Development of a Knowledge-Based Theory of Information and Its Application in Computer-Aided Decision-Making

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ABSTRACT

Data, information, and knowledge are the most fundamental concepts in the Information Systems (IS) field. Although several alternative models have been proposed to depict the relationship between these concepts, none provide a completely satisfying solution. This situation has caused difficulties in further IS research and practice, especially in assessing the organizational consequences of IS applications such as computer-aided decision-making. To solve this problem, a knowledge-based theory of information is developed, and its application in computer-aided decision-making is illustrated. The development of the theory is presented in Essay 1 and the application is described in Essay 2.

In Essay 1, the Knowledge Based Theory of Information (or KBI theory) is developed to clarify the relationship between data, information, and knowledge. This theory proposes that information, representing a status of conditional readiness for goal-directed activity, is the joint function of data and knowledge. Furthermore, lower-level information is used as input to produce higher-level information. Following this logic, different forms of IS are conceptualized as the embodiments of knowledge domains capable of transforming specific categories of data into information for business operations and decision-making. This theory helps resolve the conflict in previous understanding of the relationship between these constructs. It also provides a new approach to analyzing the organizational consequences of IS.

In Essay 2, an illustration of the KBI theory is presented based on computer-aided decision-making. This illustration shows how the KBI theory is operationalized within a particular IS context, and how it helps solve the problems in the associated studies. It is

realized that although computer-aided decision-making is a major area of IS applications, the key relationship between decision aids and decision performance is not clear. To solve this problem, a model based on the KBI theory is developed, indicating that decision performance (such as decision quality) is directly influenced by decision data, decision knowledge, and their interplay. Other factors such as the decision-maker's characteristics, DSS functionalities, and task environment are mediated by decision data and decision knowledge. A lab experiment is conducted, and the result shows that the new model, based on the KBI theory, provides an improved understanding of computer-aided decision-making. The implications of the model for other DSS research and practice are further analyzed.

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Introduction

As Information Technology (IT) users, we observe that IT is pervasive in our modern life. Yet, as Information Systems (IS) scholars, we feel unnerved that even after decades of research, the IS field still lacks the cognitive legitimacy to clearly communicate the nature of the discipline (Benbasat and Zmud, 2003). Application of IS in business has produced inconsistent results. Although suggestions have been made to address this problem (Robey and Boudreau, 1999), a solution depends on the development of theories that can effectively interpret the IS phenomena (Benbasat and Weber 1996; Orlikowski and Iacono, 2001; Robey, 1996).

In order to successfully analyze the IS phenomena, focus should be made on the internal environment or structure of IS and IT (Orlikowski and Iacono, 2001; Wand and Weber, 1995). Most fundamentally, this resides in the better understanding of the mechanism of how information is processed from data in IS for business operations and decision-making. Literature review shows that this mechanism is not clear, with considerable disagreement concerning the relationship between information and two other closely related concepts: data and knowledge. Needless to day, data, information, and knowledge are the most fundamental concepts in the IS field, and data is generally accepted to be the basis of information (Davis, 1974). Nevertheless, the relationship between these three concepts is not established. In fact, several highly cited models depict totally different relationships between these concepts (Alavi and Leidner, 2001;

Spiegler, 2000; Tuomi, 1999). This causes difficulties in IS research and practice (Spiegler, 2000).

This research develops a model to clarify the relationship between data, information, and knowledge. By comparing the strengths and weaknesses of several alternative models (e.g., Alavi and Leidner, 2001; Langefors, 1980; Tuomi, 1999) and searching reference disciplines for the intellectual basis of these concepts, a new theory named as *Knowledge-Based Theory of Information* (or KBI theory) is developed. This theory shows that information is the joint function of data and knowledge. Information, representing a status of conditional readiness for goal-directed activity under certain circumstance (MacKay, 1969), is produced from the interplay of data and knowledge for the selection of course of action, and lower-level information is used as input to produce higher-level information. Based on this theory, different forms of IS are conceptualized as the embodiments of knowledge domains (Ein-Dor, 1986) capable of processing specific categories of data into information. Application of this theory has the promise of resolving conflicts in previous IS studies, such as clarifying the different understanding of the meaning of information in computer-mediated communication, and also the relationship between information and knowledge creation.

To illustrate the operationalization of the KBI theory and its key constructs in IS research context, this theory is applied to computer-aided decision-making. It is shown that although computer-aided decision-making is a major area of IS application, the key relationship between decision aid and decision performance is not clear (Todd and Benbasat, 2000b). To address this problem, an integrative model is developed based on the KBI theory, suggesting that decision performance is directly influenced by decision data, decision knowledge, and their interplay, and other factors such as decision-maker's characteristics, DSS functionalities, and task environment are mediated by decision data and decision knowledge. A lab experiment is conducted to test the model. The results support the hypotheses, showing that data and knowledge play a focal role in computer-aided decision-making. This model therefore provides a valid solution to analyzing the performance impact of decision aids. Implications for further research and practice are then discussed.

This research by no means intends to solve all the problems in IS research. Nevertheless, with the help of the KBI theory, the most fundamental issue in the IS field, i.e., how information is produced from data for business operations and decision-making, is better understood. This provides keys to conducting more successful IS research with consistent organizational consequences. In the next sections, the development of the KBI theory is described in Essay 1, and the application in computer-aided decision-making is illustrated in Essay 2.

Essay 1: Development of a Knowledge-Based Theory of Information

1.1 Introduction

Many companies today are grappling with the "right" approach to managing knowledge via Information Systems (IS) and database technology, but what does knowledge mean to these companies and how is it related to information and data? These questions have been under debate since the beginning of Knowledge Management (KM) research (Alavi and Leidner, 2001). To many people, knowledge is a more valuable form of information, which is in turn a more valuable form of data (Grover and Davenport, 2001). Such a "data→information→knowledge" hierarchy is very popular in IS textbooks (Martz and Shepherd, 2003). Nevertheless, despite the great appeal of the hierarchy, other models have been developed that depict totally different relationships (Alavi and Leidner, 2001; Spiegler, 2000), such as the reversed "knowledge→information→data" hierarchy (Tuomi, 1999) and the infological equation (Langefors, 1980). Unfortunately, none of these models has delivered a completely satisfying solution; as a result, confusions still exist, causing difficulties in further IS research and practice (Mingers, 1996). Practitioners have complained that the enormous expenditures on KM aimed at delivering "knowledge" rarely meet company expectations (Davenport and Prusak, 1998), and scholars worry that the incapability to distinguish knowledge from information and data makes KM a buzzword or a recycled concept (Spiegler, 2000).

By comparing the strengths and weaknesses of several alternative models and searching reference disciplines for the intellectual basis of these concepts, a new model is proposed to resolve the conflict. This model, named as *the Knowledge-Based Theory of Information*, suggests that information is the joint function of data and knowledge. Information, representing a status of conditional readiness for goal-directed activity under certain circumstance, is produced from the interaction of data and knowledge, and lower-level information is used as input to produce higher-level information. Based on this theory, different forms of IS are conceptualized as the embodiments of knowledge domains capable of processing specific categories of data into information. Application of this theory has the promises of resolving conflicts in previous research, suggesting directions for further IS studies, and increasing the business value of IS practice.

To support the opinion, several representative models of the relationship between data, information, and knowledge are summarized and compared. Issues associated with the definitions of these core concepts are also reviewed, uncovering the intellectual basis of their relationship. The Knowledge-Based Theory of Information is offered, providing a more parsimonious depiction of the relationship between these concepts. Finally, the implications of the proposed relationship for both IS research and practice are discussed.

1.2 Different Views on the Relationship between Data, Information, and Knowledge

Data, information, and knowledge are the most fundamental concepts in the IS field (Hirschheim et al, 1995). Usually data refers to facts about objects or events, information is processed data or a message that makes a difference or informs, and knowledge is framed experience used to evaluate or incorporate new experiences

(Davenport and Prusak, 1998). The relationship between these concepts is a major concern in many IS studies. Up to now several models of their relationship have been developed (Alavi and Leidner, 2001; Spiegler, 2000), of which the following three are the most popular:

- **Model 1**, which may be called a *value chain model*, is the dominant "data→information→knowledge" hierarchy. It argues that data is the description of objects or events; information is data that is processed (e.g., classified, summarized, and transferred) to add meaning and value within a certain context; and knowledge is a high-value form of information, or information that is distilled from particular context and can be generalized to other contexts (Grover and Davenport, 2001; Martz and Shepherd, 2003; Nonaka, 1994). In essence, the relationship between these concepts is determined by the amount of value associated with each concept and the accumulation of value from one concept to another.

- **Model 2**, which may be called a *materialization model*, is a reversed "knowledge→information→data" hierarchy. This model, developed by Tuomi (1999), suggests that data is created from information and information is derived from knowledge. It depicts a materialization process of the conversion from knowledge to structured information, and then to data, whereby knowledge is articulated via the latter two within a specific context. According to this model, data does not become information after the addition of meaning; instead, data is created from information by putting information into a predefined data structure that determines its meaning. Furthermore, information is knowledge that is made explicit, e.g., embedded in IS.

- **Model 3**, which may be called an *interactive model*, suggests that information is produced from data and knowledge, i.e., (Data & Knowledge)→Information. Early on, Langefors (1973, 1980) proposed an infological equation, $I=i(D,S,t)$, suggesting that information I is the interpretation i that a person makes of a message D based on her pre-knowledge or receiving structure S during a specific amount of time t. Similarly, Drucker (1988) argues that information is data endowed with relevance and purpose, and converting data into information requires knowledge. Some KM researchers support this relationship (e.g., van der Spek and Spijkervet, 1997). In sum, this model depicts a non-linear relationship and emphasizes the interactivity between data and knowledge in producing information.

It is obvious that great discrepancies exist among these models. It is difficult to say which one is superior, as all these models have strengths and weaknesses in guiding IS research and practice. For instance, Model 1 highlights the roles of information in knowledge creation (Nonaka, 1994), while Model 2 and Model 3 are able to explain the replication of information transferred between persons (Langefors,1973; Tuomi, 1999). However, these models fail to explain other IS-related phenomena, such as the electronic brainstorming where knowledge is created via the iteration with information. Although the infological equation in Model 3 seems to be the most satisfactory, the role of knowledge in the relationship is often downplayed, and advocates tend to fall back on treating information as structured knowledge. In a word, none of these models provid a completely satisfying solution.

Several issues that account for the distinctions among the models are observed. First, *the definition of information differs significantly*, with both a *meaningful* view and a *meaningless* view being expressed. Some suggest that information is data or a message endowed with meaning, so that meaning is inherent to information (Drucker, 1988); others argue that information is an attribute of a message and meaning is generated from information by the person who receives it (Dretske, 1981; Mingers, 1995). As a result, both Model 3 and Model 1 seem plausible, treating knowledge as either the antecedent or the outcome of information. Furthermore, studies on information are carried out at different levels, and the *meaning* of information differs across the levels (Mingers, 1995; Stamper, 1987). Table 1.1 shows the definitions of some typical levels. Difficulties exist in IS research when the concept of "information" differs across the levels.

Table 1.1 Levels of information

Level	Definition (Mingers, 1995)	Example
Pragmatics	The study of the actual use of signs and systems of signs, such as the relations between signs and behavior.	A message "she is my sister" means I am not the only child of my parents.
Semantics	The study of the meaning of signs, i.e., the relationship between signifier and signified.	"She is my sister" signifies the identity of the person. "He is my sister" is semantically wrong.
Syntactics	The study of formal structures and systems of signs and their properties, such as linguistics.	Both "she is my sister" and "he is my sister" are syntactically correct.
Empirics (Symbolic)	The study of sign transmission and the statistical properties of the repeated use of signs, such as electronic communication.	A symbol "O" used in a message stands for letter "O" instead of number zero.

The second issue is *the still unclear relationship between data and information* (Gray, 2003). Scholars conventionally treat information as structured data that is processed and communicated with certain purposes. This treatment was criticized by

Boland (1987), who warned that the process of inward-forming, which is critical to the effectiveness of IS, should not be excluded. This problem has not been resolved and still is a major challenge in the IS field (Gray, 2003). Although a solution has been proposed that depicts data as signs used to carry information (Langefors, 1980; Mingers, 1995), a limitation exists: from the sender's point of view, information could exist before it is communicated via the signs or data, indicative of Model 2.

The third issue is *the obscure relationship between information and knowledge.* Information is commonly regarded as the basis or necessary material of knowledge (Martz and Shepherd, 2003; Nonaka, 1994), which is rooted in the separation of meaning from information and the suggestion that knowledge is created from information conveyed in a message (Dretske, 1981). Some scholars disagree, saying that information is neither necessary nor sufficient to produce knowledge (Machlup, 1980, 1983), and others further argue that knowledge is the basis of information (Drucker, 1988; Popper, 1992). Interestingly, a compromised solution is proposed that treats information as a specific type of knowledge, i.e., knowledge about some particular facts (Langefors, 1980).

The occurrence of these issues has a common basis. Several influential writings (Langefors, 1980; Mingers, 1996; Stamper, 1987) show that studies on information in the IS field have a strong semiotic tradition, i.e., the study of signs (Stamper, 1973), which analyzes data as signs or symbols that represent or signify information. For instance, the infological equation (Langefors, 1980) states that data does not contain information; instead, it is a collection of symbols or signs that are used to represent information. Although the semiotic tradition is helpful in explaining the definition of information and its relationship with a message, it is inadequate to clarify the relationship between all three constructs, especially when knowledge is expressed in statements for communication. For instance, let us consider the following three statements:

- S1: "There remain 17 pieces of article type A." (Langefors, 1980)
- S2: "It is raining." (Hirschheim et al, 1995; MacKay, 1969)
- S3: "All swans are white." (Popper, 1992)

In their corresponding literature, S1 is used as an example of inventory data, S2 is an example of the information statements, and S3 is a typical example of knowledge. The question is, since all of these statements are collections of signs, are they all data? And when a person speaks each statement, does she possess knowledge of each? Finally, is information conveyed or included in each statement? From a semiotic perspective, all these statements can be analyzed as data (or signs) conveying information, although in practice they might be best termed as data, information, and knowledge respectively. Existing models (1, 2, or 3) do not provide a consistent answer. In the remainder of the essay a solution is developed to help answer these questions.

1.3 Issues in Defining the Core Constructs

Before the introduction of the solution, a brief review on each construct is needed, as these constructs have been used differently across studies. It is hoped that a better understanding of each construct will help reveal the deeper reasons for problems and generate better answers.

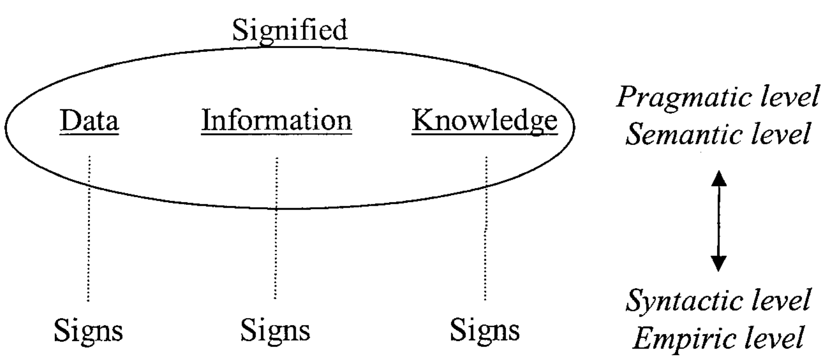
1.3.1 Issues in defining data

As the basis of IS, data has long been recognized as an important factor in the IS field. From the early years of data processing to the contemporary digital economy, data modeling and processing technologies have always been the driving forces of the IS discipline (Checkland and Holwell, 1998; Hirschheim et al, 1995). Scholars generally define data as the measure or description of facts of objects or events (Checkland and Holwell, 1998). For instance, the datum "17" in S1 is a measure of the inventory level of article type A. Data by itself has no intrinsic meaning and is therefore independent of interpretation, but may have potential meanings to the users who can interpret it (Hirschheim et al, 1995).

Several classical writings have offered comprehensive review on the studies on data (Checkland and Holwell, 1998; Hirschheim et al, 1995), so it is unnecessary to scrutinize all its aspects. One issue needs to be emphasized, i.e., the distinction between data and signs, which have been used equivalently by scholars (Langefors, 1980; Mingers, 1995). A related term, codes, is used to show the distinction. Codes are a given set of signs, particularly processed in computers, that are standardized and encoded with the corresponding rules of mapping to the signs (Hirschheim et al, 1995). Codes can be used to encode not only data but also knowledge, such as the knowledge base in Expert Systems or Knowledge Management Systems. From this perspective, signs are not restricted to representing information but also data and knowledge, as illustrated in the three statements above (S1, S2, and S3). Therefore, instead of treating data as signs (or vice versa), it should be that data, by its original definition, is represented by (numeric) signs or codes in IS.

