The effects of personality traits on business intelligence usage: A decision-making perspective

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ABSTRACT

Business intelligence (BI) has been widely employed to manage and refine vast stocks of data. However, to date, very little attention has been paid to personality traits on different BI usage patterns. The purpose of this study is to investigate the effects of personality traits on BI usage intentions. The Bagozzi, Dholakia and Basuroy (BDB) model and a personality framework are used in this study. By collecting data of 354 managers from China and Taiwan, we empirically examine the proposed model. The results show that conscientiousness and openness to experience are significantly related to the intention to read information and the desire to exchange reports respectively. Additionally, the intention to read information directly or indirectly influences the intention to create reports through the desire to exchange reports. The findings can help organizations select users with suitable traits to boost usage patterns during BI implementation.

Keywords: Decision making; Business intelligence; Personality trait; Five-factor model; BDB model; Behavioral intention

INTRODUCTION

Collectively, human begins create 2.5 quintillion bytes of data every day. The data originate from many sources, i.e. recorded pictures, keystrokes in an email, and phone calls (IBM 2012), and the data are called big data. The International Data Corporation reported that the amount of data was 161 exabytes in 2006 and grew to 988 exabytes in 2010. A digital universe study estimated that 1.8 zetabytes of information were created and replicated in 2011, representing approximately 10 times the amount of data from 2006 (EMC 2008). At the same time, big data also accumulate from and within organizations.

Recently, several organizations have implemented business intelligence (BI) to manage and refine vast stocks of data. These units also encourage their employees to use BI to support decision making (Chang, Hsu and Wu 2015). Users can read information from standard reports, ad hoc reports, and alerts, and create their own reports with query/drill-down functions (Davenport and Harris 2007; SAP AG 2008). Additionally, users can exchange reports with others to shorten the process of creating new reports. As a result, BI usage intentions have been proposed to classify into reading, exchanging, and creating (Chang, Hsu and Shiau 2014; Chang et al. 2015). Although users can apply BI to read information, exchange reports, and create reports, most users (approximately 60%) are only willing to read information instead of creating and exchanging reports (SAP 2014). Such differences in individual behaviors may be explained by personality traits (Barrick, Mount and Judge 2001; Costa and McCrae 1992).

Although previous studies have investigated the effects of individual differences on behavioral intentions to use information systems (IS) (Chang et al. 2015; Jackson and Park 2013; Wang 2014; Wang, Ngai and Wei 2012; Teh et al. 2011; Zha et al. 2014; Zhou and Lu 2011), these studies have mainly focused on traditional intentions with a vague concept of system usage. Without attention to the refined classification of usage patterns, personality traits alone cannot be used to make conclusive predictions of usage intentions. For example, conscientiousness and openness to experience are effective in predicting usage intentions in some research (Matzler et al. 2011; Svendsen et al. 2013) but are ineffective in the others (Wang, Lin and Liao 2012).

The purpose of this study is to investigate the effects of personality traits on three types of BI usage patterns, namely reading information, exchanging reports, and creating reports. In this study, personality traits, i.e. openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability, are derived from a popular and well-accepted five-factor model (FFM) (Tupes and Cristal 1992). More specifically, we attempt to answer the following questions:

a) Do the five personality traits predict the usage intentions of reading and exchanging?

b) Do the intention to read information, the desire to exchange reports, and the intention to create reports affect each other?

By answering the research questions, this study can help researchers and practitioners enhance the understanding of how individual differences influence different BI usage patterns. From a theoretical perspective, the investigation is based on a model grounded on the FFM and Bagozzi, Dholakia and Basuroy (BDB) models. We empirically validate the proposed model by examining previously unexplored relationships between personality traits and BI usage intentions. As noted, previous studies have lumped several usage patterns into a single usage intention. This study attempts to fill this gap by studying the effects of personality traits on different usage patterns and investigating the relationships among the three studied usage intentions. From a pragmatic perspective, the findings can help organizations boost different BI usage patterns according to user traits. In particular, the results can be applied to select suitable users in the early stages of BI adoption. Davenport and Harris (2007) illustrated a five-stage journey known as the Road Map to Enhanced Analytical Capabilities. In the first two stages, BI usages are not widely accepted in organizations and require pioneers to prove the effectiveness of BI. By selecting users with suitable traits, management can accelerate the adoption process.

LITERATURE REVIEW

Business Intelligence

BI applications include reporting and analytics, and it allows users to read information from standard reports, ad hoc reports and alerts. Additionally, users can create their own reports with query/drill-down functions. In this definition, the term “report” refers to an Excel-like datasheet that contains numerical information and the queries that generate the result. The purposes of reports are to provide timely information for making decisions. However, business-analytic applications include statistical analysis, predictive modeling, and optimization (Davenport and Harris 2007). Users can perform deep analysis and business knowledge discovery using advanced statistical and mathematical functions, data mining, and multidimensional analysis (SAP 2008).

The world’s largest software companies, i.e., SAP, Oracle, and Microsoft, offer BI solutions and products with similar functions (SAP 2008; Oracle 2013; Microsoft 2013). This study aims to investigate how personality traits affect user behavioral intentions in reporting environments. Thus, we primarily focus on the three types of BI usage patterns, i.e., reading information, exchanging reports, and creating reports.

Personality Traits

The concept of personality was proposed by Allport (1937) seventy years ago. Personality was defined as the dynamic organization within the individual of those psychophysical systems that determine his/her unique adjustments to his/her environment. Robbins and Judge (2007) defined personality as the sum total of ways in which an individual reacts and interacts with others. Later, the structure of personality was identified and labeled according to enduring characteristics that describe individual behavior, i.e., personality traits (Buss 1989; James and Mazerolle 2002; McCrae 2000).

