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Role of intrinsic and extrinsic factors in user social media acceptance within workspace: Assessing unobserved heterogeneity

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ABSTRACT

This study develops and empirically tests a theoretical extension of a technology acceptance model that integrates intrinsic and extrinsic motivators into IT acceptance to predict the adoption of social media within the workspace. The model was tested using cross-sectional data collected from different workplaces in different geographic regions. To detect the homogeneity of users' behavior, we used a response-based procedure for partial least squares. The model was strongly supported for the global model. Our results revealed the existence of distinct adoption behaviors for different groups within the overall sample. These findings advance theory and contribute to future research on social media adoption.

1. Introduction

Workspace investment in information systems (IS) refers to the use of IS by professionals in their workplace and has been steadily increasing over the years. Organizations are investing heavily in IS not only for improving high-level efficiency but also for strategic value. Some analysts have estimated that such investments represent about 46% of all capital investment in the US economy (Devaraj & Kohli, 2003). From around $2.1 trillion in 2013 (Arouri, Nguyen, & Youssef, 2015), global IS investments were expected to reach $3.8 trillion in 2014 (Soste et al., 2015). Moreover, the continuous growth in worldwide IS spending continues to motivate studies of the adoption and acceptance of technology (Nakata, Zhu, & Kraimer, 2008). However, to make full use of such information systems, user acceptance is critical. Without the readiness to use such systems in organizations, resistance can develop that affects technology adoption.

Innovation diffusion theory has been a popular theoretical basis for researchers investigating the adoption of organizational innovation (Damanpour, 1991). Extensive research work has led to several models and theories about the motivation behind the acceptance or rejection of a given information technology (IT) innovation. The technology acceptance model (TAM) is one (Davis, 1989; Shih, 2004; Song, Nason, & Di Benedetto, 2008). Adapted from the theory of reasoned action (TRA) developed by Ajzen and Fishbein (1980) and Ajzen and Fishbein (1980), Koh and Saad (2006), Davis (1989) proposed that TAM could be used to assess an individual's acceptance of an IT artifact (Davis, 1989). TAM predicts the likelihood of a new technology being adopted by individuals. The model has undergone many extensions, replication, and refinement (Bruner Ii & Kumar, 2005; Ha & Stoel, 2009; Kwon, Kwak, & Kim, 2015; Porter & Donthu, 2006). (Venkatesh & Davis, 2000) proposed TAM2, an extension of TAM, into which social influence processes (including subjective norm, voluntariness, and image) and cognitive instrumental processes (including job relevance, output quality, result demonstrability, and perceived usefulness) were integrated. These processes are considered to be crucial for studies of user acceptance.

In a subsequent study, Venkatesh and Bala (2008) draw on prior studies of TAM to propose an integrated model of the determinants of IT adoption and use at the individual level, TAM3. Amoako-Gyampah and Salam (2004) developed an extended TAM-based model of enterprise resource planning implementation and acceptance. All the TAM models indicate that the behavior of a potential adopter of an IT artifact is explained jointly by two interrelated beliefs, namely, perceived usefulness (PU) and perceived ease of

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use (PEOU) (Davis, 1989). A subsequent study by Koh and Saad (2006) adds a third belief, perceived enjoyment (PE). PE is one of the extrinsic factors suggested by motivation theorists to explain user acceptance of IS (Choi et al., 2013Choi, Chow, & Liu, 2013; Fisher, 1978; Hajji, Pellerin, Gharbi, Léger, & Babin, 2016; Khan, Hussain, & Saber, 2016; Koh & Saad, 2006; Wang, Gunasekaran, Ngai, & Papadopoulos, 2016). Motivation theorists believe that the intent to use and the actual use of IT are determined by key extrinsic and intrinsic factors (Choi et al., 2013; Fisher, 1978; Hajji et al., 2016; Khan et al., 2016; Koh & Saad, 2006; Wang et al., 2016).

Early studies have helped improve our understanding of the key factors that explain IS acceptance. However, we still face challenges related to IS adoption and use, such as low adoption and underutilization of IT within the workspace (Venkatesh & Bala, 2008), which constitute "major barriers to successful IT implementations in organizations" (Venkatesh & Bala, 2008). The lack of assessment of unobserved heterogeneity in IS adoption research is considered a key reason for the low acceptance of IT. Complex social and behavioral phenomena are studied in IS research and so it is highly likely that heterogeneity will exist in the samples used to develop, test, and refine models. When this heterogeneity is not uncovered and controlled it is called unobserved heterogeneity and can bias results and conclusions (Ansari, Jedidi, & Jagpal, 2000).

Becker, Rai, Ringle, & Völckner (2013) find that over the past 20 years, a limited number of papers published in top IS journals using structural equation modeling (SEM) have tested unobserved heterogeneity. Most studies assume that empirical data are homogeneous and represent a single population, leading to potential bias when assessing SEM parameters. The present situation may therefore produce invalid conclusions due to unobserved heterogeneity, constituting an important validity threat to the structural model, measurement model, or both (Becker et al., 2013). Consequently, there is call for more research into the methods and techniques for investigating unobserved heterogeneity when using SEM. This study is an initial effort to bridge this gap in the literature.

In this study we focus particularly on social media adoption in the workspace. Social media are emerging as new technological tools that enable the realization of the third wave of electronic commerce, or so-called social commerce, which is defined as "a form of Internet-based social media that allows people to participate in the marketing, selling, comparing, and buying of products and services in online marketplaces and communities" (Stephen & Toubia, 2010). First developed to facilitate communication between a network of friends through pictures, videos, and sharing of daily experiences, social media tools are gaining traction within the workspace (Shami, Nichols, & Chen, 2014) and are expected to transform traditional business processes. For example, they offer improved means of engaging with and influencing consumers (Anderson, Sims, Price, & Brusa, 2011); improving communication with key firm stakeholders (e.g., employees, customers, and suppliers) (Leonardi, Huysman, & Steinfield, 2013; Luo, Guo, & Chen, 2011; Trainor, Andzulis, Rapp, & Agnihotri, 2014); facilitating intra-organizational knowledge sharing (Luo et al., 2011); establishing new business relationships (Anderson et al., 2011; Michaelidou, Siamagka, & Christodoulides, 2011); and improving customer shopping experiences and purchasing decisions (Fisher, 2011; Zhou, Zhang, & Zimmerman, 2011).