Figure 1.1 illustrates the relationship between signs and data, information and knowledge. According to the levels of meaning of a message introduced in Table 1.1, it is suggested that studies on signs and systems of signs are at the empiric and syntactic levels, while the studies on data, information, and knowledge in the IS field should focus on the semantic and pragmatic levels. Based on this, further analysis on the three constructs will be carried out from the semantic and pragmatic aspects where data is no longer treated as synonym of signs, contrary to some IS researchers (e.g., Langefors, 1980; Mingers, 1995). Nevertheless, this does not intend to introduce a totally different concept of "data"; however, it will be shown later that this approach provides a more consistent explanation of data and its relationship with information and knowledge.

Figure 1.1 The relationship between signs and data, information and knowledge



1.3.2 Issues in defining knowledge

The studies on knowledge and KM have been conducted in several discourses (Schultze and Leidner, 2002). This research takes the normative discourse and depict knowledge as set of rules produced by human societies, such as the condition-action pairs that specify a law-like relationship. In practice knowledge can be of several different types, including know-why (e.g., understanding why a drug works), know-how (e.g., understanding how to administrate a particular drug), and know-when (e.g., when to prescribe the drug) (Alavi and Leidner, 2001). In IS research, knowledge is typically expressed in some formal structures, such as production rules (e.g., the IF-THEN statements), knowledge frames, knowledge maps, and knowledge networks (Marakas, 1999). For instance, the above mentioned statement, "*all swans are white* (S3)," can be expressed as: *IF a bird is a swan, THEN it is white.*

It is a tautology to define what is known as knowledge; a widely accepted definition is Plato's *justified true belief* of the relationship between concepts, from which other practical definitions are derived (Davenport and Prusak, 1998). A key distinction between knowledge and a belief is that the truth claims of knowledge have been approved by some qualified elite and are taken for granted at the present time for practical purposes (Hirschheim et al, 1995). Considering the three examples mentioned above, it is clear that S3 meets the requirements, assuming that no evidence has been found to reject the assertion.

But how about S1 and S2? When a person says "there remain 17 pieces of article type A," which is believed to be true, does she possess the "knowledge" of the inventory level? When a person says "it is raining now," does she have the "knowledge" of the current weather condition? The answers to these questions are of critical importance to understanding knowledge and its distinction from data and information. To answer these questions, research in other fields are utilized, including the philosophy of Popper (1992). In his study on scientific inquiry, Popper discussed a particular type of statements, which he called *strictly or purely existential statements*, or *there-is statements*, for example, "there are black ravens." Such a statement, although it is believed to be true, is not knowledge. Popper explains from his objectivism point of view that this statement cannot be rejected or falsified by another statement of an observed event, or simply, new facts.

For instance, someone may say (or observe) that "there are brown ravens"; this, however, does not conflict with or reject the previous statement. Both S1 and S2 are of this type, so that none of them is knowledge.

Although Popper's philosophy may not be shared by all, the discussion on *there-is statements* is valuable in distinguishing knowledge from non-knowledge, especially data. A data statement, such as S1, is also believed to be true and can be justified; nevertheless, it cannot be treated as knowledge. Explained in another way, a piece of knowledge should be generalizable and applicable to evaluate new experiences (Davenport and Prusak, 1998). If a statement is about the facts of some existing objects or events, such generalization is not self-evident. Therefore, generalizability and verifiability are added to the various requirements of knowledge and used as a necessary condition to judge a knowledge statement.

1.3.3 Issues in defining information

Of the three constructs, information is perhaps the one that bears the most controversies. In the IS field, information is usually defined as data processed into a form that has meaning to the user and is of real or perceived value in current or prospective action or decision (Davis and Olson, 1985). Such a definition is challenged by scholars who question how meaning and data interact to produce information (Mingers, 1995, 1996). Controversies also exists in many other fields where different information theories have been developed with little consensus achieved (Capurro and Hjorland, 2003). Shannon's (1948) communication theory has been the common basis of contemporary studies, describing information as uncertainty reduction based on a message or a statement. Nevertheless, this theory works best at the empiric or symbolic level but not at the semantic and pragmatic levels, because the semantic meaning of information is not a concern of communication engineering (Stamper, 1987). As discussed above, a statement can be used to represent data or knowledge; this begs the question: how is such a statement related to information and uncertainty reduction?

To answer this question, an important concept, *information content*, is utilized, which is first systematically analyzed by MacKay (1969) who proposed a consistent view of information across levels. According to MacKay, information content is the measure of the amount of information in a message, and it is proportional to the uncertainty reduction (or less probability) of the message. If a message is more informative than another, it suggests that it has more information content. For instance, the statement "it is pouring" is more informative, and therefore has more information content, than the statement "it is raining" because the former reduces the uncertainty about the weather condition more than the latter. This concept is helpful in analyzing information in other types of statements such as a knowledge statement. For instance, Popper (1992), in studying the testability of knowledge, suggests that the amount of information conveyed in a theory, or its empirical content, increases with its degree of falsifiability (or less probability). Based on this logic, it is convenient to compare two statements, "these swans are white" (a there-is statement) and "all swans are white": both contain information content due to the reduction in uncertainty about the color of some birds, although only the latter is generalizable (i.e., knowledge). Similarly, a data statement such as S1 also contains information content since uncertainty about the facts can be reduced with the data.

The above analysis shows that the study on information from purely a communication perspective (i.e., signs carrying information) is not sufficient in analyzing its full meaning and distinction with other concepts, as data, information, and knowledge can all be expressed in statements with information content. A more robust definition is needed that can be applied to its daily use; MacKay's seems to come closest to meeting this requirement. MacKay (1969) defines information as "*the state of conditional readiness*," or "*the selective function on the range of the recipient's states of conditional readiness for goal directed activities*". According to this view, a message or statement may contain different information and therefore cause different behavioral intention under certain circumstances. For instance, a message "it is raining" may warn someone to stay at home or fetch an umbrella before going out (Hirschheim et al, 1995). The notion of "selection from a range of possible states" implies that such a definition can be applied to other levels of information, from symbolic to pragmatic (Stamper, 1987). At the symbolic level, for instance, it complies with Shannon's communication theory if the states refer to machine status; at the pragmatic level, it confirms to the use of information in business operation and decision-making if the states represent possible courses of action (Davis and Olson, 1985).

1.3.4 Summary

The above review highlights the definitions of data, information, and knowledge and clarifies the distinctions between data and signs, knowledge and existing facts, and also information and information content. Based on the review, it is concluded that neither Model 1 (*Value-adding*) nor Model 2 (*Materialization*) are satisfactory, since a linear relationship between these constructs is incapable of explaining the existence of multiple meanings of information, i.e., why different interpretations of information exist. Model 3 (*Interaction*), especially the infological equation, has the highest potential, which is able to fulfill the job. Although values exist in the interactive relationship described in the infological equation, several limitations exist:

- First, data is treated as signs representing information, which is not completely accurate. The distinction between data and signs has been shown above, emphasizing that data is also represented by signs in IS. The infological equation's communication type of interpretation does not consider this point and cannot successfully distinguish information from data. The consequence is that the system of information (i.e., infology) is still operationalized via the system of data (i.e., datalogy; Langefors, 1973, 1980) despite the relationship built in the equation.
- Second, information is defined as a specific type of knowledge of particular facts. This issue poses the question of whether the infological equation is really about the relationship between the three constructs or just between data and information.
- Third, knowledge is never explicitly analyzed in the infological equation. Although the terms "receiving structure" and "pre-knowledge" are used, which are close to knowledge, these terms lack accuracy since not only knowledge but data, information, and their combinations have structural attributes and can be added to the receiving structure. The distinction between knowledge and other possible components in the receiving structure could have been clarified.
- Finally, a time element is included in the infological equation, indicating when the

data is collected and how long it is valid. Although time is important to information, it is a matter of data quality and can be better analyzed as a sub-issue in the latter, together with other factors which may also influence data such as spatial attributes of measurement. The inclusion of time in the equation is not necessary.

Because of these limitations, the infological equation has not been well embedded in the core of IS research. Other literature supporting Model 3 only gives expedient explanations without in-depth analysis. Effort is needed to further develop this model and sharpen its relationships.

1.4 Proposition of a Knowledge-Based Theory of Information

Based on the interactive relationship between data, information, and knowledge in Model 3, a revised model is proposed, suggesting that information is the joint function of data and knowledge, and lower level information is used as input to produce higher-level information. This model is named as *Knowledge-Based Theory of Information* (KBI). It depicts a functional relationship between the three constructs, where information is the dependent variable of both data and knowledge. Specifically, data specifies the pre-conditions or input values based on which a decision or action is to be made, and knowledge is the framework or the process through which data is converted into information for such decision or action. For instance, a typical way of expressing knowledge is using the condition-action pair, which specifies what action may be taken when particular condition exists. For example, the business rule "IF the inventory is low, THEN new material should be ordered" indicates that when the pre-condition "inventory is low" exists, the action "ordering new material" should be selected. Such a selection may or may not be made, depending on the real inventory level and the rule; in other words, the information "to order or not to order" is produced from both data and knowledge.

The interactivity between data, knowledge, and information has similar structure as that analyzed in the Artificial Intelligence (AI) research. For instance, Turban (1995) shows a general AI structure, where the initial states are converted into goals through procedures. Such a structure is very close to the relationship depicted in the KBI theory, since, as analyzed above, data refers to the description of the pre-states, information is the readiness for the goal (e.g., to order or not to order), and knowledge is the framework or process (e.g., the business rule) through which data is converted into information.

It is further argued that for the same data, different knowledge applied will produce different information. Using the same example, when the definition of "low inventory" varies or other conditions are considered, the corresponding business rule would differ, resulting in different information from even the same data (i.e., the inventory level). Generally speaking, this happens when different decision models or knowledge frameworks have been used to produce information from the same data. Therefore, both knowledge and data are variants in this relationship. To summarize, if information, knowledge, and data are represented as I, K, and D respectively, then the KBI theory can be expressed as $I=f(K,D)$. In this section, the KBI theory is further systematically developed with the core concepts defined; its implication to IS research and practice will be discussed later.

1.4.1 Definitions of the core constructs

Due to the controversies in the definition and usage of each construct in previous studies, it is needed to provide a clear definition in order to better understand these constructs. First, data is defined as:

> ***Data*** *is the measure or description of objects or events, usually referred to as a set of interrelated data items that measure the attributes of the objects or events.*

This definition of data is consistent with its popular definitions, and it indicates that data is the empirical basis of information. Statement S1 above, for instance, is an example of data since it is the measure of the inventory level of a particular item. Statement S2 is also data because it is the description of the current weather condition. Both of them are of the "there-is" type, i.e., about the facts of some existing objects or events. Many other examples can be found in various IS literature, such as a person's weight and cost of a business plan. It should be noted that the term "attributes" is emphasized in the definition because 1) only the attributes can be directly measured or described and 2) not all aspects of an object or event may fall within the interest of the information users.

In addition to the unstructured data statements, data can also be represented in structured forms such as databases and tables in IS. For instance, an inventory table may be used to show the inventory levels of several items in columns and rows. Such a structured approach is a major endeavor in data modeling research (Hirschheim et al, 1995). No matter which approach is applied, the same data is measured or described, although differences exist in the particular signs used to represent the data (e.g., statements versus tables). This further supports the earlier assertion that data is different from signs.

Contrary to the infological equation, the time element is not included in the KBI theory, nor is it included in the definition of data. While time is an important factor in data collection, since the attribute value of an object or event may change over time, this can be viewed as a technical issue in data modeling rather than a logical issue in the theory. This can be resolved most easily by adding a time dimension in the data set, such as in data warehousing and On-Line Analytical Processing (OLAP). It should be noted that other factors, such as the location (i.e., spatial dimensions) where an object is measured and the reference systems based on which the scale is developed, may also influence data collection and processing. These factors were overlooked in the infological equation and should be handled in the same way as time is. As all these factors are about data quality, it is suggested not to include them in the relational model for parsimony purpose.

Data alone does not yield information for an action or decision, because it has no inherent association with the possible consequences of an action beyond the existing facts. In other words, uncertainty may not be substantially reduced from the data alone in making a selection. In order to generate information and reduce uncertainty for an action, knowledge is needed. Based on the commonly accepted definition, knowledge is defined as:

Knowledge *is justified true belief of the relationship between constructs.*

This definition has four implications. First, knowledge is a belief rather than any on hand empirical evidence, and such a belief should be generalizable to and verifiable by additional evidence. Second, knowledge must be true or approximate the truth under certain circumstance, and is taken to be beyond questioning for practical purposes, although knowledge changes over time. Third, the truthfulness of knowledge must be justified or approved by some qualified elite, which differs it from other unjustified beliefs. These three aspects have been discussed in previous studies, including epistemology and IS research (Hirschheim et al, 1995). Finally, knowledge is the belief of the *relationship* between constructs, such as the mean-end pairs or the condition-action pairs, which could be at either the contextual level or theoretical level (Berthon *et al*, 2002). An isolated, singular construct may not be treated as knowledge since such a construct is not necessary to be *justified* but *defined*.

It is mentioned earlier that knowledge can be represented in several different forms, although the production rules (i.e., the IF-THEN pairs) are the most straightforward. Statement S3, for instance, is an example of knowledge, and it can be re-phrased as "*IF a bird is a swan, THEN it is white.*" Other examples include:

- S4: "*IF the inventory level of an item is lower than the safety stock, THEN new pieces should be ordered.*"
- S5: "*IF it rains and you do not want to get wet, THEN you should take an umbrella before going out.*"

In addition, although a purely existential statement (or a there-is statement) is not knowledge, it does not conflict with the case that such a statement can be embedded in another universal statement or knowledge statement. For instance, the following statement

- S6: "*IF the inventory level of article type A is lower than 20, THEN more items of article type A should be ordered to prevent shortage.*"

is also knowledge even though it contains a data item (20) and implies a data statement "the safety stock of article type A is 20". It is knowledge because the content is generalizable and verifiable, meeting the necessary conditions discussion above. For instance, if the inventory level is 17 but no items are ordered, the statement can then be verified based on whether the shortage occurs. In sum, a piece of knowledge (or the knowledge statement) may contain data items.

The KBI theory suggests that information is the function of data and knowledge. Given the definitions of data and knowledge and the above review on information research, information is best defined as:

> ***Information*** *is the meaning produced from data based on a knowledge framework that is associated with the selection of the state of conditional readiness for goal-directed activities.*

This definition is consistent with the definitions of information in traditional IS research, and it suggests that meaning is an inherent attribute of information. Meaning, according to some scholars (e.g., Gray et al, 1985), refers to the value judgment and interpretation assigned to an experience. Information scientists such as MacKay (1969) further elaborates the meaning of a message as its selective function on the recipient's range of states of conditional readiness. Both indicate that a selection, or judgment, or uncertainty reduction, is triggered by information, which complies with communication research and is also generalizable to semantic and pragmatic levels. For instance, statement S1, together with S6, means that "*new pieces of article type A should be ordered*", or more precisely, "*at least 3 pieces of article type A should be ordered to meet the safety stock requirement*". Similarly, statement S2 informs the person who hears it to "*grab an* *umbrella*", given that S5 is known. For both cases a state of conditional readiness is selected, although the corresponding action may not have been taken.