Several studies have proposed and defined a variety of traits in terms of individual characteristics. Approximately eighteen thousand traits were proposed by Allport and Odbert (1936); however, it is difficult to precisely predict individual behavior for large numbers of traits. Although Cattell (1973) attempted to reduce the thousands of traits to 171 traits, the reduced set of traits was superficial and lacked descriptive power. McCrae and Costa (1989) proposed the personality framework of the Myers-Briggs Type Indicator (MBTI). The MBTI is a 100-question personality test that addresses four classifications: extroverted (versus introverted), sensing (versus intuitive), thinking (versus feeling), and perceiving (versus judging). However, the MBTI lacks valid supporting evidence for its measures.

Although various personality trait measures exist, a large number of traits have been criticized as lacking a classification scheme (Barrick et al. 2001). However, the five-factor model (FFM) is considered to be the most useful taxonomy in personality research (Barrick et al. 2001). McElroy et al. (2007) performed a comparative study to predict Internet usage with the personality frameworks of the FFM and MBTI and cognitive style. The results demonstrated that the FFM is the best predictive model for explaining technology adoption and usage. Thus, the FFM has been widely accepted in the past two decades (Barrick et al. 2001; Costa and McCrae 1992). In this study, we also use the FFM to investigate the relationships between personality traits and usage intentions.

The FFM is referred to as the Big Five because the model is composed of five factors: openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability (Costa and McCrae 1992). The descriptions of the Big Five are described as follows: openness to experience means that an individual is imaginative, artistically sensitive, and intellectual; conscientiousness means that an individual is responsible, dependable, persistent, and achievement oriented; extraversion means that an individual is sociable, talkative, and assertive; agreeableness means that an individual is good-natured, cooperative, and trusting; and emotional stability means that an individual is calm, enthusiastic, and secure.

Several studies have verified that the five personality traits are related to attitudes, individual behavior, job performance, and organizational processes (Barrick and Mount 1991; Barrick et al. 2001). Over the past twenty decades, the five factors in the FFM have also been verified and re-specified in different cultures and languages, including Chinese, English, Finnish, German, Italian, Japanese, and Spanish (Cabrera, Collins and Salgado 2006; McCrae and Costa 1987; 1997). The Big Five is a valid measure of personality because a large body of studies has been accumulated.

Personality plays a role in an array of processes and outcomes related to IS (Chang et al. 2015; Devaraj, Easley and Crant 2008; Jackson and Park 2013; Svendsen et al. 2013; Wang 2014; Wang et al. 2012; Zhou and Lu 2011). Recently, the FFM has drawn attention in knowledge sharing realms. Picazo-Vela et al. (2010) investigated the effects of Big-Five personality on an individual's intention to provide an online review. The results showed that neuroticism and conscientiousness are significant predictors of the intention to provide an online review. The five individual differences were further examined in virtual communities (Zha et al. 2014). Wang et al. (2012) indicated that conscientiousness, agreeableness, and extraversion can be the antecedents of students' use of blogging. Teh et al. (2011) investigated how the big five personality factors affect Malaysian students' online entertainment knowledge-sharing behaviors. The results showed that neuroticism, agreeable, extraversion, and openness have a significant influence on the intention to share knowledge, which in turn significantly affects knowledge-sharing behavior. Matzler et al. (2011) reported that agreeableness and conscientiousness influence knowledge sharing via affective commitment and documentation of knowledge. Although previous studies have investigated the effects of personality traits on knowledge sharing, they did not distinguish between the behaviors of sharing and creating. In other words, the results did not show the types of behaviors that could be predicted by types of personality traits. Thus, based on the FFM, this study explores the relationships between personality traits and different BI usage intentions.

BDB Model

The Bagozzi, Dholakia, and Basuroy (BDB) model (2003) is derived from the Dholakia and Bagozzi (D&B) model (2002). The D&B model includes the goal and implementation intentions. The goal intention means that an individual has chosen a goal and is committed to attaining it, and the implementation intention means that an individual has chosen an action for goal attainment (Bagozzi et al. 2003). Therefore, the goal intention precedes the implementation intention. The goal is further split into two types: goal desire and intention. Similarly, the implementation is divided into two types: implementation desire and intention (Perugini and Bagozzi 2003). Based on the D&B model, Bagozzi et al. (2003)

proposed the BDB model to explain the processes from goal to implementation. The BDB model is described as follows (see Figure 1): (1) the goal desire leads to the goal intention; (2) the goal intention leads to a desire to perform, i.e., the implementation desire; and (3) the implementation desire influences the intention to act.

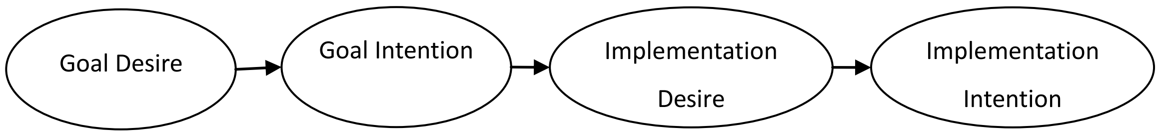

Figure 1. BDB Model

The goal desire characterizes a certain motivational intensity for attaining the goal. The goal intention means the decision maker's self-commitment to achieve a specific goal. The implementation desire characterizes the decision maker's overall motivation to act in the service of decision enactment. The implementation intention involves the decision maker's self-commitment to implementing whatever actions are necessary for goal attainment (Dholakia, Bagozzi and Gopinath 2007). Dholakia, Bagozzi and Gopinath (2007) used weight loss as an example for explaining the processes. When one desires to lose weight (i.e., the goal desire), one is motivated by the chosen goal, and one intends to lose weight (i.e., the goal intention). Next, the implementation desire is driven by the goal intention. The implementation desire could be expressed as the desire to control food intake and to enact an exercise regimen. Finally, one intends to perform the necessary actions to achieve the goal (i.e., the implementation intention). The implementation intention could be expressed for example as the intention to consume 1500 calories or less every day and to run three miles every Monday, Wednesday, and Friday.