The business literature provides evidence that supports the high operational and strategic potentials of social media tools. For example, AirTran Airways has been using Twitter to sell discounted airline tickets (Anderson et al., 2011). Dell generated $6.5 million in revenue in 2009 from its Twitter presence (Ostrow, 2009). Leidner et al. (2010) found that the use of an internal social networking system at USAA, a Texas based investment firm, helped improve the retention rate of new hires.

The use of social media in the workplace may have gained in popularity over the last few years but it is not universal. A recent survey of 1100 employees in North America by SilkRoad (Stephen, 2012) found that 43% work in organizations where access to social media is completely open, 24% work in organizations where access is monitored, and only 16% of firms completely block access. The study by SilkRoad (Stephen, 2012) also found that regardless of the corporate policy toward social media, 75% of workers access social media on the job from their personal mobile devices at least once a day, and 60% access it multiple times for work and/or personal use.

Firms from various sectors realize the high operational and strategic potentials of social media-related tools and have been pushing for its integration into daily activities in the workspace (Leonardi et al., 2013; Sajda, 1995). However, the history of innovation theory demonstrates that the path toward widespread acceptance of any given technological innovation within the business community can be very long. Therefore, an improved understanding of the factors to be addressed, which is part of the objective of this study, is critical in driving forward the acceptance of social media within the workspace.

Our objectives are:

1 To assess the unobserved heterogeneity in our SEM so as to detect the homogeneity of users' behaviors within the model.
2 To theoretically develop and empirically validate a research model that extends the models proposed by Heijden (2004) and Teo et al. (1999), integrating intrinsic and extrinsic factors into IT acceptance to predict social media adoption and use within a given workspace.

More specifically, this study seeks to answer the following research questions:

RQ1: Are users' behaviors homogenous when applying TAM to social media adoption and use in the workspace?

RQ2: What are the critical intrinsic and extrinsic factors that predict social media adoption in the workspace?

This research draws on both the extant literature on social media and IT adoption (mainly TAM and motivation theory). For our research model, we use the response-based procedure for partial least squares (REBUS-PLS) algorithm, which defines a response-based procedure for detecting unobserved unit segments in PLS path modeling.

The rest of this paper is structured as follows. First, we present social media potentials followed by the conceptual development with a focus on TAM, motivation theory, the research model, and the hypotheses. Next we present the REBUS-PLS method followed by the research methodology, results, and discussion, and conclude with the limitations of this study and directions for future research.

2. Conceptual development

2.1. Focus on TAM and motivation theory

From Ajzen and Fishbein's (1980) theory of reasoned action (TRA), (Davis, 1989) developed and proposed TAM to assess an individual's acceptance of an IT artifact. Subsequently, the model has undergone many extensions (Venkatesh, Morris, Davis, & Davis, 2003), replication, and refinement (Chad, Said, & Geoffrey, 2011; Choi, Kim, & Kim, 2011; Ha & Stoel, 2009; Kim & Park, 2011; Kwon et al., 2015; Muk & Chung, 2014; Porter & Donthu, 2006; Steven John & David, 2007; Tabitha, Taner, Katherine, Brian, & Reza, 2006; Yair & Bruce, 2009). According to all related TAM models, the behavioral intention of a potential adopter is explained jointly by two interrelated beliefs: PU—"the degree to which a person believes that using a particular system would enhance his or her job performance"

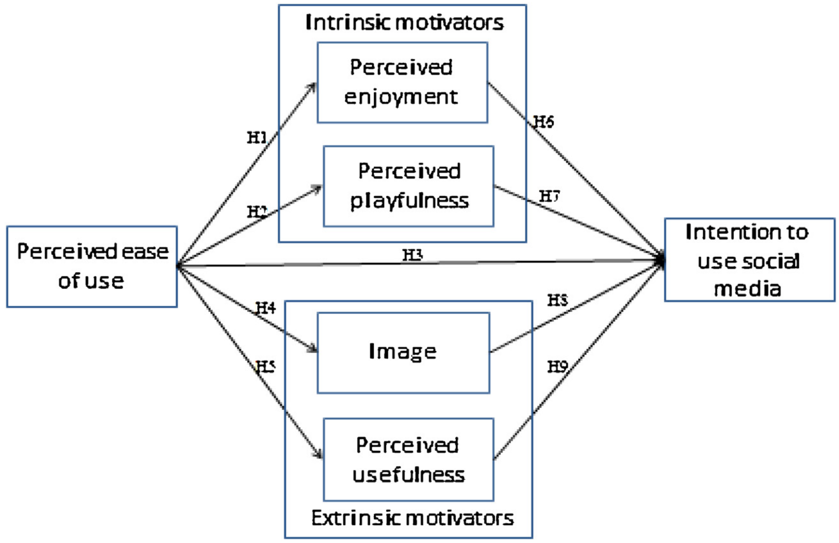

Fig. 1. Research model.

(Davis, 1989)—and PEOU—"the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989: 320). TAM posits that PU is influenced by PEOU. A later study by (Koh & Saad, 2006) adds a third belief, that is, PE—"the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated." The last belief is one of the intrinsic factors put forward by motivation theorists to explain user acceptance of IS.

For motivation theorists, the key factors determining both the intent to use and actual use of IT (Choi et al., 2013; Fisher, 1978; Hajji et al., 2016; Khan et al., 2016; Koh & Saad, 2006; Wang et al., 2016) are: (1) extrinsic factors, "the performance of an activity because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself, such as improved job performance, pay, or promotions" (Koh & Saad, 2006); and (2) intrinsic factors, "the performance of an activity for no apparent reinforcement other than the process of performing the activity per se" (Davis et al., 1992: 1112). PU and PE have been identified as key representatives of, respectively, extrinsic and intrinsic motivators of individual-level IT acceptance (Mehrtens, Cragg, & Mills, 2001). Earlier IS studies leveraged this stream of research to explore how intrinsic and extrinsic motivations influence IT acceptance and use (Kauremaa, Nurmilaakso, & Tanskanen, 2010). Many studies have found that PU (an extrinsic motivator) is the strongest determinant of the use of utilitarian or productivity oriented systems (Wu & Lu, 2013), which aim to provide instrumental value to users (Kwon et al., 2015). However, others IS studies have found that in the context of hedonic or pleasure-oriented system adoption and use, that is, systems that provide self-fulfilling value to the user (Kwon et al., 2015), PU is less important than PE, which is a key intrinsic motivator (Wu & Lu, 2013). Most IT systems are categorized into utilitarian or hedonic, based on the purpose of their use. However, some IT systems could also be both. An example of a utilitarian IT system is Blackboard, which is used for education-based tasks in universities; an example of a hedonic system is Facebook, which is used to interact and share information with friends and family. An example of a dual-purpose IT system (both utilitarian and hedonic) is Email, which can be used for work-related activities and for fun. The boundaries between the three types of IT systems are not always very clear and the IS literature has yet to offer guidance on this matter.

