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Examining the impacts of mental workload and task-technology fit on user acceptance of the social media search system

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Abstract
Information overload has been an important issue in today's big data era where a huge amount of unstructured user-generated content in different languages is being created on the Web in every minute. Social media search systems could help with it by effectively and efficiently collecting, storing, organizing and presenting user-generated content across the Web in an organized and timely manner. However, little research has been done to examine factors that could influence user acceptance on this new type of systems. To address it, this study develops a research model by integrating Mental Workload (MWL), Task-Technology Fit (TTF), and the unified theory of acceptance and use of technology (UTAUT). The model is tested on a security-related social media search system. The results indicate that both MWL and TTF can significantly influence user acceptance. We also operationalize the multi-dimensional latent construct of MWL by developing survey-based measurement items for different dimensions.

Keywords Mental workload (MWL) · Task-technology fit (TTF) · User-generated content · User acceptance · Social media search system

1 Introduction

The big data era, which we are in currently, has brought us a tremendous amount of user-generated content across the Web. It has been reported that 90% of the data over the Internet have been created in the past 2 years alone, and as to 2017, the daily generation rate of Internet data was about 2.5 quintillion bytes (one quintillion is 1018) (IFL Science 2017). In addition, the majority of these vast amount of data were generated by general Internet users on various social media sites, and there were 2.79 billion active social media users in the world as to 2017 (Stevens 2017). This type of user-generated data has value for both product and service providers as well as for the general public. For example, they can help influence companies' decision making as well as individual customers' purchasing decisions (Rubicon Consulting Inc. 2009). In addition, users' opinions expressed in social media sites have played an important and powerful role in influencing social and political events such as the Bank Transfer Day (https://www.facebook.com/Nov.Fifth) and the Spring Awakening Revolution in Egypt (Vargas 2012). Both events got a lot of attention from the general public through social media sites, and the opinions and voices expressed by people on such a platform somewhat helped shape the development directions of these social and political movements.

However, user-generated content across social media sites typically lacks a consistent structure and is written in different languages. Also considering the rapidly increasing volume associated with such type of data, it is difficult and challenging to collect, store, organize, and present them effectively. As pointed out by researchers, doing these activities can be quite tedious, time-consuming, and mentally challenging (Cao et al. 2015; Fan and Gordon 2014). To deal with this problem, social media search systems can be of great help. They are a new type of systems that can

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automatically collect huge amounts of user-generated content across heterogeneous social media sites and present them in an organized and consistent way to users via effective and efficient search support (Dang et al. 2014).

The entire process of conducting social media analytics can be categorized into three steps: capture, understand, and present (Fan and Gordon 2014), with each of the latter ones being built upon the success of the former one(s). The capture step serves as the foundation of and is a critical stage in influencing the success of social media analytics. It is reported that the most important mission in the capture step is to collect data from various social media sources and preprocess such type of data in an effective and efficient manner (Fan and Gordon 2014). However, the vast majority of existing research on social media analytics focuses on the two later steps; relatively little research effort has been put to develop or assess social media systems and techniques, such as social media search systems, that focus on the first step. Along this line, the current study aims to contribute to the literature by focusing on the capture step of social media analytics.

Specifically, to the best of our knowledge, no existing research has been done to examine user acceptance on social media search systems. To address the gap, in this study we investigate factors that can influence social media search system adoption. Considering the cognitive burden imposed on users when searching information across the huge amount of unstructured, multilingual social media data, as well as the importance of providing system functions that can better help reduce such burden via the use of the system, we look into theories of Mental Workload (MWL) (Hart and Staveland 1988; Sweller 1988) and Task-Technology Fit (TTF) (Goodhue and Thompson 1995), and assess their relationships to user acceptance. In addition, no previous research has been seen to integrate MWL, TTF and user acceptance constructs into one nomological network.

MWL is the perceived cost incurred by an individual while achieving a particular level of performance on a task with specific demands (Hart and Staveland 1988; Sweller 1988). It is an important theoretical concept that is central to many disciplines, including cognitive psychology, educational psychology, and cognitive ergonomics (Cegarra and Chevalier 2008). However, it has attracted much less attention by researchers in the Information Systems (IS) area. Derived from a broader concept of Cognitive Fit (CF) (Vessey 1991), TTF states that Information Technology (IT) is more likely to have a positive impact on an individual's task performance if the functionality of the IT matches the requirements of the tasks that the user needs to perform (Goodhue and Thompson 1995).

In this study, we investigate the impacts of MWL and TTF on user acceptance of social media search systems. Specifically, a research model is developed by integrating MWL, TTF, and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003) into one nomological network which has not been done in prior research. To empirically test the model, a lab experiment is conducted on a security-related social media search system. The results indicate that both MWL and TTF can significantly influence the UTAUT constructs. We also operationalize the multidimensional latent construct of MWL by developing a set of survey-based measurement items for its different dimensions, which has not been seen in prior IS literature.

The remainder of this paper is organized as follows. In Section 2 we discuss the background and supporting theories, followed by the proposed research model and hypothesis development in Section 3. After that, Section 4 provides details on the research method, and then data analyses and results are reported in Section 5. The paper concludes with a discussion of the research contributions and implications, and future research directions in Section 6.

2 Background and theoretical foundations

2.1 Web 2.0 and social media data

Web 2.0 enables two-way communications between Internet users and online communities (O'Reilly 2005). It provides a channel for the general public to actively participate in and contribute their own content to various types of social media sites. As a result, a huge amount of ("volume") opinion- and information-rich ("value") user-generated content has been created across different social media sites with different structures and formats ("variety") at very fast rates ("velocity") over years, leading to the big data era (Chen et al. 2012; Lau et al. 2016). Nowadays, more and more companies and researchers are interested in searching across and making sense of user-generated content over the Internet (Lau et al. 2016), since it contains valuable information that can help shape a company' decision making (Rubicon Consulting Inc. 2009) as well as influence the development of a social or political event (Vargas 2012).

However, collecting, storing, organizing and analyzing user-generated content are not easy tasks because of certain challenges associated with this new type of data. By analyzing the integration of social media data related to business, Terman (2011) identified that the large volume and lack of structure are two critical challenges. In 2011, it was reported that there were 1.2 zettabytes of data in the Internet, and 95% of them were unstructured with 70% being user-generated content (Roberts 2011). More recently, it has been reported that 90% of the data over the Internet have been created in the past 2 years alone, and as to 2017, the daily generation rate of Internet data was about 2.5 quintillion bytes (one quintillion is 1018) (IFL Science 2017). In addition, the majority of these vast amount of data were generated by general Internet users

on various social media sites, and there were 2.79 billion active social media users in the world as to 2017 (Stevens 2017). Further, the Internet contains content in more than 1000 languages (Crystal 2001). According to the latest report from Internet World Statistics, more than 70% of Internet users are non-English speaking (http://www.internetworldstats.com/stats7.htm), meaning that a large portion of user-generated content is created in languages other than English. Therefore, searching across and understanding such multilingual content becomes another challenge.

Furthermore, people search in different ways. General search engines, such as Google.com and Bing.com, are good at searching across structured data sources over the Web (such as finding a particular online publication or news article), but they typically are not good at searching for topic- or domain-specific information from multilingual, user-generated content across social media data sources (Cao et al. 2015; Fan and Gordon 2014). Even for searching across structured data sources, previous studied have developed domain-specific systems that can better support information search compared with using a general search engine. For example, Zhou et al. (2006) developed a search system (i.e., CMedPort) for the medial domain which could provide effective information search across medical-related Web pages in both simplified and traditional Chinese. Qin et al. (2006) developed a similar system (called ECBizPort) but focused on the business domain and the system provided information search across Web pages in both English and Chinese. Dang et al. (2012) developed a system that enabled information search across patents and grant documents for the nanotechnology domain. In a more recent study, Zhuhadar (2015) created a search system that could allow users to effectively and efficiently find documents across data sources about college class lectures in both English and Spanish.

When searching across social media data, some social media sites themselves (e.g., Web forums) may provide their own search support, but it is typically restricted to search a particular data source – the data collection a site maintains. In general, searching for information across multiple heterogeneous social media sites is difficult and there is not enough support to do this from existing commercial search engines. Thus, a search system developed particularly for social media data is in a great need. Along this line, in our recent research, we have proposed a framework for designing and developing social media search systems (Dang et al. 2014). To address the abovementioned challenges associated with user-generated content, the system framework focuses on providing three major functions: data integration, information search, and multilingual translation, each targeting at addressing one challenge. To enable these functions, advanced techniques and tools have been developed and adopted (Dang et al. 2014). Such social media search system can collect, store, organize, and provide search support across the large volume of heterogeneous, multilingual user-generated content in an effective and efficient manner, and serves as a fundamental infrastructure of an integrated data access point.

A brief summary of the three major system functions is as follows.