The concepts of goal and implementation have been applied to explain individual behavior, particularly decision-making behavior (Dholakia and Bagozzi 2002; Bagozzi et al. 2003; Dholakia, Bagozzi and Gopinath 2007; Perugini and Bagozzi 2001; 2003). Previous studies have supported that the BDB model can explain behavioral intentions to use IS. Chang et al. (2015) investigated the core constructs of the technology acceptance model (TAM) on two types of BI usage patterns (i.e., the intention to read information and to create reports). The results showed that the perceived ease of use significantly influences the intention to read information through perceived usefulness, which in turn significantly influences the intention to create reports. Chang et al. (2015) further integrated motivational theories into the BDB model to investigate the effects of rewards on a manager's intention to use BI. The results showed that rewards have significant effects on the intention to read information and the desire to exchange reports, both of which determine the intention to create reports. To the best of our knowledge, no other works have studied the effects of personality traits (i.e., openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability) on the three usage intentions. This study integrates the FFM and BDB models to study the issue and relationships among different usage intentions.

Usage Intentions of Information Systems

Although most IS literature treated usage patterns as a holistic construct that encompasses all aspects of system usages, a few studies proposed that this view is not adequate in many applications. According to product types and transaction process, Shih (2004) proposed that consumer e-shopping behaviors could be split into user acceptance of products/services and user acceptance of on-line offerings (i.e., ordering, requesting post-purchase service, taking delivery, and paying on-line). Shao (2009) proposed three usage behaviors of virtual communities, including reading, creating, and participating. Users read others' contents to obtain needed information, they create their own contents for self-expression, and they participate in interaction with the contents (e.g., sharing with others, posting comments, rating).

Davenport and Harris (2007) indicated that BI usage patterns include reading information from standard reports, ad hoc reports, and alerts, and creating reports with query/drill-down functions. BI can also be referred to as a repository of cooperate knowledge (SAP 2014). The designs and the contents of reports can be viewed as knowledge. As proposed by knowledge management research (Hung, Lai and Chang 2011; Kankanhalli, Tan and Wei 2005; Wasko and Faraj 2005), usage intentions of knowledge management systems should include sharing and exchanging. Chang et al. (2015) further showed that a positive relationship exists between reading information and creating reports. Chang et al. (2015) also posited that the intention to read information can lead to the desire to exchange reports. Therefore, this study argues that BI usage intentions can be classified into reading, exchanging, and creating.

RESEARCH MODEL AND HYPOTHESES

People who score high on conscientiousness are dependable, responsible, organized, hardworking, achievement oriented, and task oriented (Barrick and Mount 1991). Conscientiousness is recognized as a robust predictor of job performance (Barrick et al. 2001). People with such a trait are motivated to achieve performance at a high level and to take action to improve their job performance (Devaraj et al. 2008). Decision making is usually viewed as an important part of the job (Robbins and Judge 2007) because the results of decision making strongly affect job performance. Because general decisions based on numerical information are more convincing than pure intuition in the business environment, we expect that conscientious people are more likely to read information from reports. Thus, this study proposes the following hypothesis:

H1: Conscientiousness is positively related to Intention to Read Information.

People who score high on emotional stability are stable, controlled, calm, enthusiastic, and secure (Barrick and Mount 1991). Additionally, these individuals are more self-confident than those who are low on emotional stability (Molleman, Nauta and Jehn 2004; Picazo-Vela et al. 2010; Van Vianen and De Dreu 2001). In organizational behavior research, self-efficacy is positively associated with job performance (Bandura 1986; 1977). Similar to conscientiousness, we expect that stable emotional people are more willing to read information from reports to achieve better decision-making performance. Thus, this study proposes the following hypothesis:

H2: Emotional Stability is positively related to Intention to Read Information.

People who score high on agreeableness are good-natured, forgiving, courteous, helpful, altruistic, generous, cheerful, and cooperative (Barrick and Mount 1991). Agreeableness is a robust predictor of cooperative behavior (Barrick, Stewart, Neubert and Mount 1998). People with such a trait tend to strive for collaboration rather than competition (Liao and Chuang 2004). Thus, several studies have argued that agreeableness is linked directly to cooperative behavior (Cabrera et al. 2006; Matzler et al. 2011; Matzler, Renzl, Muller, Herting and Mooradian 2008; Picazo-Vela et al. 2010; Wang and Yang 2007). Because exchange behavior can be considered to be social interactions (Blau 1964), we expect that highly agreeable people are more likely to exchange reports with colleagues or supervisors through interpersonal interactions. Thus, this study proposes the following hypothesis:

H3: Agreeableness is positively related to Desire to Exchange Reports.

People who score high on extraversion are sociable, talkative, and assertive (Barrick and Mount 1991). When people have a higher of socialization, they are more willing to share their experiences with others and consider other people's suggestions (Tsao and Chang 2010). Several scholars have also argued that extraversion closely relates to social interactions (Costa and McCrae 1989; Picazo-Vela et al. 2010). Because exchanging reports is a type of social interaction, we expect that extraverted people are more likely to exchange reports with other people. Thus, this study proposes the following hypothesis:

H4: Extraversion is positively related to Desire to Exchange Reports.

People who score high on openness to experience are imaginative, artistically sensitive, and intellectual (Barrick and Mount 1991). This type of person tends to seek out new

experiences and consider various viewpoints and opinions (Devaraj et al. 2008; McCrae and Costa 1997; Tsao and Chang 2010). Because openness to experience reflects an individual's curiosity and originality, several studies have proposed that openness is a strong predictor of knowledge sharing (Cabrera et al. 2006; Matzler and Mueller 2011; Matzler et al. 2008; Picazo-Vela et al. 2010). We expect that highly open people are willing to exchange reports with other people. Thus, this study proposes the following hypothesis:
H5: Openness to Experience is positively related to Desire to Exchange Reports.