To further clarify the definition of information, the following two issues are emphasized:

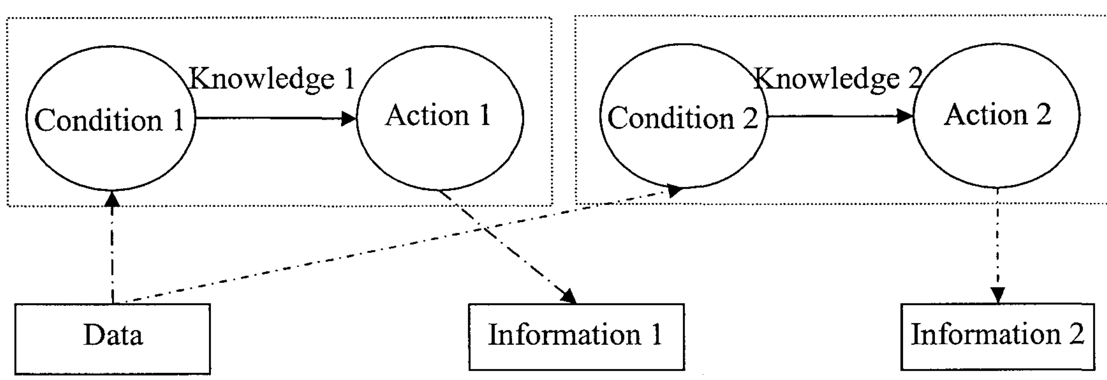
First, *information must be eventually based on data, which is regarded as the primary source of information; it can also come from a secondary source, i.e., other people's information.* The awareness of this "secondary" source of information is very important, and it is an important extension of the KBI theory beyond the essential concept that information is the function of data and knowledge. Often, information processing is not directly based on a person's own or other persons' observed facts, but their interpretation of the observations they make; i.e., the "data" a person receives might be actually information processed and communicated by others (von Hayek, 1937). When this happens, it might be that the possibilities of multiple meanings within a data set is restricted by the sender's own knowledge, and in this sense data received has the characteristic of information. The information sent, or data received, will undergo a re-interpretation process through which the intended meaning is recovered. Despite these differences regarding interpretation and re-interpretation, the essence is the same, that information is the meaning of data.

Second, *the production of information from data needs knowledge, and when knowledge varies, so does information.* This is the essence of the KBI theory, as it addresses the question of how data is converted into information, i.e., via certain knowledge. It also helps explain why different information may be produced from the same data when different knowledge is applied. It further calls attention to knowledge when misinterpretation happens. For instance, it is shown above that the information "to grab an umbrella" is produced based on statement S2 and S5; nevertheless, when the person who hears the message (S2) applies a different piece of knowledge due to different goals, for example:

- S7: "*IF it is raining and you do not want to get wet, THEN stay at home.*"

then information generated by S2 differs, which, in this case, is to "*stay at home*". The interaction between data and knowledge, from which information is produced, is illustrated in Figure 1.2. This figure shows that, even with the same data collected, different knowledge applied will produce different information. It therefore highlights the issue of "fit" between data and knowledge, i.e., in order to produce the needed information for an action, knowledge must fit the data provided, or vice versa.

Figure 1.2 Illustration of the interaction between data and knowledge



The second issue is important for IS researchers, as scholars (e.g., Schultze and Leidner, 2002) find that IS research is dominated by the assumption that knowledge has positive impact on organizations, ignoring potential negative outcomes. The KBI theory highlights this pitfall by indicating that when knowledge is misused, information can be misinterpreted from the data, resulting in unintended organizational consequences. Therefore, it is the job of knowledge managers to create situations where the 'right' knowledge is available to fit the data, depending on the information requirement of the tasks at hand (Becerra-Fernandez and Sabherwal, 2001).

The above discussion on interpretation and perception does not imply that the content of knowledge and the corresponding interpretation process are subjective. Instead, both are objective or at least intersubjective, given that the same knowledge is shared by different interpreters. Nevertheless, it is acknowledged that *the use of knowledge is subjective*, as learning and accumulation of knowledge differs from person to person, so that the interpretation is bounded within a person's knowledge domain or rationality. Additionally, the application of knowledge is influenced by a person's values or goals. An important role of IS is therefore to augment the IS user's capabilities in dealing with information for better operations or decisions.

1.4.2 General information processing model

The relationship between knowledge, data, and information described in the KBI theory provides the basis of understanding information processing in IS. The examples described above are, however, of simplified situations where only a single data statement and a single knowledge statement are involved, from which a particular piece of information is produced. Such model is an *element model.* In practice, an IS built upon a single element model rarely exists, as information is often produced from other *information* rather than pure raw data (as discussed above, information can also be based on other people's manipulation of the data). For instance, in organizational decision-making, high-level managers make the decision based on information provided by lower-level employees rather than raw data collected at the low levels. In this and many other situations where information is processed in a hierarchical or nested manner, the initial relationship where information is the dependent variable is not sufficient, and calls for refinement.

To address the seemingly paradoxical relationship between data and information and to explain more complicated information processing behaviors of IS, the fundamental logic described above is extended to common situations, and a *General Information Processing Model* is proposed, suggesting that *all information-processing models can be decomposed into a system of element models*. From a system perspective (Simon, 1960), it claims that no matter how complicated the information processing may be, it can always be operationalized in a system (e.g., network or hierarchy) of element models of the interaction between data and knowledge. In this hierarchy, lower-level information is produced from a subset of data and knowledge and then used as input to produce higher-level information with other knowledge elements; when "information" exists in a data set, it only means that part of the data has been pre-processed. For instance, the information "*at least 3 piece of article type A should be ordered*" can be used as input to processing orders; correspondingly, the earlier definition of data is extended to include the pre-treatment on whole or part of data set.

1.4.3 Information processing and knowledge creation

It is mentioned earlier that a common problem in available studies on the relationship between data, information, and knowledge is their incapability to consistently interpret the roles of information in knowledge creation. Although Model 3 has a similar structure to the KBI theory, especially the infological equation, such an issue is not explicitly addressed. It has been shown that the stance that information is the basis of knowledge is problematic; however, the importance of information in knowledge creation is also inarguable. How can this dilemma be resolved? A solution is inspired by the evolutionary theorists (e.g., Popper, 1992) who suggest that new knowledge is developed or modified from existing knowledge and then selected or verified based on information produced from the modification. Because of the inherent uncertainty, the infusion of new information does not necessarily improve the performance of knowledge variation or the quality of new knowledge; instead, it helps to eliminate or prevent less effective variations and accelerate the selection of more effective variations. In other words, the knowledge variation generated from existing knowledge needs to be justified by information before it can be treated as "new knowledge"; otherwise, it remains as conjecture, with the risk of being falsified by empirical evidence.

Such an evolutionary knowledge creation process is complicated and beyond the scope of this study; but a simple case is on order to illustrate the basic picture of the process. For example, in new product development, a new product model is usually developed from variations of some existing models with the expectation of delivering higher performance. Such a new model is tested and compared against criteria values in order to decide the acceptance or rejection of the variation. In this process, the test result refers to the information based on which a judgment is to be made, and according to the evolutionary scientists such as Popper, such a result does not predict the new directions of a successful variation; rather, new result are to be collected to verify the variations. This example describes the rudimentary logic of knowledge creation and the basic roles of information in the process as selection criterion. It also supports the KBI theory that knowledge is the basis of information. Future research should work towards fully deliberating the logic of information-supported knowledge creation.

1.5 Discussions and Conclusions

In this research, a new theory, the KBI theory, is develop to analyze the fundamental relationship between data, information, and knowledge. It demonstrates that information is produced from the interaction between data and knowledge, and low-level information is used as input to produce high-level information. This theory adopts the interactive view of some earlier models, such as the infological equation, while addressing their limitations with a sharpened relationship. Specifically, it highlights the distinction between data and signs, knowledge and facts, and information and information content, which have been used interchangeably in the infological equation and other models. The contribution of this theory, compared to Model 3 and the infological equation, is summarized in Table 1.2.

The key distinction between the KBI theory and the infological equation is that the KBI theory is built upon a sharpened understanding of each construct, especially the definition of information. It is realized that MacKay's (1969) definition of information is the most accurate, which has been used as the conceptual foundation of the KBI theory. Because of this and other improvements, the KBI theory has higher generalizability than the existing models, especially those from a pure communication perspective and based on semiotic theories.

A condition of applying the theory is that both data and knowledge can be directly recognized and measured, i.e., what the pre-conditions are, and what is the process through which the condition is converted into action. In addition, in order to measure the effectiveness of information produced from data and knowledge, other possible selections should be available. Since the KBI theory addresses a fundamental issue in the IS field, it has promises of application in various IS areas. Some of the applications are discussed next.

Table 1.2 Contribution of the KBI theory

Issues	Model 3 (The Infological Equation)	KBI Theory
Relationship between data and information	The infological equation treats data as signs representing information; an information system is operationalized as a data system.	The KBI theory does not treat data as the representation of information; instead, it is the measure of objects, from which information is produced. While data is descriptive, information is selective.
Relationship between information and knowledge	Information is a specific type of knowledge, i.e., knowledge about some particular facts.	Information is not any type of knowledge; it is not about some particular facts. Instead, it is the selective conditional readiness generated from the interaction between knowledge and data for possible action.
Treatment of knowledge	Knowledge is not explicitly analyzed in the infological equation; how it interacts with data to produce information is not directly specified.	Knowledge is the framework from which data is converted into information. Knowledge has distinct characteristics as compared to data and information.
Consideration of other factors	A time element is included in the infological equation	To establish a more parsimonious theory, no other factors are included in KBI. KBI holds that other factors, such as time and space, are sub-issues of the corresponding constructs.

1.5.1 The KBI theory and multi-levels of communication

It is mentioned earlier that studies on information are carried out at different levels, from empiric, syntactic, semantic, to pragmatic levels (Mingers, 1995; Stamper, 1987), and the understanding of information differs significantly across these levels. For instance, a person may say or write on a note something like "*I t i s r a i n i n g*"; it is then asked what information is generated from these symbols (or handwritings) at each communication level, and what are the corresponding data or knowledge? KBI theory can help answer these questions. Although originally developed from a pragmatic perspective, KBI theory can be consistently applied to the other levels, as shown in Table 1.3. At the lowest empiric or symbolic level, data refers to the signs used to represent the words, knowledge is the rules of sign transmission and statistical properties, and information is the string "I t i s r a i n i n g" generated from the signs. This string is then processed at the syntactic level through linguistic knowledge, yielding the sentence "it is raining". At the semantic level, this sentence further yields the information that it is about the weather condition and it is raining but not snowing, and the corresponding knowledge is semantics. Finally, at the pragmatic level, the message yields the information that "you should stay at home" based on the receiver's knowledge of S7. This example shows that at different communication levels, combinations of data and knowledge yields information to be processed at other (higher) levels. What remains the same is the relationship as depicted in the KBI theory.

The KBI theory is a useful research framework at each level. For IS researchers, the primary interest in analyzing information in communication is at the pragmatic or practical level; specifically, how information is related to the selection of action in business operations or decisions, which has direct impact on IS design. Information at other levels is the focus of such disciplines as information sciences, computer sciences, and electronic engineering. The KBI theory may represent a unifying mechanism to start to tie research across these levels and disciplines.

Table 1.3 Application of the KBI theory to multi-levels of information

Level of communication	Data	Knowledge	Information	Information content
Pragmatics	It is raining, rather than snowing.	S7 (IF-THEN production rule)	You should stay at home.	Weather condition that predict behavior.
Semantics	It is raining.	Semantics and the meaning of words.	It is raining, rather than snowing.	Words and sentence that predict the weather condition.
Syntactics	I t i s r a i n i n g.	Linguistics.	It is raining.	Letters that predict words and sentences.
Empirics (Symbolic)	*I t i s r a i n i n g.*	Rules of sign transmission and statistical properties of signals	I t i s r a i n i n g.	Signs that predict letters.

1.5.2 Apply the KBI Theory in IS: The case of computer mediated communications (CMC)

In CMC research, there are two frequently asked questions: W*hy are there different interpretations (or information) of the same message in communications* and *how do people design and implement IS to effectively facilitate CMC?* Early attempts to answer these questions have produced mixed results. For example, in testing Media Richness Theory (Daft and Lengel, 1986), empirical studies find contradictory results of whether information richness is determined by communication media (Daft et al, 1987; Dennis and Kinney, 1998; Markus, 1994). The controversies have roots in taking either a mechanistic view (i.e., signal contains information) or semantic view (i.e., information only emerges at the destination) of information. The former seeks to replicate the signal sent at the destination of the communication channel, thus requiring the same rules (or *knowledge*) for interpretation, which is a typical requirement of the channels (MacKay, 1969). For human communication, however, as no two persons possess exactly the same knowledge, they may have different anticipation for, or interpretation of, the same message, thus information conveyed in the same message prior to and after the communication may differ (Ackoff, 1958). In addition, the information receiver does not always accept the information passively; instead, she may actively produce meaning out of the message (Lee, 1994; Miranda and Saunders, 2003). In other words, the receiver re-interprets information embedded in the message based on her own knowledge and previous experiences (Langefors, 1973), which may generate different information that is not uniquely determined by the communication channel (Miranda and Saunders, 2003). The same information is communicated only when "intelligent cooperation" for catching the same meaning exists between the persons (Polanyi, 1966). This finding suggests that IS scholars involved in CMC research should design their studies in light of the relationship outlined in the KBI theory, i.e., building in proper controls and training in the communication process to best ensure that they are actually testing what they intend to investigate – accurate transfer of information.

1.5.3 Apply KBI theory in broader IS research and practice

Since the KBI theory depicts how information is produced from raw data and knowledge, it illustrates the generic process of information processing, which is central to the various applications of IS (Davis, 1974). To provide a holistic view of the different applications of IS in various contexts, Ein-Dor's (1986) early conceptualization of IS as knowledge repositories is adapted, envisioning IS as the *different embodiments of* *knowledge domains that are designed to process specific categories of data to produce needed information*. The different forms of IS are determined by different information requirement and the need of related data and knowledge to deliver the information; additionally, the degree of sophistication of an IS reflects the complexity in modeling data (e.g., database design) and knowledge (e.g., information processing models) in the design and deployment process.

A better understanding of the core roles of IS and the associated factors enables IS scholars to conduct further research on established areas in the IS field. For instance, the KBI theory can be applied to the Technology Acceptance Model (Davis, 1989) to help explain why users perceive an IS to be useful: an IS is perceived to be useful when the data is timely and accurate, knowledge embedded in the system is understandable and valuable, and the output information is illuminative. It can also be applied to the Adaptive Structuration Theory (DeSanctis and Poole, 1994) to prescribe how the functionalities of IS can be faithfully appropriated in organizations: since organizations are knowledge-based, it is therefore important for the knowledge embedded in IS to be compatible with organizational knowledge; otherwise, information produced from IS is not expected by organizations, resulting in the abandon of IS.

For the KM area, the KBI theory has promise in guiding innovative research. For instance, practitioners argue that IT only inspires but cannot deliver KM (McDermott, 1999), and scholars warn that if knowledge is not distinguished from information or data, then KM is simply a buzzword (Spiegler, 2000). Based on the KBI theory, it can be argued that KM can move beyond a buzzword if the right approach is taken. This approach is to manage knowledge via its information content or informational attributes.

To make it happen, pieces of knowledge should be first codified based on its attribute values (e.g., who, when, where, how, and why, etc.), saved in a knowledge base, and managed via some meta-knowledge. Following this approach, knowledge can be managed via advanced IT such as knowledge-mining, similar to other information management approaches. Clearly, this issue should be further analyzed. In sum, many sub-areas of the IS field can apply the KBI theory to facilitate research and practice for more valuable output. The key is to understand how IS meets an individual's or an organization's information requirement by providing the necessary data and appropriate knowledge for the information.

1.5.4 Limitations and future research directions

The major purpose in this essay is to address the conflicts in understanding the relationship between data, information, and knowledge by proposing more consistent definitions and relation. As a theory early in its development, KBI requires further refinement in future research. First, the proposed relationship has not been empirically tested, and the theory is constructed and verified purely on logic. Empirical research should be conducted to test the theory with proper measurement of the three core constructs. Second, only a high-level conceptual model is proposed. Further research could be conducted to explore the practical meaning of the relational model and develop some directly applicable models or guidelines for specific contexts or types of IS. Third, the relationship between information and knowledge creation is briefly described based on the KBI theory. Future research is needed to fully explore this process and provide empirical evidence of whether this model provides enhanced understanding of the knowledge creation process compared with other competing models such as Model 1 (*value-adding*). Finally, as this theory is focused on the underlying logic of information processing in IS, follow-up studies could be extended to analyze the influence of IS on environmental factors (Orlikowski and Barley, 2001), which may be promising in clarifying the contradictory organizational consequences of many IS studies (Robey and Boudreau, 1999).

