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# An empirical investigation of factors influencing the adoption of data mining tools

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ABSTRACT

Previous studies explored the adoption of various information technologies. However, there is little empirical research on factors influencing the adoption of data mining tools (DMTs), particularly at an individual level. This study investigates how users perceive and adopt DMTs to broaden practical knowledge for the business intelligence community. First, this study develops a theoretical model based on the Technology Acceptance Model 3, and then examines its perceived usefulness, perceived ease of use, and its ability to explain users' intentions to use DMTs. The model's determinants include 4 categories: the task-oriented dimension (job relevance, output quality, result demonstrability, response time, and format), control beliefs (computer self-efficacy and perceptions of external control), emotion (computer anxiety), and intrinsic motivation (computer playfulness). This study also surveys the moderating effect of experience and output quality on the determinants of DMT adoption and use. An empirical study involving 206 DMT users was conducted to evaluate the model using structural equation modeling. Results demonstrate that the proposed model explains 58% of the variance. The findings of this study have interesting implications with respect to DMT adoption, both for researchers and practitioners.


## 1. Introduction

With the issue of globalization becoming increasingly widespread, global competition among enterprises to profit is fiercer now than it has been in the past. To face the challenges arising globally, more managers are using information technology (IT) and information systems (IS) in business. This allows them to be more efficient and accurate when acquiring information or making decisions. According to a Gartner report (Gartner, 2011a), worldwide enterprise IT spending is projected to total $2.7 trillion dollars in 2012, a 3.9% increase from 2011. Data warehousing technology is one of the paramount investments in establishing IT infrastructure (Gartner, 2011b), enabling enterprises to collect and store vast amounts of data. These data can be extracted and analyzed by data analytics, helping managers find better ways to generate value and compete in the marketplace (Goeke & Faley, 2007; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). A report by Gartner (2011c) lists data (next-generation) analytics as one of the top 10 strategic technologies. Data analytics has been successfully used in many fields, such as insurance (Hopkins & Brokaw, 2011), e-commerce (Kohavi, Rothleder, & Simoudis, 2002), health care fraud (LaValle, Hopkins, Lesser, Shockley, & Kruschwitz, 2010), and e-retailing (LaValle et al., 2010). Data analytics has had significant effects on both operational and strategic dimensions in enterprises (Davenport & Harris, 2007).

For enterprises, data mining (DM) is a data analysis technology that is widely applicable to a variety of businesses, including sales, marketing, and customer relations (Davenport & Harris, 2007; Jackson, 2002; Kohavi et al., 2002). Software companies have integrated DM functions and launched data mining tools (DMTs) in markets to assist users (consumers of DMT outputs) perform data analysis. DMT can be used to predict future trends and behaviors from historical data, allowing businesses to make proactive, knowledge-driven decisions (Sharma, Goyal, & Mittal, 2008). Managers can use DMTs to spot sales trends, develop smarter marketing campaigns, and accurately predict customer loyalty (Rygielski, Wang, & Yen, 2002; Sumathi & Sivanandam, 2006). Therefore, DMT achieves the goals of improving customer service, building long-term customer relationships, reducing marketing costs, and increasing sales (Hui & Jha, 2000; Nemati & Barko, 2002; Rygielski et al., 2002; Shaw, Subramaniam, Tan, & Welge, 2001).

In previous studies on DMT, computer science and information engineering scholars have developed various algorithms to improve the efficiency of DMT (Han & Kamber, 2006). Davenport and Harris (2007) and LaValle et al. (2010) argued that the critical determinant of successfully using data analytics is to reduce

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the gap between human beings and technologies, and not just to enhance the latter functions. Hence, users like to use DMTs because it offers a variety of functions and good algorithmic performances, improves task performances, and decreases managerial costs, i.e., increases effectiveness. The same idea appears in research on the task-technology fit (Goodhue & Thompson, 1995). Because enterprises have invested a substantial amount of funds into DMT applications, examining the factors that affect DMT users is a beneficial research topic. Dahlan, Ramayah, and Mei (2002) and Dahlan, Ramayah, and Koay (2002) addressed the readiness of telecommunication employees and the banking industry in adopting DM technologies. Chang, Chang, Lin, and Kao (2003) studied the adoption of DM techniques in the financial service industry using five characteristics: organizational size, organizational culture, attitude of data resource, style of decision-making, and competitiveness of the outside environment. Huang and Chou (2004) proposed an analytical model to explore the relationships influencing the stage of web mining adoption. Although prior studies investigate the adoption of DMT, they do so from the perspective of the firm (Chang et al., 2003; Dahlan, Ramayah, & Mei, 2002; Dahlan, Ramayah, & Koay, 2002; Huang & Chou, 2004). No studies investigate this issue at the individual level completely, as stated by Goodhue and Thompson (1995).

Researchers in the IT/IS domain have discussed the problems of individual adoption and acceptance using different theoretical formulations and constructs. The goal of these studies is to understand and explain the important factors affecting acceptance behavior and subsequent IT/IS usage. Fishbein and Ajzen (1975) developed a well-supported behavioral theory, called the theory of reasoned action (TRA), which describes the psychological determinants of behavior. In 1989, Davis and his colleagues proposed an extension of the TRA (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989), called the technology acceptance model (TAM). This model examines the mediating role of perceived usefulness and perceived ease of use in the relationships between system or individual characteristics (external variables) and probability of system use (an indicator of system success). To make the TAM more complete, Venkatesh and Bala (2008) integrated the models proposed by Venkatesh (2000) and Venkatesh and Davis (2000) and developed a comprehensive nomological network of IT adoption and use, called TAM3. TAM3 investigates the determinants of perceived usefulness and perceived ease of use, and discusses various interventions that can influence the known determinants of IT adoption and use. The findings and research agenda of Venkatesh and Bala (2008) provide important implications for IT implementation. Response time and format remain the major issues in the DM research community (Chen, Han, & Yu, 1996; Chung & Gray, 1999), and have been studied by computer science and information engineering scholars. According to previous studies on DMTs, two significant determinants primarily influence behavioral intention to use DMTs.

As mentioned previously, previous research fails to address the problem of behavioral intention to use DMTs. Because DMT is a type of decision tool for users, research on individual-level IT adoption is a particularly important path to understanding DMT usage. Therefore, this study proposes a comprehensive theoretical model based on TAM3 to address this issue. The findings of this study have significant implications for DMT implementation for researchers and practitioners.

The remainder of this paper is organized as follows. Section 2 reviews the literature on DM and TAM3. Section 3 discusses the research model and hypotheses, and Section 4 describes the research methodology. Section 5 presents the finding of analyzing the empirical data. Section 6 discusses the results and concludes the paper with contributions and implications, discussions of the limitations, and directions for future research.

## 2. Literature review

### 2.1. Data mining (DM) and data mining tools (DMTs)

The IT capabilities of both generating and collecting data have been increasing rapidly. The widespread use of barcodes in many commercial products and the computerization of many businesses and government transactions have provided us with huge amounts of data. This information is stored in the data warehouses of enterprises, where it can then be analyzed to transform insights into action (LaValle et al., 2011). Data mining (DM) is a data analysis technology that has seen widespread use (Jackson, 2002; Kohavi et al., 2002). DM extracts implicit, previously unknown, and potentially useful information from databases (Chen & Huang, 2008; Chen et al., 1996). It uses pattern recognition logic to identify trends in a sampling dataset and extrapolate that information against a larger data pool. Because DM first became available for business analytics, its development has become an important research field in academics (Chen et al., 1996; Chung & Gray, 1999).

Although the development of DM is available to businesses, DM algorithms such as Apriori, FP-growth, GSP, PrefixSpan, *k*-means, and C5 (Han & Kamber, 2006) must be implemented on workable programs by Java or C++, and are still not practical for end users. These programs are often executed by DM experts or researchers and not end users because (1) end users cannot understand program settings and (2) the program interface is not user friendly. Therefore, many companies and research institutes have developed DM software, i.e., data mining tools (DMTs), such as SPSS Clementine, XL Miner, and WEKA, and subsequently introduced them to the market. Three statements on DMTs are given as follows.

(1) Because DMTs perform data analysis and uncover important data patterns, they contribute greatly to business strategies, knowledge bases, and scientific and medical research (Han & Kamber, 2006).
(2) DMTs include software components and theories that automatically search for significant patterns or correlations in data (Greenberg, 2004).
(3) DMTs provide individuals and companies with the ability to gather large amounts of data and use it to make decisions on a particular user or groups of users (Wisegeek, 2011).

Based on the statements above, this study defines DMT from the Input-Processing-Output (IPO) perspective: software that allows users to input their required data-mining models and arguments and then perform the computation of the models. This software outputs implicit, previously unknown, and potentially useful information from databases by visualization. These outputs can assist individuals and companies in making decisions.