The goal intention causes the implementation desire (Bagozzi et al. 2003). When decision makers choose "accessing to information" as a goal, they will take specific actions to attain the chosen goal. Although people tend to read information, they can choose "exchanging reports with others" to attain it. In other words, exchanging reports is a form of action. As Quigley et al. (2007) argued, individuals could rely on exchanging information with others to access additional knowledge. We expect that people are likely to exchange reports for reading information. Thus, this study proposes the following hypothesis:
H6: Intention to Read Information is positively related to Desire to Exchange Reports.

The goal intention is viewed as influencing one's implementation intention (Dholakia and Bagozzi 2002). BI allows users to easily create reports using drag-and-drop objects and mouse clicks (SAP AG. 2008). It is expected that users will easily create reports when they need additional information. Creating Reports is expressed as another means of reading information. Similarly, we expect that people are likely to create their own reports for reading information. Thus, this study proposes the following hypothesis:
H7: Intention to Read Information is positively related to Intention to Create Reports.

The implementation desire precedes the implementation intention (Bagozzi et al. 2003). Mele (1995) proposed that the implementation is targeted at a means to the chosen goal and energizes the intention to perform instrumental acts. Because decision makers can exchange reports to obtain information that they need for their decision-making process, exchanging reports could be a driver of creating reports. As Nahapiet and Ghoshal (1998) propose, the exchange of information is one of the major requirements for creating knowledge. We expect that people's desire to exchange reports is likely to cause their willingness to create reports. Thus, this study proposes the following hypothesis:
H8: Desire to Exchange Reports is positively related to Intention to Create Reports.

The research model is shown in Figure 2. The model suggests that the five personality traits (i.e., conscientiousness, emotional stability, agreeableness, extraversion, and openness to experience) influence BI usage intentions. Conscientiousness and emotional stability influence the intention to read information, which in turn directly or indirectly influences the intention to create reports through the desire to exchange reports. Agreeableness, extraversion, and openness to experience influence the desire to exchange reports, further determining the intention to create reports.

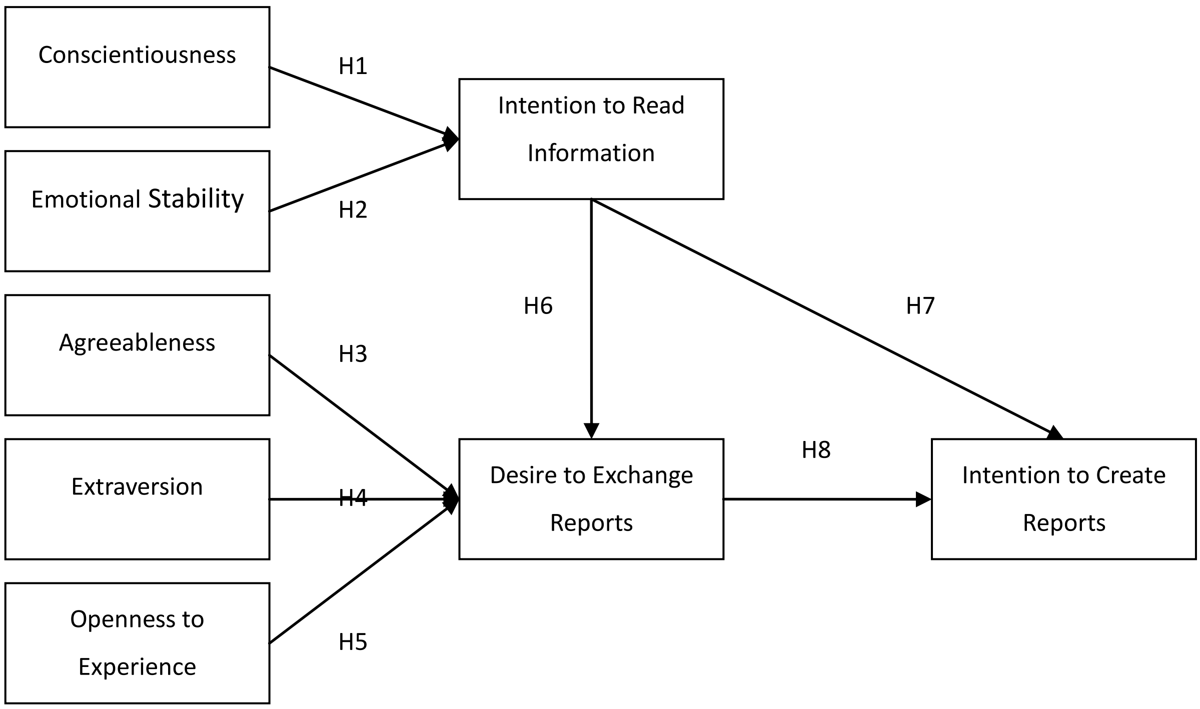

Figure 2: The Research Model

RESEARCH METHODOLOGY

Sample and Data Collection

The data set was collected from executive master of business administration (EMBA) students at Chinese and Taiwanese universities. The EMBA students from China and Taiwan were invited to participate in this study. Among the 1080 surveys distributed in EMBA classes, 354 were returned for a response rate of 32.8%. Most of the 354 respondents were males (79.7%). A majority of the respondents were 36 to 45 years of age (46.3%), worked in a strategy department (22.9%), and were employed in electric manufacturing industries (37.9%). All of the respondents had experience with BI usage. Appendix 1 lists the respondent characteristics, including gender, age, department, industry type, time in reading information and creating reports per month, and experience in BI.

