms of knowledge internalization and those factors influencing knowledge sharing of the three groups, especially practitioners, significantly contribute to the literature. Examples of future research directions that can build upon our findings are discussed in the limitation and future research directions section.

3.10 Practical Implications

Our findings can also be particularly useful for managers as described below. First, as tacit knowledge is a key to sustainable competitive advantage, organizations need to regularly assess the extent to which their knowledge workers actually possess it. Unlike many techniques in psychology (see Royer et al., 1993) which can be challenging and costly to administer, our reliable, easy-to-use, and, importantly, domain-independent survey instrument of knowledge internalization can be used to assess knowledge workers' ability to produce tacit knowledge in their professions by identifying which areas need reinforcement. That is, through those cognitive mechanisms, the instrument can help detect whether a worker needs to increase declarative, procedural knowledge, or perhaps both. For example, if a worker's declarative knowledge is low (i.e. indicated by low scores of the first few mechanisms), managers should provide educational resources that are conveniently accessed and rather easy to use to help the worker increase it first, before moving on to emphasize procedural knowledge. On the other hand, if procedural knowledge is low (i.e. mainly indicated by a low score of automaticity), managers should provide hands-on opportunities for the worker to consistently practice his or her skills (e.g. periodic interactive trainings and assessments). Incorporating these practices can help ensure that existing knowledge workers can actively produce tacit knowledge for organizations.

The differences of factors influencing knowledge sharing found among novices, practitioners, and experts should also help organizations develop practices that will facilitate knowledge sharing and ultimately improve effectiveness of organizational KM initiatives. Two areas that should directly benefit from these insights are how to manage projects and how to provide technology that fits people's needs. By understanding the nature of the three groups, managers should be able to form teams that can function for specific purposes more effectively. For example, given that the gap of knowledge between novices and experts are much larger than that between novices and practitioners, if the goal is to transfer declarative knowledge used in a project to another project (e.g. less experience-intensive and less action-oriented knowledge), pairing novices with practitioners may be more effective than pairing novices with experts, because practitioners may be able to articulate their knowledge more comfortably than experts can. This approach should be even more appropriate, if they have to communicate mostly through certain computer-mediated channels such as online internal message boards, because practitioners are found to be comfortable with codification strategy a little more than experts are. With the findings about the groups' preferences for different knowledge sharing strategies, managers should also be able to provide technology that better fits their preferences. For example, to facilitate knowledge sharing between experts and novices, technology that does not require formal knowledge codification and supports direct people-to-people communications such as video conferencing is strongly needed.

3.11 Limitations and Future Research Directions

Although this study has accomplished the objectives that we believe significantly contribute to both research and practice, its limitations need to be discussed so that future research directions can be identified. First, since all the data is self-reported, the influence of common method variance may affect the research findings (Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). We conducted the Harman's single-factor test by including all items from all of the constructs into a factor analysis to determine whether the majority of the variance can be accounted for by a single factor (Podsakoff et al., 2003). The results of principal component analysis without rotation show that the first factor explained only about 28% of the total variance, thus suggesting that common method variance does not bias the findings. Nonetheless, future researchers may use third-party measures (e.g. supervisors or peers' ratings) for factors such as expert power. In addition, a lab experiment can also be used to study whether, for instance, the individuals classified as experts using our instrument of knowledge internalization will actually prefer using personalization over codification strategy to share knowledge.

Second, to improve our understanding of knowledge sharing between experts and novices, we have developed and proposed using the cognitive mechanisms of knowledge internalization to classify knowledge workers in organizations. For this classification purpose, cluster analysis is an ideal method. Following the practices and recommendations from a number of prominent studies (Green, Frank, and Robinson, 1967; Hair et al., 1992; Ketchen and Shook, 1996; Segars and Grover, 1999; Wallace, Keil, and Rai, 2004), we believe that both the solution of the cluster analysis and the variations of the factors influencing knowledge sharing found across the clusters are valid. Despite insightful findings, this study is exploratory in nature; as a result, prudence should be exerted when interpreting the findings in different contexts. Building on this study, future researchers are encouraged to replicate our study to examine further whether all of our findings can be supported. In addition, future studies can hypothesize and test the effects of each cognitive mechanism on factors that are associated with knowledge sharing, including the ones in this study using more objective measures.

Finally, although this study found the similarities and differences of multiple factors that can impact knowledge sharing, all of them are individual characteristics. While doing so contributes to knowledge sharing literature as recommended in Wang and Noe (2010)'s review study, other factors should be jointly examined. We suggest that future researchers search for moderation and mediation effects among the factors included in this study, along with other organizational factors such as the extent of knowledge sharing culture (e.g. King, 2007; Sackmann, 1992). In particular, we believe that our findings of different preference for personalization and codification strategy in different groups of knowledge workers can help future researchers identify potential research directions to push forward the KM field. For example, an interesting direction is to investigate whether the effect of preference for codification strategy in practitioners on knowledge sharing may even be stronger, either when supporting technology has features that facilitate both people-to-people and person-to-document approaches, or when the nature of the task requires more sharing of codified knowledge, or both. Such a finding should help organizations make an informed decision on how to adopt these KM strategies.

3.12 Conclusion

To sustain their competitive advantage, organizations need to tap into rare and valuable knowledge embedded in their knowledgeable workers. Thus, it is critical that organizations can determine the extent to which their workers can produce tacit knowledge, and understand how factors influencing knowledge sharing may vary among different groups of knowledge workers. By drawing from Anderson (1983)'s ACT theory and Glaser et al. (1985)'s dimensions of cognitive skills, we develop and use the construct of knowledge internalization to profile knowledge workers. Based on the cognitive mechanisms of knowledge internalization, knowledge workers can be classified as novices, practitioners, and experts. While fundamental cognitive mechanisms improve from novices to practitioners and to experts, advanced mechanism (i.e. automaticity) is significantly highest in experts. The variations of factors that can have an impact on knowledge sharing are also found to correspond to the nature of each group. Knowledge self-efficacy and expert power are highest in experts, moderate in practitioners, and low in novices. Both experts and practitioners intend to share knowledge much more than novices do. While both experts and practitioners are fonder of personalization strategy than of codification, practitioners appear to prefer codification a little more than experts do. Finally, novices are not as eager to adopt personalization as experts, and codification strategy as practitioners are. To research, this study contributes by offering the knowledge internalization construct, by providing insightful profiles of knowledge workers, and by finding how factors influencing knowledge sharing vary among the profiles. To practice, our findings can help managers develop strategies to facilitate knowledge sharing between more and less knowledgeable workers in organizations.

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BIOGRAPHICAL INFORMATION

Kamphol Wipawayangkool received his Ph.D. in Information Systems from the University of Texas at Arlington. He holds an M.S. in Management Information Systems from University of Houston-Clear Lake and a B.S. in Computer Science from Prince of Songkla University. His current research interests include knowledge management, information security management, virtual teams, and IT-HR collaboration. He has published in *Journal of Information and Knowledge Management, Journal of Knowledge Management Practice,* and *Issues in Information systems,* as well as proceedings of the *Americas Conference on Information Systems, Decision Sciences Institute,* and *Global Information Technology Management Association.* He has been awarded the UTA Graduate School Dissertation Fellowship.