- To implement the *Data Integration* function, spidering programs were developed to collect user-generated content across social media sites over the Web. To make the data collection process more efficient, both complete spidering and incremental spidering techniques were utilized. When a social media site was added as a new data source to the system, complete spidering was conducted in order to obtain all postings from that site. This process was typically very time-consuming because of the huge data volume. After that, incremental spidering was performed on a regular basis (e.g., every week) to collect only new postings after the last update of a social media site. In this way, the data collection process was more computationally efficient. Once data were collected, parsing programs were created to extract detailed data fields (e.g., posting title, posting body, writer's name, and posting date), and then stored them in a relational database. A unified database design was adopted across data sources for a consistent organization of data.
- The *Information Search* function enables searches either within a particular data source or across all data sources included in the system. Particularly, the across-all search function can be very helpful when the user wants to get more comprehensive information across different data sources. To do that, the user only needs to conduct a search task once, and all related postings from different data sources will be returned simultaneously. When conducting searches, the user can specify keyword(s) in various data fields such as posting title, posting body, writer's name, and/or posting date. Logical operations ("AND" or "OR") can be used in conjunction with keywords to obtain related postings. A unified search interface design is used for searching for information in a given data source as well as across all data sources. By doing this, once the user has learned how to use the search interface to find information in one data source, he or she can easily adapt it to search for information in other data sources in the same way.
- The *Multilingual Translation* function provides real-time processing of user-generated content written in different languages. It is used to better support users' information search and understanding. When conducting searches in a non-English data source, the system allows the user to express the search terms in either the original language or in English. If the search terms are specified in English, the Multilingual Translation function will convert them to the equivalent terms in the original language and then trigger the Information Search function. This process

is automatically conducted without user awareness. For example, when conducting searches in an Arabic data source, the user does not need to enter the search term(s) in Arabic. Instead, he or she needs to simply enter the English term(s) in the search field. A two-column display format is designed to show the multilingual search results, with one column containing postings in the original language and the other showing their English translations.

After an extensive search across existing literature, a similar and more recent attempt of developing such type of systems has been found, which is conducted by Baur (2016). In that study, Baur and his team have proposed a framework (called MarketMiner) that can automatically collect, store, integrate and present user-generated content in languages other than English. Following the framework, a system has been created for the automotive industry with data sources of Chinese automotive Web forums. The system contains a collection of around 2 million customer postings from 16 major Chinese automotive Web forums. A translation function is provided to translate those forum messages from Chinese to English.

Once a new type of systems is developed, it is important to investigate the adoption and acceptance from the user's point of view. Also considering the cognitive impacts and burden that the large volume, lack of structure, and multilingual nature of user-generated content could make to the user, it is of great importance and need to examine user acceptance and their perceptions toward the social media search system. In addition, providing effective system functionality that can better deal with such data sources is essential as well. Therefore, we decide to utilize theories of MWL (Hart and Staveland 1988; Sweller 1988) and TTF (Goodhue and Thompson 1995) as our theoretical lenses, and investigate their impacts on user acceptance. The user acceptance constructs that we utilize are from UTAUT (Venkatesh et al. 2003), one of the most well-known system adoption theories. We discuss the three supporting theories of this study in the following subsections.

2.2 Mental workload

The concept of mental workload (or sometimes referred to as cognitive load) is central to many disciplines, including cognitive psychology, educational psychology, and cognitive ergonomics (Cegarra and Chevalier 2008). Mental workload (MWL) is defined as the cost incurred by an individual while achieving a particular level of performance on a task with specific demands (Hart and Staveland 1988; Sweller 1988).

An individual has two types of memory: working memory and long-term memory. Humans are only conscious of the information currently being held and processed in the working memory and are oblivious to the information stored in the long-term memory (Sweller 1988; Sweller et al. 1998). When handling new information, working memory is limited in both capacity and duration. It can hold only seven (plus or minus two) chunks of information at a time (Miller 1956). Unlike working memory, the capacity of long-term memory is theoretically infinite (Van-Merriënboer and Ayres 2005). Information held in long-term memory is organized and stored in the form of knowledge structures known as schemas (Sweller 1988).

Schemas are stored in the long-term memory, while their construction occurs in the working memory (Sweller 1988). Although working memory can hold only a limited number of items at a time, the size and complexity of those items are unlimited (Sweller et al. 1998). A complex schema containing a large number of interrelated pieces of information can be held in working memory as a single item (Artino 2008). Therefore, to support effective learning of new materials (such as adopting a new information system), the primary importance is to help users easily construct schemas by reducing the cognitive burden imposed on working memory and increasing the ease of information processing in working memory (Artino 2008; Schmutz et al. 2009). When studying Web-based search systems, Gwizdka (2010) found that the user's cognitive load was significantly higher during the stages of query formation and his or her description of a relevant document, and lower in examining search results and viewing individual documents. In addition, it was also found that by providing semantic information shown next to the search results the user's mental demands during query formation could be significantly decreased.

How to systematically measure MWL remains an important issue. Little effort has been put in developing systematic measurement items for this multidimensional construct in previous IS literature. MWL has been examined mostly in psychology and ergonomics literature but has generally attracted much less attention in IS research. One of the most popular measures of MWL that has the highest user acceptability is the NASA Task Load Index (NASA-TLX) (Cain 2007; Gwizdka 2010). However, NASA-TLX shows only a general description of each dimension of MWL instead of providing detailed measurement items for those dimensions.

As shown in Table 1, NASA-TLX is a multidimensional rating scale containing six bipolar dimensions, including mental demand, physical demand, temporal demand, performance, effort, and frustration level (Hart and Staveland 1988). When using it, an overall MWL score is calculated based on a weighted average of ratings on these six bipolar dimensions (Hart and Staveland 1988). The inclusion of these six dimensions was based on extensive research and psychometric analyses conducted by Hart and her colleagues in a variety of contexts (Hart 1986; Hart and Staveland 1988; Lysaght et al. 1989).

Table 1 NASA-TLX rating scale descriptions (Hart and Staveland 1988)

Dimension	Endpoints	Description
Mental Demand	Low/High	How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?
Physical Demand	Low/High	How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
Temporal Demand	Low/High	How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
Performance	Good/Poor	How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?
Effort	Low/High	How hard did you have to work (mentally and physically) to accomplish your level of performance?
Frustration Level	Low/High	How insecure, discouraged, irritated, stressed, and annoyed or secure, gratified, content, relaxed, and complacent did you feel during the task?

As a well-established rating scale, NASA-TLX is believed to be a robust technique for measuring MWL; the generic items make it possible to be applied to different domains (Battiste and Bortolussi 1988; Hart and Staveland 1988; Hill et al. 1992; Rubio et al. 2004; Stanton et al. 2005). It has been used in a variety of applications and settings such as aviation (Averty et al. 2004; Hart and Staveland 1988), nuclear power plants (Jou et al. 2009; Park and Jung 2006), ground transportation (Hakan and Nilsson 1995; Takao et al. 2002), healthcare and clinical systems (Bertram et al. 1992; Saleem et al. 2007; Wachter et al. 2006), mobile communication systems (Christiansson and Svidt 2006; Kamvar and Baluja 2008), disaster monitoring systems (Bayrak 2007), and robot control (Parikh et al. 2007). It also has been translated into more than a dozen languages (Hart 2006). Different versions of the measurement descriptions have been produced, including verbal, written, and computer-based versions (Noyes and Bruneau 2007; Noyes and Garland 2008).

In the IS area, a few studies have utilized MWL to assess alternative designs of information systems. For example, Saleem et al. (2007) compared four possible designs of computerized clinical information systems based on MWL, efficiency, and usability. Kamvar and Baluja (2008) compared two search interfaces of mobile phones, with and without query suggestions, and found that the interface with query suggestions had less MWL and higher enjoyment for users. Schmutz et al. (2009) compared users' MWL of using the websites of four e-Commerce systems and found a significant negative correlation between MWL and user satisfaction. In a more recent study, Torre et al. (2016) used an adapted version of NASA-TLX to assess the workload perception in drone flight simulator training, and found that across different dimensions of MWL, the mental demand had the highest ratings. It was also found that participants who gave higher ratings on mental demand had greater difficulty in finishing training tasks. In another recent study, Robinson and Brewer (2016) compared MWL between the use of traditional (wooden) form and using a touch screen tablet to complete both the Tower of Hanoi and Corsi Block tasks among players. They used the six dimensions of NASA-TLX to measure MWL and found a statistically significant difference on the physical demand dimension, showing that it was higher for the traditional version of each task compared with the use of the tablet.

However, most of these studies either used an aggregated value calculated based on NASA-TLX to measure MWL of alternative system designs or came up with six scores based on the six different dimensions of NASA-TLX, each for one dimension. None of them has developed or utilized a set of systematic measurement items for each dimension of NASA-TLX. Furthermore, none of them has examined MWL as a theoretical construct in a nomological network to investigate its impact on users' system acceptance.

2.3 Task-technology fit

There are two important "fit" theories in the IS literature: task-technology fit (TTF) (Goodhue and Thompson 1995) and cognitive fit (CF) (Vessey 1991). TTF was derived from CF with the focus of the fit between tasks and the information technology that is designed to support users in the performance of tasks (Goodhue and Thompson 1995).