Measures

Openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability items were adapted from Gosling, Rentfrow and Swann, (2003). Intention to Read Information, Desire to Exchange Reports, and Information to Create Reports items were adapted from Bagozzi et al. (2003) and Perugini and Bagozzi (2001). A pretest was conducted with 20 BI consultants. After reviewing and filling in the pre-test questionnaire, these consultants provided suggestions related to wording, length, and format of the items in the questionnaire. Based on the suggestions, the items were revised (see Appendix 2). The English measurements were translated to traditional and simplified Chinese. A back-translation method was applied to ensure consistency between versions (Mullen 1995). All of the items were measured on a seven-point Likert scale ranging from strongly disagree (1) to strongly agree (7). Table 1 describes the operational definitions of the eight constructs.

Table 1: Definition of Constructs

Construct	Operational Definitions	Source
Conscientiousness (C)	The extent to which one is responsible, dependable, persistent, and achievement oriented.	Robbins and Judge (2007)
Emotional Stability (ES)	The extent to which one is calm, enthusiastic, and secure.	Robbins and Judge (2007)
Agreeableness (A)	The extent to which one is good-natured, cooperative, and trusting.	Robbins and Judge (2007)
Extraversion (E)	The extent to which one is sociable, talkative, and assertive.	Robbins and Judge (2007)
Openness to Experience (O)	The extent to which one is imaginative, artistically sensitive, and intellectual.	Robbins and Judge (2007)
Intention to Read Information (IR)	The strength of one's willingness to read information from reports.	Bagozzi et al. (2003)
Desire to Exchange Reports (DE)	The strength of one's desire to exchange reports with others.	Bagozzi et al. (2003)
Intention to Create Reports (IC)	The strength of one's willingness to create reports.	Bagozzi et al. (2003)

DATA ANALYSIS

This study uses AMOS 17.0, a structural equation modeling (SEM) software package, to test our research model and uses SmartPLS 3.0 to examine common method bias (CMB). SEM allows researchers to assess measurement and structural models. The measurement model examines the convergent and discriminant validity of items and constructs. The structural model examines the hypothesized relationships between constructs in the research model. Additionally, CMB allows researchers to examine potential bias during the data collection process.

RESULTS

Common Method Bias

This study uses statistical analyses to assess common method bias. First, Harman's one-factor test is examined using a principal component analysis. If a single construct accounts for more than 50% of the variance, common method bias may threaten the validity (Harman 1976; Podsakoff et al. 2003). The results show that the combined eight constructs account for 82.48% of the total variance. The variance of the eight constructs ranges from 5.57% to 15.01%, which are all less than 50% of the variance. Second, we use the method developed by Podsakoff et al. (2003) and Williams, Edwards and Vandenberg (2003) to assess the common method factor included in a PLS model. If the method factor loadings are insignificant and the indicators' substantive variances are substantially greater than their method variances, common method bias may be not a serious concern. The results show that most method factor loadings are insignificant, and the average substantive variance of the indicators is 0.737, which is greater than 0.017 of the average method variance (see Appendix 3). Therefore, common method bias can be excluded from the items in this study.

Assessment of the Measurement Model

This study examines the measurement model by testing the convergent and discriminant validity. All constructs are modeled as reflective based on the existing literatures (Bagozzi et al. 2003; Gosling et al. 2003; Perugini and Bagozzi 2001). The convergent validity of the measurements is assessed by the item reliability, the composite (construct) reliability, and the average variance extracted (AVE) (Fornell and Larcker 1981). First, the item reliability is assessed using the factor loadings. The factor loadings for all of the measures range from 0.72 to 0.93, which exceed the 0.7 loading criterion (Hair et al. 1992). Second, the construct reliability is assessed using Cronbach's alpha. Cronbach's alpha for all of the constructs ranges from 0.80 to 0.95, which exceeds the 0.7 recommended level (Nunnally 1978). The composite reliability (CR) is calculated based on standardized factor loadings and error variances (Hair et al. 1998). The CR for all of the constructs range from 0.82 to 0.94, which exceeds the 0.7 recommended values.

As shown in Table 2, the AVE for all of the constructs ranges from 0.72 to 0.88, which exceeds the 0.5 recommended values (Fornell and Larcker 1981). Additionally, Table 3 shows that the square root of the AVE of each construct is larger than its correlations with other constructs. Therefore, the convergent and discriminant validity are both confirmed.

Table 2: Convergent Reliability of the Measurements

Construct	Item	Item Reliability	Composite Reliability	Cronbach's alpha	AVE
Conscientiousness (C)	C1	0.80	0.86	0.80	0.76
	C2	0.72			
Emotional Stability (ES)	ES1	0.84	0.84	0.82	0.76
	ES2	0.72			
Agreeableness (A)	A1	0.86	0.82	0.82	0.72
	A2	0.74			
Extraversion (E)	E1	0.72	0.85	0.88	0.79
	E2	0.87			
Openness to Experience (O)	O1	0.87	0.82	0.80	0.72
	O2	0.75			
Intention to Read Information (IR)	IR1	0.77	0.89	0.88	0.73
	IR2	0.82			
	IR3	0.76			
Desire to Exchange Reports (DE)	DE1	0.91	0.94	0.95	0.88
	DE2	0.93			
	DE3	0.91			
Intention to Create Reports (IC)	IC1	0.85	0.93	0.94	0.85
	IC2	0.90			
	IC3	0.87			

The fitness measures for the measurement model are shown in Table 4. χ^2, GFI (good-of-fit index), AGFI (adjusted good-of-fit index), NFI (normed fit index), and CFI (comparative fit index) are used to test the fitness measures for the proposed model. χ^2/d.f. should not exceed 3 (Kettinger and Lee 1994), GFI and AGFI should be greater than the 0.8 recommended values (Scott 1995), and NFI and CFI should be higher than the 0.9 recommended values (Bentler and Bonett 1980).