Comparing the influence of PU (extrinsic) and PE (intrinsic) on the intention to use computers in the workplace, (Koh & Saad, 2006) concluded that both PU and PE strongly influence intention. Similarly, (Santhanam & Hartono, 2003) studied both intrinsic (i.e., PE) and extrinsic (i.e., PU) motivation to use the Internet and found that "local Internet users used the Internet mainly because they perceived the Internet to be more useful to their job tasks and, secondarily, because it is enjoyable and easy to use.". Heijden (2004) studied the user acceptance of hedonic IS and found strong indications that PE and PEOU are stronger determinants of intention to use than PU. (Wu & Lu, 2013) conducted a meta-analysis of the effect of extrinsic and intrinsic motivators on using utilitarian, hedonic, and dual-purpose IS and identified six extrinsic motivators (PU, job relevance, image, affiliation motivation, reward, and punishment) and five intrinsic ones (PE, perceived playfulness or PP, flow, pleasure, and arousal). The authors confirmed that extrinsic motivators are of great importance in utilitarian systems and that intrinsic motivators play a strong role in hedonic and dual-purpose systems. The same authors further realized that extrinsic motivators are more important than intrinsic motivators in utilitarian systems; the opposite is true for hedonic systems. They argued that the predictive power of extrinsic and intrinsic motivators varies with IT applications; this finding substantiates the necessity of developing context-dependent models for technology acceptance. (Wu & Lu, 2013) found that in the context of behavioral intention studies, enjoyment and usefulness are the most salient intrinsic and extrinsic motivators, respectively. They concluded (p. 168) that "extrinsic motivation is key to engaging individuals in using utilitarian IT, whereas intrinsic motivation is their strongest incentive for using hedonic IT. When a hedonic system is employed for utilitarian purposes, individuals are more likely to be motivated to accept and use it for that purpose because, in such a system-use scenario, both extrinsic and intrinsic motivations can drive the behavior." The authors confirmed that firms are now integrating hedonic systems (e.g., blogs) into new business models to improve productivity and performance. The authors called for additional studies on context-dependent models for system-use behavior. In this research we focus on a specific context, i.e. social media tools, which are dual-purpose IS when used in an organizational or workspace setting.

Image, which is defined as "the degree to which use of an innovation is perceived to enhance one's status in one's social system" (Moore & Benbasat, 1991), has been identified as an important

Table 1
Demographic profile (n = 2556).

	No.	%
Gender		
Male	1277	50
Female	1279	50
Age (years)		
18–24	374	15
25–34	482	19
3–44	504	20
4–54	442	17
55+	754	30
Education level		
No formal education	20	1
Primary school	76	3
Secondary school	677	26
Technical/Vocational training or apprenticeship	588	23
University degree, undergraduate	689	27
University degree, postgraduate	506	20
Country		
Australia	516	20
Canada	520	20
U.K.	519	20
U.S.	518	20
India	483	20
Living area		
Metropolitan	1303	51
Regional	761	30
Rural	492	19

extrinsic motivator of the intention to adopt and use utilitarian, hedonic, and dual-purpose IS (Wu & Lu, 2013). In TAM2 (Venkatesh & Davis, 2000), image, as well as subjective norm, is considered a determinant of PU that represents social influence processes. The desire to gain social respect or image has been considered a key motivation during the adoption of an innovation (Moore & Benbasat, 1991; Rogers, 1995; Trinchera, 2007). In sum, "image plays a role among peer group attitudes and actions among individuals. This postulation is based on evidence that points to the fact that image is important to individuals in socialization" (Trinchera, 2007).

2.2. Research model and research hypotheses

Drawing on this discussion, we propose the conceptual research model depicted in Fig. 1. The model extends the models of Kwon et al. (2015) and Santhanam and Hartono (2003) by integrating two additional key motivations, namely PP and image (IMG), to predict social media acceptance within the workspace. Indeed, these two studies proposed a research model that displayed the direct effect of PEOU on PU, PE, and intention to use (IU) as well as the mediating effects of PU and PE on the relationship between PEOU and IU.

2.3. PEOU (H1, H2, H3, H4, and H5)

All TAM models and their subsequent extensions postulate that PEOU has a positive effect on the behavioral intention of a potential adopter of an IT artifact (Davis, 1989). These models also posit that PU is influenced by PEOU (Davis, 1989). This last result has been tested and validated by prior studies (Choi & Totten, 2012; Donna Weaver, 2006; Lee, Park, Chung, & Blakeney (2012); López-Nicolás, Molina-Castillo, & Bouwman, 2008; Moon & Kim, 2001; Yu, Ha, Choi, & Rho, 2005). For example, when assessing predictors of electronically mediated commerce using interactive television or t-commerce, (Yu et al., 2005) found that consumers' PEOU of t-commerce was positively related to PU of t-commerce. Similarly, (López-Nicolás et al., 2008) found a positive significant relationship between users' PEOU of advanced mobile services and their PU. Other studies (Bruner Ii & Kumar, 2005; Ha & Stoel, 2009; Lee et al., 2012; Moon & Kim, 2001; Muk & Chung, 2014; Porter & Donthu, 2006) identified a positive significant relationship between PEOU and PU in the context of the World Wide Web (WWW), acceptance of handheld Internet devices, SMS advertising, acceptance of e-shopping, acceptance of U.S. Navy Combat IS, and the adoption of mobile financial services. Since in this work, we posit that IMG is an important predictor of employees' acceptance of social media tools, we argue that the PEOU of these tools will enhance employees' image of using these tools. In addition, (Bruner Ii & Kumar, 2005; Koh & Saad, 2006) found that PEOU has a significant influence on PE. The study by (Trinchera, 2007) on the adoption of instant messaging in enterprises revealed that PEOU has a positive impact on PU, PE, and the intention to use instant messaging in the enterprise. Although evidence shows that users often adopt technology for pleasure—"It's fun"—(K. Chien, Lin, & Shih, 2014; Toubia & Stephen, 2013), we argue that the level of pleasure related to such technology depends on how easily users can interact with it or how users perceive its ease of use. Therefore, the following hypotheses are proposed:

H1: PEOU has a positive significant effect on PE.
H2: PEOU has a positive significant effect on PP.
H3: PEOU has a positive significant effect on IU.
H4: PEOU has a positive significant effect on IMG.
H5: PEOU has a positive significant effect on PU.