Essay 2: Application of the Knowledge-Based Theory of Information in Computer-Aided Decision Making

2.1 Introduction

In the previous essay, the Knowledge-Based Theory of Information, or the KBI theory, is developed to clarify the relationship between data, knowledge, and information, three of the most fundamental concepts in the IS field. A conceptual model of their relationship is provided with an improved understanding of each concept. However, how these concepts and their relationship are operationalized and measured in the IS context is not discussed. Although it is premature to provide an ultimate solution due to the complexity of each concept, an illustration is needed to show the application of this theory in particular IS context. Essay 2 provides such an illustration: it shows how the KBI theory is operationalized in computer-aided decision-making, which is a major area of IS applications. It also shows how this theory is capable of resolving the conflicts in the associated studies.

Computer-aided decision-making refers to the use of Information Technology (IT), typically the Decision Support Systems (DSS), to support complex decision-making tasks. It has evolved significantly since its commencement in the 1970s, with the latest development found in network-based organization-wide applications such as data warehousing, On-Line Analytical Processing (OLAP), data mining, and web-based decision (Shim *et al*, 2002). For IS professionals, a critical mission is to design and develop DSS that improves the decision performance of individuals (Kottemann and

Remus, 1987); as a prerequisite, the relationship between DSS and decision performance must be clearly understood. Numerous studies have been done to analyze this relationship; in general, the DSS field has not made consistent progress and the relationship is still not well understood (Todd and Benbasat, 2000b). It is observed that studies from different theoretical perspectives have produced incomplete and sometimes contradictory results.

Several reasons for this lack of understanding have been analyzed, such as an extensive set of DSS capabilities, a multitude of task settings, and a wide variety of performance measurements (Todd and Benbasat, 2000b). Most importantly, there is no unifying theory that could integrate the various research from different theoretical perspectives and serve as the basis for accumulating knowledge in this field and consolidating diverse factors to produce a better understanding (Eierman et al, 1995). Available DSS theories focus primarily on the external factors or ancillary antecedents of computer-aided decision-making, such as DSS functionalities, decision-makers' attributes, and task environment. Nevertheless, the internal process of decision-making, i.e., how information is produced in a DSS to support the generation and selection of alternatives, is less sufficiently analyzed.

To better understand the internal process of computer-aided decision making and its relationship with decision performance and other antecedents, the KBI theory is applied. This theory suggests that an IS is the embodiment of some knowledge domains capable of processing specific categories of data into information for business operations and decision-making. For a DSS, it implies that it is the embodiment of decision knowledge (such as the decision models) designed to process decision data into decision-goal-oriented information. Following this logic, the decision performance of a DSS can be better understood via the analysis of the interaction between data and knowledge in the DSS context, and such an interaction mediates the impact of other antecedents such as DSS functionalities, decision-maker's attributes, and task environment. Such a solution has promise in providing a better, consistent view of the performance impact of DSS.

The rest of the essay is constructed as follows. First, existing literature on the performance impact of DSS is reviewed, and the problems in existing research are recognized. Next, how KBI theory is capable of solving the problems is discussed, followed by the proposition of the research model based on the KBI theory and several other theories. An experiment is then designed to find empirical evidence of this model. Finally, findings from the experiment are discussed and the implications for research and practice are analyzed.

2.2 Literature Review

Academic research on the performance impact of DSS started in the 1980s, with several important theories and research frameworks developed and applied in this field that have dramatically changed its intellectual structure (Eom, 1998). Of all the theories applied, cognitive fit theory (Vessey, 1991), system restrictiveness/decision guidance theory (Silver, 1991), cognitive cost-benefit theory (Payne, 1982; Todd and Benbasat, 1991) and task-technology fit theory (Goodhue and Thompson, 1995) are the most popular, based on which many studies have been conducted. A brief description of each theory is shown in Table 2.1. The literature review will focus on each of the theories.

Table 2.1 Summary of typical theories in DSS research.

Theory	Major Proposition
Cognitive fit theory (Vessey, 1991)	The cognitive fit between problem representation format and problem-solving task determines the decision performance.
Decision guidance / system restrictiveness theory (Silver, 1990)	DSS influences the decision performance via the provision of change agents such as decision guidance and system restrictiveness that support or inhibit the decision-making process.
Task-technology fit theory (Goodhue and Thompson, 1995)	The fit between task characteristics and technology characteristics determines the decision performance.
Cognitive cost-benefit theory (Todd and Benbasat, 1991, 1999)	The decision performance with decision aid is contingent upon the tradeoff between expected effort and accuracy; different decision strategies are selected based on the tradeoff.

2.2.1 Cognitive fit-based research

In addressing the inconclusiveness of a considerable amount of research on the effects of graphical and tabular representations on decision-making performance, Vessey and colleagues (Vessey, 1991, 1994; Vessey and Galletta, 1991) proposed cognitive fit theory (CFT). They suggest that problem-solving performance (such as effort and accuracy) is determined by the fit between problem representation formats (e.g., DSS interface) and problem-solving tasks. When a problem representation format is matched to the task, a suitable mental representation is formulated in the human mind, which, together with a proper problem-solving skill, leads to effective and efficient problem-solving performance (Vessey, 1991, 1994). For instance, a graphical problem representation that emphasizes spatial information should fit a spatial task, and a tabular problem representation that emphasizes symbolic information should fit a symbolic task.

This theory received great popularity in DSS research; Appendix 2.1 summarizes some of the typical studies and primary findings. The appendix shows that mixed and conflicting results exist in this line of research. For instance, Wright (1995) found that when information acquisition and mental integration demand was high, the availability of graphs in addition to tables resulted in better judgment performance (lower bias and less error); however, when much simpler information integration was required, the incremental effect of graphs became trivial. Similarly, Frownfelter-Lohyke (1998) found that the presentation format predicted to support each task did not significantly affect accuracy; however, the combined format was better than the graphical format.

Several reasons for the inconsistencies have been analyzed. In many studies, the problem representation format was pre-specified, so that the preference of the subjects was prohibited (Wilson and Zigurs, 1999); in some other research, the decision-making tasks might be beyond the subject's ability to solve the problem (Mahoney et al, 2003). Some other reasons are also recognized, including lack of theoretical basis, differences in measurements between studies, use of poor graphical formats, content differences in graphical and tabular formats, and uncontrolled learning effects (Frownfelter-Lohyke, 1998). The most important reason, however, lies in the cognitive fit theory itself. As Vessey (1991, p.225) states, "The paradigm of cognitive fit can be applied to those tasks in which the nature of the task and/or subtasks can be determined. These are elementary tasks and some of the simpler decision-making tasks." Similarly, Todd and Benbasat (1999, p.358) point out, "The model developed by Vessey (1991) applies most specifically to lower level spatial and symbolic tasks…In such instances, there may be a clear solution and strategy that directly lead to that solution. For tasks that are more complex, there may be a greater variety of strategies and determining an optimal strategy may not be straightforward." Therefore, the application of CFT in more complicated decision-making tasks should be made very carefully, as the misspecification of the type of task may result in misalignment of the appropriate presentation format.

2.2.2 System restrictiveness/decision guidance-based research

It has long been recognized that change agency is a key to DSS, as change is both a necessary precondition and an inevitable result of DSS use (Alter, 1980; Barki and Huff, 1985; Ginzberg, 1978). Through an array of studies, Silver (1988a, 1988b, 1990, 1991) illuminates the nature of change in DSS and classifies several types of change agencies. Two basic attributes of DSS are the most important, namely system restrictiveness and decision guidance. System restrictiveness measures the degree to which and the manner in which a DSS restricts its users' decision processes to a particular subset of possible processes. Decision guidance describes how a DSS enlightens or sways its users as they structure and execute the decision process, i.e., how they choose to use the system's functionalities. Two generic types of decision guidance are introduced: informative guidance and suggestive guidance. Informative guidance provides users with pertinent information without indicating how the user might proceed, while suggestive guidance proposes courses of action to the user. Other types of decision guidance are also analyzed, such as dynamic guidance and deliberate guidance (Parikh *et al*, 2001).

Of all the change agents affecting decision performance, decision guidance and system restrictiveness are the focus in further studies, and experiments were conducted to analyze the impact of these two. Appendix 2.2 summarizes some typical studies in this area. The findings show that contradictions exist in this line of research. For instance, Wilson and Zigurs (1999) showed that guided display resulted in higher accuracy of problem-solving, and subjects performed no better with their preferred display than with a randomly assigned display for the spatial task. Interestingly, subjects welcomed decision guidance as long as it did not limit their options. Montazemi *et al* (1996) showed that for less complex tasks, subjects using suggestive guidance performed better than those using informative guidance, and both outperformed the subjects with no decision aid. Nevertheless, for more complex tasks, informative guidance-aided subjects performed the best, but there was no difference between subjects using suggestive guidance and those with no aids.

It is concluded, based on these studies, that the impact of decision guidance and system restrictiveness is contingent on other factors, such as task characteristics, purposes of using the system, built-in functionality of the system, users' personal characteristics or preferences, and their experience with the system and acceptance of the system-induced change. It would be too arbitrary to say whether decision guidance and system restrictiveness are beneficial or not; it all depends on how they are designed and used in directing the decision-making process.

2.2.3 Cognitive cost-benefit-based research

It was recognized that decision-makers focus on trade-offs between accuracy and effort in making decisions (Payne, 1982). In many situations, the conservation of effort may be more important than increased decision quality in choosing a decision strategy, which explains why the use of DSS may result in poor decision quality but save effort (Todd and Benbasat, 1991, 1992, 1993, 1994, 1999, 2000a). Experiments confirmed this theory, showing that DSS is used in such a way as to replace rather than augment decision-making effort, and subjects using a decision aid tend to use less information than those without a decision aid (Todd and Benbasat, 1991). Based on this theory, it is argued that a DSS should provide support in such a way as to make a more accurate strategy at least as easy to employ as a simpler but less accurate one (Todd and Benbasat, 1999).

To understand the reduced effort in compensation for improved accuracy, decision strategies were analyzed, since decision-makers usually select an overall strategy before actually solving the problem (Beach and Mitchell, 1978; Einhorn and Hogarth, 1981). A decision strategy, such as Additive Compensation (AC) or Additive Difference (AD), consists of a set of procedures that decision makers engage in when attempting to select among alternative courses of action (Todd and Benbasat, 1999). Different decision strategies, due to their inherent heuristics and numbers of operations needed to process information, may require different cognitive effort, and the selected decision strategy mediates the impact of cognitive effort and accuracy expectations. It should be noted that the various strategies analyzed in this line of research (such as AC or AD) are used for preferential-choice decisions.

As with other DSS research, the cognitive cost-benefit based research has its drawbacks. Studies show that under certain circumstances, the decision-makers may spend more effort on DSS in order to improve decision accuracy (Mackay et al, 1992; Power et al, 1994); specifically, familiarity with the decision task and/or the DSS tool has an impact on the cognitive effort in certain activities in the decision process. It is also found that consideration of effort saving alone is not sufficient for inducing changes in decision strategy; instead, the impact of a decision aid on effort must be considered jointly with the decision quality associated with various decision strategies (Chu and Spires, 2000). Therefore, cognitive effort functions as a threshold rather than an offset of decision strategy selection; when decision guidance and/or system restrictiveness are present, the users' behavior will be directed toward the supported decision strategy, disregarding its inherent effort requirement.

2.2.4 Task-technology fit-based research

A relatively new approach to understanding the performance impact of DSS is task-technology fit (TTF) theory (Goodhue, 1998; Goodhue and Thompson, 1995; Zigurs and Buckland, 1998). This theory suggests that for DSS to have a positive impact on decision performance, the technology must be utilized and it must fit the task supported (Goodhue and Thompson, 1995; Zigurs and Buckland, 1998). The TTF construct has been further developed (Goodhue, 1998), and some TTF profiles are proposed based on task complexity and technology dimensions (Zigurs and Buckland; 1998). Although being a new theory, TTF received wide recognition in DSS research as well as in many other sub-fields of IS. For instance, Dow (2000) used the TTF framework to examine the impact of data architecture on organizational decision-making; the result confirmed the importance of TTF. Barkhi (2000) applied TTF in the analysis of the impact of Group Decision Support Systems (GDSS) on group decision-making and found that when there was a task-technology fit in GDSS, the use of a problem-modeling tool improved solution quality significantly.

The application of TTF theory in DSS research is not without questions. A meta-analysis by Dennis et al (2001) shows that fit between tasks and technologies alone does not explain the diverse results of DSS use. Specifically, the appropriation process will improve the efficiency of its use, but may diminish decision quality. Todd and Benbasat (2000b) argue that TTF influences the way in which individuals and groups use the technology, and it is this use that affects performance, not the fit itself. Although utilization is included in the original theoretical framework of TTF, it is unfortunately overlooked in further research. In addition, it is noticeable that the treatment of the TTF concept in empirical studies varies significantly, as most studies used TTF as a profile to match tasks with technologies in a specific research context rather than operationalizing it as a construct, despite the availability of a measurement instrument (Goodhue, 1998).

2.2.5 Other research perspectives

The above four theories and associated studies represent the major frontiers in contemporary DSS research, but some other theoretical perspectives have also been developed to identify additional factors that may influence DSS performance. For instance, individual characteristics are a major concern in DSS research, especially the cognitive styles of individuals (Benbasat and Taylor, 1978; Todd and Benbasat, 2000b). Task complexity, referring to the number of information cues to be processed to fulfill a task, also frequently falls under consideration (Campbell, 1988; Montazemi *et al*, 1996; Wood, 1986). Other factors such as appropriation factors (Dennis *et al*, 2001; Wheeler and Valacich, 1996), field dependency (Mahoney *et al*, 2003), and interruptions during the systems use (Speier *et al*, 2003) are analyzed as well. Identification of these factors improved the knowledge of the performance impact of DSS; nevertheless, limitations exist as well. For instance, Huber (1983) warns that focus on individual characteristics such as cognitive styles is unlikely to provide a satisfactory body of knowledge to DSS research. A meta-analysis (Alavi and Joachimsthaler, 1992) indicates that user-situational variables (e.g., involvement, training and experiences) are more important than the psychological and demographical traits of decision-makers. Limitations in other factors have also been addressed.

In order to aggregate and clarify the impact of the various factors identified in previous studies, several integrative frameworks have been developed. For instance, Alavi and Joachimsthaler (1992) developed a user-DSS implementation framework and meta-analyzed the impact of four major user factors: cognitive style, personality, demographics, and user-situational variables. Eierman *et al* (1995) developed a DSS theory with eight major constructs, including environment, task, DSS capability, user behavior, and performance, etc. Finally, Todd and Benbasat (1999, 2000b) developed a model where the impact of such factors as desired effort expenditure, desired accuracy, incentives, and task-technology fit is mediated by decision strategy. While these integrative frameworks are helpful in providing a more comprehensive view of DSS, limitations exist. For instance, the decision strategies depicted in Todd and Benbasat's (2000b) model are primarily for preferential choice tasks, which may not be readily applicable to other more complicated decision tasks. Also, people seldom choose a pure strategy, but develop a mixed strategy that differs across contexts, depending on the different decision aids being used (Chu and Spires, 2000). The framework by Eierman *et al* (1995), on the other hand, contains relationships that lack consistent empirical evidence. Due to these drawbacks, the application of these models in general DSS research is still limited.

2.2.6 Summary

It is concluded, from the above review, that a complete understanding of the relationship between DSS and decision performance has not been achieved, and there has been no notable progress in consolidating the multiple theoretical perspectives. While many causes of these problems have been recognized (Frownfelter-Lohyke, 1998), a fundamental reason exists in the limitation of the existing theories. Available theories do not provide an in-depth analysis of the internal processes through which a decision is made on DSS. Instead, emphasis is put on the ancillary antecedents, including DSS functionalities, the decision-maker's characteristics, task attributes, and their interaction (e.g., task-technology fit), while assuming the direct impact of these factors. What is missing, as implied by Todd and Benbasat (2000b), is a better understanding of the underlying mechanisms or internal processes that mediate the impact of the antecedents. Such a limitation in previous studies left a black box between the antecedents and the decision performance, as shown in Figure 2.1. Clarification of this black box has therefore become the first step in resolving conflicts and developing a unified view of DSS.

As forerunners of contemporary DSS research, decision scientists have particularly analyzed the roles of information in decision-making. For instance, Ackoff (1958) argued decades ago that a decision process is driven by information that determines a person's purposeful state, including the objectives, valuation of each objective, possible courses of action, efficiency of each course of action, and probability of choice. For each of the elements, information is needed to reduce the uncertainty, for instance, what alternatives are available and what are the corresponding payoffs, based on which the decision is made. Simon (1960) further used the concept of "information process" to build his executive decision-making theory, depicting decision-making as a series of information processes. These and many other studies show that information plays a critical role in decision-making, and that the improvement of decision performance is determined by the improvement of information performance.