Very few studies discuss the adoption of DMTs. Dahlan, Ramayah, and Mei (2002) studied the readiness of telecommunication employees to adopt data mining technologies. They investigated the contextual factors in telecommunication organizations, and how these factors influence employees' data mining readiness index. Their theoretical framework was adapted from a model for building analytical capability (Davenport, Harris, Russell, De Long, & Jacobson, 2001), stating that the more analytically capable the individual, the higher the readiness. Dahlan, Ramayah, and Koay (2002) applied the same model to the banking industry. Chang et al. (2003) explored the effects of organizational attributes on the adoption of DMTs in the financial services industry. In addition, Huang and Chou (2004) focused on the web mining adoption of B2C firms in terms of organizational innovation. Their findings reveal that a firm's Internet strategy, business complexity, and internationalized strategy, along with competitive pressure, have an effect on the stage of web mining adoption. Though these studies

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suggest that organizational factors influence the adoption of DMTs, no empirical studies discuss the individual factors affecting DMT adoption. Therefore, this study proposes a theoretical model to predict and explain intention of using DMTs from a user's perspective.

### 2.2. The theoretical background of TAM3

Since its introduction by Davis (1989), the TAM has been used for predicting the acceptance, adoption, and use of IT. The TAM plays an important role in the field of IT adoption and has been applied extensively in subsequent research. However, more and more researchers are finding flaws in this model (e.g., the exclusion of significant variables). In response to this situation, Taylor and Todd (1995) added some significant determinants to the TAM. Venkatesh and Davis (2000) revised the original model and proposed an extended model of the technology acceptance model (referred to as TAM2). TAM2 can be separated into two parts: social influence and cognitive instrumental processes. Venkatesh and Davis suggested that social influence and cognitive instrumental processes are both significant factors affecting user acceptance. The former includes subjective norms, voluntariness, and images. The latter includes job relevance, output quality, result demonstrability, and perceived ease of use. Venkatesh and Davis conducted longitudinal research with three points of measurement (i.e., after initial training, one month later, and three month later) in four different organizations. TAM2, which was developed through two processes to explain individual intention toward using IT, indicates that these important determinants affect perceived usefulness.

Venkatesh (2000) subsequently proposed the determinants of perceived ease of use to foster user acceptance and usage. Venkatesh's research model uses three different constructs (control, intrinsic motivation, and emotion) as general anchors that change into adjustments (perceived enjoyment and objective usability) with increasing experience. To ensure the completeness of TAM and enhance the robustness of the model, TAM3 (Venkatesh & Bala, 2008) integrated the studies by Venkatesh (2000) and Venkatesh and Davis (2000) and explained user acceptance more deeply.

The TAM has been applied and investigated in many studies (Chang, 2010; Lin & Lu, 2000; Liao, Palvia, & Lin, 2006; Park, Roman, Lee, & Chung, 2009; Pontiggia & Virili, 2010; Teo, Lim, & Lai, 1999; Teo, 2001; Youngberg, Olsen, & Hauser, 2009) and continues to be explored by scholars. TAM3 synthesizes many previous studies on the TAM and proposes a theoretical framework to explain user acceptance more deeply. In this model, there are four types of constructs (individual differences, system characteristics, social influence, and facilitating conditions) that influence perceived usefulness and perceived ease of use. Longitudinal studies have been conducted on TAM3, including surveys during three different periods (after initial training, one month after implementation, and three months after implementation). Because few studies mention the role of intervention by organizations in assisting managers make decisions on IT usage, TAM3 proposes a research agenda for intervention and indicates how it can affect individuals' behavioral intentions and acceptance. Through deliberate investigation and surveying, Venkatesh and Bala (2008) developed TAM3 to identify the factors and interventions that play roles in the TAM field. Järveläinen and Vahtera (2010) combined the Unified Theory of Acceptance and Use of Technology (UTAUT) with TAM3 to the acceptance of mobile systems.

Traditional information systems are generally used to make programmed decisions for organizational problem solving through formal (routine) information processing (Lyytinen, 1987; Varga, 2005). However, DMTs provide nonprogrammed decisions (Varga, 2005) and are capable of solving nonroutine problems through knowledge of the past (what has happened), the present (what is happening), and the future (what might happen) (Nemati & Barko, 2002). This approach bridges many technical areas, including databases, statistics, machine learning, and human-computer interaction (Pechenizkiy, Puuronen, & Tsymbal, 1998), making it more difficult to use than other IT (e.g., online shopping or online games) or types of application software (e.g., spreadsheets or word processors). Because of its complexity, it is increasingly complicated for users to make decisions on the adoption and acceptance of DMTs. Instead, users focus on utilitarian benefits such as performance and effectiveness (i.e., usefulness) (Rygielski et al., 2002; Shaw et al., 2001). Professional statistical software is a type of DMT. Designing DMTs to be easy to use is crucial to the success of DM technologies (Smith, Willis, & Brooks, 2000). Based on the discussion above, this study uses TAM3 to investigate the DMT usage because (1) TAM3 is an integrated model of the determinants of perceived usefulness and perceived ease of use and (2) TAM3 is a more comprehensive nomological network than the TAM. The issue of efficiency is also a concern in the field of DMT (Blockeel & Sebag, 2003). Therefore, this study considers the factors of response time and format. The following subsections explain why response time and format are contained in this model.

### 2.3. Response time

Response time is one of the achievement indicators for DMTs. The faster a DMT responds, the more efficient it is. The issue of response time has also been addressed in other types of systems. Bailey and Pearson (1983) analyzed computer users' satisfaction with computer tools. They interviewed 32 middle managers in eight different organizations and identified 39 factors of satisfaction. The 32 middle managers ranked these 39 important factors according to their level of importance, and included response time in the top 15 factors. Conklin, Gotterer, and Rickman (1982) conducted a set of experiments to determine the role of response time. They explored the response time of an online system by running various jobs in the background. Computer managers can use these results as a reference for making decisions when conducting such tasks. Researchers in the DM field have developed many approaches to improve the runtime of DM algorithms, such as FP-growth for mining association rules and PrefixSpan for mining sequential patterns (Han & Kamber, 2006). Because of these efforts, DMTs can be used to tackle higher time-complexity problems. Hence, response time is a significant factor influencing user beliefs and attitudes in using DMTs (Chen et al., 1996; Chung & Gray, 1999; Nelson, Todd, & Wixom, 2005).

### 2.4. Format

Hendrickson, Massey, and Cronan (1993) showed that an effective DM process requires the user in a data exploration process to combine his or her flexibility, creativity, and general knowledge with the enormous storage capacity and the computational logic of computers. DMT format design seeks to integrate users into the data exploration process. The basic idea of this approach is to present the results in a visual form that allows users to gain insight and generate conclusions. Format design reduces the users' cognitive work, allowing them to perform more specific tasks and gain more understanding. This concept is especially useful when a primitive idea is known but the goal of exploration is ambiguous. Because users are directly involved in this process, the goal of exploration must be modified according to their requirements. For example, managers would like to know which customers bring the greatest, average, or lowest profits to companies. Therefore, they can adjust DMT arguments by visualization to comprehend the outcomes from the different profit levels. Some studies in the

DM field use visual techniques to present mining results (Keim, 2001; Kreuseler & Schumann, 2002).

Nelson et al. (2005) proposed a measure of user satisfaction in the DM setting. Their study investigates 465 users from seven different organizations, indicating that user satisfaction is determined by format. Hence, this study treats format as a significant factor affecting user impressions of DMT through outlet designs; that is, if users think that the display is presented in a useful format, they have more positive beliefs on DMT.

## 3. Research model and hypotheses

Prior TAM studies show that user perceptions of usefulness and ease of use are the key determinants of individual technology adoption (Legris, Ingham, & Collerette, 2003). The TAM offers several advantages, including its basis in social psychology, parsimony, validity, and instrument reliability. Response time in the dimension of system quality and format in the dimension of information quality are two determinants of DMT adoption and use. This study develops a theoretical model based on the concepts of TAM3 to predict and explain the use of DMTs by individuals. These determinants are grouped into four categories based on previous studies (Venkatesh, 2000; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). These categories include the task-oriented dimension (job relevance, output quality, result demonstrability, response time, and format), control beliefs (computer self-efficacy and perceptions of external control), emotion (computer anxiety), and intrinsic motivation (computer playfulness). Two interventions, experience and output quality, are posited to influence the determinants of DMT adoption and use. Fig. 1 illustrates the research model.

Section 2 reviews previous studies related to DMTs and TAM3. Based on the findings of the studies discussed above, this study presents a research model and proposes the following hypotheses.