Table 3: Inter-Construct Correlations

	C	ES	A	E	O	IR	DE	IC
C	0.87							
ES	-0.01	0.87						
A	0.69	-0.05	0.85					
E	0.02	-0.00	0.08	0.89				
O	0.03	0.03	0.08	0.01	0.85			
IR	0.22	0.14	0.61	0.06	0.09	0.85		
DE	0.24	0.13	0.57	0.08	0.08	0.46	0.94	
IC	0.14	0.11	0.39	0.07	0.08	0.69	0.44	0.92

Table 4: Overall Fits of Models

Fit Index	Results	Recommended Value	References
χ^2	367.8	-	-
d.f.	138	-	-
χ^2/ d.f.	2.67	< 3	Kettinger and Lee (1994)
GFI	0.94	≧ 0.80	Scott (1995)
AGFI	0.91	≧ 0.80	Scott (1995)
CFI	0.98	≧ 0.90	Bentler and Bonett (1980)
RMSEA	0.07	≦ 0.08	Jarvenpaa, Tractinsky, and Vitale (2000)
NFI	0.96	≧ 0.90	Bentler and Bonett (1980)
NNFI	0.98	≧ 0.90	Bentler and Bonett (1980)

Assessment of the Structural Model

This study examines the structural equation model by testing the hypothesized relationships among the eight constructs (Figure 3). The results show that conscientiousness significantly affects Intention to Read Information (β=0.183, $p<0.001$), thus providing support for H1. This variable explains 13% of the variance in Intention to Read Information. Unexpectedly, emotional stability has no direct effect on Intention to Read Information (β=-0.005, $p>0.05$). Thus, H2 is not supported. Additionally, the results show that openness to experience (β=0.103, $p<0.05$) and Intention to Read Information (β=0.430, $p<0.001$) have significant effects on Desire to Exchange Reports, thus supporting H5 and H6. Together, the two paths account for 21% in Desire to Exchange Reports. Contrary to expectations, agreeableness (β=-0.010, $p>0.05$) and extraversion (β=0.030, $p>0.05$) have no direct influence on Desire to Exchange Reports, and thus, H3 and H4 are not supported. Intention to Read Information (β=0.582, $p<0.001$) and Desire to Exchange Reports (β=0.155, $p<0.001$) have significant effects on Intention to Create Reports, supporting H7 and H8. The model accounts for 44% of the variance in Intention to Create Reports.

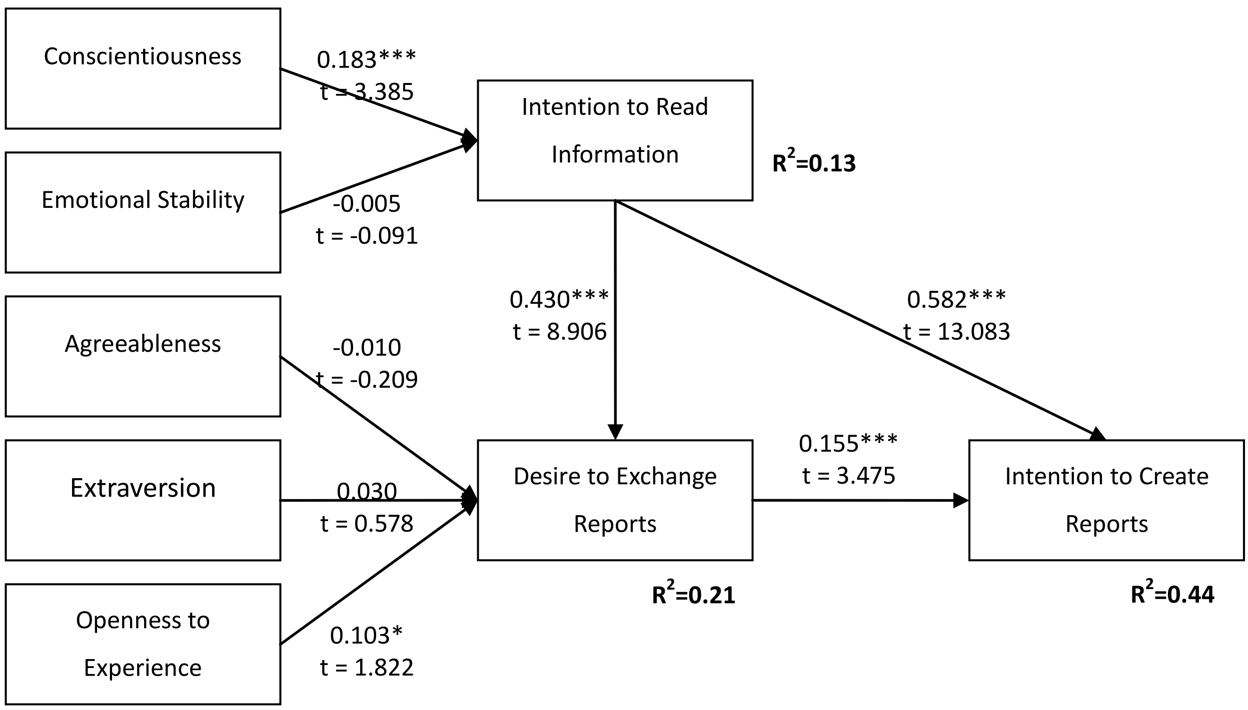

Figure 3: Results of Structural Modeling Analysis

DISCUSSION

This study proposes five factors for predicting three types of BI usage patterns. We demonstrate that conscientiousness is positively related to Information to Read Information and openness to experience is positively related to Desire to Exchange Reports. We also find that Intention to Read Information directly or indirectly influences Intention to Create Reports through Desire to Exchange Reports.

However, emotional stability is not related to Intention to Read Information. We explain this finding by noting that emotional stability has been linked to the characteristic of self-confidence. People who are low in emotional stability have low self-confidence and tend to be anxious and insecure. Such people will carefully perform a particular behavior or task. Even if they do not directly care about job performance, they still read additional information to support their decision making. The converse dual effects reduce the influence of emotional stability. Thus, emotional stability does not significantly affect an individual's intention to read information.