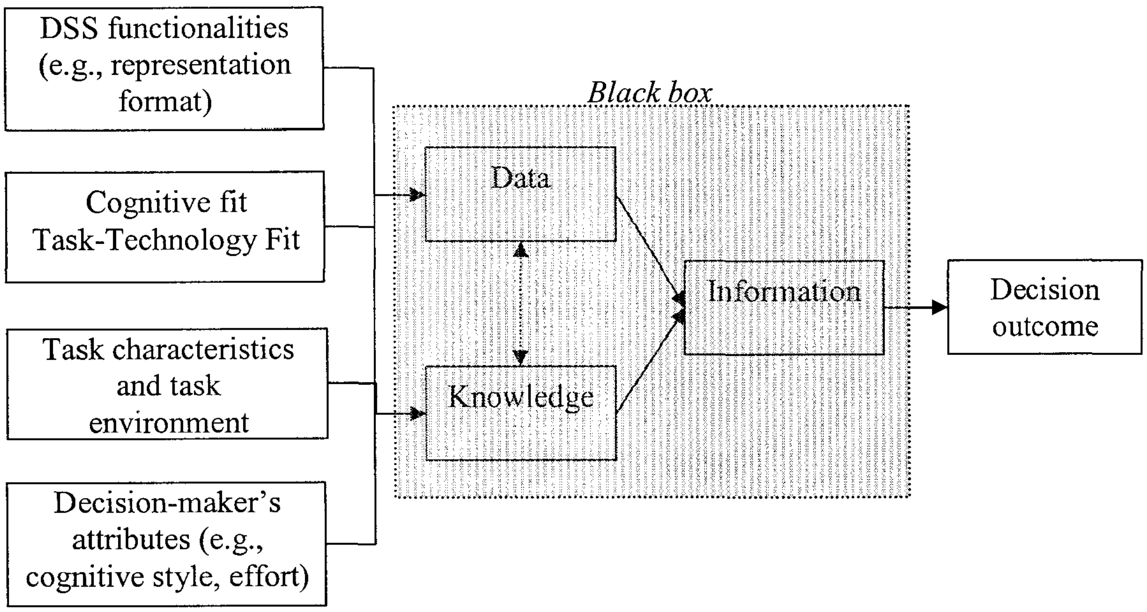
IS scholars accept the position that information is the basis of decision, and an information process involves decision processes (Langefors, 1973). Such an information-based approach was popular in the early years of DSS research (Alter, 1977; Gorry and Scott Morton, 1971; Sprague, 1980); it has also been used to interpret the DSS phenomenon in more recent studies (Todd and Benbasat, 1991, 2000b). Unfortunately, this approach has not become the mainstream in the DSS field, which is dominated by the studies on the ancillary antecedents. What is needed is an in-depth analysis of how information is processed in DSS to support decisions.

The KBI theory developed in Essay 1 suggests that information is produced from data and knowledge, and an IS is the embodiment of knowledge domain capable of processing specific categories of data. This theory has the potential of clarifying the black box in Figure 2.1. It implies that a DSS, being a particular type of IS, is the embodiment of decision-related knowledge that converts input data into information for the decision-making. It highlights two critical factors in the decision process: decision knowledge (such as decision models) and decision data. The decision knowledge provides a general framework from which a course of action (such as an alternative) is evaluated and selected from other courses of action, for instance, a decision tree that evaluates the payoffs of a group of alternatives based on certain criteria (Turban, 1995). The decision data specifies the particular context or pre-conditions from which the decision is to be made, such as the alternatives and their specifications. Therefore, both data and knowledge determine the information to be used for the decision.

Since information is produced from data and knowledge, it is conceived that other factors, such as DSS functionalities, the decision-maker's attributes, and task characteristics, have an impact on decision performance via the influence on data and knowledge. Previous studies have found preliminary evidence. For instance, Gregor and Benbasat (1999) found that the explanation facilities in some knowledge-based DSS helps improve decision performance by providing better understanding of the reasoning process (i.e., decision knowledge). Other factors have impact on data and/or knowledge in the decision process as well, such as task complexity (Wood, 1986) and the decision-maker's field dependency (Mahoney et al, 2003). Therefore, both data and knowledge are thought to mediate the impact of the other factors on decision performance.

Based on the above analysis, it is proposed that decision is directly influenced by information, which is then influenced by data and knowledge. Other antecedents such as DSS functionalities, the decision maker's attributes, and task characteristics have their influence via data and knowledge. The KBI theory therefore explains the black box left in previous studies. A conceptual framework is developed from the analysis, shown in Figure 2.1. In the next section, a research model is developed from this framework.

Figure 2.1 Conceptual framework



2.3 Research Model

This research focuses on the impact of DSS on individual decision-making. Although there exist several different measures of decision performance, such as decision efficiency, decision-maker's satisfaction, and learning effect (Eierman et al, 1995; Udo, 1992), this research only analyzes decision quality, referring to the effectiveness of the decision as compared to other alternatives in achieving certain goals (Agarwal et al, 1998; Dennis and Kinney, 1998; Kahai and Cooper, 2003; Parikh *et al*, 2001). Since the above review recognized two groups of influential factors, including the core factors (i.e., data, knowledge and their interaction) and other previously studied antecedents, in the next these factors are analyzed separately in building the research model.

2.3.1 Influence of the core factors

The influence of the core factors can be better understood via the analysis of the information-driven decision process. According to Simon's (1960) well-known intelligence-design-choice framework, a decision process consists of several major phases, including environmental scan for information, development of alternatives, and selection of the best solution (Marakas, 1999). The issue is, since more than one alternative may surface, there exists uncertainty concerning which one should be chosen, as each alternative has equal chances of being selected (Ackoff, 1958). To make a choice, information is needed to reduce the uncertainty and narrow the scope of choices to those that have the highest potential to achieve the goal. As described in Essay 1, such information, standing for the selective function of the conditional readiness for goal-directed activities, is the basis of selection: it specifies what alternative should be selected for a given condition. For instance, in production planning, production information is needed to develop the production plan that yields the maximum output. The decision process is therefore made through the production of information from the corresponding data (e.g., product parameters) and knowledge (e.g., planning methods).

High quality decision demands high quality information. Although several information quality dimensions have been analyzed, such as accessibility, believability, and relevancy (Lee et al, 2002), in this research, only the effectiveness dimension of information quality is concerned due to the selection of the dependent variable, indicating the extent to which an effective decision can be made based on the information. In addition, since information produced from a DSS is treated as the only source of decision in this research, information quality and decision quality become equivalent concepts;

however, in other situations where decision-makers form a judgment based on other information sources, the relationship between information and the decision should be further analyzed.

Data is necessary material for information. As the KBI theory defines, data is the measure or description of objects or events associated with a particular task. In the decision context, data consists of the measures of the alternatives, typically their attribute values, that have an influence on the decision. For instance, in production planning, each alternative plan is measured with production quantity, material cost, labor hours, and machine capacities, etc.; the corresponding data items form the basis of information and decision, and will influence the decision performance. Therefore, in order to improve decision quality, high quality data is needed. Similar to the above discussion of the dimensions of information quality, in this research, only the effectiveness of data is concerned, referring to the extent to which a data set contains relevant information that contributes to making an effective decision. Other data quality dimensions such as timeliness, consistency, and accessibility (Wang and Strong, 1996) are temporarily beyond the scope of the research.

Another important factor, which is also analyzed in previous DSS research, is knowledge. Knowledge refers to the justified true belief of the relationship between constructs; in the decision-making context, it refers to the various decision models from which information is produced for the selection of alternatives. The importance of knowledge for information and decision has been fully analyzed in Essay 1; here a simple case is used to elaborate such a relationship. Decision trees, for instance, are a typical type of decision model, which include a set of rules designed to make a decision based on a series of conditions (Turban, 1995). These rules include a set of relationships between conditions and actions, so that when a specific condition is met, a certain action or decision to act is to be made. Based on different rules, decision models, or knowledge, the relationship between conditions (i.e., the available alternatives, such as production plans) and actions (i.e., the selection and/or execution of the best alternative or plan) will differ. Therefore, the quality of a decision model applied is another determinant of decision quality. Similarly, in this research only the effectiveness of knowledge is discussed in the decision process, representing the extent to which a decision model is capable of producing high quality information for a particular task.

The KBI theory suggests that neither knowledge nor data alone can completely determine information and decision, since the same data set processed by different knowledge will produce different information. In order to produce the needed information for an action, knowledge must fit the data provided, or vice versa. This is the issue discussed in Essay I and illustrated in Figure 1.2. In other words, the same data set, representing the existing conditions or courses of action, may result in a different action or readiness for action due to a different condition-action pair in the decision model. For a specific decision task, there may exist a decision model that best fits the given data set. For instance in classification tasks, several classification models may be chosen, such as logistic regression, neural network, multivariate discriminant analysis (MDA), kth-nearest neighbor (kNN), and decision tree (Kiang, 2003). Meanwhile, different data characteristics may influence the classification results, such as nonnormality, nonlinearity, and sample size. For different data characteristics, there are corresponding "best performing" methods: for instance, if the data set is nonlinear, then logistic regression and neural network are preferred over other models; if the data set has a multimodal distribution, then kNN would be the best. This example, together with the above analysis, shows that data-knowledge fit, referring to the extent to which information contained in the data set can be generated through the decision model, is also an important factor for decision quality.

With the recognition of the fundamental logic and important factors in information-driven decision-making, it is important to understand how the logic and the factors are operationalized or materialized in DSS. To address this issue, the structure of DSS is analyzed. A typical DSS consists of four generic components, namely a database management system, a model base management system, a user interface, and a knowledge engine (Ariav and Ginzberg, 1985; Sprague, 1980). The basic functions of each component are described here (Marakas, 1999):

- The database management system (DBMS) deals with the retrieval, storage, and organization of the relevant data for the particular decision context;
- The model base management system (MBMS) performs the retrieval, storage, and organization of various decision models that provide the analytical capabilities for the DSS;
- The user interface, sometimes referred to as the dialog management system, is the channel through which the data, decision models, and processing components of the DSS are accessed and manipulated by the users;
- The knowledge engine performs the activities of problem recognition, generating interim or final solutions, and other functions related to the management of the problem-solving process.

Comparing the DSS structure with the KBI theory, it is clear that the DBMS component is responsible for providing high quality data to the decision-maker. Such responsibilities include coordinating all tasks related to storing and accessing data in the database, maintaining logical independence between the database and other components of the DSS (Marakas, 1999), and managing both the internal and external sources of data (Turban 1995). All these activities ensure that high quality data, or data with high effectiveness, is fed into the decision process. It is hypothesized that:

***H1**: The effectiveness of data utilized in computer-aided decision-making is positively related to decision quality.*

The MBMS of a Decision Support System manages structured knowledge in the form of decision models, including the execution and integration of the models available to the DSS (Marakas, 1999). It allows users to access the existing models, control and select the model most useful for a decision, maintain existing models for changing conditions, and construct new models (Turban 1995). In other words, the MBMS aims at improving the knowledge effectiveness in the decision process, representing the extent to which a decision model is capable of producing high quality information for a particular task. Therefore, it is hypothesized that:

***H2**: The effectiveness of knowledge applied in computer-aided decision-making is positively related to decision quality.*

The classic structure of DSS does not contain a particular component dedicated to the fit between data and knowledge; previous theories did not consider this factor, either. Although a knowledge engine is recognized in the structure, it performs such functions as reasoning for unstructured tasks within a specific problem domain (Marakas, 1999).

Nevertheless, the roles of a knowledge engine should be extended from specific tasks to all decision tasks, as a decision that can be made without reasoning is really not a decision at all (Marakas, 1999). It should be noted that the knowledge engine performs the pre-selection of decision models within a particular decision context via the reasoning process; it is therefore closely related to data-knowledge fit. Based on this, it is hypothesized that:

***H3**: The degree of fit between data and knowledge is positively related to the decision quality.*

Finally, the potential relationship between decision data and decision knowledge should be analyzed. KBI theory suggests that the data a person or a system receives may contain information that has been processed by other persons or systems, so that the quality of data is influenced by the knowledge used to process that information. This relationship is further described in the general information processing model of the KBI theory. In computer-aided decision-making, it means that data is not fixed input to the process; instead, it may undergo changes in the process based on specific knowledge applied, such as the adjustment of production plans. Therefore, the effectiveness of knowledge may influence the effectiveness of data, and the following hypothesis is developed:

***H4**: The effectiveness of knowledge applied in computer-aided decision-making is positively related to the effectiveness of data.*

The definitions of the three core constructs are further summarized in Table 2.2.

Table 2.2 Definitions of core constructs

Independent variables	Definitions
Data effectiveness	The extent to which a data set contains information that contributes to making an effective decision. Data effectiveness is low when irrelevant and/or distractive information is included in the data set.
Knowledge effectiveness	The extent to which a decision model is capable of producing information across a general context for making effective decisions.
Data-knowledge fit	The extent to which information contained in the data set can be produced by the decision model to support an effective decision.

2.3.2 Influence of previously analyzed antecedents

Physiological constraints on human beings imply that DSS should be used to augment the decision maker's cognitive capabilities by expanding her bounded rationality (Chu and Spires, 2000; Todd and Benbasat, 2000b). This can be achieved via the expansion of the decision-maker's capability in information processing for decision. Many factors recognized in previous studies have the potential to fulfill this job and therefore influence decision performance; however, it is not realistic to analyze all the factors in a single study. Instead, only those that are most pertinent are selected in the current study. The above analysis illustrates the direct impact of data effectiveness, knowledge effectiveness, and data-knowledge fit on decision quality, which implies that the addition of other factors should help to improve data effectiveness, knowledge effectiveness, and/or their fit. In the next section the factors related to DSS functionalities, decision-maker's attributes, and task environment are analyzed.

Decision guidance: informative and suggestive

Two major types of decision guidance, namely informative guidance and suggestive guidance, are thought to have an influence on the decision process and decision performance. While both are DSS functionalities to assist users to make decisions, the way they exert influence is different. Informative guidance, as defined above, provides users with pertinent information without indicating how the users might proceed with that information. In fact, decision-makers may be given a list of available operators together with an analysis of how they differ with respect to their decision properties, and similarly, they may be given tables of reference data to help them choose input values for the operators (Silver, 1990). In none of the cases is the method of making the decision directly specified. In the experiment by Montazemi *et al* (1996), for instance, historical information of how the data items were used is provided, which gives the users a clue of what data item to use without a clear suggestion.

From the KBI theory perspective, the provision of informative guidance complies with the notion that lower-level information is used as input data to produce higher level information. Such lower-level information enables the decision-makers to narrow their scope in search of the best solution. Such guidance is helpful in improving the pre-conditions in the decision process rather than specifying the associated actions, which is not the function of data. Therefore, informative guidance may have a direct impact on data rather than knowledge, and it is hypothesized that:

***H5**: Informative guidance has a positive relationship with data effectiveness.*

Suggestive guidance, on the other hand, directly proposes courses of action to the decision-maker (Silver, 1990). In the experiment by Montazemi *et al* (1996), suggestive guidance takes the form of corrective prompts, which are presented to the decision-makers whenever they make mistakes in judgment. In the study by Jiang and Klein (2000), suggestive guidance is provided in the form of a weighted score for the selection of the most appropriate forecasting model, with the highest score indicating that a model should be selected. In both cases, a clear suggestion of how to act, based on the specific condition, is provided. Explained from the KBI's perspective, suggestive guidance helps to improve a user's control of the decision process based on the suggestion of possible actions in the conditions, but such control has no particular requirement on the quality of the suggestion. It is therefore hypothesized that:

***H6**: Suggestive guidance has a positive relationship with knowledge effectiveness.*

Other DSS attributes or change agents, such as system restrictiveness, may also have an influence on decision data or knowledge. Nevertheless, their impact is not straightforward: for different purposes of using the system, there may exist quite different requirements for system restrictiveness (Silver, 1990). Therefore, these factors are not included in the current research, but their influence could be analyzed in further studies.

Task complexity

Of all the factors related to task and task environment, task complexity is one of the most important (Campbell, 1988), and many studies have particularly compared simple tasks with complex tasks (e.g., Speier et al, 2003). Wood (1986) developed a widely accepted three-dimensional model of task complexity, which includes component complexity, coordinative complexity, and dynamic complexity. Each dimension contains some "information cues", referring to the pieces of information about the attributes of the task upon which an individual can base her judgments. If a task involves more information cues to be processed than other tasks, it is more complex. Although this approach provides an objective measure of task complexity, difficulties exist in accurately counting the number of information cues, and in many cases pragmatic approaches are used to qualitatively judge the task complexity level. Nevertheless, the information cue-based approach is helpful in developing a better understanding of task complexity in the decision process.