### *3.1. The task-oriented dimension*

According to TAM2 (Venkatesh & Davis, 2000), there are two major processes affecting the perceived usefulness of information systems: social influence (subjective norm, voluntariness, and image) and cognitive instrumental (job relevance, output quality, result demonstrability, and perceived ease of use) processes, respectively. This study overlooks the former because of the characteristics of DMTs. According to the decision-type classification proposed by Varga (2005), a data analysis technique can be used to make non-programmed decisions. Because executives and managers or knowledge workers typically make such decisions, they generally have greater freedom to decide whether DMT should be adopted in their work. Another system, data warehousing (DW), is similar to DMT. This type of system functions as a specially prepared repository of data created to support decision-making (Hartono, Santhanam, & Holsapple, 2007). Because DMT and DW have a similar characteristic, decision-support, this study reviews previous research related to the adoption of DW (Foshay, Mukherjee, & Taylor, 2007; Goeke & Faley, 2007; Gorla, 2003). Though these theoretical models are based on the TAM, they do not include social influence. These are two reasons why the proposed model does not include the former. Nevertheless, the latter is more important than the former. Therefore, this study considers the latter as a significant dimension for the use of DMT.

This study also proposes two essential determinants of DMT use: response time and format. The main reason why managers use DMTs is to administrate affairs or plan important strategies for their company. Time is so precious that it cannot be wasted arbitrarily. Therefore, response time is an important factor here, especially when using DMTs. Managers can find some useful information to enhance the performance of their work. They can also retrieve useful information if it can be well presented by DMTs. An understandable and interpretable outcome can help managers complete their tasks more easily. Consequently, format is the other significant factor in DMT usage.

*Job relevance.* Previous studies show that job relevance has an effect on users' perceived usefulness of information systems (Venkatesh & Davis, 2000). They indicate that job relevance is an individual's perception of the degree to which an information system is applicable to users' jobs. People use information systems to complete or attain some goals under normal situations. Goodhue and Thompson (1995) proposed the task-technology fit (TTF) theory, which is similar to job relevance in its discussion of user acceptance. This theory indicates that IT is more likely to have an effect on a user's performance and be used if its capabilities fit the tasks that the user must implement. DMTs are adopted in applications of information management, query processing, decision making, and process control, to discover task-specific knowledge from large databases (Chen et al., 1996). The mathematical models in DMTs, such as association rules, sequential patterns, classification, and clustering (Han & Kamber, 2006), can facilitate managerial tasks. DMT has been successfully applied in business, including sales marketing, finance, banking, and insurance (Sumathi & Sivanandam, 2006). Therefore, users must consider whether these capabilities are helpful to accomplishing their tasks by adopting DMTs. Therefore, this study hypothesizes the following:

**Hypothesis 1.** (H1) Job relevance is positively associated with the perceived usefulness of a DMT.

*Output quality.* Davis, Bagozzi, and Warshaw (1992) discussed the effects of output quality on perceived usefulness. They suggested that output quality is an essential factor in the use of IS. Output quality is "the degree to which an individual believes that the system performs his/her job tasks well" (Venkatesh & Davis, 2000). Venkatesh and Davis (2000) found that job relevance and output quality have an interactive effect on perceived usefulness. They omitted the main effects of job relevance and output quality because they could not be interpreted after including the interaction term. However, this study retains the direct effects of output quality and perceived usefulness. DMTs are applied to analyze the logic of data and reveal knowledge and trends. Output quality is an important requirement for DMTs. If DMTs produce higher output quality, users may feel that DMTs are helpful in completing their tasks. Hence, this study proposes the following hypotheses:

**Hypothesis 2a.** (H2a) Output quality is positively associated with the perceived usefulness of a DMT.

**Hypothesis 2b.** (H2b) Output quality positively moderates the relationship between the job relevance and perceived usefulness of a DMT.

*Result demonstrability.* Users notice if the results of IS can be discriminated easily when they use it. If users cannot grasp the system's characteristics easily, they are definitely unable to understand it. In other words, they do not realize how useful the system really is. Even a great system cannot be accepted by users if they have difficulty attributing their job performance to their use of the system (Venkatesh & Davis, 2000). Result demonstrability is "the tangibility of the results of using the innovation" (Moore & Benbasat, 1991). Users can get meaningful rules or find some previously undiscovered patterns by using a DMT, thus gradually enhancing the perception of its usefulness. However, the above condition works on the premise that they understand the advantages of using the DMT. Mining results can be interpreted by managers who formulate strategies in business. Therefore, it is

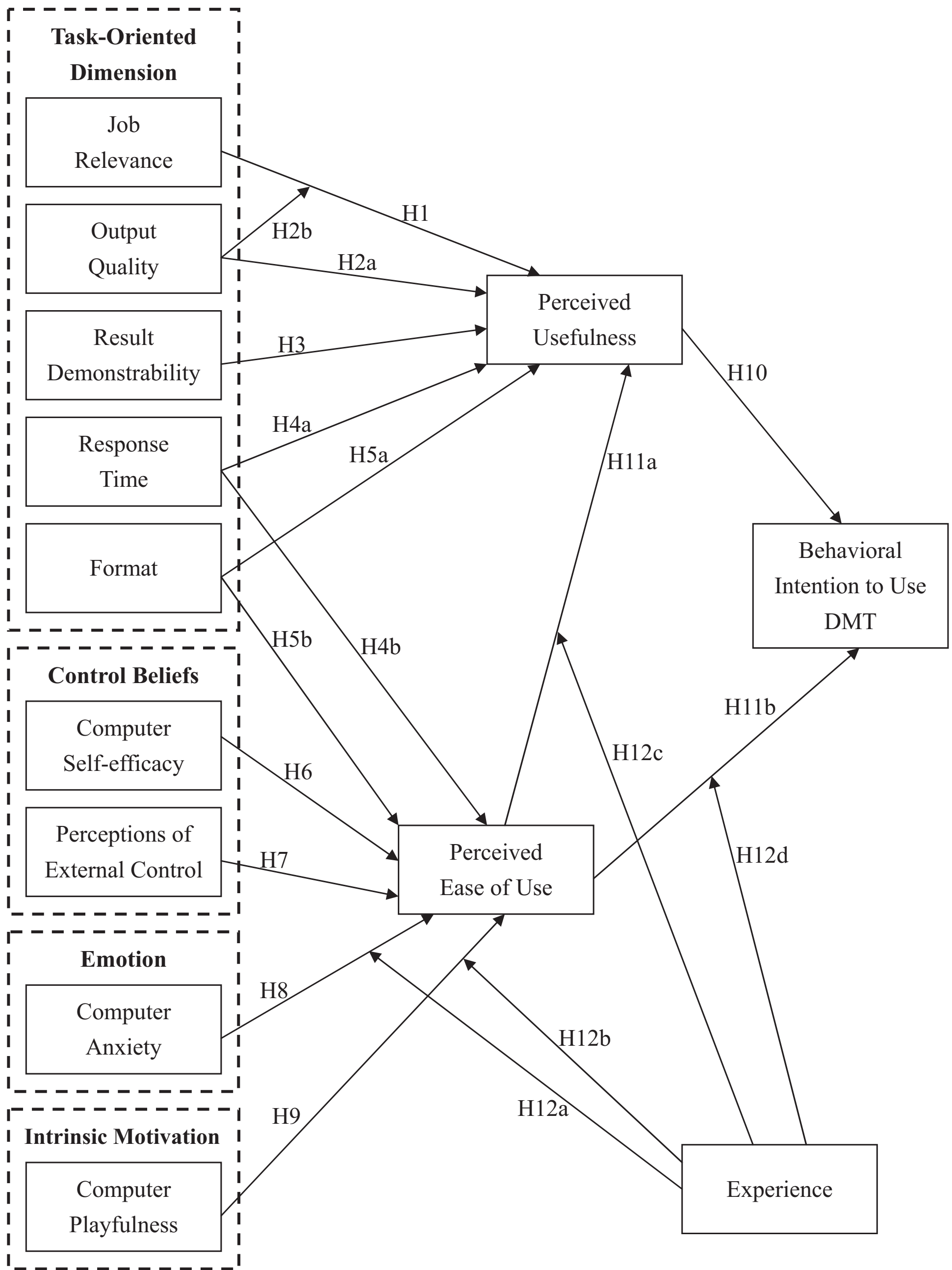


**Fig. 1.** The proposed research model and hypotheses.

important to understand the advantage of a tool thoroughly. As discussed above, this study hypothesizes the following:

**Hypothesis 3.** (H3) Result demonstrability is positively associated with the perceived usefulness of a DMT.

*Response time.* Nelson et al. (2005) defined response time as "the degree to which a system offers quick or timely responses to requests for information or action." This is the measurement of the performance of DM algorithms in discovering knowledge rules. When the amount of raw data is huge, it is necessary to devise more efficient algorithms to improve the runtimes of the mining process. Therefore, computer science and information engineering researchers have developed many approaches to address this problem (Han & Kamber, 2006). As mentioned by Kohavi et al. (2002), the time required to analyze data must be reduced to narrow the gap between the relevant analytics with DMTs and users' strategic business needs. As for intuitiveness, the quicker the runtimes of DMT are, the more likely it is that users perceive that the DMT is easy to use and useful. Therefore, this study hypothesizes the following:

**Hypothesis 4a.** (H4a) Response time is positively associated with the perceived usefulness of a DMT.

**Hypothesis 4b.** (H4b) Response time is positively associated with the perceived ease of use of a DMT.

*Format.* Format is "the degree to which information is presented in a manner that is understandable and interpretable to a user, and thus aids in the completion of a task" (Nelson et al., 2005). This is especially critical when assessing a decision-making and information-processing system such as a DMT. Information, in terms of patterns or rules, often provides many interesting results to users. However, it is difficult to identify valuable information

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directly. This is because a DMT is often designed for quantitative analysis, and lacks output that is translated into language and visualizations (Kohavi et al., 2002). A well-formatted design to present the outcomes of a DMT can create a virtual environment that allows users to understand the results and feel that they are useful. If users can easily operate the format functions of a DMT to show different presentations for the results, they feel that it is easy to use and helps them complete their tasks. This study hypothesizes the following:

**Hypothesis 5a.** (H5a) Format is positively associated with the perceived usefulness of a DMT.

**Hypothesis 5b.** (H5b) Format is positively associated with the perceived ease of use of a DMT.

### 3.2. Control beliefs, emotion, and intrinsic motivation

Venkatesh (2000) showed how to decide the determinants of perceived ease of use. That study presented and tested an anchoring (control, emotion, and intrinsic motivation) and adjustment-based (perceived enjoyment and objective usability) model of the determinants of system-specific perceived ease of use. In contrast to the current study, Venkatesh conducted a longitudinal study. Three different periods (post-training, one month post-implementation, and three months post-implementation) were conducted to measure the different effects of the determinants on perceived ease of use. In the current study, the main stress falls on the cross-sectional aspect. Therefore, the proposed model only tests one period, looking at users with different experiences of using DMTs. The anchors include internal control, external control, emotion, and intrinsic motivation. Internal control is conceptualized as computer self-efficacy, external control refers to facilitating conditions (perceptions of external control), emotion represents computer anxiety, and intrinsic motivation signifies computer playfulness. This study discusses these determinants and ascertains how they influence perceived ease of use for DMTs.

*Computer self-efficacy*. Control is regarded as an individual's perception of the availability of related knowledge, resources, support, or opportunities required to carry out a task or accomplish a specific purpose. Ajzen (1991) and Mathieson (1991) noted that control affects individual intentions and behavior. Venkatesh (2000) developed this idea further and reported that control is one of the important determinants of perceived ease of use, and can be separated into internal (computer self-efficacy) and external (perceptions of external control) controls. Computer self-efficacy is therefore "the degree to which an individual believes that he/she has the ability to perform a specific task or job using the computer" (Compeau & Higgins, 1995). Users prefer to use tools (e.g., DMTs) that they are capable of using. Because the successful operation of a DMT depends on computer-based skills, users dislike DMTs for which they lack related knowledge. The confidence of an individual's computer-based knowledge and abilities serve as the basis for his or her judgment on the level of difficulty for DMT usage. This reasonably leads to the following hypothesis:

**Hypothesis 6.** (H6) Computer self-efficacy is positively associated with the perceived ease of use of a DMT.

*Perceptions of external control.* Perceptions of external control (i.e., facilitating conditions) are the related resources or technical infrastructures in an organization that help people perform their jobs smoothly using the tools they believe in (Venkatesh, Morris, Davis, & Davis, 2003). In this case, external controls are more important factors, as they affect user beliefs that tools have highly effective skills or complicated characteristics (e.g., DMTs). For instance, the support of a consultant is a kind of resource (Harrison, Mykytyn, & Riemenschneider, 1997). This can help users solve technical problems related to tools, increasing the likelihood of their use. A DMT is a type of high-use-skill tool. As such, it is not easy to use without the appropriate support, training, and resources. Technical infrastructure is another key point related to DMTs. An organization must build the infrastructure of a data warehouse before executing DMT. Therefore, this study proposes the following hypothesis:

**Hypothesis 7.** (H7) Perceptions of external control are positively associated with the perceived ease of use of a DMT.

*Computer anxiety*. Computer anxiety is an emotion experienced by IT users. It is defined as "the degree of an individual's apprehension, or even fear, when he/she is faced with the possibility of using computers" (Venkatesh, 2000). Because DMTs are high-use-skill tools, users may encounter some troubles. They may feel anxiety, fearfulness, or misgivings because of their unfamiliarity with DMT usage. Because they do not know how to use a DMT initially, it may take a long time for them to learn and operate it. For managers, a new DMT may break the usual routine, and they must try to adapt to new work conditions. If users become familiar with the functionality of a DMT, they may reduce their initial feelings of anxiety. Some studies confirm that computer anxiety has an effect on behavior and performance (Anderson, 1996). Therefore, this study suggests that computer anxiety has a negative effect on beliefs on using a DMT. In other words, as computer anxiety increases, individual perception on the ease of use of a DMT decreases. Therefore, this study hypothesizes the following:

**Hypothesis 8.** (H8) Computer anxiety is negatively associated with the perceived ease of use of a DMT.

*Computer playfulness.* Motivation is a basic aspect for users, and is necessary to minimize their physical pain and maximize pleasure. Previous research indicates that motivation has a significant effect on behavior, and can be categorized as intrinsic and extrinsic motivation (Vallerand, 1997). Extrinsic motivation comes from outside users. Examples include rewards, money, or promotions. In contrast, intrinsic motivation comes from the user's inherent perceptions of enjoyment or love of a specific behavior or activity. Computer playfulness is a type of intrinsic motivation defined as "the degree of cognitive spontaneity in microcomputer interactions" (Webster & Martocchio, 1992). Users with a playful attitude experience more joy when using a DMT than those without playfulness. They usually enjoy the process of usage instead of simply using the DMT to accomplish tasks. For this reason, they generally concentrate their attention on using DMT and feel that DMT is easier to use. Thus, computer playfulness has a positive relationship with the ease of using a DMT. Therefore, this study hypothesizes the following:

**Hypothesis 9.** (H9) Computer playfulness is positively associated with the perceived ease of use of a DMT.

### 3.3. Constructs of the original TAM

Why do people use IT? A lot of research in this field examines the motives for using IT. The original TAM (Davis, 1989) has led to many follow-up investigations on this issue. Although the TAM is not without its flaws and has been criticized by many scholars, it is the foundation of the user acceptance model of IT. A number of studies present modified or extended TAM models that address the defects of the original TAM. A review of these studies reveals that both perceived usefulness and perceived ease of use are important beliefs associated with an individual's behavioral intention to use, or attitude toward using IT (Davis et al., 1989; Venkatesh & Davis, 2000). Thus, a DMT is essentially a complex problem-solving information system (Tejaswi, Prakash, Manaswi, Swarup Kumar, & Srinivas, 2010). As such, the intention to use a DMT can be explained by the TAM; that is, both perceived usefulness and perceived ease of use are indispensable factors affecting behavioral intention. The easier it is to use a DMT, the more useful an individual perceives that DMT to be. That is, an easy-to-use tool provides helpful guidance in doing jobs, and people feel that it is useful to use. Based on the statement above, this study hypothesizes the following:

**Hypothesis 10.** (H10) Perceived usefulness is positively associated with users' behavioral intentions to use a DMT.

**Hypothesis 11a.** (H11a) Perceived ease of use is positively associated with the perceived usefulness of a DMT.

**Hypothesis 11b.** (H11b) Perceived ease of use is positively associated with users' behavioral intentions to use a DMT.

### 3.4. The moderating variable: experience

To determine whether the experience moderator affects individual behavioral intention to use IT, some studies use longitudinal research to collect data from different periods (Venkatesh & Davis, 2000; Venkatesh et al., 2003). However, this study focuses on how many years an individual uses DMT, and therefore adopts a cross-sectional approach. This study treats the number of years spent using DMT as individual usage experiences. TAM3 (Venkatesh & Bala, 2008) shows how experience plays an important role in the moderating effect. This study follows a similar concept of experience but adopts a more suitable method of data collection. People usually become anxious when using DMT when they lack related experience, and feel that it is difficult to use a DMT. Increased experience decreases the effect of computer anxiety regarding the ease of use of a DMT.

The next change related to experience is computer playfulness. People with computer playfulness often enjoy the process of using a DMT, and may decide to use it without any specific purposes. This intrinsic motivation urges them to use computers and affects their perception of the ease of use of a DMT. People with abundant experience using computers often experience less playfulness than those in the early stages of usage. They feel that it is very interesting and creative in the beginning. As time goes by, it may become boring and dreary because of the routine nature of the process. Hence, the effect of computer playfulness on perceived ease of use of DMT can be moderated by experience.

People perceive IT as useful in their work if they feel that it is easy to use (Davis, 1989). The additional factor of experience moderates the relationship between perceived ease of use and the perceived usefulness of a DMT. Users with enough experience generally have more knowledge of how to use a DMT, and operate it more accurately without difficulty. Therefore, this study infers that experience strengthens the effect of perceived ease of use on the perceived usefulness of a DMT.