Developed by Vessey (1991), CF suggests that the match between the task and the information presentation format can lead to the increase in an individual's task performance. When the information presentation format fits the task, a consistent problem-solving process will be formed, resulting in the creation of a consistent mental representation (Vessey 1991). CF provides an explanation for performance differences among users across different presentation formats such as tables, graphs, and schematic faces (Umanath and Vessey 1994; Vessey 1991; Vessey and Galletta 1991).

Focusing on information technology (IT), TTF states that IT is more likely to have a positive impact on an individual's

task performance if the functionality of the IT matches the requirements of the tasks that the user needs to perform (Goodhue and Thompson 1995). In TTF, tasks refer to any actions carried out by individuals in turning inputs into outputs. Technology is viewed as tools used by individuals in carrying out their tasks. In the context of IS research, technology refers to computer systems (e.g., hardware and software) and user support services (e.g., training and help lines) used to assist users in performing their tasks (Goodhue and Thompson 1995). Lim and Benbasat (2000) extended TTF to a task-representation fit model to examine the relationship between the richness of representation and the analyzability of tasks.

As a popular theory, TTF has been applied to the contexts of both general Web-based services and systems (D'Ambra and Rice 2001) and a diverse range of specific information systems, including group support systems (Dennis et al. 2001; Maruping and Agarwal 2004), communication tools (Goette 2000), e-commerce systems (Gebauer and Shaw 2004; Klopping and McKinney 2004), spatial decision support systems (Jarupathirun and Zahedi 2007; Erskine et al. 2018), travel systems (D'Ambra and Wilson 2004), and green supply chain management and green information systems (Yang et al. 2018). For example, Dow et al. (2013) developed a framework for organizational memory information systems, a type of systems that organizations could use to store past and current business processes with a flexible set of data attributes and architecture to facilitate the sharing of knowledge, and assessed its performance from the TTF perspective. They found TTF to be an important factor in influencing system efficiency and effectiveness. In addition, D'Ambra et al. (2013) developed a research model based on TTF to examine the adoption of e-books, and found that the task, technology, and an individual's attributes had significantly positive impacts on TTF, which in turn significantly influenced individual performance and the use of e-books. In a more recent study, Yang et al. (2018) examined the fit between green supply chain management and green information systems, and conceptualized the operational fit between these two innovations.

Previous research also has leveraged TTF to study social media sites. For example, Lu and Yang (2014) developed a research model as an extension of TTF to examine users' behavioral intention to use social networking sites. In addition to the two dimensions of task and technology, they added a third dimension of social characteristics into the model and found that both the fit between task and technology and the fit between social characteristics and technology could significantly influence users' intention to use social networking sites. In a very recent study, Wu and Chen (2017) applied TTF to the education area to examine learners' continuance intention to use Massive Open Online Courses (MOOCs) which provide online supportive learning platforms and communities to students with the emphasis on openness and self-organization. They found that TTF could significantly influence the perceived usefulness and ease of use of this new online-based, social learning environment.

2.4 The unified theory of acceptance and use of technology (UTAUT)

When studying information systems adoption and acceptance, one of the most widely used and recognized theories is the unified theory of acceptance and use of technology (UTAUT) which aims to explain users' intentions to use an information system and subsequent usage behavior (Venkatesh et al. 2003). The theory was developed through a review and consolidation of the constructs from eight models that earlier research had employed to explain information system usage behavior. The theory holds that four key constructs, performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI), are direct determinants of usage intention and behavior.

UTAUT (Venkatesh et al. 2003) has been applied to study information systems adoption in different contexts. For example, Nysveen and Pedersen (2016) applied and extended it to study the adoption of RFID-enabled services. Significant influences were found from PE, EE and technology anxiety on attitude to use RFID-enabled services, while FC and attitude to use both had significant influences on intention to use the services. Seethamraju et al. (2018) utilized UTAUT as the theoretical foundation to investigate the factors influencing the acceptance and use of a mobile-based IT solution for tuberculosis treatment monitoring. They found that all four indicators, EE, FC, PE, and SI, significantly and positively influenced healthcare professionals' behavioral intention to use the proposed mobile-based IT solution. Niehaves and Plattfaut (2014) applied UTAUT to investigate the adoption of Internet technology by elderly people. They found that the three independent variables of PE, EE, and SI together could explain more than 70% of the variance of BI. Shibl et al. (2013) used UTAUT to examine the acceptance of clinical decision support systems among general practitioners, and found that PE, EE, FC, and trust in the knowledge base could significantly influence user acceptance and use. Brown et al. (2010) examined UTAUT in the context of collaboration technology use. Their results showed that collaboration technology characteristics, individual and group characteristics, task characteristics, and situational characteristics were important antecedents of UTAUT constructs. As an extension to UTAUT, UTAUT 2 (Venkatesh et al. 2012) was developed to incorporate additional, consumer goods related factors, including hedonic motivation, price value, and habit. It states that these factors can influence the adoption of new technologies that are directly purchased by their users and viewed (in whole or part) as consumer goods.

Some existing studies also have made efforts to synthesize TTF with either UTAUT or Technology Acceptance Model (TAM) (Davis 1989) (one of the theories based on which UTAUT was derived from) by investigating the relationships between TTF and some of the UTAUT or TAM constructs. For example, Zhou et al. (2010) integrated TTF and UTAUT to study mobile banking user adoption, and found that TTF could significantly influence performance expectancy, one of the UTAUT constructs. In another study, Yen et al. (2010) integrated TTF and TAM to examine users' intention to adopt wireless technology (such as cellular phones, laptops, and personal digital assistants) in organizations. In their model, they proposed the causal links from TTF to perceived ease of use and usefulness (two TAM constructs). However, the relationships were not found to be statistically significant. In a more recent study with a similar attempt to incorporate TTF and TAM but in the context of online learning (Wu and Chen 2017), significant relationships were found between TTF and perceived usefulness as well as between TTF and perceived ease of use.

Based on the above discussions, we find it is appropriate to leverage MWL, TTF, and UTAUT as our theoretical foundations. To further extend existing theories and assess the adoption of the new type of social media search systems, we aim to make contributions to existing research in three folds: (1) integrate the three theoretical perspectives and particularly propose MWL and TTF as two antecedents of the UTAUT constructs, (2) utilize the proposed research model to assess user acceptance of social media search systems, and (3) operationalize the multidimensional latent construct of MWL by creating a set of measurement items for each of its dimensions based on NASA-TLX. In the next section, we present our research model with hypothesis development.

3 Research model and hypotheses

As mentioned earlier, we utilize the theories of MWL, TTF, and UTAUT as the theoretical foundations of this study. Focusing on an individual's cognitive ability, MWL can help assess the cognitive burden imposed on the user when performing tasks, and examine whether the functions provided in the system could help reduce such burden. TTF provides a lens to investigate the extent to which the system functions match the tasks that the user would perform when using the system. UTAUT can serve as the theoretical basis for understating user acceptance toward the system. Figure 1 shows our proposed research model.

MWL refers to the cognitive burden imposed on an individual's working memory when using a system to perform a particular task (Hart and Staveland 1988; Sweller 1988).[1] It is a multidimensional construct aiming to examine different aspects of burden added to the user's cognitive system during the process of performing tasks (Hart and Staveland 1988). According to UTAUT, performance expectancy (PE) is defined as the extent to which the user believes the system can help improve his or her task performance (Venkatesh et al. 2003).

When using a system to perform the task, a knowledge formation process (i.e., schema construction) occurs in the user's working memory (Sweller 1988). High MWL indicates the lack of smoothness in the formation of schemas that will serve as the knowledge basis for completing future tasks using the same system (Hart and Staveland 1988; Sweller 1988). This will lead to the reduction of effectiveness in schema construction, and thus negatively influence the user's perceptions toward the completion of the task. In other words, the negative feeling about the burden perceived by the user associated with using a system to work on the task could lead him/her to believe that the level of help of the system in improving his/her task performance is low. Thus, it can be expected that MWL will negatively impact PE.

Although no previous research has been found to specifically examine the causal relationship between MWL and PE, in a recent study on human space flights, Cohen et al. (2016) argued that perceived cognitive load should be expected to be a predictor for perceived task performance. As to social media search systems, they are developed to enable effective and efficient collection, organization, and presentation of the vast amount of unstructured, multilingual, user-generated content across various social media data sources via search support. With the help of these systems, the mental burden as perceived by the user when searching information across user-generated content is expected to be significantly reduced, which could naturally lead to a feeling of increased performance of tasks. Thus, we hypothesize:

> H1: MWL will negatively influence PE in social media search systems.

According to UTAUT, effort expectancy (EE) refers to the degree of ease associated with using the system (Venkatesh et al. 2003). As discussed in Section 2, high MWL indicates the lack of smoothness in the formation of schemas in the working memory. In other words, it means that the schema construction process associated with using a system to complete the task is complex and difficult (Artino 2008; Schmutz et al. 2009). Such complexity and difficulty can result in the

[1] There are generally two ways to measure MWL, including objective and subjective measures. In this study (please see details in Section 4.3), we used the subjective measure by creating measurement items based on NASA-TLX and asking users to provide self-assessment on those items. Therefore, the MWL concept used in this study is about the perception, which is consistent with all other constructs in the proposed research model.