Since task complexity is determined by the number of information cues, the decision task is therefore broken down into a hierarchy or series of sub-problems with their corresponding information cues (Simon, 1960). Therefore, the difficulties in making a decision increase as the number of information cues and their interactions grows. As discussed earlier, each piece of information is to be processed via data and knowledge, so that the increased number of information cues requires more data items to be analyzed with enhanced decision models that contain more relations. The result is that the performance in selecting effective data and knowledge will drop. Therefore, task complexity is negatively related to data effectiveness and knowledge effectiveness. In addition, the decision-makers would have to spend more time to search for the best data and knowledge, but not knowing whether they would fit because of the uncertainty. Because of these, it is hypothesized that,

***H7**: Task complexity is negatively related to data effectiveness, knowledge effectiveness, and the fit between data and knowledge.*

Decision-maker's personal knowledge

The third component of computer-aided decision-making involves decision-makers. As discussed above, many personal attributes have been analyzed, although limitations were recognized (Huber, 1983). Some recent studies have begun to analyze the cognitive capabilities of individuals in the DSS context (e.g., Mahoney et al, 2003), which has promise in producing better results. A person's cognitive capability refers to her general knowledge or competence within a specific task domain, for instance, capability in making production plans or developing market strategies. Studies have shown that higher cognitive capability is related to improved decision quality (Amason, 1996).

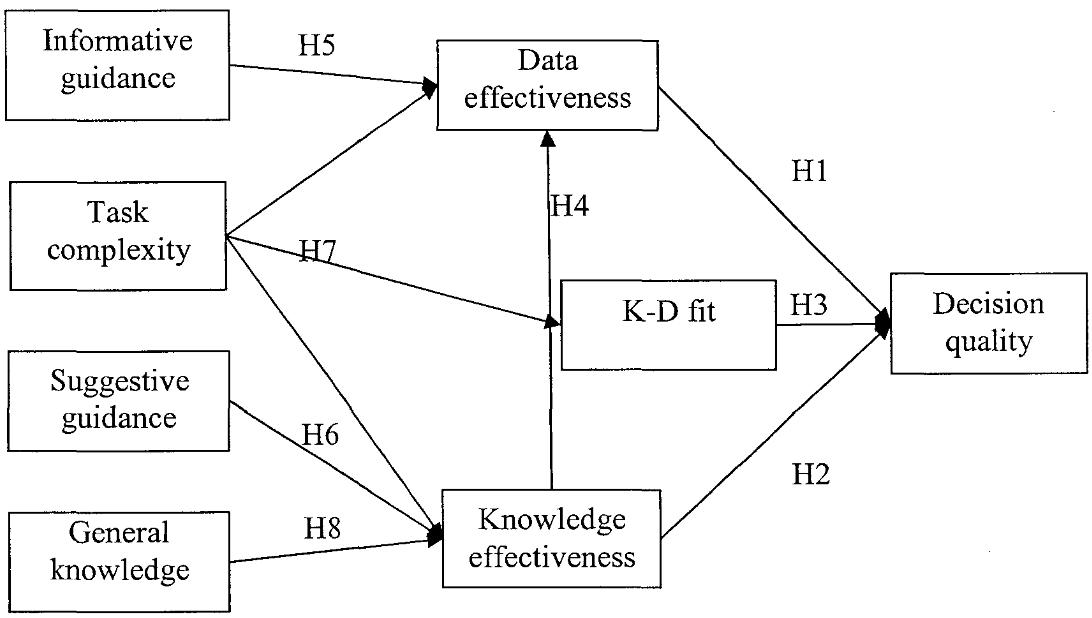
How is a person's cognitive capability, or general knowledge, related to the decision process? Although general knowledge may have an influence on all aspects of the process and factors, including decision data and decision knowledge, most importantly, it has a direct impact on decision knowledge, since decision knowledge can be treated as the application of the general knowledge in a particular decision context. This is to say, a person who has a general knowledge of the decision task may be able to apply the knowledge effectively. Therefore, it is hypothesized that:

***H8**: A decision-maker's personal knowledge of the decision task is negatively related to the knowledge effectiveness.*

In addition to the above factors, some other factors have also been analyzed in previous studies that may have an impact on decision performance, such as cognitive effort and accuracy, cognitive fit, and task-technology fit. Despite the pragmatic reason that it is unrealistic to testify all the factors in a single study, the exclusion of these factors is primarily due to the ambiguity in their relationship with the core factors analyzed. Cognitive effort, for instance, is supposed to influence decision strategy and then decision performance; nevertheless, as Todd and Benbasat (1999) point out, the provision of DSS support is to release the constraints on cognitive effort by supporting more accurate strategies with the same or even less cognitive effort expectations. Therefore, based on the different decision aids provided, the impact of cognitive effort may become unstable and even reversed.

Cognitive fit and task-technology fit (TTF), on the other hand, are believed to represent specific versions of the data-knowledge fit. Both cognitive fit and TTF are about the match between DSS capabilities (such as problem representation format) and the decision task; the difference is that the former is at the interface level, while the latter is at the system level. Nevertheless, as depicted in the KBI theory, an Information System is the embodiment of knowledge domains capable of processing data for some problem domains, which is therefore consistent with both cognitive fit theory and TTF theory. For instance, at the interface level, the KBI theory helps to explain the fit between data representation formats (either in tables or in charts) and the corresponding knowledge (spatial or analytical). Therefore, these three theories depict the same problem in different ways; since data and knowledge are included in the research, the other theories are temporarily not considered. The overall research model is shown in Figure 2.2. In the next section the research design is described to provide empirical evidence for the model.

Figure 2.2 Research model



2.4 Research Design

2.4.1 Research method

Studies on the performance impact of DSS are dominated by experimental research. This approach not only has its roots in the "Minnesota Experiments" that set the basis of DSS research, but it is also regarded as an appropriate approach to testing theories (Benbasat, 1989; Zmud et al, 1989). Even though critiques have been made about the drawbacks of this approach, mechanisms, such as conducting a theory-based experimental design, using previously used and validated measuring instruments to improve reliability and validity, and having a well defined task (Jarvenpaa et al, 1985), are proposed to rectify those drawbacks to enhance the research validity. A lab experiment is conducted in this research to test the hypotheses.

The decision task in the experiment is production planning, which is a popular task in previous DSS research (e.g., Speier et al, 2003). Appendix 2.3 introduces the scenario of this task. In the experiment, subjects were asked to make a production plan of several computer products for a four-week period. Since the production of the computers requires the production of corresponding components (such as keyboards and mice), a balance is to be made to both. The key to success, i.e., to maximize the estimated net income based on certain production scheduling, is to meet the customer's demand while controlling inventory and overtime.

To fulfill the research purpose, an Excel-based experimental DSS tool was developed based on a similar system (called *ITEC*) that had been used in the Operation Management (OM) courses in an American university. A screenshot of the system is shown in Appendix 2.4. Different change agents, such as the informative guidance and suggestive guidance, were built into this tool for hypotheses test, which will be explained later. Some earlier versions of this tool have been tested with students enrolled in an introductory IS course, and feedback was collected for removing bugs in the system. A total of 168 students enrolled in an introductory OM course were recruited for this experiment due to their relevant knowledge and experience.

2.4.2 Operationalization of the constructs

The constructs in the research model are either measured with questionnaires or manipulated in the experimental tool. Specifically, decision quality is directly measured on the system, which is operationalized as the estimated net income (see Appendix 2.4). Production planning algorithms were used to calculate this variable on the Excel spreadsheet.

Data effectiveness is operationalized via the key data items on the spreadsheet that have direct impact on decision quality, such as the inventory levels and overtime. It is considered that decision-makers are flexible in applying the data items available on the system to make a judgment; it is therefore arbitrary to directly "control" those data items. Instead, the subjects are given all the data they may need to make a decision, and data effectiveness is measured based on what data items they have actually used. For instance, the inventory level should be utilized in the decision process due to its relevance to the net income; if the inventory level is too low or too high after a decision is made, it suggests that this data item has not been effectively used, and the decision effectiveness measure would be low. A verbal protocol analysis might have been used to ask each subject what data items he or she has used; nevertheless, it would be a tremendous work due to the large number of subjects, and it may pose the problem of subjectivity in assessment. An economic and objective approach is applied, by observing the data items that have actually been used in the process, to be discussed later.

Both knowledge effectiveness and general knowledge are measured with questionnaires designed for this particular decision context. Similar to the data effectiveness, it would be arbitrary to control the knowledge in the experiment, since subjects are flexible in applying their own knowledge or knowledge embedded in the system to make a decision. A questionnaire with seven multiple-choice questions (see Appendix 2.6) were developed based on the decision tool and the decision task to measure the actual knowledge applied. These questions covered the knowledge of production scheduling, material requirement, inventory levels, and overtime, and were verified by an OM instructor. Similarly, ten multiple-choice questions (see Appendix 2.5) were generated from the test bank of the OM textbook adopted by the subjects in order to measure the general knowledge. These questions were also verified by the OM instructor to examine their suitability for the subjects. Finally, the data-knowledge fit is statistically derived from both data effectiveness and knowledge effectiveness.

Informative guidance, suggestive guidance, and task complexity are directly manipulated, which is a common approach in the associated studies (e.g., Montazemi et al, 1996; Speier et al, 2003). A 2 * 2 * 2 factorial design was used to control these three constructs. In doing so, two levels of informative guidance were controlled: one with informative guidance and one without. Informative guidance was operationalized via highlighting the data items (i.e., cells on the spreadsheet) that the decision-maker should pay attention to, such as the occurrence of overtime or low inventory. It is anticipated that this aid may help the decision-makers make better use of needed data items.

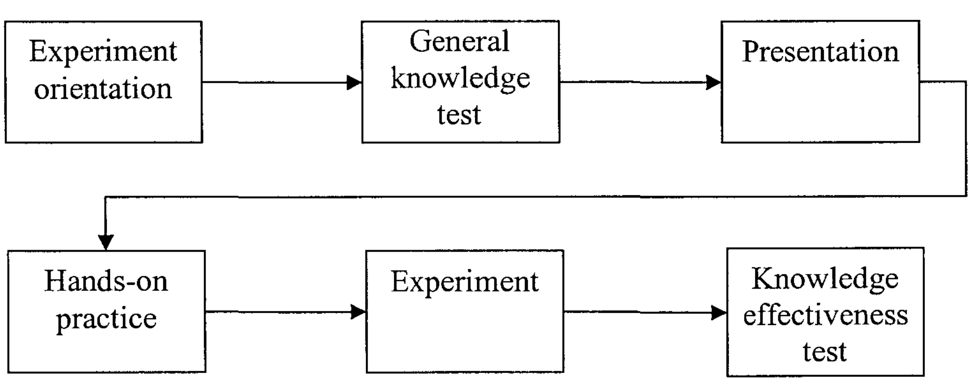
Two levels of suggestive guidance were also controlled: one with suggestive guidance and one without. The suggestive guidance was operationalized via the provision of a list of actions that a decision-maker may follow to make a good decision, for instance, what actions should be taken in order to improve the outcome and what actions should be done when a problem occurs. Finally, two-levels of task complexity, namely simple task and complex task, were controlled, where simple task involves the production of one type of computer products and the complex task involves the production of two. Because the two-product-type plans involve the shared components between computers models, according to Wood (1986), it has higher coordinative complexity and is therefore more complex. The combination of the three factors generates eight treatments in the experiment.

2.4.3 Experiment process

The experiment proceeded as follows. First, each student was given a copy of the experiment scenario description (see Appendix 2.3), which introduces the purpose of the experiment. Then, the students were tested on their general knowledge on production planning with the ten multiple-choice questions in Appendix 2.5. Next, a presentation of the production planning process and the decision tool was given. This presentation highlighted the concepts closely related to the decision tool and also the process through which the production planning was made on the DSS tool. After the presentation, the students were asked to do a hands-on practice with the tool and were encouraged to ask questions.

When the hands-on exercise was finished, each student was randomly assigned to one of the eight treatment groups and asked to finish the experiment by themselves; sufficient time was given so that all the students could finish the experiment. Finally, the students were tested on their knowledge with regard to the particular decision context based on the seven multi-choices question in Appendix 2.6, which was used as the measure of knowledge effectiveness. Figure 2.3 shows the whole process of the experiment.

Figure 2.3 Experiment process.



2.4.4 Measurement approaches

Informative guidance, suggestive guidance, and task complexity were measured as dummy variables, with 1 standing for "with informative guidance", "with suggestive guidance", "complex task", and 0 standing for "without informative guidance", "without suggestive guidance", and "simple task". General knowledge was measured with the ten production planning questions in Appendix 2.5, with 1 point for each question. Knowledge effectiveness was measured with the seven questions in Appendix 2.6, with 1 point for each question.

Data effectiveness was measured by counting the correct data items that the decision-makers used. The abnormal inventory levels (such as negative inventory and none-zero ending inventory in the last week) and the occurrence of overtime are treated as incorrect data items, because the decision-makers should modify the production plan based on those data items. In total there are 20 such data items in the simple task and 28 in the complex task. The data effectiveness measure for each subject is therefore determined by how many cells he or she has correctly filled.

Data-knowledge fit is treated as the interaction between data effectiveness and knowledge effectiveness. According to Venkatraman and Camillus (1989), fit can be interpreted in one of six different forms, depending on the criterion specificity and functional specificity. In this research, fit depends on both the data effectiveness and knowledge effectiveness, and it represents the interaction between the two; therefore, it should be treated as a moderating factor, i.e., knowledge moderates the effect of data and vice versa.

Finally, decision quality was measured by the extent to which a decision was properly made, indicated by the estimated net income. Since the simple task and the complex task do not have the same best answer due to the particular settings, the best answer was found for each task, with the help of several PhD students in an IS program. The results are further varied by the experiment outcomes.

2.5 Research Results

Of all the 168 participants in this experiment, several did not follow the instructions closely and failed to finish the experiment. Their results were excluded from further analysis. A total of 156 valid responses were collected, with approximately 20 subjects in each treatment group.

As different scale lengths have been used to measure the constructs in different treatment groups (e.g., data effectiveness measure and decision quality measure), the raw data were normalized and/or standardized to eliminate the impact of measurement scales. Two constructs were normalized for consistency across the observations: data effectiveness and decision quality. Data effectiveness was normalized by dividing the raw score by the corresponding criterion value (20 for simple tasks and 28 for complex tasks). The normalized data effectiveness measure therefore represents the percentage of correct data items utilized by the decision-maker. Decision quality was normalized based on the best result of each decision task. All metric independent variables were then standardized to reduce the influence of scale length, including general knowledge, knowledge effectiveness, and data effectiveness. Decision quality was not standardized since it is the dependent variable. The correlation matrix of the variables is shown in Table 2.3.