Davis (1989) proposed that intention to use IT is affected by the perceived ease of use. If a DMT requires less effort, individuals are inclined to use it and feel that it is easier to operate than to a type of DMT that is complicated to use. Experience also plays a significant role here, and has a reverse effect on the relationship between perceived ease of use and behavioral intentions regarding a DMT. An experienced individual familiar with DMT has less difficulty using it. Therefore, experience attenuates the effects of perceived ease of use on the behavioral intention of a DMT. Based on the discussion above, this study hypothesizes the following:

**Hypothesis 12a.** (H12a) Experience negatively moderates the relationship between computer anxiety and the perceived ease of use of a DMT.

**Hypothesis 12b.** (H12b) Experience negatively moderates the relationship between computer playfulness and the perceived ease of use of a DMT.

**Hypothesis 12c.** (H12c) Experience positively moderates the relationship between perceived ease of use and the perceived usefulness of a DMT.

**Hypothesis 12d.** (H12d) Experience negatively moderates the relationship between perceived ease of use and users' behavioral intention to use a DMT.

## 4. Research methodology

The measurement items used in this study were derived from prior studies and adapted slightly to suit the purposes of this study. The Appendix presents the questionnaire used in this study. Research variables were measured on a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7).

### 4.1. Pretest and pilot test

To avoid problems of vague wording and meaning, a pretest was performed to validate the instrument. The pretest involved two experts in the DM field and two experienced DMT users. These four participants reviewed the entire instrument and provided some comments regarding the content of the items in the survey. The content validity of the instrument was confirmed based on their feedback and instructions.

To verify consistency between the constructs and scale items, a pilot test was conducted after the pretest. The pilot test involved 30 subjects, all of whom had previously used a related DMT, and marked the appropriate answers based on their experience of usage. We applied a statistical tool (SPSS) to test the internal consistency and calculated the index of Cronbach's $\alpha$, whose value should be above 0.7 (Nunnally, 1978). All of the Cronbach's $\alpha$ coefficients of the respective constructs are above 0.7, ranging from 0.723 to 0.962, confirming that the instrument has no problems with reliability.

### 4.2. Data collection

A web-based survey method was used to collect the data. Subjects were recruited from 800 people randomly selected from a list of 2500 information management and business administration alumni of a university who work in enterprises in Taiwan. A direct mail containing a hyperlink to online survey web pages was sent to each one, inviting them to participate in this survey. The related information (including the definition of DMT in Section 2.1) was attached to the questionnaire to confirm that these respondents were qualified (i.e., they had previously used a DMT). The majority of the subjects were office workers from small and medium-sized enterprises in Taiwan. This survey attracted 212 respondents to answer the questionnaire, but 6 had to be dropped because they were outliers (only strongly disagree or strongly agree to all questionnaire items) or repeated the same values. Thus, the final sample consisted of 206 participants.

## 5. Data analysis and results

SPSS (v. 15.0 for Windows) and Amos 6.0 were adopted for the data analysis in this study. The statistical methods included descriptive statistics, reliability analysis, confirmatory factor analysis (CFA), and structural equation modeling (SEM). A two-stage analysis method of SEM, including measurement and structural models, was used for data analysis.

**Table 1**
Descriptive statistics of respondents.

| Measure | Items | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 134 | 65.05 |
| | Female | 72 | 34.95 |
| Age (years) | Under 20 | 1 | 0.49 |
| | 21–30 | 105 | 50.97 |
| | 31–40 | 65 | 31.55 |
| | 41–50 | 33 | 16.02 |
| | Over 50 | 2 | 0.97 |
| Education | College (2 years) | 1 | 0.49 |
| | Bachelor's degree (4 years) | 67 | 32.52 |
| | Master's degree | 124 | 60.19 |
| | Ph.D. | 14 | 6.80 |
| Industry | Manufacturing | 38 | 18.45 |
| | Wholesale and retail trade | 12 | 5.83 |
| | Information and communication | 45 | 21.84 |
| | Financial and insurance | 30 | 14.56 |
| | Technology | 26 | 12.62 |
| | Education | 19 | 9.22 |
| | Others | 36 | 17.48 |
| Seniority | Under 1 year | 68 | 33.01 |
| | 1–5 years | 60 | 29.13 |
| | 5–10 years | 41 | 19.90 |
| | 10–15 years | 20 | 9.71 |
| | Over 15 years | 17 | 8.25 |
| Years of using DMT experience | Under 1 year | 96 | 46.60 |
| | 1–2 years | 41 | 19.90 |
| | 2–3 years | 25 | 12.14 |
| | 3–5 years | 25 | 12.14 |
| | 5–7 years | 12 | 5.83 |
| | 7–9 years | 2 | 0.97 |
| | Over 9 years | 5 | 2.43 |
| The software of DMT usage | Microsoft SQL Server | 59 | 28.64 |
| | WEKA | 15 | 7.28 |
| | IBM Intelligent Miner | 15 | 7.28 |
| | SPSS Clementine | 76 | 36.89 |
| | SPSS Statistics | 95 | 46.12 |
| | Minitab | 27 | 13.11 |
| | SAS | 45 | 21.84 |
| | XL Miner | 12 | 5.83 |
| | STATISTICA | 32 | 15.53 |
| | Others | 22 | 10.68 |
| The models of DMT usage | Association rules mining | 72 | 34.95 |
| | Sequential pattern mining | 27 | 13.11 |
| | Data classification | 123 | 59.71 |
| | Data clustering | 85 | 41.26 |
| | Regression | 125 | 60.68 |
| | Time series | 56 | 27.18 |
| | Others | 6 | 2.91 |

### 5.1. Descriptive statistics

Table 1 shows the demographic distributions, with 65.05% male subjects and 34.95% female subjects. Most subjects ranged in age from 21 to 50 years old. The largest age group was 21–30 years old (50.97%). Most subjects held bachelor and master's degrees. Subjects with master's degrees made up the majority (60.19%). The information and communication industry accounted for the largest percentage of occupation (21.84%), with manufacturing coming in second (18.45%). The largest group of subjects had job seniority less than 10 years (82.04%), and more than half had less than 5 years of seniority (62.14%).

Most of the subjects had relatively little experience using a DMT (46.60% of the samples had used a DMT less than 1 year). These subjects may help reveal the reasons or factors affecting why people intend to use a DMT. Subjects were divided into two groups to determine whether the factor of experience affects perceptions or decisions: those who lack experience, and those with significant experience. The former includes those who had not used DMT for more than one year, and the latter includes those who had used DMT for more than one year. This approach is similar to that adopted by Bellman, Johnson, Kobrin, and Lohse (2004) and Xu and Gupta (2009).

**Table 2**
The results of KMO and Bartlett tests.

| Dimensions | KMO value | Bartlett's test of sphericity | | |
|---|---|---|---|---|
| | | Chi-square | *df* | Significance |
| Job relevance | 0.75 | 627.98 | 3 | 0.000 |
| Output quality | 0.75 | 444.77 | 3 | 0.000 |
| Result demonstrability | 0.77 | 465.19 | 6 | 0.000 |
| Response time | 0.64 | 300.58 | 3 | 0.000 |
| Format | 0.75 | 432.34 | 3 | 0.000 |
| Computer self-efficacy | 0.61 | 264.86 | 3 | 0.000 |
| Perceptions of external control | 0.67 | 313.87 | 6 | 0.000 |
| Computer anxiety | 0.69 | 290.90 | 6 | 0.000 |
| Computer playfulness | 0.69 | 202.10 | 6 | 0.000 |
| Perceived usefulness | 0.87 | 953.26 | 6 | 0.000 |
| Perceived ease of use | 0.67 | 313.87 | 6 | 0.000 |
| Behavioral intention to use | 0.63 | 221.31 | 3 | 0.000 |

SPSS Statistics was the tool most commonly used by the largest number of subjects (46.12% of the entire sample). SPSS Clementine had also been used by a large number (36.89% of the entire sample). Many different DM models can be applied or selected to mine useful information from enormous amounts of data. Regression analysis is the most widely applied model. Up to 60% of the subjects had previously used this model to solve specific problems. Data classification was another model commonly used by the subjects (59.71% of the entire sample).

### 5.2. Measurement model

Confirming data normality is the first step of multivariate analysis. Data normality can be tested by a $Z$ test of skewness and kurtosis. This study achieved multivariate normality because the absolute value of skewness was under 3 and the absolute value of kurtosis was under 8 (Kline, 1998).

Factor analysis was performed using principal component extraction with varimax and Kaiser normalization. The appropriateness of factor analysis was determined by the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test. The KMO values of the sampling adequacy fell within the acceptable range of 0.61–0.87, and the Bartlett test of sphericity was significant (Table 2), providing support for the validity of the instrument.

Some indices must be computed and tested to demonstrate a reasonable fit for the model. These indices include the Chi-square/degrees of freedom ($\chi^2/df$), Goodness-of-fit Index (GFI), Comparative Fit Index (CFI), Normed Fit Index (NFI), Incremental Fit Index (IFI), and Root Mean Square of Approximation (RMSEA). The overall model fit indices for CFA were as follows: $\chi^2/df = 1.62$, GFI = 0.80, CFI = 0.94, NFI = 0.87, IFI = 0.94, and RMSEA = 0.05. All the indices in our model met the suggestions of others researchers (Bagozzi & Yi, 1988; Etezadi-Amoli & Farhoomand, 1996; Hair, Anderson, Tatham, & Black, 1998).