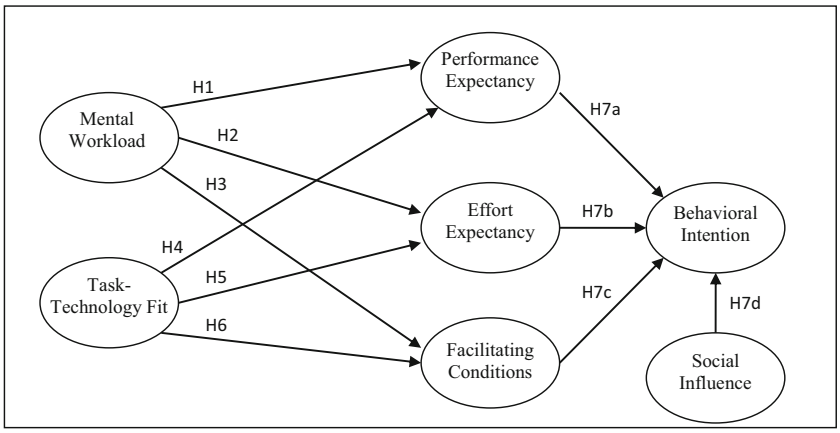

Fig. 1 Research model

user's feeling of a decreased degree of ease associated with the system use. On the contrary, low MWL indicates that schemas are formed in an effective and efficient manner. Thus, an increased feeling of ease is expected toward the system use. Since the goal of the social media search system is to provide better support for users' information search across large amount of unstructured, multilingual social media data, it is expected that the formation of schemas when using the system to conduct searches could be much more effective compared with not having such a system, thus leading to the feeling of an increased level of ease. Therefore, we hypothesize:

> H2: MWL will negatively influence EE in social media search systems.

According to UTAUT, facilitating conditions (FC) is defined as an individual's belief on the existence of organizational and technical support of using an information system (Venkatesh et al. 2003; Venkatesh and Bala 2008). When the user perceives high MWL associated with using a system to perform the task, it will generally make the user feel less comfortable in using the system and doubt the capability of the system functionality (Saleem et al. 2007; Schmutz et al. 2009). Such negative impression will probably lead to the user's belief that there is no sufficient or effective external support to assist his or her use of the system. Thus, it can be expected that if the user perceives high MWL of using a system, he or she will be more likely to believe the facilitating conditions provided to use the system is not enough.

For the social media search system, advanced techniques need to be developed and incorporated into it in order to make the collection, storage, organization, and presentation of the vast amount of unstructured and multilingual user-generated content across social media sites in an effective and efficient manner. Thus, sufficient and advanced technical support is expected. When using the system to conduct information searches, if the user experiences a low level of MWL, it could lead to his or her belief that the technical support provided by the system is sufficient and satisfactory. Otherwise, high MWL is likely to indicate that users may feel the technical support of the system is not good enough. Therefore, we hypothesize:

> H3: MWL will negatively influence FC in social media search systems.

TTF is defined as the level of fit between the tasks that the user needs to perform and the technology that he/she uses to carry out the tasks (Goodhue and Thompson 1995). According to the theory, a match between the technology (e.g., an information system) and the task requirements can lead to the use of similar, and therefore consistent and improved problem-solving processes (Goodhue and Thompson 1995). Thus, when information systems are designed to fit the task, the outcome of system use should contribute positively to the overall productivity (Goodhue and Thompson 1995). As argued in previous literature, when there is a fit between information presentation and the task, users believe they can perform tasks better and that is true (Fuller and Dennis 2009; Speier and Morris 2003). Since PE represents the degree to which an information system is perceived to enhance one's task performance (Venkatesh et al. 2003), it can be expected that a fit between the information system and task can result in the increase in PE.

Previous research also found that TTF could significantly influence PE in the adoption of different types of systems. For example, Zhou et al. (2010) found that TTF had a significant impact on PE in the adoption of online banking services. In another study, Wu and Chen (2017) found TTF to be a significant indicator of the user's perceived usefulness (a concept from TAM that is theoretically similar to PE) in the adoption of the massive online learning environment. In our study, we also expect such relationship to exist and be significant in the adoption of social media search systems. Since the system is designed to address challenges associated with user-generated content (as described in Section 2.1) via better search support,

system functions are created specifically to deal with these challenges. Thus, a perceived fit between system functions and the information searching tasks can be expected, which can then lead to a belief of high level of and better performance on the tasks. Therefore, we hypothesize:

> H4: TTF will positively influence PE in social media search systems.

The fit between an information system being used and the tasks to be performed will result in a belief of increased consistency and familiarity (Goodhue and Thompson 1995). Such consistency perceived in an individual's cognitive system could help increase his or her perception of the level of ease associated with completing similar types of tasks by using the system (Goodhue and Thompson 1995). Therefore, a better fit could result in the feeling of an increased degree of ease associated with using the system which is the concept of effort expectancy (EE) (Venkatesh et al. 2003). On the contrary, when a mismatch occurs between the system and the task, similar cognitive processes cannot be used to act on the representations of task characteristics or technology characteristics (Goodhue and Thompson 1995). As a result, the lack of consistency in the user's problem-solving process will reduce his or her feeling of ease associated with using the system.

In previous studies, Wilson and Addo (1994) found that when there was a fit users could complete tasks more efficiently with less effort, and Mathieson and Keil (1998) found that a poor fit could lead to a feeling of difficult to use. When studying user adoption of the massive online learning environment, Wu and Chen (2017) found that TTF had a significant impact on perceived ease of use (a concept from TAM that is theoretically similar to EE). Similarly, we expect the same relationship exists in the context of the social media search system. If the user perceives the system functions fit their information searching needs, he or she is more likely to experience a high degree of ease associated with using the system. Otherwise, the user will find the system difficult to use. Thus, we hypothesize:

> H5: TTF will positively influence EE in social media search systems.

A fit between an information system and the task generally indicates that there is an effective interaction between the two components - system and task (Mathieson and Keil 1998). Once such effective interaction is perceived by the user, it could be expected that he or she would perceive a high degree of capability of the system to perform certain type of tasks (Fuller and Dennis 2009; Goodhue and Thompson 1995). Such positive feeling on system capability is acquired toward both effectiveness (quality) and efficiency (speed) associated with using the system to complete tasks (Fuller and Dennis 2009). While both dimensions (effectiveness and efficiency) are important, there is often a trade-off between them (Fuller and Dennis 2009). Therefore, in order for a system to provide both high effectiveness and efficiency in task performance, a strong and advanced technical infrastructure and other related support (i.e., facilitating conditions, FC) are needed. If the user perceives a high degree of fit between the system and the task, he or she could possibly gain a positive feeling toward the system capability in task performance, which in turn leads to a positive belief of FC associated with system use. In the context of this study, if the user perceives a good fit between the functions of the social media search system and the information search task, it is reasonable to expect that he or she will perceive a high level of FC. Thus, we hypothesize:

> H6: TTF will positively influence FC in social media search systems.

The dependent variable examined in this study is behavioral intention (BI), which refers to an individual's intention to use technology, and it has been widely accepted as an important dependent variable when studying how and why individuals adopt new information technologies (Davis et al. 1989; Venkatesh et al. 2003). According to UTAUT, social influence (SI) is defined as the degree to which an individual perceives that important others believe he/she should use the system (Venkatesh et al. 2003).

As pointed out by UTAUT (Venkatesh et al. 2003), PE, EE, and SI are three major direct determinants of BI. In this study, we assume these relationships still hold in the context of the social media search system. Specifically, when the user perceives that the system can better help him or her search across the vast amount of unstructured, multilingual user-generated content, he or she will be more likely to use it. In addition, such a system is expected to reduce the user's effort to conduct searches across data from heterogamous social media sources, which will possibly lead to a stronger intention to use it. Furthermore, users' perceptions about a system are generally believed to be influenced by others as well. An increased level of positive belief among others about the system could lead to one's own greater intention to use it. Thus, we hypothesize:

> H7a: PE will positively influence BI in social media search systems.
> H7b: EE will positively influence BI in social media search systems.
> H7d: SI will positively influence BI in social media search systems.