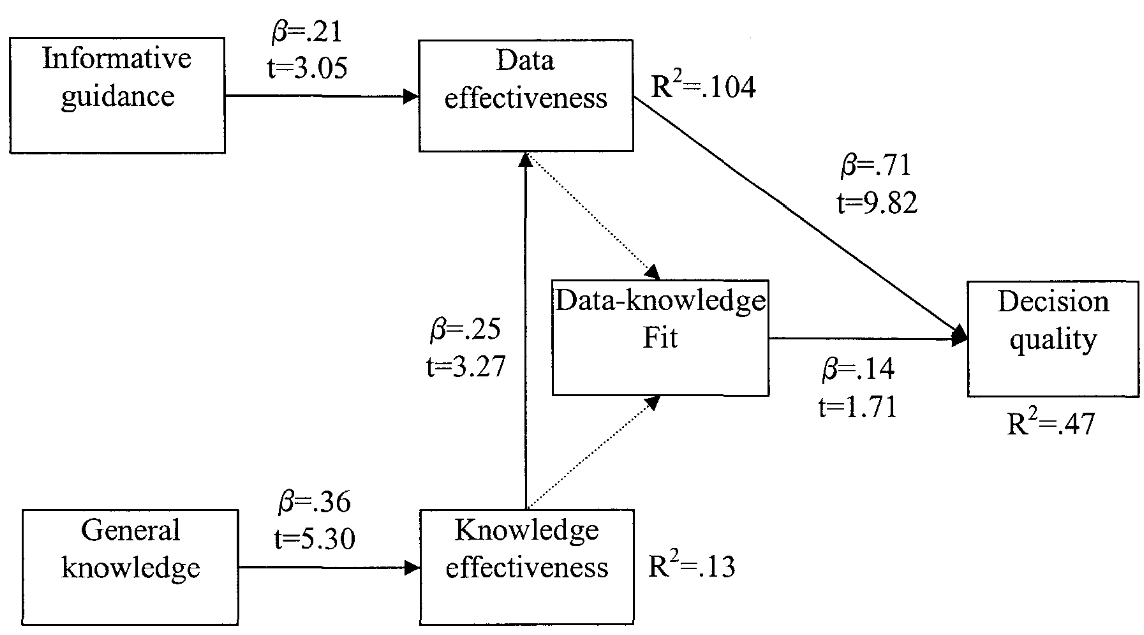
Table 2.3 Correlation matrix of the variables

	Task	Informative guidance	Suggestive guidance	General Knowledge	Knowledge effectiveness	Data effectiveness	Decision quality
Task	1						
Informative Guidance	-0.065	1					
Suggestive Guidance	-0.038	0	1				
General knowledge	0.082	0.076	0.019	1			
Knowledge effectiveness	0.028	0.071	-0.076	0.358	1		
Data effectiveness	0.040	0.212	-0.082	-0.035	0.218	1	
Decision quality	0.028	0.097	-0.005	-0.057	0.040	0.670	1

Since the main purpose of this research is to test the impact of the three core constructs, data, knowledge and their fit, on decision performance, this part of the model was first analyzed. To examine the main effect of data effectiveness and knowledge effectiveness, linear regression analysis was applied. The result shows that both data effectiveness (β=.10, t=11.40) and knowledge effectiveness (β=-.02, t=-1.83) are significant; nevertheless, the direction of the impact of knowledge effectiveness is opposite to the expectation, which does not support H2. This is interpreted based on the fact that knowledge is mediated by data effectiveness (i.e., H4), so that its main effect may be partialed out by data effectiveness. Nevertheless, as this main effect is only marginally significant, it is dropped from further analysis. The interaction between data and knowledge, i.e., the data-knowledge fit measure, is added to the regression model. The result shows that both data (β=.11, t=11.50) and fit (β=.02, t=2.21) are significant at .05 level, supporting both H1 and H3. The removal of the knowledge effectiveness variable only reduced the variance explained (R^2) of the performance measure by 1%, from 47.6% to 46.6%.

With the main effect and the interaction term determined, the whole model was then analyzed using path analysis. The preliminary results show that neither task complexity nor suggestive guidance is significant. For task complexity, the path coefficients with data effectiveness, knowledge effectiveness, and data-knowledge fit are .05 (t=.57), -.01 (t=-.06) and -.10 (t=-1.5) respectively, rejecting H7. For suggestive guidance, the path coefficient with knowledge effectiveness is -.08 (t=-1.04), rejecting H6. There paths were excluded from the next rounds of model testing. With the non-significant paths removed, the reduced model was tested again, and the results are shown in Figure 2.4. The reduced model shows that both informative guidance (β=.21, t=3.05) and general knowledge (β=.36, t=5.30) are significant at .01 level, supporting H5 and H8. Additionally, the path between knowledge effectiveness and data effectiveness is also significant (β=.25, t=3.27) at .01 level, supporting H4. The path model further supports H1 and H3.

Figure 2.4 Test of the research model



2.6 Discussions

In this research, an illustration of the KBI theory is provided based on the computer-aided decision-making context. It shows the operationalization of the theory and its constructs in the particular IS application area. Based on the theory, an integrative model was developed to resolve the conflicts in previous understanding of the performance impact of DSS. This model analyzes the impact of data, knowledge, and their fit on decision quality, and also the impact of several selected antecedents associated with DSS, decision-makers, and decision task. Of the factors analyzed, it is found that data effectiveness and data-knowledge fit both have direct impact on information and decision quality, although the impact of knowledge effectiveness is mediated by data effectiveness. It also found empirical evidence of the impact of informative guidance and general knowledge in the decision process. The results suggest that the model has the promise of aggregating various research perspectives in the DSS field in order to make consistent progress for both research and practice. Since the purpose of this essay is to provide an illustration of the KBI theory in the computer-aided decision-making context, the implications for IS research and practice are therefore discussed from these two aspects.

2.6.1 Implications for the KBI theory

This research is the first to empirically test the relationship between data, knowledge, and information in the IS application context. It depicts the process through which information is produced from data and knowledge in computer-aided decision-making. With the existence of multiple competing models of the relationship between these three constructs, as discussed in Essay 1, the empirical evidence supports the position that information is the joint function of data and knowledge. This is of fundamental importance to IS scholars who perceive Information Systems as systems that convert data to information. Specifically, it calls for the attention to the knowledge dimension when analyzing the production of information from data.

Since information is based on data and knowledge, and data is also a function of knowledge, it yields a quadratic relationship between information and knowledge, shown as these:

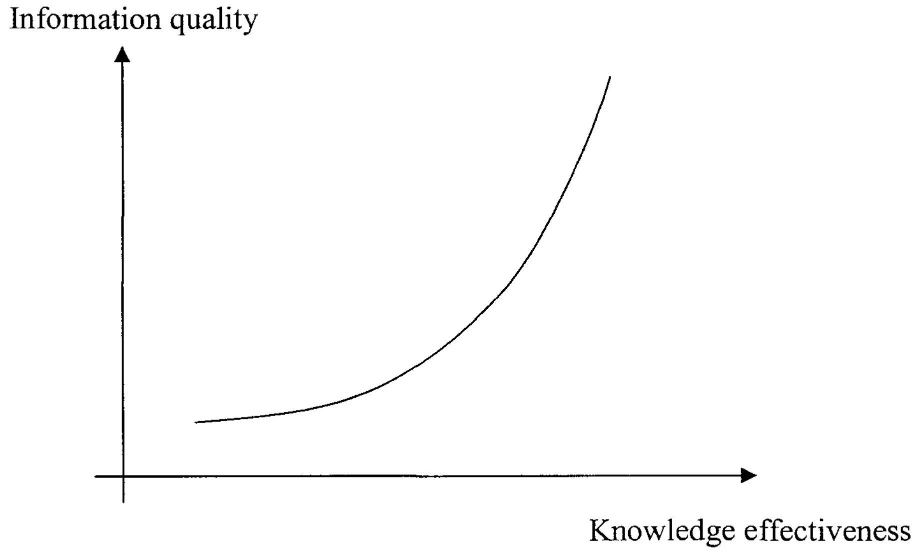
Given: $Information = a_0 + a_1{*}Data + a_2{*}Knowledge{*}Data + error$, and

$Data = c_0 + c_1{*}Knowledge + error$

It has: $Information = b_0 + b_1{*}Knowledge + b_2{*}Knowledge^2 + error$

Here a_i, b_i and c_i refer to the coefficients of the constructs. It is noted that these equations are not strictly mathematical formulas, but symbolic representations of the relationship between the constructs. Figure 2.5 depicts the relationship between information and knowledge in the last equation. It suggests that the impact of knowledge on information accelerates as knowledge effectiveness improves. Such an accelerating effect is caused by the application of knowledge in data collection and processing, which further improves information quality. This has practical value for companies that are interested in building data warehouses to produce information for decision. It implies that data quality is not only a data issue that may be solved by data modeling technologies, such as data extraction, transformation, and loading (i.e., ETL); quite often, it is a matter of how the data can be analyzed via high quality knowledge. This warns the companies that have launched the data warehousing projects from a pure technical perspective to focus more on organizational and managerial issues.

Figure 2.5 A quadratic relationship between information and knowledge



The interaction between data and knowledge in information processing is fundamental to IS research and practice. It is observed that the IS field has shifted from data processing to information processing in order to better serve the IS users' demand. This has been followed by the proliferation of the IS field since 1970s. In the recent decade, scholars began to pay attention to the Knowledge Management issues, hoping to further improve the IS payoffs (Alavi and Leidner, 2001). Such effort, however, may not result in additional IS value without a correct understanding of where knowledge fits in information processing and IS applications. The KBI theory therefore helps solve the problem, suggesting that knowledge should be treated as the second antecedent of information rather than its output, in contrast to the conclusion of some KM scholars (e.g., Nonaka, 1994).

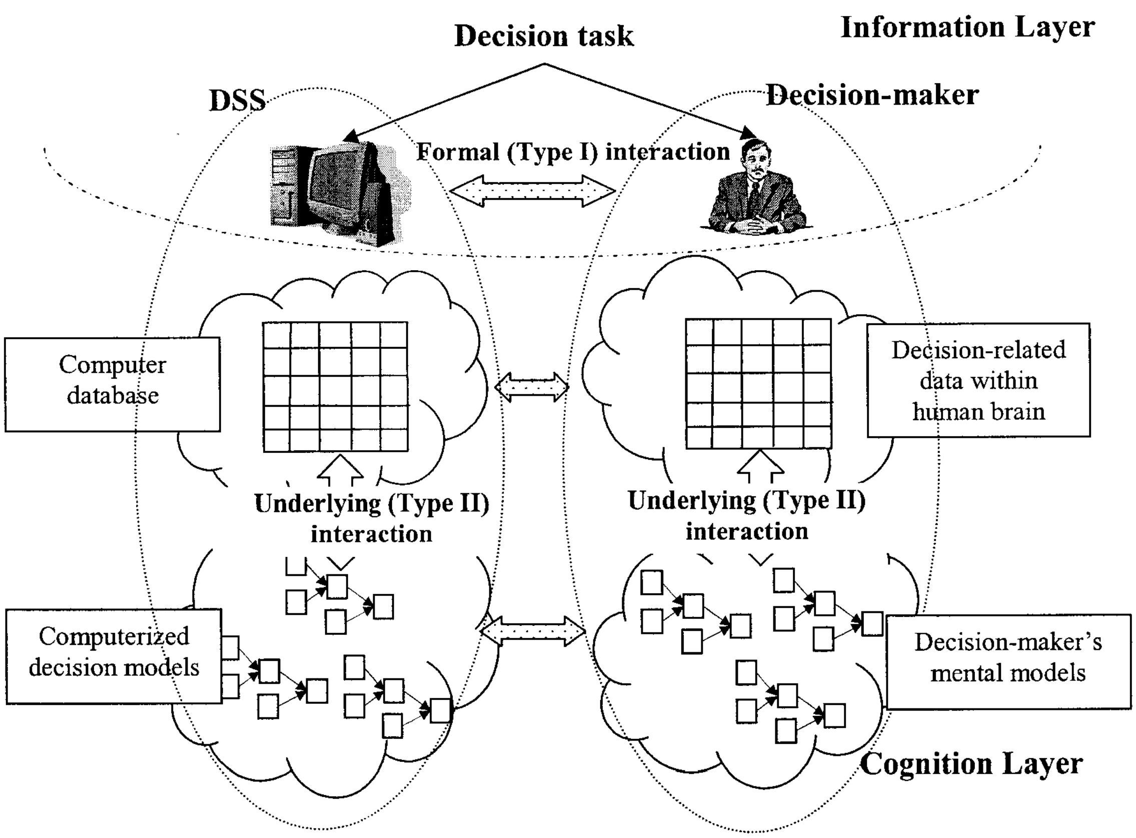
2.6.2 Implications for the DSS field

For DSS researchers and designers, this study provides a deeper understanding of computer-aided decision-making and its relationship with the DSS architecture. The result shows that decision quality is directly determined by data, knowledge, and their fit, from which information is produced to support the decision. Other factors, such as DSS functionalities, decision-maker's attributes, and task characteristics, have indirect impact on decision performance. This is different from previous studies that assume the direct impact of these factors. The clarification between the direct factors and indirect factors in computer-aided decision-making has implication for further DSS research and practice.

Based on the distinction, factors that influence decision performance can be aggregated to two layers: an *information layer* of the direct factors, which constitutes the logical process through which information is produced for a decision, and a *cognition layer* of the indirect factors, which covers the interaction between DSS, decision-makers, and task environment. Their relationship is that factors on the cognition layer performs the cognitive functions of identifying data and knowledge for the production of information on the information layer. Such relationship is shown in Figure 2.6.

Improvement in the decision performance of computer-aided decision-making is indebted to the interaction between decision-makers and DSS capabilities, or more specifically, the exchange of supplementary information-processing capabilities between humans and computers in a decision context. Since DSS is the embodiment of human knowledge applied to process data, this type of interaction is actually the exchange of decision knowledge and decision data between DSS and decision-makers. It may be called a "Type I Interaction", or a formal interaction between decision-makers and DSS capabilities. This type of interaction, as shown in Figure 2.6, is the focus of the behavioral school of DSS research.

Figure 2.6 A dual-layer architecture of computer-aided decision-making



In addition to the formal interaction, another type of interaction is also observed, i.e., the interaction between decision data and decision knowledge. For instance, classification is a typical decision-making task, where an alternative is to be assigned to a particular category (Kiang, 2003). There exist many different classification models, and different models applied to the same data set will produce different classification results. Therefore, to make a good decision, not only data but also the decision model (or knowledge) should be correctly selected, the interaction of which determines the quality of information produced and also the decision made. This type of interaction may be called a “Type II Interaction”.

The relationship between Type I and Type II interactions is this: the Type I interaction facilitates the fulfillment of the Type II interaction by providing needed data and knowledge, and the Type II interaction determines the performance of the Type I interaction. That is to say, the decision performance of computer-aided decision-making is determined by how data, knowledge, and their interaction can be improved with the aid of DSS, compared to an unaided decision. If the use of DSS were to save cognitive effort only, then expected decision quality may not happen. Therefore, both types of interaction should be considered to achieve a better performance of computer-aided decision-making.

The awareness of the dual-layer architecture implies that the underlying decision process, i.e., what data is used and how the decision is made, should be made transparent to the decision-makers who are responsible for the improvement or deterioration in the decision performance. Detailed explanations of the data and knowledge applied in the decision process should be provided to the decision-makers in order to mitigate the “illusion of control” (Davis and Kottemann, 1994). This requires the DSS developers to add such features in the design in order to actually improve decision performance.

2.6.3 Limitations and future research directions

Several limitations exist in this research. First, the measurement of data effectiveness, knowledge effectiveness, and their fit lacks generalizability to other decision contexts and other information processes. This happens because an objective measurement approach is undertaken in this research, which demands an accurate account of what data and knowledge are used in a particular context. Such an objective approach to measuring knowledge and data is not very popular in contemporary IS research, which has been dominated by subjective assessments based on IS users' perceptions. Although some perception-based scales, such as the data quality measures developed by Wang and Strong (1996), can be used as alternatives, more advanced objective measures could be developed for more generalizable research.

The second limitation is the selection of the dependent variable: in addition to decision quality, some other performance indicators have been analyzed in DSS research, such as learning and satisfaction (Parikh et al, 2001). Although decision quality is the most critical concern in decision-making, other indicators are also pertinent to the DSS users. Those factors could be added to the research model in further studies.

The third limitation is related to the research design. The task complexity construct, for example, was not significant in the current research. A possible reason is that its impact might be contingent on some other factors not included in this research, such as interruption during decision (Speier et al, 2003). Another reason is that the two task settings, i.e., production of one type of computer versus production of two types, may not be distinct enough. Although theoretically the latter has more information cues than the former, and is therefore more complex, in practice such difference may not yield significant results. One approach, as some researchers have used (e.g., Speier et al, 2003), is to employ totally different decision tasks.

Finally, many other factors that have been analyzed in DSS research were not included in the current study. The reasons have been explained above; nevertheless, those factors should be included in further research in order to develop a more comprehensive understanding of DSS.

Appendix 2.1: Overview of cognitive fit-based research.

Literature	Research purpose	Decision tasks	Experimental settings	Findings
Dennis and Carte (1998)	Extending CFT to the geographic task context.	Determining the area with the greatest business potential.	Two different types of information presentation (i.e., map-based vs. tabular) and two map-based tasks (i.e., geographical containment vs. geographical adjacency).	Differences exist between various types of map-based tasks with the same map-based representation: decision-makers with geographic adjacency tasks require less time and make more accurate decisions than those using the tabular representation; in contrast, decision-makers with geographic containment tasks require less time but make less accurate decisions than those using the tabular representation.
Dull and Tegarden (1999)	Investigating the relationship between visual representations of data and decision performance.	Making predictions based on multidimentional (e.g., wealth, momentum, and impulse) accounting data.	Three visual representations of the data: 2-D, 3-D fixed, and 3-D rotatable.	Subjects using the 3-D data that can be rotated provide the most accurate predictions.
Dunn and Grabski (2001)	Providing additional evidence of how cognitive fit works with the concept of localization.	Answering questions of how to obtain data from accounting information systems for a set of accounting tasks.	Two accounting models, i.e., debit-credit-account and resource-events-agents.	Localization of relevant objects or linkages is important in establishing cognitive fit.