Surveys often involve measurement errors. To accurately reflect the measurement error inherent in each test, this study examines the reliability and validity of the proposed model. Several referral indices can be used to test reliability and validity. Table 3 indicates the results of reliability and validity with CFA. The internal consistency of each construct was tested by composite reliability (CR). The CR for each construct in this study was above 0.7, achieving the highest possible reliability level suggested by Hair et al. (1998). The average variance extracted shows what percentage of the variance of the construct is explained by an observed

**Table 3**
The results of the reliability and validity with CFA.

| Construct | Variable | Factor loading | *t*-Value | Composite reliability | Average extracted variance |
|---|---|---|---|---|---|
| Job relevance (JR) | JR1 | 0.90 | 20.98 | 0.95 | 0.85 |
| | JR2 | 0.95 | 24.55 | | |
| | JR3 | 0.92 | – | | |
| Output quality (OQ) | OQ1 | 0.90 | 18.72 | 0.92 | 0.80 |
| | OQ2 | 0.87 | 16.54 | | |
| | OQ3 | 0.91 | – | | |
| Result demonstrability (RD) | RD1 | 0.90 | 16.62 | 0.92 | 0.75 |
| | RD2 | 0.90 | 16.58 | | |
| | RD3 | 0.87 | 16.75 | | |
| | RD4 | 0.79 | – | | |
| Response time (RT) | RT1 | 0.82 | 17.79 | 0.91 | 0.77 |
| | RT2 | 0.85 | 17.80 | | |
| | RT3 | 0.95 | – | | |
| Format (FOR) | FOR1 | 0.86 | 16.57 | 0.91 | 0.77 |
| | FOR2 | 0.89 | 17.46 | | |
| | FOR3 | 0.89 | – | | |
| Computer self-efficacy (CSE) | CSE1 | 0.76 | 13.92 | 0.88 | 0.71 |
| | CSE2 | 0.91 | 17.37 | | |
| | CSE3 | 0.85 | – | | |
| Perceptions of external control (POEC) | POEC1 | 0.92 | 19.68 | 0.90 | 0.68 |
| | POEC2 | 0.87 | – | | |
| | POEC3 | 0.79 | 14.82 | | |
| | POEC4 | 0.71 | 12.71 | | |
| Computer anxiety (CA) | CA1 | 0.81 | 14.10 | 0.93 | 0.78 |
| | CA2 | 0.86 | 16.58 | | |
| | CA3 | 0.95 | 20.65 | | |
| | CA4 | 0.90 | – | | |
| Computer playfulness (CP) | CP1 | 0.86 | 11.65 | 0.88 | 0.65 |
| | CP2 | 0.82 | 11.62 | | |
| | CP3 | 0.80 | 10.86 | | |
| | CP4 | 0.74 | – | | |
| Perceived usefulness (PU) | PU1 | 0.93 | – | 0.96 | 0.85 |
| | PU2 | 0.94 | 25.89 | | |
| | PU3 | 0.92 | 25.62 | | |
| | PU4 | 0.90 | 20.61 | | |
| Perceived ease of use (PEOU) | PEOU1 | 0.83 | – | 0.93 | 0.77 |
| | PEOU2 | 0.89 | 17.52 | | |
| | PEOU3 | 0.89 | 17.67 | | |
| | PEOU4 | 0.90 | 15.05 | | |
| Behavioral intention to use (BIU) | BIU1 | 0.89 | – | 0.90 | 0.76 |
| | BIU2 | 0.94 | 25.53 | | |
| | BIU3 | 0.78 | 16.67 | | |

variable. If the constructs possess an average variance extracted that exceeds the benchmark of 0.5 (Fornell & Larcker, 1981), the average variance demonstrates satisfactory reliability and convergent validity. All the average variances extracted from the constructs in this study ranged from 0.65 to 0.85, exceeding the acceptable value of 0.5.

Discriminant validity is the lack of a relationship among measures that theoretically should not be related. Thus, the relationships between constructs must be low to verify the significant difference of each construct. Table 4 lists the results of the discriminant validity test. The diagonals in Table 4 are the values of the average variance extracted (AVE), and the others are the squared values of the correlations with other latent variables. These squared values must be lower than the AVE of each construct to achieve discriminant validity (Fornell & Larcker, 1981). These results show that this study achieves satisfactory discriminant validity.

An examination of the important indices shown above ensured that there were no problems related to the reliability, validity, or model fit in this study. All the values achieved the levels

**Table 4**
Squared inter-correlation among constructs.

| | JR | OQ | RD | RT | FOR | CSE | POEC | CA | CP | PU | PEOU | BIU |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| JR | 0.85 | | | | | | | | | | | |
| OQ | 0.16 | 0.80 | | | | | | | | | | |
| RD | 0.23 | 0.19 | 0.75 | | | | | | | | | |
| RT | 0.14 | 0.44 | 0.18 | 0.77 | | | | | | | | |
| FOR | 0.08 | 0.43 | 0.18 | 0.48 | 0.77 | | | | | | | |
| CSE | 0.06 | 0.07 | 0.16 | 0.09 | 0.10 | 0.71 | | | | | | |
| POEC | 0.29 | 0.16 | 0.32 | 0.18 | 0.19 | 0.16 | 0.68 | | | | | |
| CA | 0.00 | 0.01 | 0.05 | 0.01 | 0.03 | 0.12 | 0.02 | 0.78 | | | | |
| CP | 0.07 | 0.06 | 0.21 | 0.11 | 0.08 | 0.18 | 0.12 | 0.17 | 0.65 | | | |
| PU | 0.30 | 0.49 | 0.23 | 0.50 | 0.38 | 0.12 | 0.25 | 0.01 | 0.10 | 0.85 | | |
| PEOU | 0.11 | 0.32 | 0.17 | 0.38 | 0.41 | 0.15 | 0.23 | 0.02 | 0.10 | 0.50 | 0.77 | |
| BIU | 0.12 | 0.25 | 0.12 | 0.27 | 0.25 | 0.08 | 0.15 | 0.01 | 0.06 | 0.45 | 0.45 | 0.76 |

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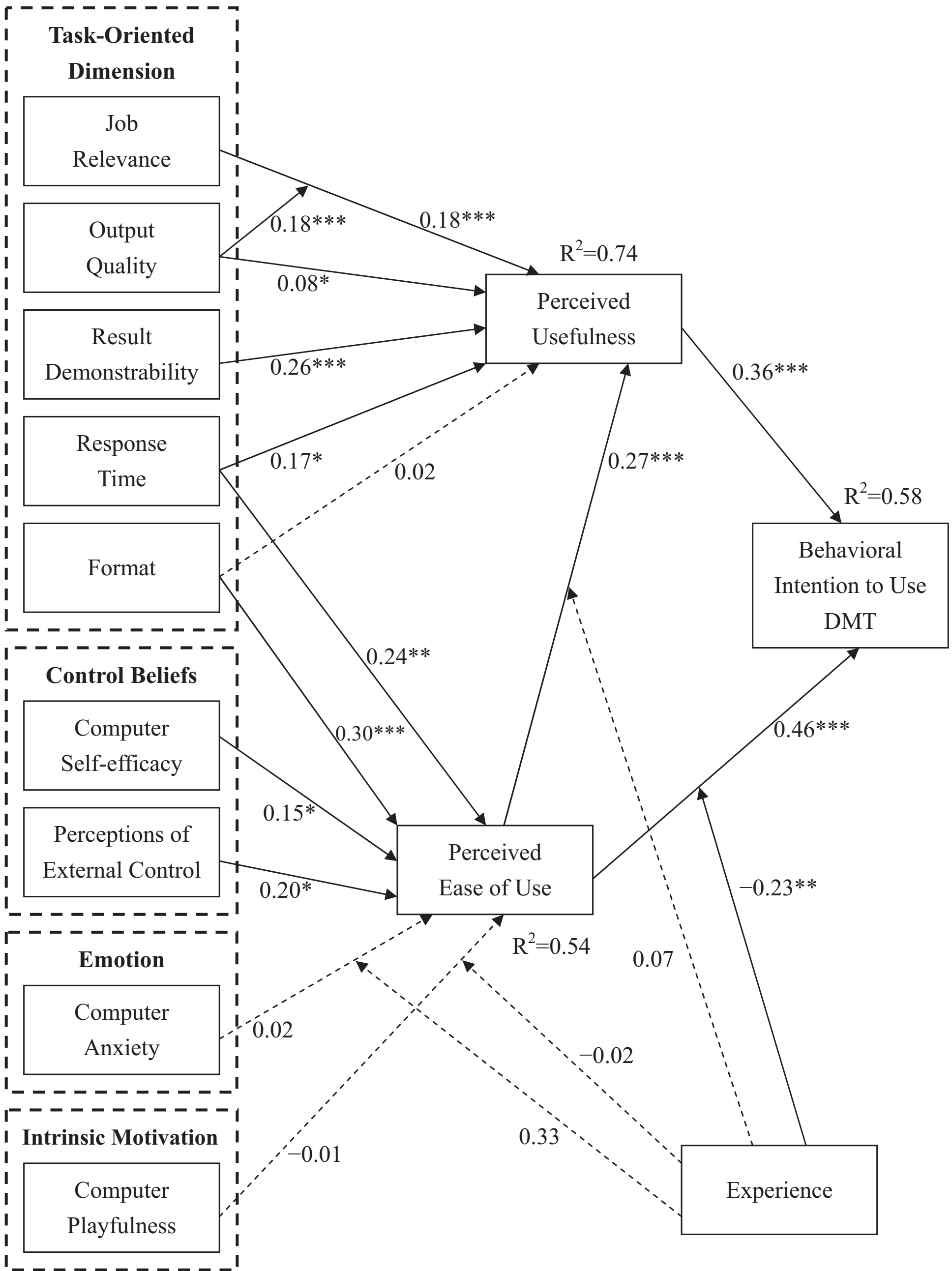