As to the impact of FC on BI, although the original UTAUT paper (Venkatesh et al. 2003) proposes that the relationship from FC to BI is nonsignificant (i.e., H4a), in their updated model (i.e., UTAUT 2), Venkatesh et al. (2012) adds the casual

relationship back and states that FC can significantly influence BI. In addition, previous research has validated the casual relationship from FC to BI in varous contexts, such as e-commerce (Martín and Herrero 2012), education (Teo 2011), and healthcare (Boontarig et al. 2012). For example, Teo (2011) conducted an empirical study with about 600 teachers from 31 different schools, and found that FC could significantly and positively influence teachers' intention to use technology. In another study, Boontarig et al. (2012) found FC to be a significant factor in influencing elder people's intention to use e-healthcare services via the smartphone. Furthermore, as argued in previous literature (Martín and Herrero 2012; Venkatesh et al. 2012), based on the definition of FC (which is an individual's belief on the existence of organizational and technical support of using an information system), this construct actually reflects the perceptions of the individual and not reality, thus affecting the cognitive processes that generate the intention and not necessarily the behavior. Therefore, it is reasonable to believe the existance of the casual relationship from FC to BI (Martín and Herrero 2012; Venkatesh et al. 2012). In our case, we also expect such relationship exist in the context of the social media search system. Since the system needs to have the ability to effectively and efficiently collect, store, organize, and present the overwhelming amount of data that lack a common structure and are generated in different languages, the belief toward technical resources and other types of related support are expected to have a strong impact on users' system usage intention. Thus, we hypothesize:

> H7c: FC will positively influence BI in social media search systems.

In the proposed research model, we do not hypothesize the causal relationship from either MWL or TTF to SI. This is because SI aims to measure how others' perceptions toward a system can influence an individual's use of it. However, both TTF and MWL focus on an individual's own perceptions of the system. Thus, it is inappropriate to link either MWL or TTF to SI.

4 Research method

4.1 Study site

Our study site is a social media search system developed for the security domain. The technical details and the results of benchmark comparisons for system performance can be found in (Dang et al. 2014). Specifically, that study described the design and implementation details of the system framework following the three-layer architecture, and evaluated the system performance by comparing it with the search functions provided by benchmark forums augmented with Google Translate in the dimensions of accuracy, time efficiency, system quality, perceived usefulness, ease of use, user satisfaction, and intention to use. It was found that the system outperformed the benchmark in all dimensions, indicating the high level of quality and support that the system could provide for searching information across unstructured, multilingual social media data. This current study differs a lot from Dang et al. (2014) in that here we investigate user adoption of the system by developing a research model that incorporates three theoretical perspectives of MWL, TTF, and UTAUT.

4.2 Lab experiment

The research method used in this study is the lab experiment. Our subjects were undergraduate students enrolled in a junior/senior-level introductory information systems class at a major public university located in the southwest United States. The instructors assisted the recruiting by providing extra course credit as an incentive for students' voluntary participation. We choose to use lab experiment as the research method because it fits the nature of the study – the participants could get the chance to first experience the system by using it to complete some related tasks, and then provide their perceptions based on the usage experience. Since social media search systems are a relatively new type of systems with little commercialized effort yet, and the system we developed and used in the study was new to all participants, it was a need to give them the chance to get familiar with the system and use it to perform some tasks before asking them to fill out the questionnaire. This is why we need to give participants the chance to get familiar with the system and use it to perform some tasks before asking them to fill out the questionnaire.

The process of the lab experiment included several steps. We first informed the participants that they were participating in a research study, and their job was to use a new type of system – a social media search system – to complete several information search tasks. Then, we gave them a brief introduction of the system to show them where to find different functions to use. After that, each participant got a package. The first part of the package included the tasks they needed to perform and places for them to provide their answers, and the second part of the package listed the questionnaire items, shown in 7-Likert scale, for them to provide their ratings based on their usage experience. To reduce any potential biases, we did not inform the participants the specific objective of the study. But we did let them know that this was a research study, with the general purpose of evaluating a new type of systems. For each participant, the entire lab experiment took about an hour. Because of the capacity limitation of the computer lab, we run multiple sections of the lab experiment, and the participants had the flexibility to choose the time slot they preferred.

Since the system includes data collections in different languages, and has two types of search functions (i.e., search information in one specific data collection and across all data sources), we would like the participants to explore and get the experience with all these features. Therefore, by consulting several security researchers and educators, seven search tasks were developed based on three scenarios (searching information in an English data collection, in a non-English data collection, and across all data sources). Each participant needed to complete all seven tasks and then fill out the questionnaire.

In total, 190 subjects (77 females and 113 males) participated in the study with an average age of 21.8, 12.6 years of using computers, 10.2 years of using the Internet, and 9.3 years of using Web-based search systems. In the experiment, the non-English tasks were mainly based on Arabic. Only 3 out of the 190 participants could read or write Arabic in a very elementary level. This means that all participants needed to use the multilingual translation function provided in the system to conduct the information search tasks for non-English data collections (without skipping it), thus making their ratings on the measurement items related to the multilingual translation function of TTF convincing. The tasks are listed in Appendix 1, and an example of the screenshot of the search system is provided in Appendix 2.

4.3 Measurement of MWL

In this study, we develop the measurement of MWL based on NASA-TLX (Hart and Staveland 1988). As discussed in Section 2.2, most previous studies using NASA-TLX simply provided subjects the original descriptions of the six dimensions, each description as one question item. To the best of our knowledge, no existing study has developed survey-based items for different dimensions of NASA-TLX. To address the gap and to systematically assess MWL in our study, we have developed survey items for different dimensions of MWL by using the original description for each dimension as its definition.

Further, to make sure the face and content validities of these items remain intact, most of the original wording from the definitions is kept with only minor changes as appropriate to the context. We have followed a simplified version of the measurement item development process presented by Moore and Benbasat (1991). A card sorting mechanism is used. To do that, we have printed out the measurement items on index cards, and ten IS experts are invited to conduct the card sorting process to separate those cards into different groups. Based on the card soring results and their suggestions, we have fine-tuned the items. Furthermore, a pilot test has been conducted to once again check the validity and readability of those items. The results show that participants appear to understand the items well and the preliminary analysis indicates the measures are reliable and valid.

When studying Web-based services, previous studies suggested dropping the physical demand dimension in NASA-TLX due to the fact that the keyboard and mouse actions needed to navigate through Web pages were not assumed to produce noticeable physical demand compared to operating aircrafts or other large-scale machines (Schmutz et al. 2009; Li et al. 2009). Following that suggestion, we exclude the physical demand dimension in our study as well.

In addition, the original NASA-TLX asks the user to rate each dimension based on a 0 to 100 numeric score range (Hart and Staveland 1988). Later research has adapted that to point scales, such as the 10-point scale (Schmutz et al. 2009) and 7-point scale (Chen et al. 2009). In this study, we use the 7-point Likert scale. Table 2 lists the specific measurement items that we have developed based on NASA-TLX and the Cronbach's alpha value for items associated with each dimension. All Cronbach's alpha values range from 0.79 to 0.94 which are greater than the recommended minimum value of 0.7 (Nunnally 1978; Hair et al. 1998). Therefore, all items are reliable.

4.4 Measurement of TTF

To measure TTF, we follow Fuller and Dennis' (2009) suggestion to develop system function specific measures. Different from some other studies that utilized general items to measure TTF, Fuller and Dennis (2009) showed an example about measuring TTF of a particular system based on its specific features and functions. Following this idea, we created our own TTF measures based on the three specific functions of our system (i.e., Data Integration, Information Search, and Multilingual Translation), instead of leveraging any existing generic ones from prior literature. Table 3 shows the specific items and the Cronbach's alpha value of TTF on each system function. All Cronbach's alpha values are greater than the recommended minimum value of 0.7 (Nunnally 1978; Hair et al. 1998), indicating that items for all system functions are reliable.

4.5 Measurement of PE, EE, FC, SI and BI

To measure PE, EE, FC, SI, and BI, we adopt the standard items from the original UTAUT paper (Venkatesh et al. 2003). For PE, three out of the four items are kept ("If I use the system, I will increase my chances of getting a raise" is dropped because it is not appropriate for the context of this study). For SI, two out of the four item are kept ("The senior management of this business has been helpful in the use of the system" and "In general, the organization has supported the use of the system" are dropped because they are not appropriate for the context

Table 2 Survey-based measurement items of MWL developed in this study

Dimension (Cronbach's Alpha)	Item No.	Item
Mental Demand Dimension (0.832)	MDD1	A large amount of thinking was required when using the social media search system to complete the tasks.
	MDD2	A large amount of deciding was required when using the social media search system to complete the tasks.
	MDD3	I had to remember a large amount of things to use the social media search system to complete the tasks.
	MDD4	Overall, using the social media search system to complete the tasks was: easy / demanding.
	MDD5	Overall, using the social media search system to complete the tasks was: simple / complex.
Temporal Demand Dimension (0.788)	TDD1	I felt a lot of time pressure when using the social media search system to complete the tasks.
	TDD2	When using the social media search system to complete the tasks, the pace was: relaxed leisurely / extremely hurried.
	TDD3	When using the social media search system, I had spare time to complete the tasks: very often / almost never.
Performance Dimension (0.943)	PD1	Using the social media search system, I successfully achieved the task goals.
	PD2	I was successful in accomplishing the goals of the tasks using the social media search system.
	PD3	I was satisfied with my performance in accomplishing the tasks using the social media search system.
	PD4	I was pleased with the results of my task performance using the social media search system.
Effort Dimension (0.904)	ED1	I needed to work very hard to get familiar with the social media search system to complete the tasks.
	ED2	I needed to work very hard to get satisfactory performance when using the social media search system to complete the tasks.
Frustration Level Dimension (0.876)	FLD1	When using the social media search system to complete the tasks, I felt: gratified / discouraged.
	FLD2	When using the social media search system to complete the tasks, I felt: relaxed / irritated.
	FLD3	When using the social media search system to complete the tasks, I felt: content / stressed.
	FLD4	When using the social media search system to complete the tasks, I felt: complacent / annoyed.

of this study). As shown in Table 4,[2] the Cronbach's Alpha values for PE, EE, and SI are all greater than the 0.7 guideline (Nunnally 1978; Hair et al. 1998). For FC, the reliability test results (see the next section) suggest dropping items FC3 and FC4. After that, the Cronbach's Alpha value increases to 0.716, passing the 0.7 guideline.