Frownfelter-Lohyke (1998)	Identifying the most useful format of information presentation via the investigation of multiple influential issues.	Predicting the financial performance of a firm.	Three presentations (tables, graphs, and their combination) and two tasks (symbolic and spatial).	The presentation format predicted to support each task does not significantly affect accuracy; however, the combination format is superior to the graphical format when controlling for task type.
Mahoney et al (2003)	Investigating the effects of decision guidance and cognitive ability on decision-making.	Predicting the financial status of companies.	Two task types (spatial and symbolic) and two question types (spatial and symbolic).	Cognitive fit improves decision accuracy and reduces the decision time; field dependency is an additional factor in determining performance.
Speier and Morris (2003)	Analyzing the influence of query interface design on decision-making performance under data warehousing context.	Simulating a real estate acquisition decision of home-finding.	Two query interfaces (text-based vs. visual), two levels of task complexity (low vs. high) and two levels of spatial ability (low vs. high).	Decision performance based on the text-based interface is more accurate when task complexity is low; when task complexity is high, decision-makers using the visual interface perform better.
Tuttle and Kershaw (1998)	Investigating the relationship between information presentation and judgment strategies and the applicability of CFT to the selection of judgment strategies.	Performance evaluation on plant managers.	Two presentation modes (graph vs. table) and two judgment strategies (holistic vs. analytic) are manipulated.	With a holistic judgment strategy, judgment accuracy is greater for graphs than for tables, which confirms to CFT; however, with an analytic judgment strategy, there is no significant difference in judgment accuracy between graphs and tables.

Umanath and Vessey (1994)	Assessing the ability of CFT to explain the performance of certain display formats on multiattribute judgment tasks.	Making bankruptcy prediction.	Three information presentation formats (schematic faces, graphs and tables), each with two levels of information load.	Decision accuracy with graphs is higher, and accuracy increases with higher information load.
Wright (1995)	Testing the effect of incremental availability of graph on financial judgment performance.	Evaluating a hypothetical loan to a vendor.	A set of financial judgment tasks and graph vs. tabular presentations.	When information acquisition and mental integration demand is high, availability of graphs (table plus graphs) results in better judgment performance (lower bias and less error); however, when much simpler information integration is required, the incremental effect of graphs is trivial.

Appendix 2.2: Overview of decision guidance/system restrictiveness-based research

Literature	Research purpose	Decision tasks	Experimental settings	Findings
Wilson and Zigurs (1999)	Studying the impact of decision guidance on display preferences and decision performance.	Selecting (guided or non-guided) a display format and comparing the financial status of a company.	Three levels of display choices (user preference, guided assignment, and random assignment) and two types of task (symbolic and spatial).	Guided display results in higher accuracy of problem-solving, and subjects perform no better with their preferred display than with a randomly assigned display for spatial tasks.
Montazemi et al (1996)	Analyzing the impact of suggestive guidance (SG) and informative guidance (IG) on problem formulation.	Assessing the financial status of a company and developing recommendations to senior managers.	Three treatments (DSS with SG, DSS with IG, and no DSS) and two task levels (complex vs. simple).	For less complex tasks, subjects using SG perform better than those using IG, and both outperform the subjects with no decision aid. For more complex tasks, IG-aided subjects perform the best; however, there is no significant difference between subjects using SG and those with no aids.
Jiang and Klein (2000)	Testing the side effect of decision guidance on decision model selection.	Making decision via selecting a suitable forecasting model.	Two types of guidance (information vs. suggestive) and four different forecasting models.	An increase in guidance provided by the system leads to a significant change in the decision model selected.

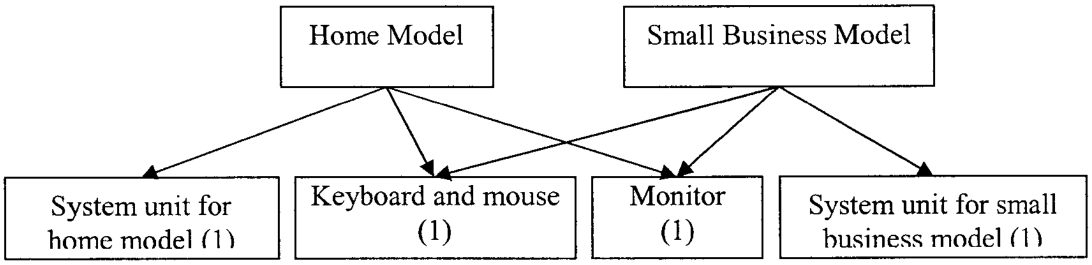
Parikh et al (2001)	Empirically testing the effectiveness of decision guidance.	Examining a historical data set, evaluating several forecasting models, and choosing the most appropriate model.	Four types of decision guidance (deliberate, suggestive, informative, and dynamic) and four criteria (decision quality, user satisfaction, user learning, and efficiency).	Deliberate decision guidance is more effective on all four criteria. Suggestive decision guidance is more effective in improving decision quality and user satisfaction. Informative guidance is more effective in user learning about the problem domain. And dynamic guidance is more effective than predefined guidance in improving decision quality and user learning.
Wheeler and Valacich (1996)	Testing the effectives of facilitation, system configuration and training on group decision performance.	"Hidden-profile tasks".	Facilitation, system configuration and training each having two levels.	These factors significantly impact the faithful adoption of anticipated decision techniques.
Limayem and DeSanctis (2000)	Examining the impact of decision guidance on group decision-making.	Fund allocation.	A single experimental setting.	System explanations at breakpoints in group interaction improve perceived decision quality and other performance indicators.

Appendix 2.3: Introduction to experiment

Production Planning Using Excel Spreadsheets

As a student of the Operations Management course, you may have learned the basic concepts of production planning and scheduling. You can see that production planning is a complicated task with many factors to consider, such as customer demand, inventory, cost, and labor hours. In industry, many companies use computers to support production planning; some use Excel spreadsheet based solutions. In this exercise, you have a chance to play with a simple production planning system developed with Excel. This tutorial introduces you to the concepts and procedures of production planning needed for this system.

Assume that you are working for a local computer company, and your job is to manage the production schedule of several computer systems. As a planner, your target is to maximize the net income of the company by utilizing the available manufacturing resources to meet customer demand. Currently, your company produces two models of Personal Computers, namely Home Model and Small Business Model. The figure below shows the Bill of Material of both models; the numbers refer to the quantity of components needed. Notice that both share some common components (such as the monitor), but they require different system units. Both the assembly of the computer models and the production of the components require certain amounts of labor hours and material costs. Other constraints of the production process are temporarily not considered.



The production planning process is as follows. Usually at the beginning of each month, your company receives orders from customers for each computer model; these orders are split into each of the four weeks. You need to decide how many computers to assemble and how many components to produce in each week in order to meet the customer demand. To plan a schedule, you first develop a master production schedule (MPS), specifying how many computers to assemble in each week based on customer demand; then you develop a material requirement plan (MRP) for the manufacturing of the components needed for the assembly of the computers. In addition, since both the assembly of the computers and the manufacturing of the components need labor hours, you need to balance the MPS and the MRP with respect to both customer demand and available labor. If the labor hours are not sufficient for a week, overtime is automatically added, which is costly. You need to balance the production in order to use available labor hours while minimizing overtime.

The production planning system is composed of four main tables:

- Master Production Schedule (MPS): This table shows customer demand for each computer model in each week. (Notice that it could happen that only one computer model is ordered.) It also shows the inventory level of each model at the end of each week. If you produce more PCs in a week than customer demand, the extra amount will be held in the inventory and used in the next week; if a negative inventory appears, it means you did not produce enough computers and you will lose revenue. Note that negative inventory only means a shortage in computers produced, but in reality there is no inventory. Also note that backordering is not allowed in this exercise.

- Material Requirement Plan (MRP): This table shows the components needed to produce the PCs in the master schedule. The number of components needed (i.e., material demand) is determined by the production in the MPS: the more PCs you produce in a week, the more components needed for that week. If more components are produced than needed, they will be held in the inventory and used in the next week. Remember: You may utilize inventory to adjust the production capacity, but do not hold any inventory at the end of the month (i.e., in Week 4), assuming no further customer demand.
- Labor hour requirement table: This table shows the labor hour requirements for the assembly of the computers and the manufacturing of the components. If the available labor hours are lower than the total requirement, overtime is added to meet the shortage, which incurs higher labor fees and reduces net income.
- The Net income analysis table shows the estimated revenue, cost, and net income based on the production plan. The revenue is determined by how many PCs you can actually deliver to the customers; therefore, you need to meet the customer demand if possible (in MPS table). In addition, the actual delivery of the PCs is also restricted by component availability, so that you need to make sure that sufficient numbers of components are available to assemble the PCs. These numbers are calculated by the

system.

The production planning tool helps you to make the decision by showing you all the necessary information. To utilize the information provided and make a good decision, consider the following tips:

- Since the available labor hours are limited and overtime is costly, you need to utilize available labor hours as much as possible. To do so, you can shift the production of PCs and components ahead of time where the customer demand is low.
- In the MPS table and the MRP table, try to keep the ending inventory of Week 4 as low as possible (i.e., close to zero).
- The amount of PCs to be produced in the MPS table determines the demand for the components; on the other hand, the amount of components produced will restrict the amount of PCs to be assembled and delivered. Therefore, you need to balance the component demand and availability of those components.
- You do not need to use other Excel features to finish the task. Just manually adjust the numbers based on your understanding. There may not be an optimal solution, but some are better than others. Try to adjust the plan and increase net income as much as possible.

Note that you will be randomly assigned to different groups for the exercise, and some may receive additional guidance. Such guidance is used to test the functionality of the system for further improvement. If you receive such guidance, please follow it; otherwise, perform the required tasks by yourself. All concepts will be explained in class.

Appendix 2.4: Screenshot of the experimental system

Master Production Schedule		Week 1	Week 2	Week 3	Week 4
Home Model	Customer demand	30	50	70	40
	Production				
	Ending inventory	-30	-80	-150	-190
Small Business Model	Customer demand	30	40	30	30
	Production				
	Ending inventory	-30	-70	-100	-130

Material Requirement Plan		Week 1	Week 2	Week 3	Week 4
Keyboard and mouse	Material demand	0	0	0	0
	Production				
	Ending inventory	0	0	0	0
Monitor	Material demand	0	0	0	0
	Production				
	Ending inventory	0	0	0	0
System unit for Home Model	Material demand	0	0	0	0
	Production				
	Ending inventory	0	0	0	0
Systems unit for Small Business Model	Material demand	0	0	0	0
	Production				
	Ending inventory	0	0	0	0

Net Income Analysis		
Estimated revenue:	$0.00	
Material and inventory cost:	0.00	
Labor fees:	13,000.00	Net income of
Estimated total cost:	13,000.00	the previous plan
Estimated net income:	**-$13,000.00**	$0.00

Labor hour requirement	Week 1	Week 2	Week 3	Week 4
Master production	0	0	0	0
Material production	0	0	0	0
Total requirement	0	0	0	0
Currently Available	130	130	130	130
Overtime needed	0	0	0	0

Follow these steps when you modify the production plan:
1 Adjust the Master Production Schedule first to meet customer demand while minimizing overtime and/or inventory holding cost.
2 Then adjust the Material Requirement Plan to meet the material demand while minimizing overtime and/or inventory holding cost.
3 Repeat the above two steps to further reduce cost.
4 Make sure that in each table, the demand (customer demand or material demand) can be fulfilled by production and available inventory.
5 Keep a zero inventory at the end of Week 4.

No other suggestions.

Appendix 2.5: Measurement of general knowledge

1. The aggregate planning problem _____:
   A) Is narrow in nature
   B) Only affects marketing and production
   C) Is solved using either demand influencing variables or supply influencing variables
   D) Needs to consider multiple tradeoffs such as customer service level, inventory levels, labor force stability, and costs

2. Which of the following statement(s) best describes aggregate planning ____?
   A) Aggregate planning is concerned with matching supply and demand of output.
   B) Aggregate planning determines not only the output levels planned but also the appropriate resource input mix to be used.
   C) The aim of aggregate planning is to set overall output levels in the long-term future in the face of fluctuating or uncertain demand.
   D) All of the above

3. Inventory level is influenced by _____ :
   A) On-hand inventory
   B) Gross requirement
   C) Scheduled receipts
   D) All of the above

4. Production costs do not include ______ :
   A) hiring and layoff costs
   B) overtime and undertime costs
   C) part-time labor costs
   D) inventory ordering costs

5. Which of the following relationships between projected inventory at the end of this week (Y), inventory from the last week (W), production in this week (X), and requirement in this week (Z) is correct? _____
   A) Y=W+X-Z
   B) Y=W+X+Z
   C) Y=W-X-Z
   D) Y=W-X+Z

6. Which of the following options is used for short- or medium-range labor adjustment? _____
   A) Overtime and undertime
   B) Subcontracting
   C) Layoff
   D) None of the above

7. Which of the following statement(s) about overtime is correct? _______

A) Overtime is used when the changes in demand is considered temporary.
B) The overtime cost often consists of regular wages plus a 50 to 100 percent premium.
C) Because of the high cost, managers are sometimes reluctant to use overtime.
D) All of the above.

8. The bill of materials ______:
A) shows how much inventory is available.
B) is a bill sent to the customer for material ordered.
C) is a list of all materials required to produce a product.
D) none of the above.

9. Which of the following statement is true about MRP (material requirement planning)? ______
A) forecast is based on past demand
B) lot sizing is EOQ
C) demand pattern is random
D) objective is to meet manufacturing needs

10. The benefit of MRP includes _______:
A) MRP calculates the dependent demand of components from the production schedule of their parent, thereby providing a better forecast of components requirement.
B) MRP systems provide managers with information useful for planning capacities and estimating financial requirements.
C) MRP systems automatically update the dependent demand and inventory replenishment schedules of components when the production schedules change.
D) All of the above

Appendix 2.6: Measurement of knowledge effectiveness

____ 1. In Week 1, the customers' demand on home computers is 30 units; suppose the company decided to produce only 20 units, how much inventory would the company actually have at the end of this week?

a. 20 b. -10
c. 10 d. 0

____ 2. In Week 4, the customers' demand on home computers is 30 units; suppose the inventory from previous week were 10 units, how many computers should the company produce to meet the demand and have a zero inventory?

a. 10 b. 20
c. 30 d. 40

Question 3 and Question 4 are based on this table:

	Week 1	Week 2	Week 3	Week 4
Customer demand	40	50	40	40
Production	40	50	35	40

____ 3. What might be a problem in the current production plan?
a. There is extra inventory at the end of this month.
b. The customer's demand in Week 3 cannot be fulfilled.
c. This plan cannot be fulfilled due to components shortage.
d. There is no problem in this plan.

____ 4. Based on the current production plan, if the production in Week 2 increases, what does not change?
a. Demand on monitor in Week 2
b. Demand on keyboard and mouse in Week 2.
c. Inventory level at the end of Week 2.
d. The inventory from Week 1.

____ 5. Which of the following has a direct impact on labor hour requirement?
a. Changes in customer demand
b. Changes in production amount
c. Changes in material requirement
d. Inventory levels.

Question 6 and question 7 are based on this table:

	Week 1	Week 2	Week 3	Week 4
Total requirement	122	138.5	136	122
Currently Available	130	130	130	130
Overtime needed	0	8.5	6	0

____ 6. IF you see the above labor hour requirement table, what do you think would be the best solution?

a. Keep the current plan.
b. Adjust the plan so that more products can be produced in Week 1.
c. Adjust the plan so that more products can be produced in Week 4.
d. Produce more PCs in Week 2 than in Week 3.

____ 7. Based on the above table, if you decides to produce more computers in Week 1 in order to cut overtime in Week 2, which of the following statement would be true?

a. The demand on keyboards, mice, and monitors in Week 1 would increase.
b. The production of keyboards, mice, and monitors in Week 1 should increase.
c. The production of keyboards, mice, and monitors in Week 2 should decrease.
d. All of the above.

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