This study finds that extraversion and agreeableness are not related to Desire to Exchange Reports. A possible reason for the lack of support for agreeableness is that although agreeable people tend to cooperate with other, the cooperative behavior should be based on trust (Robbins and Judge 2007). In general, decision makers in organizations have the ability of sufficient judgment and do not fully trust others. Even if people are high on agreeableness but low on trust, they are still unwilling to exchange reports with others. Thus, agreeableness does not significantly affect an individual's desire to exchange reports.

Finally, extraversion is found to be unrelated to Desire to Exchange Reports. Extraverts (high on extraversion) tend to spend much of their time maintaining and enjoying a large number of relationships (Robbins and Judge 2007). Because decision making is a professional job in an organization, decision makers may not consider exchanging reports to be a method of maintaining friendship and relationship. Thus, the findings imply that an individual's desire to exchange reports cannot be influenced by the trait of extroversion.

Although conscientiousness has a positive impact on usage intentions for some IS (Devaraj et al. 2008; Svendsen et al. 2013), it fails to do so in some other case (Wang et al. 2012). Devaraj et al. (2008) examined the effects of personality traits on usage of a collaborative system. Since the targeted system allows users to access documents and discussion, the main usage pattern is reading information. The findings showed that conscientiousness has a positive effect on the usage intention. Svendsen et al. (2013) also found that conscientiousness positively affects accessing digital contents through mobile phones and PCs. However, Wang et al. (2012) discovered that conscientiousness has no significant effect on the usage intention of blog systems. The usage patterns implicitly include reading and sharing. Although it is not an outright proof, the phenomenon indeed shows that mixing different usage patterns into a holistic intention can significantly distort the outcome.

Openness to experience is found to be effective in predicting knowledge sharing in some research (Cabrera et al. 2006; Matzler et al. 2008; Teh et al. 2011) but is ineffective in the others (Devaraj et al. 2008; Wang et al. 2012). The former three studies have focused on the effects of personality traits on knowledge sharing. The results showed that openness to experience significantly influences knowledge sharing. However, the research of Devaraj et al. (2008) and Wang et al. (2012) did not support the relationship between openness to experience and usage intentions. We speculate the reason may be that the usage patterns in former study is mainly reading and in the latter is mixture of reading and sharing.

This study distinguishes usage intentions into reading information, exchanging reports, and creating reports. The results show that conscientiousness is positively related to reading information and openness to experience is positively related to exchanging reports. The findings show that different usage patterns can be predicted by different personality traits. Thus, future IS research on personality traits should distinguish among different usage patterns more discernibly.

This study also employs the BDB model to investigate how the intention to read information, the desire to exchange reports, and the intention to create reports affect each other. Our results show that the intention to read information influences the desire to exchange reports, which in turn influences the intention to create reports. In addition, the intention to read information directly influences the intention to create reports. Thus, we provide empirical evidence to demonstrate that the BDB model can explain the relationships among the three usage intentions.

The findings in this study can be applied to expedite the process of adopting BI in organizations that have attempted to broaden BI usage. In practice, many organizations that test the waters of BI will choose a handful of units to experiment on the effectiveness of BI. To find suitable users in these units, the results can be used as a guideline. This study finds that conscientious people are more inclined to read information to make sound decisions. Because conscientious people are achievement oriented and task oriented (Barrick and Mount 1991; Costa and McCrae 1992), they are more willing to make the effort to use IS for job performance. Generally, user adoption is a significant determinant of a successful IS implementation (Amoako-Gyampah and Salam 2004; Amoako-Gyampah 2007). At the beginning of implementation, management should select conscientious people to use the systems. With their utilization, the benefit and the usefulness of BI will become apparent to others who will subsequently be attracted to use BI.

This study also finds a positive relationship between openness to experience and the desire to exchange reports. Open people tend to develop more expertise (Matzler et al. 2008). If they have higher levels of expertise, they are more willing to engage in contributing their knowledge and sharing it with others (Constant, Sproull and Kiesler 1996). After the BI project was implemented, using BI reports will be a routine task for employees. In the next phase, the organization should encourage employees to share their own reports and the information in the reports. Thus, management should further select open people to adopt the sharing roles within the teams. Team members with high levels of openness to experience will be effective in sharing their reports and influence report sharing within and across teams.

In testing the model, this study finds that the intention to read information and the desire to exchange reports influence the intention to create reports. If reading information and exchanging reports are important determinants of creating reports, management should strive to increase employees' willingness to read information and to exchange reports. Personality traits are often used as part of a selection system because they are directly and indirectly associated with job performance and work-related behaviors (Barrick et al. 2001). It is hoped that the practical implication of this study will be useful to management for improving the selection process and understanding the personality traits that influence employees' BI usage patterns.

CONCLUSION

This study has addressed a significant gap between personality traits and IS usage patterns. Previous studies have merged several usage patterns into a single usage intention. The results showed that openness to experience and conscientiousness are effective in predicting usage intentions in some research (Matzler et al. 2008; Svendsen et al. 2013) but are ineffective in the others (Wang et al. 2012). In other words, these results were different even if the same personality traits were investigated.

This study proposes to distinguish usage intentions into reading, exchanging, and creating. We find that conscientiousness and openness to experience influence the intention to read information and the desire to exchange reports, respectively. Future studies can follow the logic to investigate personality traits on different usage intentions to verify the findings and to broaden the knowledge in this area. The findings can also help organizations select users with suitable traits to boost usage patterns during BI implementation. For example, management can select conscientious people to be the information consumers to read information from the system while selecting open people to adopt the sharing roles within the teams.