**Fig. 2.** The results of the structural modeling analysis. *Note*: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; dotted line represents no significance.

recommended by previous researchers. These internal consistency and validity results enabled us to subsequently estimate the structural model.

### 5.3. *Structural model*

The structural model in this study was analyzed to identify the links between variables. The constructs and their hypothesized relationships were tested simultaneously. Thirteen hypotheses were supported, whereas the other six hypotheses did not reach the level of significance. Only one hypothesis of the moderator of experience was supported, and the rest were unsupported. Fig. 2 shows all the results of the structural model. This research model explains 58% of the variance of behavioral intentions to use a DMT.

## 6. Conclusion and implications

### 6.1. *Discussion of findings*

The proposed model is based on TAM3 (Venkatesh & Bala, 2008), and explains how various determinants influence individuals' intentions to adopt a DMT. The empirical findings of this study present some interesting results.

Perceived usefulness and perceived ease of use are two important factors affecting intentions to use IT. These factors have been confirmed by many researchers in the past (Davis, 1989; Venkatesh & Davis, 2000). Not surprisingly, these factors also have a significant effect on an individual's intentions to use a DMT. Perceived usefulness and perceived ease of use directly influence users' behavioral intentions. Perceived ease of use also has a direct effect on perceived usefulness. Human beings attempt to use DMTs when they perceive it to require less effort or create benefits in their work. If they expend less effort to use a DMT, their perception of usefulness increases. However, the willingness to use DMTs increases spontaneously. These results confirm that the two beliefs discussed above, the perceived usefulness and perceived ease of use of a DMT, are the most important factors affecting user intentions. Therefore, this study conducts further research to identify the key antecedents affecting the two beliefs.

The effects of job relevance on perceived usefulness are significant in this model. The greater the relationship between a DMT and the user's job, the greater its perceived usefulness. These results also support result demonstrability as a significant factor that directly influences perceived usefulness. Making the mining outcomes of a DMT more understandable for users is an important task. The easier it is for users to interpret findings, the more they perceive the DMT to be useful. This is consistent with previous findings from Venkatesh and Davis (2000). The results of TAM2 reveal an interactive effect of job relevance and output quality in determining perceived usefulness. Because of this special DMT characteristic, output quality is a critical factor in this study. Without the support of excellent output quality, users do not accept a tool, even if a strong relationship exists between job relevance and perceived usefulness. The proposed research model not only tests this interactive effect, but also examines the direct effects of job relevance and output quality. It comes as no surprise that both the interactive and direct effects are significant. Because a DMT is designed to reveal new knowledge and assist managers in making decisions, poor output quality may cause managers to make wrong decisions, resulting in great losses. Thus, inappropriate DMT outcomes can cause serious problems. Users base the perceived usefulness of a DMT on the quality of its outcomes. Output quality also positively moderates the effects of job relevance on the perceived usefulness of a DMT. These results show that the degree of the effect of job relevance on perceived usefulness is reinforced when the output quality is excellent.

The other two essential factors that should be noted are response time and format. The source processed by a DMT usually comes from volumes of enterprise data. How to cope with a high volume of data efficiently and quickly is a trial for managers. Thus, the response time of a DMT is a primary concern. Response time is a significant antecedent affecting perceived usefulness and perceived ease of use. Time is an important resource and limitation in business, especially for decision-making managers. The faster a DMT runs, the more useful its users perceive it to be. Users perceive that it is easier to use a DMT if it requires no patience to execute the mining process. Format is another vital predictor of intentions to use a DMT. However, the hypotheses related to format are only partially supported. Format does not have a significantly positive effect on perceived usefulness, but does have a positive effect on perceived ease of use. This indicates that format does not influence the belief of perceived usefulness even with well-demonstrated output. This result could be explained by considering user objectives when adopting DMT. The main goal is to extract useful knowledge from volumes of data and then proceed with further analysis. Therefore, a well-formatted output is insufficient to support the usefulness of adopting this tool. Format is a significant antecedent affecting a DMT's perceived ease of use.

This study reveals that almost all task-oriented antecedents are significantly related to perceived usefulness (except for the relationship between format and perceived usefulness). These results reveal the instrument-oriented characteristic of DMTs. Moreover, a DMT can be used to help users solve some specific problems. Consequently, these factors must be considered when an enterprise adopts a DMT.

DMT is more difficult to use than other IT (e.g., online shopping or online games) or various types of application software (e.g., spreadsheets or word processors). Because of the complexity of DMT, it is increasingly difficult for employees to make effective decisions on the adoption and acceptance with DMT. Computer self-efficacy can play a role in increasing perceived ease of use. The results of this study show that computer self-efficacy increases a DMT's perceived ease of use. One of a DMT's characteristics is the barrier to entry, which makes it difficult to learn and operate. If users can easily operate a computer on their own, they are able to use a DMT more easily. Dahlan, Ramayah, and Koay (2002) showed that user skills and experience (i.e., computer self-efficacy) is positively associated with DM usage. Many firms have recently made an effort to develop and introduce IT. However, the common problem they encounter is that numerous employees may resist organizational change because they lose their authority or position in their organization. Controlling employee perceptions of external control could be a means to solve this problem. The empirical results of this study indicate that the appropriate resources or supports in an organization can help users perform their jobs smoothly using DMTs. Providing resources, opportunities, and knowledge decreases employee resistance to using DMTs and increases their perceived ease of use. Companies that provide training programs before introducing a DMT can decrease employee resistance to the DMT. In other words, the training courses enhance employees' understanding and skills related to using the DMT. Both computer self-efficacy and perceptions of external control have direct effects on the perceived ease of use of a DMT. These results agree with the findings of Venkatesh (2000) and Chang et al. (2003).

Emotion and intrinsic motivation factors include computer anxiety and computer playfulness. However, the results of these two predictors are not consistent with previous findings. According to Venkatesh (2000), these two constructs significantly influence perceived ease of use. The negative association between computer anxiety and perceived ease of use suggests that individuals with increased anxiety toward computers perceive that a DMT is harder to use. As a result, this hypothesis is not suitable for the proposed model because of the special feature of the tool. A DMT is a specific tool that differs from other IT. In general, people who use a DMT are Management Information Systems (MIS) managers or personnel who have abundant experience with computers. Therefore, anxiety on computer usage is unlikely to be a significant factor.

DMTs can assist managers in making important decisions in business. Because of the instrument-oriented characteristic of DMTs, managers are likely to use them to meet certain goals or solve particular problems. Though DMTs are not suited to entertainment-oriented IT usage (e.g., online games), they are considered to improve the productivity of organizations. Therefore, the antecedents of both computer anxiety and computer playfulness have a relatively unimportant effect on a user's perception of ease of use.

With the exception of the effect of the relationship between perceived ease of use and behavioral intention on adopting a DMT, the moderating effect of experience does not play an important role in the DMT acceptance model. These results differ from those of previous research on TAM3 (Venkatesh & Bala, 2008). According to previous discussions, computer anxiety does not have a direct effect on perceived ease of use. This is because emotion does not have a direct effect on DMT usage. Because users use tools to complete their tasks or achieve certain objectives, computer anxiety is not a critical factor in perceived ease of use. This instrument-oriented characteristic of users makes DMT less playful. Computer playfulness, therefore, does not have a significant effect on perceived ease of use. Regardless of what influence experience has, computer anxiety and computer playfulness exhibit no moderating effects on perceived ease of use.

TAM3 indicates that increased experience enhances the effects of perceived ease of use on perceived usefulness. This study reveals no moderating effect between perceived ease of use and perceived usefulness. A DMT is a special type of tool that is considered to be both instrument-oriented and data-driven IT. Increased experience using DMTs increases the effect of perceived ease of use for instrument-oriented IT. However, in analyzing volumes of data, managers often have great difficulty making the most useful decisions every day. Because data are continually updated in enterprises, managers must continually use DMTs to obtain up-to-date results. Although managers may be familiar with operating DMT, it is difficult to accumulate the same types of personal experience to explain the usefulness of the mining results from different types of data in a changing business environment. As a result, experience does not moderate the effect of perceived ease of use on perceived usefulness.