2.4. Intrinsic motivators: PE (H6) and PP (H7)

Individuals may use a technology if it yields enjoyment, fun, and playfulness. Feelings of joy, elation, pleasure, disgust, and displeasure may affect behavior (Triandis, 1971), so when these emotions are associated with technology usage they may affect technology acceptance directly or indirectly.

Davis et al. (1992) defined PE as the extent to which the activity of using a computer system is perceived to be enjoyable in its own right, apart from the instrumental value of the technology. (Koh & Saad, 2006; Sun & Zhang, 2006) found that PE has a direct impact on the intention to use technology.

Moon and Kim (2001) defined PP as the extent to which an individual focuses attention on interaction with WWW; is curious during the interaction; and finds the interaction intrinsically enjoyable or interesting. Playfulness is thus the degree of an individual's tendency to interact spontaneously and creatively. In their study, Moon and Kim (2001) found that PP had a significant positive relationship with attitudes toward using WWW. Venkatesh (2000) showed that playfulness was related to perceived ease of use.

Therefore, we propose the following hypotheses:
H6: PE has a positive significant effect on IU.
H7: PP has a positive significant effect on IU.

2.5. Extrinsic motivators: Image (H8) and PU (H9)

PU is one of two beliefs at the core of all TAM models. For these models, the behavioral intention of a potential adopter of an IT artifact is explained by both PU and PEOU (Davis, 1989). IMG is one of the six extrinsic motivators identified by (Wu & Lu, 2013) in their meta-analysis of the effect of extrinsic and intrinsic motivators on the use of utilitarian, hedonic, and dual-purpose IS. Prior studies have found a positive association between IMG and the intention to use technology (Trinchera, 2007). In this work, we argue that IMG plays an important role in employees' decisions to adopt or reject social media tools. The adoption and use of social media tools are mainly driven by IMG-related utility. For example, users of Twitter, one of the fastest-growing social media platforms, take the number of their followers to measure their popularity among the general

Table 2
Descriptive statistics of measurement: manifest variables.

Latent variable	Items	GM		LM1		LM2		LM3	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
PEOU	PEOU1	4.806	1.792	4.914	1.515	4.834	1.874	4.688	1.929
	PEOU2	4.935	1.697	4.924	1.486	4.749	1.846	5.110	1.716
	PEOU3	4.946	1.777	5.113	1.508	4.895	1.897	4.844	1.873
IU	IU1	3.748	2.076	3.889	1.868	4.627	1.912	2.849	2.024
	IU2	4.597	2.011	4.861	1.722	4.851	1.903	4.141	2.244
	IU3	3.752	2.099	3.942	1.879	4.716	1.894	2.737	2.002
	IU4	4.598	1.989	4.866	1.711	4.814	1.892	4.173	2.214
PU	PU1	4.669	1.948	4.945	1.635	4.813	1.887	4.302	2.182
	PU2	3.562	1.948	3.714	1.651	4.662	1.827	2.460	1.682
	PU3	3.428	1.975	3.505	1.685	4.634	1.836	2.299	1.654
	PU4	3.504	1.969	3.583	1.691	4.661	1.818	2.414	1.703
	PU5	3.588	2.011	3.718	1.744	4.661	1.844	2.529	1.826
PE	PE1	4.434	1.992	4.725	1.656	4.880	1.941	3.785	2.134
	PE2	4.376	1.994	4.664	1.671	4.919	1.935	3.645	2.086
	PE3	4.496	2.001	4.794	1.659	4.946	1.934	3.837	2.155
PP	PP1	4.629	1.963	4.970	1.592	5.048	1.944	3.962	2.092
	PP2	4.523	2.016	4.844	1.678	5.044	1.924	3.782	2.145
IMG	IMG1	3.748	1.814	4.206	0.819	4.797	1.840	2.422	1.608
	IMG2	3.255	1.869	3.947	0.808	4.720	1.775	1.357	0.610

Table 3
Factor loadings.

Latent variable	Items	Standardized loadings			
		GM	LM1	LM2	LM3
PEOU	PEOU1	0.932	0.917	0.977	0.914
	PEOU2	0.842	0.780	0.962	0.727
	PEOU3	0.940	0.920	0.979	0.926
IU	IU1	0.846	0.758	0.929	0.784
	IU2	0.918	0.906	0.963	0.920
	IU3	0.844	0.784	0.948	0.752
	IU4	0.912	0.897	0.962	0.918
PU	PU1	0.772	0.733	0.945	0.743
	PU2	0.920	0.864	0.969	0.860
	PU3	0.927	0.878	0.964	0.881
	PU4	0.937	0.910	0.968	0.889
	PU5	0.929	0.897	0.964	0.877
PE	PE1	0.982	0.972	0.983	0.983
	PE2	0.979	0.968	0.986	0.977
	PE3	0.981	0.966	0.985	0.984
PP	PP1	0.987	0.981	0.992	0.984
	PP2	0.987	0.982	0.992	0.985
IMG	IMG1	0.938	0.838	0.976	0.585
	IMG2	0.937	0.706	0.975	0.925

Table 4
Correlation matrix for the GM and the square root of AVE.

	PEOU	PU	PE	PP	IMG	IU
PEOU	**0.906**					
PU	0.576	**0.899**				
PE	0.711	0.746	**0.981**			
PP	0.689	0.751	0.935	**0.987**		
IMG	0.333	0.605	0.500	0.518	**0.938**	
IU	0.703	0.800	0.858	0.861	0.515	**0.881**

Note: The square roots of AVE are displayed on the diagonals.

public and as a barometer of their self-worth (Toubia & Stephen, 2013). Therefore, we propose the following hypotheses:

H8: IMG has a positive significant effect on IU.

H9: PU has a positive significant effect on IU.

2.6. Evaluating unobserved heterogeneity in PLS path modeling: the REBUS-PLS method

SEMs make it possible to estimate the causal relationships, defined by a theoretical model, linking two or more latent complex concepts, each measured through a number of observable indicators. Traditionally, the component-based estimation of SEMs by means of partial least squares assumes homogeneity over the observed set of units. However, it is reasonable to expect that classes made of units will show heterogeneous behaviors in the data.