This study contains certain limitations that require further examination and additional research. First, we focus on the roles of the five traits on BI usage intentions. Future studies should take a more comprehensive view and consider other traits. Second, we apply a short version of the Big Five personality measures (Gosling et al. 2003). Because future studies might use a longer version, the construct reliability and explanatory variance for all of the constructs might be higher. Third, because the data are cross-sectional and not longitudinal, the posited casual relationships could only be inferred rather than proven. Future longitudinal studies should compensate for this deficiency. Fourth, because the data in this study are collected from organizations in a single Chinese culture, the generalizability of the results may be limited. Future studies should examine organizations in different national cultures. Fifth, self-report bias may exist because respondents often answer in such a way as to portray themselves in a good light. Last, as Devaraj et al. (2008) argued, personality has been largely ignored in the IS literature over the past two decades. Thus, future studies can apply the proposed model in studying other enterprise information systems.

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Appendix 1: Demographic Profile

Measure	Items	Frequency	Percent
Gender	Male	282	79.7
	Female	72	20.3
Age	26-35 years	61	17.2
	36-45 years	164	46.3
	46-55 years	117	33.1
	56-65 years	12	3.4
Location	China	150	42.4
	Taiwan	204	57.6
Department	Administration	19	5.4
	Financial Accounting	23	6.5
	Human Resources	12	3.4
	Information Technology	38	10.7
	Manufacturing	31	8.8
	Purchase	19	5.4
	Research and Development	34	9.6
	Sales and Distribution	60	16.9
	Strategy	81	22.9
	Others	37	10.5
Industry Type	Automotive	11	3.1
	Chemical and Energy	12	3.4
	Construction	11	3.1
	Electricity and Gas	10	2.8
	Electric Manufacturing	134	37.9
	Finance and Insurance	31	8.8
	Information Service	17	4.8
	Logistic and Transportation	11	3.1
	Machinery	12	3.4
	Medical	10	2.8
	Semiconductor	38	10.7
	Telecommunication	7	2.0
	Others	50	14.1
Time in Reading Information per Month	Under 0.5 hours	40	11.4
	0.5 to 1 hour	84	23.6
	1 to 1.5 hours	78	22.1
	1.5 to 2 hours	30	8.5
	2 to 2.5 hours	34	9.6

	2.5 to 3 hours	16	4.4
	Over 3 hours	72	20.3
Time in Creating Reports per Month	Under 0.5 hours	93	26.2
	0.5 to 1 hour	111	31.4
	1 to 1.5 hours	55	15.5
	1.5 to 2 hours	27	7.7
	2 to 2.5 hours	18	5.2
	2.5 to 3 hours	8	2.2
	Over 3 hours	42	11.8
Experience in BI	Under 1 Year	42	11.9
	1-2 Years	59	16.7
	3-4 Years	72	20.3
	5-6 Years	64	18.1
	7-8 Years	24	6.8
	9-10 Years	52	14.7
	Over 10 Years	41	11.6

Appendix 2: Measurement Items of Constructs

Construct	Measurement Items	Source
Conscientiousness	I see myself as: 1. Dependable, self-disciplined 2. Disorganized, careless [Reverse]	Gosling et al. (2003)
Emotional Stability	I see myself as: 1. Anxious, easily upset 2. Calm, emotionally stable [Reverse]	Gosling et al. (2003)
Agreeableness	I see myself as: 1. Critical, quarrelsome 2. Sympathetic, warm [Reverse]	Gosling et al. (2003)
Extroversion	I see myself as: 1. Extraverted, enthusiastic 2. Reserved, quiet [Reverse]	Gosling et al. (2003)
Openness to Experience	I see myself as: 1. Open to new experiences, complex 2. Conventional, uncreative [Reverse]	Gosling et al. (2003)
Intention to Read Information	Please express the strength of your intention to read information from reports when making decisions… 1. I am planning to read information from reports. 2. I intend to read information from reports. 3. I will expend effort to read information from reports.	Perugini and Bagozzi (2001)
Desire to Exchange Reports	Please express the strength of your desire to exchange reports with others when needing information for decision making… 1. I desire to exchange reports with others. 2. I feel an urge or need to exchange reports with others. 3. My overall wish is to exchange reports with others.	Bagozzi et al. (2003)
Intention to Create Reports	Please express the strength of your intention to create reports with others when needing information for decision making… 1. I am planning to create reports. 2. I intend to create reports. 3. I will expend effort to create reports.	Perugini and Bagozzi (2001)

Appendix 3: Common Method Bias Analysis

Construct	Indicator	Substantive Factor Loading (R1)	$R1^2$	Method Factor Loading (R2)	$R2^2$
Conscientiousness (C)	C1	0.748**	0.560	0.147	0.022
	C2	0.846**	0.716	-0.157	0.025
Emotional Stability (ES)	ES1	0.807**	0.651	0.230**	0.053
	ES2	0.745**	0.555	-0.218**	0.047
Agreeableness (A)	A1	0.731**	0.534	-0.032	0.001
	A2	0.751**	0.564	-0.032	0.001
Extraversion (E)	E1	0.782**	0.612	0.159	0.025
	E2	0.849**	0.721	-0.168	0.028
Openness to Experience (O)	O1	0.719**	0.517	0.226**	0.051
	O2	0.839**	0.704	-0.261**	0.068
Intention to Read Information (IR)	IR1	0.854**	0.729	0.010	0.000
	IR2	0.947**	0.897	-0.010	0.000
	IR3	0.896**	0.803	0.001	0.000
Desire to Exchange Reports (DE)	DE1	0.965**	0.931	-0.016	0.000
	DE2	0.960**	0.922	0.015	0.000
	DE3	0.947**	0.897	0.000	0.000
Intention to Create Reports (IC)	IC1	0.967**	0.935	-0.022	0.001
	IC2	0.922**	0.850	0.014	0.000
	IC3	0.951**	0.904	0.009	0.000
Average		**0.854**	**0.737**	**-0.006**	**0.017**

*p < .05; **p < .01