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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