Behavioral sciences and related research fields (including IS) usually use heterogeneous samples (Lubke & Muthén, 2005). Heterogeneity within samples may be observed or unobserved. The sources of sample heterogeneity are observed when it is possible to define subgroups based on observed variables (e.g., education and gender). In this case, scholars usually use moderators or con-

Table 5
Cronbach's Alpha, rho DG, and AVE values.

		Cronbach's alpha				rho DG				AVE			
Latent variable	#	GM	LM1	LM2	LM3	GM	LM1	LM2	LM3	GM	LM1	LM2	LM3
PEOU	3	0.891	0.849	0.972	0.829	0.898	0.909	0.981	0.898	0.821	0.765	0.946	0.741
IU	4	0.903	0.859	0.964	0.867	0.933	0.905	0.974	0.910	0.808	0.704	0.903	0.726
PU	5	0.939	0.910	0.980	0.906	0.955	0.935	0.984	0.932	0.962	0.737	0.925	0.963
PE	3	0.980	0.967	0.984	0.981	0.987	0.979	0.990	0.987	0.974	0.938	0.969	0.969
PP	2	0.973	0.962	0.983	0.968	0.987	0.981	0.992	0.984	0.880	0.963	0.983	0.599
IMG	2	0.863	0.339	0.950	0.379	0.936	0.752	0.975	0.763	0.776	0.600	0.952	0.717

Table 6
Structural model: Coefficients of determination R^2 and goodness of fit values.

Dependent latent variables	Independent latent variables	* p < 0.1; ** p < 0.05 ; *** p < 0.01 ; **** p < 0.001				R^2(%)			
		GM	LM1	LM2	LM3	GM	LM1	LM2	LM3
PE	PEOU	0.711****	0.572****	0.941****	0.657****	51%	33%	88%	43%
PP		0.689****	0.519****	0.940****	0.633****	48%	27%	88%	40%
IMG		0.333****	-0.095***	0.882****	0.043	11%	1%	78%	0%
PU		0.576****	0.443****	0.924****	0.458****	33%	20%	85%	21%
IU	PE	0.237****	0.224****	0.170****	0.263****				
	PP	0.308****	0.331****	0.151****	0.334****				
	PEOU	0.144****	0.172****	0.481****	0.122****	82%	70%	94%	76%
	IMG	0.003	-0.017	-0.013	0.005				
	PU	0.307****	0.256****	0.199****	0.267****				
Goodness of Fit	Absolute	0.618	0.483	0.903	0.529				
	Relative	0.942	0.883	0.995	0.850				

textual factors (e.g., individual cultural differences, individualism versus collectivism, or demographic differences—gender, income levels, and education) to explain group differences (Becker et al., 2013). However, when the variables underpinning heterogeneity are not known in advance, we focus on the unobserved heterogeneity in the data (Lubke & Muthén, 2005). Unobserved heterogeneity is emerging as a key research topic in many fields, including marketing (Jayaram, Dixit, & Motwani, 2014; Sarstedt, Henseler, & Ringle, 2011; Sarstedt & Ringle, 2010) and information systems (Becker et al., 2013).

Identifying the sources of unobserved heterogeneity is increasingly considered an important step in validating the overall results of empirical data in various fields of research, especially when using mature theories such as TAM (Becker et al., 2013). Scholars have proposed several approaches to the evaluation of unobserved heterogeneity. These include the finite mixture partial least squares (FIMIX-PLS) method, which allows for the estimation of model parameters and the simultaneous segmentation of the affiliations of observations (Sarstedt & Ringle, 2010); and the REBUS-PLS, a response-based method through which unobserved heterogeneity can be assessed in predictive SEM (Zhao, Liu, & Lin, 2012). In the present work, we propose the use of the REBUS-PLS method, mainly because this technique can provide useful information for assessing unobserved heterogeneity in PLS path modeling. The technique allows a simultaneous estimation of both unit membership of latent classes and class-specific parameters of detected local models (Jayaram et al., 2014; Zhao et al., 2012). FIMIX-PLS only evaluates heterogeneity in the structural model, whereas REBUS-PLS detects possible sources of heterogeneity in both the measurement and structural models without any normality distribution assumption (Esposito Vinzi, Trinchera, Squillacciotti, & Tenenhaus, 2008; NWang, Liang, Zhong, Xue, & Xiao, 2012). In addition, the use of FIMIX-PLS requires a normality assumption to ensure model identification. When FIMIX-PLS is used, "the number of classes is not known a priori nor is it included as a parameter in the estimation process" (Esposito Vinzi et al., 2008). In sum, REBUS-PLS is "an iterative algorithm, which allows us to estimate at the same time both the unit memberships to latent classes and the class specific parameters of the local models without making any kind of distributional assumption either on the manifest variables or on the latent variables" (Trinchera, 2007).

3. Methodology

3.1. Sample and data collection

A cross-sectional survey design was used to test our proposed hypotheses. From our literature review, we developed a web-based questionnaire that we used to collect data from 2556 social media users within their workplaces in the UK, USA, Canada, India, and Australia. The data collection process uses a well-defined approach designed for this type of study (Dubey, Gunasekaran, & Samar Ali, 2015) and is based on a modified version of Dillman's (2007) total design method. The data collection was carried out in January 2013. These countries were chosen because they have different cultural and economic backgrounds and are from different geographic regions (Hofstede, 1980). Data collection was realized by a leading market research provider, Survey Sampling International (SSI), from its panels. SSI offers sampling and data collection through various means, including postal or landline phones, mobile phones, face-to-face interviews, and online (via tablets and smartphones).

3.2. Measures

To measure users' intention to adopt social media, we used constructs adapted from prior studies (Davis, 1989; Trinchera, 2007). All constructs were measured using a seven-point Likert scale with anchors ranging from strongly disagree (1) to strongly agree (7) (Appendix A).

3.3. Data analysis

We used XLSTAT-PLS version 2013.6.04 to test our proposed model. The measurement model was assessed in terms of item loadings, composite reliability, and convergent and discriminant validities. More precisely, discriminant validity, which "infers that

Table 7
Results of hypotheses testing.

Hypotheses	Results			
	GM	LM1	LM2	LM3
H1: PEOU has a positive significant effect on PE.	Supported	Supported	Supported	Supported
H2: PEOU has a positive significant effect on PP.	Supported	Supported	Supported	Supported
H3: PEOU has a positive significant effect on IU.	Supported	Supported	Supported	Supported
H4: PEOU has a positive significant effect on IMG.	Supported	Not supported	Supported	Not supported
H5: PEOU has a positive significant effect on PU.	Supported	Supported	Supported	Supported
H6: PE has a positive significant effect on IU.	Supported	Supported	Supported	Supported
H7: PP has a positive significant effect on IU.	Supported	Supported	Supported	Supported
H8: IMG has a positive significant effect on IU.	Not supported	Not supported	Not supported	Not supported
H9: PU has a positive significant effect on IU.	Supported	Supported	Supported	Supported

Table 8
Descriptive statistics of categorical variables.