5 Data analyses and results

Following the original UTAUT study (Venkatesh et al. 2003), indicators of BI, EE, FC, PE, and SI are modeled as reflective measures. However, indicators of MWL and TTF are modeled as formative measures since each dimension of indicators contributes to one certain aspect of the corresponding latent construct. These indicators are causes, rather than caused by, their latent constructs (Chin 1998; Petter et al. 2007). For MWL and TTF, each of them has several dimensions and each dimension has several measurement items. To simplify the analysis and presentation, we adopt the method proposed by Au et al. (2008) to use summated scales (standardized to 7-Likert scale) to measure each dimension, resulting in five summated scales for MWL and three for TTF.

5.1 Measurement model assessment

Two streams of structural equation modeling (SEM) techniques can be used to measure causal models, including covariance-based (e.g., SAS and LISREL) and component-based (e.g., SmartPLS and PLS-Graph) methods (Chin 1998). The covariance-based methods are not appropriate for this study, since there are formative measures in the proposed research model and, by nature, formative indicators are not expected to have covariation within the same latent construct (Lee and Xia 2010). Thus, we choose to use the partial least squares (PLS) method for this study. PLS is a component-based method and therefore can handle both formative and reflective constructs (Chin 1998). Specifically, Smart PLS 2.0 (M3) beta (Ringle et al. 2005) is used to conduct the detailed analyses. Reflective and formative indicators require different approaches and criteria for reliability and validity testing (Gefen et al. 2000; Petter et al. 2007). We present the detailed tests and their results as follows.

[2] We used the past tense for EE and PE based on the rationale that participated had already used the system before working on the questionnaire, and their ratings on the related measures were based on this prior system usage experience. As to BI, SI, and FC, they are constructs that are not directly related to participants' prior system usage behavior, but about their general perceptions and feelings. We understand that this is not consistent with the original UTAUT paper, in which all measurement items are in the present tense, and we acknowledge that it might be a potential limitation.

Table 3 Measurement items of TTF developed based on the three system functions

Dimension (Cronbach's Alpha)	Item No.	Item
Data Integration Fit (0.891)	DIF1	The social media search system fit the way I preferred to view messages across forums.
	DIF2	In the social media search system, the integration of messages from different forums fit my cross-forum search tasks.
	DIF3	In the social media search system, data from different forums were displayed in a consistent manner.
	DIF4	Using the social media search system, it was easy for me to compare and consolidate data from different forums.
	DIF5	The social media search system organized the output across forums in a meaningful manner.
Information Search Fit (0.891)	ISF1	The social media search system fit the way I needed to view information to accomplish my search tasks.
	ISF2	The social media search system was compatible with my search tasks.
	ISF3	The search interfaces of the social media search system were clear and adequate for performing my tasks.
	ISF4	The search results were displayed in a readable and understandable format in the social media search system.
	ISF5	The data relating to my tasks that were returned by the search functionality of the social media search system was easy to find out.
Multilingual Translation Fit (0.883)	MTF1	The social media search system fit the way I preferred to get the translations of multilingual forum messages.
	MTF2	The social media search system was compatible with my multilingual translation tasks.
	MTF3	The translation functionality of the social media search system made it easier to understand the multilingual forum messages.
	MTF4	I found the translation functionality of the social media search system useful in helping me get a better understanding of multilingual forum messages.
	MTF5	It was easy to learn how to use the translation functionality of the social media search system to conduct my tasks.
	MTF6	The social media search system's display of the original message and its English translation helped me to understand the content.

5.1.1 Reliability test

To test reliability, the weights for formative items and loadings for reflective items (Chin 1998; Au et al. 2008), and their t-values are calculated (as shown in Table 5). Except for TDD, the weights for all formative measures are statistically significant at the 0.01 level, indicating satisfactory item reliability (Au et al. 2008). TDD is dropped from later analyses. The loadings for all reflective measures are well above the minimum value of 0.4 (Hair et al. 1998) and statistically significant at the 0.01 level. Items FC3 and FC4 do not pass the more stringent threshold of 0.7 (Hair et al. 1998; Au et al. 2008), thus being dropped from later analyses.

5.1.2 Internal consistency and validity tests

Table 6 shows the descriptive statistics, composite reliability, average variance extracted (AVE), square root of AVE, and correlations among constructs. The composite reliability values of all reflective constructs are above the recommended level of 0.70, indicating adequate internal consistency between items (Bagozzi and Yi 1988; Hair et al. 1998; Au et al. 2008). Convergent validity is demonstrated as the AVE values for all reflective constructs are higher than the suggested threshold value of 0.50 (Fornell and Larcker 1981), which is the same as the requirement of the square root of AVE to be at least 0.707 (Gefen et al. 2000). Comparing the square root of AVE with the correlations among the constructs indicates that each construct is more closely related to its own measures than to those of other constructs, and discriminant validity is therefore supported (Chin 1998).[3]

5.1.3 Variance inflator factor (VIF) test for formative indicators

Very high reliability could be undesirable for formative constructs because excessive multicollinearity among formative indicators can destabilize the model (Petter et al. 2007). Multicollinearity is a statistical phenomenon in which two or more predictor variables in a model are highly correlated. In this situation, the coefficient estimates may change erratically in response to small changes in the model or the data.

In this study, to ensure that multicollinearity is not a significant issue, we perform the variance inflator factor (VIF) test. The VIF statistic for a formative indicator Xi was calculated by using the formula: $\mathrm{VIF}(X_i) = 1/(1-R_i^2)$, where R_i^2 is the coefficient of determination of the regression equation: $X_i = \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \ldots + \alpha_k X_k + e$. As shown in Table 7, the results suggest that all indicators have VIF

[3] We acknowledge that some correlation values are closer, and this could be a potential limitation of the study. However, as mentioned in the main text, they did not exceed the general guideline.

Table 4 Measurement items of PE, EE, FC, SI, and BI

Construct (Cronbach's Alpha)	Item No.	Item
Behavioral Intention (0.948)	BI1	The next time I need to search and translate multilingual forum messages on this topic, I intend to use the social media search system.
	BI2	The next time I need to search and translate multilingual forum messages on this topic, I predict I would use the social media search system.
	BI3	The next time I need to search and translate multilingual forum messages on this topic, I plan to use the social media search system.
Effort Expectancy (0.928)	EE1	My interaction with the social media search system was clear and understandable.
	EE2	It was easy for me to become skillful at using the social media search system.
	EE3	I found the social media search system easy to use.
	EE4	Learning to operate the social media search system was easy for me.
Facilitating Conditions (0.627*)	FC1	I have the resources necessary to use the social media search system.
	FC2	I have the knowledge necessary to use the social media search system.
	FC3	The social media search system is NOT compatible with other systems I use.
	FC4	A specific person (or group) is available for assistance with system difficulties.
Performance Expectancy (0.898)	PE1	I found the social media search system useful in doing my tasks.
	PE2	Using the social media search system enabled me to accomplish tasks more quickly.
	PE3	Using the social media search system increased my productivity.
Social Influence (0.908)	SI1	People who influence my behavior think that I should use the social media search system.
	SI2	People who are important to me think that I should use the social media search system.

*After the reliability test (see the next section), FC3 and FC4 are dropped, and then the Cronbach's Alpha value increases to 0.716

statistics lower than the traditional threshold of 5 or 10 (Lee and Xia 2010) and even the most stringent threshold of 3.3 (Diamantopoulos and Siguaw 2006; Lee and Xia 2010). Therefore, the two formative constructs in this study do not suffer from multicollinearity.

5.2 Structural model assessment and hypothesis testing

Figure 2 shows the PLS testing results of the research model. MWL has significant negative impacts on PE, EE, and FC with path coefficients of −0.202 ($p < 0.001$), −0.373 ($p < 0.001$), and − 0.409 ($p < 0.001$), respectively. Thus, H1-H3 are supported. TTF has significant positive impacts on PE, EE, and FC with path coefficients of 0.675 ($p < 0.001$), 0.533 ($p < 0.001$), and 0.247 ($p < 0.001$), respectively. Therefore, H4-H6 are supported. This indicates that both MWL and TTF are significant determinants of user acceptance in the adoption of the social media search system. The R-squared values show that MWL and TTF together have explained 70.4% of the variance of PE, 72.5% of the variance of EE, and 38.2% of the variance of FC. This also indicates that the explanation power of MWL and TTF together is stronger on PE and EE compared with that on FC.