Perceived ease of use affects behavioral intentions to use a DMT. TAM3 also indicates that there is a negative moderating effect on this path with increasing experience. The proposed model yields the same results as TAM3. With increasing experience, perceived ease of use is no longer the main determinant of intention to adopt a DMT. Although managers must still cope with many kinds of data, the moderating effect of experience diminishes the relationship between perceived ease of use and behavioral intentions.

### 6.2. Theoretical contributions

As for academic implications, this study contributes to a theoretical understanding of technology adoption in the field of DM. Although previous studies investigate IT/IS adoption, a comprehensive focus on the factors of individuals' behavioral intentions to use DMTs is surprisingly absent from the literature. Therefore, this study investigates the acceptance of DMTs from the individual perspective. The determinants of perceived usefulness and perceived ease of use are relatively parsimonious and important. Because new business models are continuing to appear in contemporary business environments, managers may often alter their considerations to use DMTs. Therefore, this study suggests that further testing of the model may reveal its stability and robustness across various IT/IS circumstances. Evolving business or technological factors might also change the nature and strength of the relationships in the proposed model. There is also an opportunity to review or investigate business intelligence (BI) tools, which are similar to DMTs, from the outlook of TAM3. Though some studies (Foshay et al., 2007; Goeke & Faley, 2007; Gorla, 2003) address the usage of data warehousing (DW) from the traditional TAM, new determinants can be considered to enhance the ability to predict and explain the usage of DW. The adoption of other BI tools, such as business analytics, automated decision systems, dashboards, or visualization tools, can also be investigated further. Because these BI tools are related to decision-making, new variables such as response time and format can be added to test their adoption as well.

### 6.3. Practical implications

This study offers several practical implications for enterprises and software developers. To increase DMT usage, users must perceive that a DMT enhances their job performance and is easy to use. By developing high-performance and easy-to-use DMTs, users can mine data more efficiently and gain a significant return on investment. Companies that provide relevant resources and offer training programs before implementing DMTs can reduce the problem of employee resistance. In addition, the determinant of perceptions of external control plays a key role on the perceived ease of use of a DMT. Therefore, enterprises could construct better IT infrastructures to meet the requirements of DMTs. Creating useful and easy-to-use DM tools is necessary to induce users' adoption. Improving DMT design and providing a high performance DM tool is vital to enticing users to adopt the DMT and ensure DMT success.

Three factors in the task-oriented dimension, output quality, response time, and format, provide valuable points of reference for the designers and developers of DMTs and relevant software. This study suggests that outputs can be customized to meet specific needs in the processes of DM. Each process can generate output with graphical, tabular, or textual displays for different users at the right time using the right output method. This study also suggests that designing DMTs to better match job-relevant needs, improving the quality of their outputs, making DMTs easier to use, and creating practical interventions to increase result demonstrability can provide more important leverage for increasing users' adoption and acceptance. A long response time is one of the most serious problems concerning DM technologies (Morzy, Wojciechowski, & Zakrzewicz, 2000). Therefore, DM algorithms with higher performance make DMTs more practical for users, allowing them to analyze huge quantities of data without waiting too long. Enterprises that use DMTs should also consider this factor to increase efficiency and productivity. For example, this can improve the efficiency of operation and marketing led enterprises, reducing costs and increasing sales. The developers of DMTs should take advantage of these three factors, output quality, response time, and format, to develop user-friendly software and achieve remarkable success in DMT software development. When enterprises plan to purchase DMTs, the three factors also play an important role in comparing competing vendor solutions for commercial off-the-shelf DMTs. This helps businesses choose the most practical software.

### 6.4. Limitations and future research

This study uses TAM3 to investigate the factors affecting human use of DMTs. However, this study examines the behavioral intentions of a specific tool rather than general information technology in the field of MIS. Therefore, it may be difficult to generalize the findings of this study to other instrument-oriented technologies. Future research should investigate this phenomenon as it relates to other types of technologies. This study also investigates individual intentions to use DMTs, which could help managers make decisions or improve productivity. A cross-sectional study was performed in our work. The research results would be more robust if we can investigate this model over time rather than at one point in time. Therefore, a longitudinal study could be conducted in the future to obtain more comprehensive results.

This study investigates factors at the individual level. However, there might be more intrinsic/extrinsic motivation factors, such as the difficulties and challenges of finding hidden patterns in DM and the joy of discovering new ones. There might also be organizational factors, e.g., top management directives and mandates, that are not considered in this study. Scholars interested in this topic can extend this research model and increase its explanatory capability by adding other factors.

### 6.5. Conclusion

This study takes a step in the direction of investigating user intentions to use DMTs. We draw the following conclusions. First, based on the results of this study, perceived usefulness and perceived ease of use are the factors most affecting an individual's intention to use DMTs. Furthermore, the task-oriented dimension and control beliefs are two important antecedents that have significant effects on perceived usefulness and perceived ease of use, respectively. Emotional and intrinsic motivations are not major factors in this study. Second, the task-oriented dimension and control beliefs are the major predictors in this study. In fact, both categories are the keys to explaining the adoption and acceptance of DMTs. Third, experience does not have a significant moderating effect in this study, except for the effect of perceived ease of use on behavioral intentions. Consequently, experience is not a critical factor in this research model. Finally, people use DMTs to gain useful information or interesting knowledge. Therefore, most DMT users would like to improve their task efficiency or achieve work-related goals rather than just use the DMT for fun in their leisure time.

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## Appendix A. Questionnaire items

**Job relevance** (Davis et al., 1992)
JR1. In my job, usage of the data mining tool is important.
JR2. In my job, usage of the data mining tool is relevant.
JR3. The use of the data mining tool is pertinent to my various job-related tasks.
**Output quality** (Davis et al., 1992)
OQ1. The quality of the output I get from the data mining tool is high.
OQ2. I have no problem with the quality of the data mining tool's output.
OQ3. I rate the results from the data mining tool to be excellent.
**Result demonstrability** (Moore & Benbasat, 1991)
RD1. I have no difficulty telling others about the results of using the data mining tool.
RD2. I believe I could communicate to others the consequences of using the data mining tool.
RD3. The results of using the data mining tool are apparent to me.
RD4. I would have difficulty explaining why using the data mining tool may or may not be beneficial.
**Response time** (Nelson et al., 2005)
RT1. It takes too long for the data mining tool to respond to my requests.
RT2. The data mining tool provides information in a timely fashion.
RT3. The data mining tool returns answers to my requests quickly.
**Format** (Nelson et al., 2005)
FOR1. The information provided by the data mining tool is well formatted.
FOR2. The information provided by the data mining tool is well laid out.
FOR3. The information provided by the data mining tool is clearly presented on the screen.
**Computer self-efficacy** (Brown & Venkatesh, 2005)
CSE1. I feel comfortable using a computer on my own.
CSE2. If I wanted to, I could easily operate a computer on my own.
CSE3. I can use a computer even if no one is around to help me.
**Perceptions of external control** (Mathieson, 1991; Taylor & Todd, 1995)
POEC1. I have control over using the data mining tool.
POEC2. I have the resources necessary to use the data mining tool.
POEC3. Given the resources, opportunities and knowledge it takes to use the data mining tool, it would be easy for me to use the tool.
POEC4. The data mining tool is not compatible with other tools I use.
**Computer anxiety** (Venkatesh, 2000)
CA1. Computers do not scare me at all.
CA2. Working with a computer makes me nervous.
CA3. Computers make me feel uncomfortable.
CA4. Computers make me feel uneasy.
**Computer playfulness** (Webster & Martocchio, 1992)
The following questions ask you how you would characterize yourself when you use computers:
CP1. . . .spontaneous
CP2. . . .creative
CP3. . . .playful
CP4. . . .unoriginal
**Perceived usefulness** (Davis, 1989; Davis et al., 1989)
PU1. Using the data mining tool improves my performance in my job.
PU2. Using the data mining tool in my job increases my productivity.
PU3. Using the data mining tool enhances my effectiveness in my job.
PU4. I find the data mining tool to be useful in my job.
**Perceived ease of use** (Davis, 1989; Davis et al., 1989)
PEOU1. My interaction with the data mining tool is clear and understandable.
PEOU2. Interacting with the data mining tool does not require a lot of my mental effort.
PEOU3. I find the data mining tool to be easy to use.
PEOU4. I find it easy to get the data mining tool to do what I want it to do.
**Behavioral intention to use** (Davis, 1989; Davis et al., 1989)
BIU1. Assuming I had access to the data mining tool, I intend to use it.
BIU2. Given that I had access to the data mining tool, I predict that I would use it.
BIU3. I plan to use the data mining tool in the next <*n*> months.

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