Variable	Categories	Relative frequency per category (%)			
		GM (n = 2556)	LM1 (n = 812)	LM2 (n = 817)	LM3 (n = 927)
Gender	Male	50%	47%	53%	50%
	Female	50%	53%	47%	50%
Age	18–24	15%	17.61%	17.75%	9%
	25–34	19%	18.60%	26.68%	12%
	35–44	20%	17.73%	21.91%	20%
	45–54	17%	16.50%	14.69%	20%
	>55	29%	29.56%	18.97%	39%
Education	No formal education	1%	1%	1.35%	0%
	Primary school	3%	3%	3.92%	2%
	Secondary school	26%	29%	19.34%	31%
	Technical	23%	23%	19.09%	26%
	Undergraduate	27%	28%	26.56%	27%
	Postgraduate	20%	17%	29.74%	14%
Country	Australia	20.2%	20%	16.52%	23.6
	Canada	20.3%	22%	15.91%	22.8%
	UK	20.3%	22%	16.89%	22.0%
	USA	20.3%	21%	17.14%	22.5%
	Indian	18.9%	15%	33.54%	9.1%
Geographic location	Metropolitan	51%	47%	58%	48.33%
	Regional	30%	33%	26%	30.20%
	Rural	19%	20%	16%	21.47%

each item correlates weakly with all the constructs besides its theoretically related constructs," was assessed by checking that the square root of the average variance extracted from each construct was higher than the inter-construct correlation (Trinchera, 2007). The structural model was evaluated by analyzing the path coefficients (Leung, Cheung, & Chu, 2014). All item loadings with values higher than 0.70 is considered suitable. A composite reliability value higher than 0.70 is also considered acceptable (Leung et al., 2014). With regard to the average variance extracted (AVE), a value higher than 0.50 is acceptable, thus justifying the use of a construct (Leung et al., 2014).

4. Results

The execution of REBUS-PLS allows the automatic detection of three local models: LM1, LM2, and LM3.

Table 1 presents the respondents' demographics. There is an equal distribution of male and female respondents as well as country representation. Most respondents (50%) fall in the 35–44 and 55+ age groups. Among the respondents, 20% were postgraduate degree holders, and 27% held undergraduate degrees; 23%, 26%, and 3% had completed technical/vocational training or apprenticeship, secondary school, and primary school, respectively. A majority of the respondents (51%) originated from metropolitan areas.

Table 2 presents descriptive statistics for all the manifest variables in the model. The mean values and standard deviations are presented for the overall dataset (GM) and for each of the detected groups (LM1, LM2, and LM3). All groups exhibit different mean values. Overall IMG has the smallest mean value across all groups. LM3 has the smallest mean value for many manifest variables (e.g., IMG, PU).

Table 3 shows that all standardized item loadings are greater than the minimum threshold of 0.7 in the GM and the three detected local models, except for IMG1 in LM3. However, we decided to keep the item for the remaining analysis because all items in the GM meet the minimum threshold of 0.7.

Table 4 presents the correlation matrix for the GM and the square roots of AVE. In addition, the square roots of AVE (numbers in bold in the diagonal of Table 4) are greater than the inter-construct correlation values.

Table 5 shows the Cronbach's alpha, the Dillon-Goldstein's (or Joreskog's) rho (rho DG), and AVE values of the GM and the three detected local models. All the AVE and rho DG values are greater than the minimum thresholds of 0.5 and 0.7, respectively (Table 5). All Cronbach's alpha values are greater than the minimum threshold of 0.7, except for the IMG construct with values of 0.339 and 0.379 in LM1 and LM3, respectively. In fact, rho DG (Werts, Linn, & Jöreskog, 1974), better known as composite reliability, is a measure of internal consistency and block homogeneity (Vinzi, Trinchera, & Amato, 2010). In 1978, Nunnally suggested using a value of 0.70 as a benchmark for "modest" reliability, applicable in early stages of research, and a value of 0.80 as a more "strict" reliability, applicable

Table 9
The difference in path coefficient testing.

Groups	Difference	t (Observed value)	t (Critical value)	DF	p-value	Significant
Path coefficient (PEOU → PU):						
2 vs 1	0.480	14.376	1.961	1627	0.000	Yes
3 vs 1	0.014	0.381	1.961	1737	0.703	No
3 vs 2	0.466	19.174	1.961	1742	0.000	Yes
Path coefficient (PEOU → PE):						
2 vs 1	0.368	13.758	1.961	1627	0.000	Yes
3 vs 1	0.085	2.603	1.961	1737	0.009	Yes
3 vs 2	0.284	12.709	1.961	1742	0.000	Yes
Path coefficient (PEOU → PP):						
2 vs 1	0.421	13.741	1.961	1627	0.000	Yes
3 vs 1	0.114	3.225	1.961	1737	0.001	Yes
3 vs 2	0.306	13.748	1.961	1742	0.000	Yes
Path coefficient (PEOU → IMG):						
2 vs 1	0.977	19.419	1.961	1627	0.000	Yes
3 vs 1	0.138	2.233	1.961	1737	0.026	Yes
3 vs 2	0.839	19.699	1.961	1742	0.000	Yes
Path coefficient (PEOU → IU):						
2 vs 1	0.309	5.668	1.961	1627	0.000	Yes
3 vs 1	0.051	1.358	1.961	1737	0.175	No
3 vs 2	0.360	7.180	1.961	1742	0.000	Yes
Path coefficient (PU → IU):						
2 vs 1	0.056	1.401	1.961	1627	0.161	No
3 vs 1	0.011	0.306	1.961	1737	0.760	No
3 vs 2	0.067	1.822	1.961	1742	0.069	No
Path coefficient (PE → IU):						
2 vs 1	0.054	0.741	1.961	1627	0.459	No
3 vs 1	0.038	0.497	1.961	1737	0.619	No
3 vs 2	0.092	1.226	1.961	1742	0.221	No
Path coefficient (PP → IU):						
2 vs 1	0.180	2.756	1.961	1627	0.006	Yes
3 vs 1	0.003	0.034	1.961	1737	0.973	No
3 vs 2	0.183	2.693	1.961	1742	0.007	Yes
Path coefficient (IMG → IU):						
2 vs 1	0.004	0.106	1.961	1627	0.915	No
3 vs 1	0.022	0.590	1.961	1737	0.555	No
3 vs 2	0.018	0.610	1.961	1742	0.542	No

Table 10
Indirect effects testing using the Aroian version of the Sobel test.