In addition, as hypothesized, PE, EE, FC, and SI can significantly influence BI, with path coefficients of 0.352 ($p < 0.001$), 0.386 ($p < 0.001$), 0.156 ($p < 0.001$) and 0.078 ($p < 0.05$), respectively. Thus, H7a-H7d are supported. This indicates that the major causal relationships in UTAUT still hold in the adoption of the social media search system. The R-squared value shows that PE, EE, FC, and SI together have explained 67.1% of the variance of BI.

To assess whether or not potential common method bias is a significant issue, the marker variable technique is used (Lindell and Brandt 2000; Malhotra et al. 2006). In this study, SI is the post hoc marker variable since it has "the smallest correlation among the manifest variables" (p. 115) (Lindell and Whitney 2001). The common method variance (CMV) adjusted correlation and the associated t-stats between variables are calculated as: $r_A = \frac{r_U - r_M}{1 - r_M}$, $t_{\alpha/2,n-3} = \frac{r_U - r_M}{1 - r_M}$, where r_A is an adjusted correlation value; r_U is the original correlation value; r_M is the smallest positive value in the correlation matrix; and n is the sample size. Using the adjusted correlation values, we find that all significant relationships in the model remain significant. Thus, the present study is relatively robust against the common method bias.

6 Discussion

6.1 Research contributions and implications

This study makes several important research contributions. First, it is among the first and earliest attempts to

Table 5 Reliability test result

Construct	Cronbach's Alpha	Item	Weight	Loading	T-statistics
MWL		MDD	0.163		2.654*
		TDD (dropped)	*−0.052*		*0.780*
		PD***	0.527		8.876*
		ED	0.292		3.936*
		FLD	0.332		5.460*
TTF		DIF	0.364		5.132*
		ISF	0.387		6.581*
		MTF	0.348		5.158*
BI	0.948	BI1		0.944	82.720*
		BI2		0.964	145.741*
		BI3		0.947	122.238*
EE	0.928	EE1		0.900	67.435*
		EE2		0.896	55.143*
		EE3		0.930	72.525*
		EE4		0.903	51.630*
FC	0.627	FC1		0.819	23.099*
	(0.716**)	FC2		0.873	46.342*
		FC3 (dropped)		*0.514*	*8.439**
		FC4 (dropped)		*0.420*	*4.863**
PE	0.898	PE1		0.926	87.481*
		PE2		0.937	101.264*
		PE3		0.871	43.412*
SI	0.908	SI1		0.965	85.720*
		SI2		0.948	73.684*

* Significant at the 0.01 level. ** Reliability after dropping some items. *** Reverse coding

assess the adoption of social media search systems, which are a new type of systems aiming at providing effective and efficient collection, storage, organization, and presentation of the vast amount of unstructured, multilingual user-generated content from various social media sites via information search support. The results of this study indicate that both MWL and TTF are two important factors that should be considered when assessing user acceptance of this new type of systems. In other words, users' cognitive burden associated with using the system as well as the level of fit between the system functionality and users' information search needs can ultimately lead to their willingness in using the system.

Second, this study integrates the theories of MWL, TTF, and UTAUT by incorporating them into one nomological network (as shown in the proposed research

Table 6 Internal consistency and validity test results

Construct	Mean	Standard Deviation	Composite Reliability	AVE	BI	EE	FC	MWL	PE	SI	TTF
BI	5.958	0.981	0.966	0.906	**0.952**						
EE	6.267	0.818	0.949	0.823	0.766	**0.907**					
FC	5.695	1.215	0.869	0.769	0.597	0.592	**0.877**				
MWL	2.634	0.898	n/a	n/a	−0.770	−0.778	−0.597	**n/a**			
PE	6.132	0.883	0.937	0.831	0.748	0.774	0.551	−0.715	**0.912**		
SI	3.889	1.336	0.956	0.916	0.244	0.195	0.238	−0.221	0.149	**0.957**	
TTF	6.464	0.829	n/a	n/a	0.812	0.816	0.558	−0.760	0.829	0.196	**n/a**

Diagonal elements in bold case are the square root of average variance extracted (AVE) by latent constructs from their indicators; off-diagonal elements are correlations among constructs

Table 7 Descriptive statistics and VIF statistics for formative indicators

Construct	Indicator	R_i^2	VIF
MWL	MDD	0.381	1.616
	PD*	0.414	1.707
	ED	0.468	1.878
	FLD	0.192	1.237
TTF	DIF	0.633	2.724
	ISF	0.594	2.465
	MTF	0.693	3.253

*To be consistent with other dimensions of MWL, reverse coding is used for PD

model), which has not been done in previous literature. Specifically, MWL and TTF are introduced as two important antecedents of UTAUT constructs (i.e., PE, EE, and FC). Derived from the well-known theory of Technology Acceptance Model (TAM) (Davis 1989), UTAUT is currently considered as one of the most popular and widely accepted adoption theories. A lot of research has been done to extend UTAUT and TAM to see what antecedents can further influence the independent variables in the models (Venkatesh and Bala 2008; Brown et al. 2010; Venkatesh and Davis 2000). For example, Brown et al. (2010) extended UTAUT in the context of collaboration technology use, and found that collaboration technology characteristics, individual and group characteristics, task characteristics, and situational characteristics were important antecedents. In this study, we extended UTAUT in the context of systems that can deal with mentally challenging tasks, and more specifically, information searches from overwhelming amounts of unstructured, multilingual social media data. And we found MWL and TTF to be two important antecedents in such context.

Third, this study also contributes to the IS literature by developing and providing a set of survey-based measurement items for MWL. MWL is a very important multidimensional construct for assessing people's perceptions toward using a system or technique from the cognitive perspective. However, a very limited amount of attention has been paid to it in the IS field. Although some previous studies utilized MWL to assess alternative system designs (Saleem et al. 2007; Kamvar and Baluja 2008; Schmutz et al. 2009), most of them used an aggregated value to measure MWL instead of a set of systematically developed measurement items. In addition, none of them has put it into a nomological network to investigate its relationships with other IS constructs. In this study, we address the gap by operationalizing the latent construct of MWL based on NASA-TLX (Cain 2007), one of the most popular assessment tools of MWL. Specifically, by using the original description provided by NASA-TLX as the definition for each dimension of MWL, we have developed a set of survey-based measurement items, which future research can adopt and further validate in different contexts.

In addition, we also hope the results of this study could provide some implications and suggestions to information systems developers and IT managers. The significant impact of MWL on user acceptance that we found in this study shows that, when creating or adopting a new information system, it is important to make sure that the system can help reduce users' mental burden when performing tasks (searching for information across heterogeneous data sources in our case) by using the system. If a system is designed to help users perform mentally challenging tasks, it is critical to develop functions and consistent data presentations that can help ease the process of performing those tasks through the system use. As

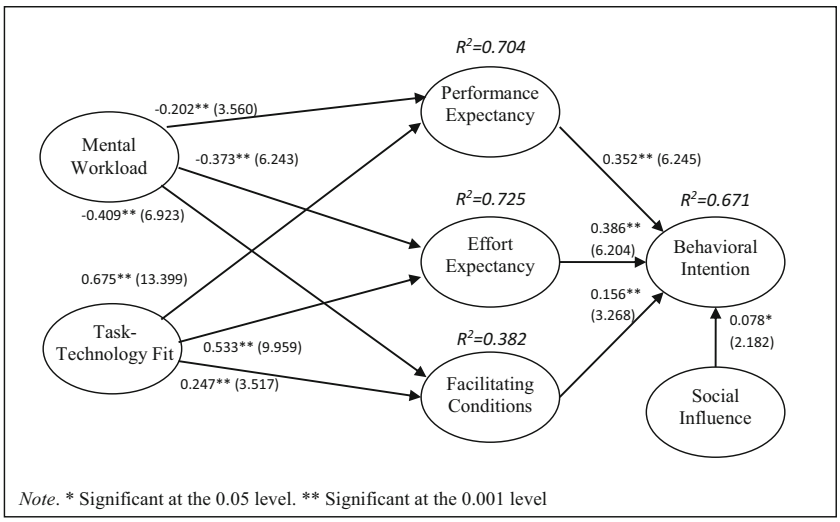

Fig. 2 PLS testing result of the research model

indicated in the results of this study, doing this can then lead to an increased intention to use the system from the users' perspective. Based on what we found in this study, some specific suggestions on developing systems with search support across vast amounts of heterogeneous data sources include: (1) creating efficient data collection mechanism, (2) adopting unified data storage, (3) providing consistent user interfaces for data access, and (4) including effective translation support with a clear presentation format. For IT managers, when they need to make decisions about adopting a new system for the organization, they should evaluate system functions from the MWL perspective. Specifically, it is important to check whether the mental burden imposed on employees when they use the system to complete their work is reasonably low. The survey-based measurement items of MWL developed in this study can be leveraged as a way to do such assessment.

Another implication and suggestion we would like to give to information systems developers and IT managers is based on the significant impact we found from TTF to user acceptance, that is to include system functions that are important, needed, and sufficient for users to perform and complete their tasks. When creating a new system, developers first need to systematically investigate the characteristics of tasks that users are going to perform by using the system. Specific system functions can then be designed and created to match those characteristics. Overall, system functions that are important, needed, and sufficient for users to complete tasks should be included in the system. For IT managers, if they want to ensure that employees are willing to use a new system, they need to investigate its functions from the employees' points of view to see whether those functions can fit the tasks that employees need to complete. By doing this, they can expect better performance, decreased effort, and higher levels of facilitating conditions as perceived by their employees, thus leading to a stronger desire to use the system.

6.2 Limitation and future directions

The use of student subjects could be a limitation, but we believe it is reasonable for this study since students are part of the system's target users of interest (Compeau et al. 2012). We acknowledge that social media analysts are going to be important users of the system. However, our subject selection was made for the following two reasons. First, the use of the system is not completely restricted to social media analysts; rather it can be used by anyone interested in searching for information from user-generated content. This necessarily includes social media analysts, students, and general citizens who are simply inquisitive. In addition, to fully test the hypotheses requires a reasonably large number of subjects. This would have been difficult to achieve had we relied entirely on social media analysts. Based on these two reasons, we believe the use of student subjects is reasonable. Future research could further evaluate the system performance and validate the proposed research model by using social media analysts as the subjects. Second, there might be some potential overlap conceptually between the effort dimension in MWL and EE, and between the performance dimension in MWL and PE. However, they are different constructs, and we believe it is reasonable to keep them separately in the proposed research model. Future research may want to take more effort to assess how different they are conceptually. Third, this study examined the social media search system using the theoretical lenses of MWL, TTF, and UTAUT. Future research could possibly study this type of systems from other theoretical perspectives. Further, the research model developed in this study could be applicable to systems other than the social media search system. Future research could further validate and extend it on the adoption of other types of systems.

7 Conclusion

Social media search systems are a new type of systems that can automatically collect huge amounts of user-generated content across heterogeneous social media sites and present them in an organized and consistent way to users via effective and efficient search support. The purpose of this study is to investigate factors that could influence user acceptance on this type of systems. To do it, we turn into theories of MWL, TTF, and UTAUT. A research model is developed by integrating the three theoretical perspectives, and a lab experiment is conducted to empirically test it. The data analysis results show that both MWL and TTF can significantly influence PE, EE, and FC, which in turn (and together with SI) have significant impacts on BI. We also operationalize the multi-dimensional latent construct of MWL by developing survey-based measurement items for different dimensions, which future research can leverage. Overall, this research makes contributions to social media analytics and information systems adoption.

Appendix 1. The seven tasks used in the experiment

Scenario 1: Please login the system using the provided user name and password, and then click the forum

"IslamicNetwork" (i.e., the 3rd forum) under "Forums in English." The following two questions are about this forum.

> Q1. Please choose the menu tab "By Member" and then use this search function to find the messages posted by user "catalyst." Please write down the total number of messages posted by user "catalyst."
>
> Q2. Please choose the menu tab "By Time" and then use this search function to find the messages posted during March, 2008 (i.e., from March 01, 2008 to March 31, 2008). Please choose and write down one of the messages returned by the search function as your answer to this question. If the message is very long, write down the first 30 words as your answer. Please also write down the date when this message was posted. (The search function may return more than one message. Please choose any one of them.)

Scenario 2: Please choose the menu tab "Home" to go back to the home page of the system. Then click the forum "Alokab" (i.e., the 2nd forum) under "Forums in Arabic." The following two questions are about this forum.

> Q3. Please choose the menu tab "By Topic" and then use the "Search for Terms in Thread Names" to find the threads talking about "nuclear." Please use the English word "nuclear" to conduct the search. For the returned thread titles, please use the embedded translation function to get their English translations by clicking the button "Translate Titles" at the bottom of the result list. Please choose and write down one of them as your answer to this question. (The search function may return more than one thread. Please choose any one of them and write down its English translation.)
>
> Q4. Please choose the menu tab "By Topic" and then use the "Search for Terms in Message Bodies" to find the messages talking about "Iraq." Please use the English word "Iraq" to conduct the search. For the returned message bodies, please use the embedded translation function to get their English translations by clicking the button "Translate" at the bottom of the result list. Please choose one of the messages and write down the English translation of the sentence in this message that has the word "Iraq." (The search function may return more than one message. Please choose any one of them and write down the English translation of the sentence in the message that has the word "Iraq.")

Scenario 3: Please choose the menu tab "Home" to go back to the home page of the system. Then click "Cross Forum Search" under "Search all forums" at the bottom of the home page. The following three questions are about this cross forum search function.

> Q5. Please use this function to find the threads talking about "bomb" in different forums. Please use the English word "bomb" to conduct the search. Please write down the number of threads identified for each forum. Then click the Arabic forum "AlFirdaws" (i.e., the 1st forum in the result list) to view all the threads talking about "bomb" in this forum in a pop-up webpage. Please use the embedded translation function to get the English translations of these threads by clicking the button "Translate Titles" at the bottom of the result list. Please choose and write down one of them as your answer to this question. (The search function may return more than one thread. Please choose any one of them and write down its English translation.)
>
> Q6. Please close the pop-up result webpage of the previous question Q5. Then choose the menu tab "By Topic (Cross Forum)" to start a new search session. Please find the threads talking about "extremist" in different forums. Please use the English word "extremist" to conduct the search. Then click any one of the Arabic forums to view all the threads talking about "extremist" in that forum in a pop-up webpage. Please write down the name of the forum that you choose. Then use the embedded translation function to get the English translations of these threads by clicking the button "Translate Titles" at the bottom of the result list. Please choose and write down one of them as your answer to this question. (The search function may return more than one thread. Please choose any one of them and write down its English translation.)
>
> Q7. Please close the pop-up result webpage of the previous question Q6. Then choose the menu tab "By Topic (Cross Forum)" to start a new search session. Please find the threads talking about "peace" in different forums. Please use the English word "peace" to conduct the search. Then click any one of the Arabic forums to view all the threads talking about "peace" in that forum in a pop-up webpage. Please write down the name of the forum that you choose. Then use the embedded translation function to get the English translations of these threads by clicking the button "Translate Titles" at the bottom of the result list. Please choose and write down one of them as your answer to this question. (The search function may return more than one thread. Please choose any one of them and write down its English translation.)

Appendix 2. An example of the screenshot of the search function

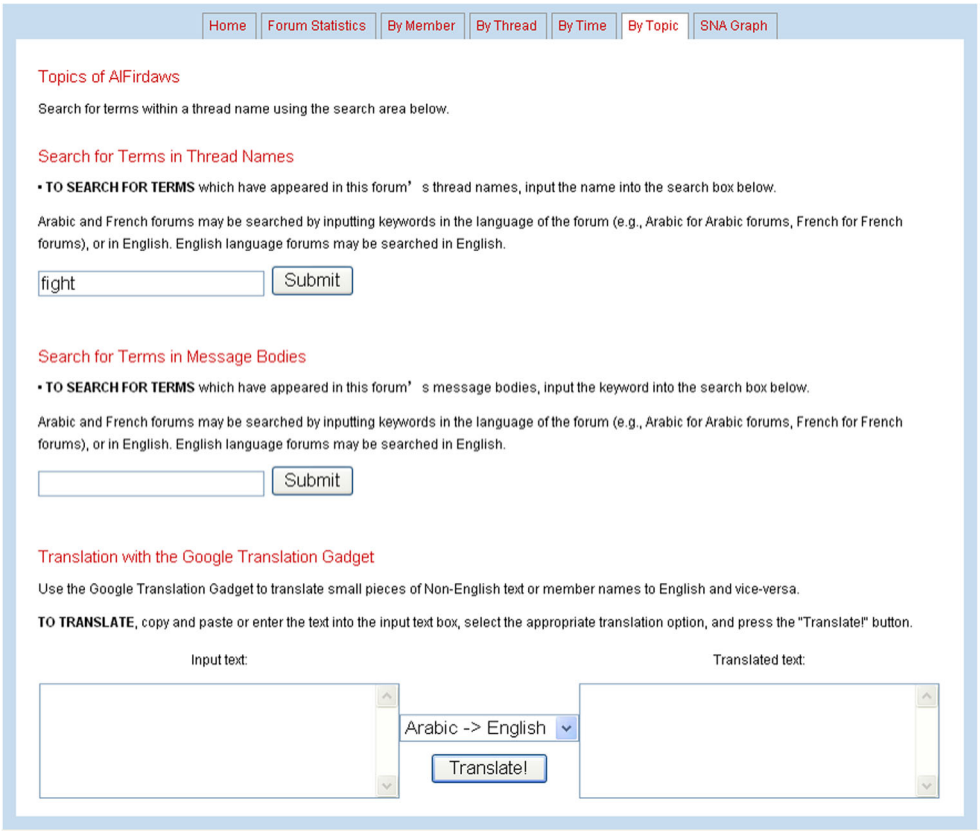

Fig. 3 A screenshot of the search function of the system

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