Mediator	Indirect effect of PEOU on IU	SE	Test statistics	Pr > |z|
PE	0.168	0.018	9.27	0.000
PP	0.212	0.018	12.05	0.000
IMG	0.001	0.004	0.29	0.772
PU	0.177	0.010	18.50	0.000

Table 11
Results of mediation effects testing.

Hypotheses	Results
H10: PE mediates the impact of PEOU on IU.	Supported
H11: PP mediates the impact of PEOU on IU.	Supported
H12: IMG mediates the impact of PEOU on IU.	Not supported
H13: PU mediates the impact of PEOU on IU.	Supported

in basic research (Nunnally, 1978). In 2005, Tenenhaus et al. (2005) proposed that a block can be considered homogenous if rho DG is larger than 0.7.

Table 6 shows that PP is the strongest predictor of IU in the GM (0.308, $p < 0.001$), followed by PU (0.307, $p < 0.001$), PE (0.237, $p < 0.001$), and PEOU (0.144, $p < 0.001$). LM1 and LM3 show similar patterns. PEOU (0.481, $p < 0.001$) in the LM2 is by far the strongest predictor of intention to use social media, followed by PU (0.199, $p < 0.001$), PE (0.170, $p < 0.001$), and PP (0.151, $p < 0.001$). These results validate H1, H2, H4, and H5 for the GM and the three detected local models (H3 is not supported). Surprisingly, the effects of IMG on the intention to use social media showed no significance in any of the models. We have a negative relation between IMG and intention to use social media in both LM1 and LM2.

Table 6 also shows that PEOU is a significant predictor of PE, PP, and PU in the GM and all the three detected local models (at $p < 0.001$), thus validating H6, H8, and H9, which in turn validate TAM for these models. However, the strongest relationship between PEOU and PE is in LM2 (0.941, $p < 0.001$), followed by GM (0.711, $p < 0.001$), LM3 (0.657, $p < 0.001$), and LM1 (0.572, $p < 0.001$). We observe similar patterns in the relationship between PEOU and PP and PEOU and PU. However, even though PEOU is a predictor of IMG (0.333, $p < 0.001$) in GM and LM2 (0.882, $p < 0.001$) (validating H7 in the GM and LM2), PEOU has a negative significant relation with IMG in LM1 (−0.095, $p < 0.01$) and a non-significant relation with IMG in LM3 (0.043).

The variance in IU is 70% in LM1, 76% in LM3, 82% in the GM, and 94% in LM2. The values are higher than those in similar TAM-related studies (Kwon et al., 2015; Venkatesh & Davis, 2000). The goodness of fit index (GoF) suggests that our four models (GM, LM1, LM2, and LM3) fit our data well. An absolute GoF greater than 0.5 is considered satisfactory, whereas a relative GoF equal to or higher than 0.90 demonstrates excellent fit (Lim, Stratopoulos, & Wirjanto, 2011).

Table 7 summarizes the results of our hypotheses testing and Table 8 presents the descriptive statistics of the categorical variables. The distribution of males and females is very similar in all groups, ranging from 47% males in LM1 to 53% males in LM2. The LM2 is dominated by people aged 25–44 (about 48.59%) who are highly educated (almost 56.3% had at least an undergraduate degree), of Indian descent (33.54%), and living in metropolitan areas (58%). The LM3 includes those aged 55 and above (39%).

Table 9 shows that the REBUS-PLS method was able to detect differences in several path coefficients, especially for the relationships between PEOU and PE, PEOU and PP, PEOU and IMG, PEOU

Table 12
Path coefficients before and after correcting for CMB.

Dependent latent variables	Independent latent variables	* p < 0.1; ** p < 0.05; *** p < 0.01; **** p < 0.001 (two-tailed)	
		Original estimates	CMB adjusted estimates ($r_M = 0.333$)
PE	PEOU	0.711****	0.567****
PP		0.689****	0.534****
IMG		0.333****	0.000
PU		0.576****	0.364****
IU	PE	0.237****	0.237****
	PP	0.308****	0.308****
	PEOU	0.144****	0.144****
	IMG	0.003	0.003
	PU	0.307****	0.307****

and PU, PEOU and IU, and PP and IU. The results highlight the capability of the REBUS-PLS method to automatically detect distinctive groups that underscore the presence of unobserved heterogeneity within the sample.

4.1. Testing mediation effects

Following Baron and Kenny (1986), we decided to test for mediation effects using a modified version of the Sobel test. The structural model results for the global model have been used as input for the mediation analysis.

Tables 10 and 11 report the results. Three out of the four proposed mediation effects are verified. In particular, PE, PP, and PU partially mediate the relation between PEOU and IU (p-value < 0.000 for the three effects), while IMG does not mediate PEOU's impact on IU due to its non-significant impact on IU. The mediation effect associated with PP is the highest among the three significant ones. The overall indirect impact of PEOU on IU is equal to 0.558 and its total effect on IU equals 0.703.

4.2. Testing for common method variance (CMV) bias

Relations in the structural model may be inflated because of common method bias (CMB) (Chin, Thatcher, & Wright, 2012). Several methods have been proposed to account for CMB (Lindell & Whitney, 2001; Malhotra, Kim, & Patil, 2006; Podsakoff & Organ, 1986). In this study, we test for CMB in the structural model using the post-hoc marker variable approach (Lindell & Whitney, 2001; Malhotra et al., 2006)

Following Malhotra et al. (2006), we first adjusted correlations among the latent variables (LV) for CMB, then used the adjusted correlations to estimate structural model parameters. Table 12 reports the structural model estimates obtained without considering CMB (i.e. the original path coefficient estimates) and after correcting for CMB (i.e. the CMB-adjusted estimates). We used the smallest original correlation among the LV (i.e. the correlation among IMG and PEOU) as a proxy for CMB. As a consequence, the adjusted correlation between IMG and PEOU is automatically set to zero, shown as the corresponding path coefficient in Table 12.

Comparing the path coefficient values and significances in Table 12 we can verify that adjusting for CMV bias does not affect interpretation of the structural model. In particular, structural relations between IU and its predictors are unchanged, and IMG is still the unique non-significant predictor in this relation.

5. Discussion

In this article, we have theoretically developed and empirically validated a research model that extends the models proposed by Kwon et al. (2015) and Santhanam and Hartono (2003) and integrates intrinsic and extrinsic factors into IT acceptance for predicting the adoption and use of social media within a given workspace. This extends the body of knowledge about IT adoption and use at the individual level, as well as TAM. We used the REBUS-PLS algorithm, a response-based procedure to detect unobserved heterogeneity, within our sample data. The algorithm was able to identity unit segments of users' behaviors within the model. More precisely, the algorithm automatically detected three local models with distinctive model parameters, thus confirming the existence of heterogeneous behavioral patterns within the data sample.

The variance in IU is 70% in LM1, 76% in LM3, 82% in the GM, and 94% in LM2. The values are higher than those in similar TAM-related studies (Kwon et al., 2015; Venkatesh & Davis, 2000). In parallel, the study revealed that the adoption of social media within the workspace can be predicted by intrinsic and extrinsic motivators not only at the global level (R = 82%), but also at all detected local models, namely, LM1 (R = 70%), LM2 (R = 94%), and LM3 (R = 76%). Whereas Kwon et al. (2015) found that PE and PEOU are stronger predictors of IU than PU, this study revealed that PP is the stronger predictor at GM, LM1, and LM3, followed by PU, PE, and PEOU. PEOU is only the strongest in LM2. The results highlight the existence of distinctive groups within the overall sample with different adoption behaviors, thus confirming the ability of the REBUS-PLS method to automatically detect these groups and underscore the presence of unobserved heterogeneity.

Also, consistent with prior studies, our findings confirm that PEOU is an important predictor of PE, PU (Kwon et al., 2015; Santhanam & Hartono, 2003), IU (Kwon et al., 2015; Lee, 2008; Santhanam & Hartono, 2003), PP (Chien et al., 2014; Toubia & Stephen, 2013), and IMG.

Furthermore, our results suggest that in the context of social media adoption and use within the workspace, while PE, PEOU, PP, and PU are all predictors of the IU in the global model and all detected local models, PU is consistently a stronger predictor of the IU than PE. This contradicts the results found by (Kwon et al., 2015) when studying user acceptance of hedonic information systems. Moreover, our study found like (Kwon et al., 2015) that PEOU is a stronger predictor of IU than PU in the local model LM2. However, this finding is no longer valid for the global model and the local models LM1 and LM3.

Surprisingly, our study found that IMG is not a predictor of intention to use social media within the workspace. IMG even has a negative effect on IU in the local models LM1 and LM2. Indeed, prior studies argued that IMG is a strong predictor of IU (Liu et al., 2014; Moore & Benbasat, 1991).

From the mediation tests we observed that PE, PP, and PU partially mediate the relation between PEOU and IU (p-value < 0.000 for the three effects), while IMG does not mediate PEOU impact on IU due to its non-significant impact on IU. Three out of the four proposed mediation effects are verified.

5.1. Implications for research

Our study contributes to the stream of research on IT adoption and use at the individual level as well as the TAM in several ways. First, by integrating two new motivating factors (one intrinsic and one extrinsic) into earlier models (Koh & Saad, 2006; Kwon et al., 2015), and by applying the models in a new context, the study has "significant scientific and practical implications to the context of technology use behaviors" (Sambamurthy, Bharadwaj, & Grover, 2003), thus contributing to a deep understanding of the nature of social media adoption within the workspace. Second, the study attempts to bridge the existing knowledge gap identified by (Becker et al., 2013). These authors found that over the past 20 years, very few papers published within top IS journals using SEM have "examined unobserved heterogeneity" and called for research on the methods and techniques for investigating unobserved heterogeneity when using SEM. The present study applies the REBUS-PLS to automatically detect three distinctive groups of social media users with different adoption behaviors, highlighting the presence of unobserved heterogeneity in PLS path modeling. Furthermore, the use of the REBUS-PLS to detect distinctive groups of users with similar adoption intention behaviors suggests that IS scholars should pay more attention to subgroups that may exist within a research sample. Indeed, some research conclusions at the global level may no longer hold at local levels. By taking into consideration the distinctive characteristics of each local group, IS scholars may be able to develop more specific sets of intention determinants that may foster the adoption and use of IT, and even its extended use. This finding suggests that the improved understanding of the behavior of each detected group may encourage user acceptance of IT within the workspace and reduce the current level of underutilization. Our study is one of very few that focus on social media adoption in the workspace where the factors affecting the intent to adopt could be different from the factors that influence personal use.

5.2. Implications for practice

The ability of REBUS-PLS to automatically detect three distinctive groups of social media users may allow IS practitioners to improve the design of IT interfaces and features that fit each user group's requirements and therefore facilitate user acceptance and use. Such information has important implications for CIOs, IT project managers, and those in charge of providing training during the implementation and adoption of IT. The results may facilitate targeted interventions by CIOs and IT project managers, while improving personalized training for each group identified by REBUS-PLS (Felipe, Roldán, & Leal-Rodríguez, 2016).

The results show that employees use social media mainly in the belief that they provide them with enjoyment and playfulness, and because they are useful and easy to use. This leads us to conclude that the type of IS studied plays a big role in explaining TAM. In the case of social media, which is a hedonic IS, perceived enjoyment, playfulness, ease of use, and usefulness emerged as the constructs responsible for explaining employees' behavioral IU. One of the practical implications of this empirical research is that it is important for system developers to include some aspects of enjoyment and playfulness in the systems they build to increase their acceptance by employees. It is also important that system developers pay attention to ease of use apart as well as usefulness when it comes to hedonic IS, because this increases the likelihood of user acceptance.

5.3. Limitations and suggestions for future research

The current study is bounded in multiple ways. First, it considers only a limited number of intrinsic and extrinsic motivators. Future studies may consider integrating all intrinsic and extrinsic motivators that are identified in the meta-analysis by Wu and Lu (2013). Second, the study did not focus on a specific type of social media tool. Emerging literature on social media adoption and use shows that different tools may lead to different types of adoption factors (Fosso Wamba & Carter, 2013; Teo & Tan, 1998). Future studies might build on the present study by focusing on a specific tool to confirm our results. Third, our study may run the risk of self-report bias, which is inherent in any survey-based study. Future studies could consider using qualitative data to validate our findings. Fourth, we did not test the interaction effects of the variables in our research. Testing these might provide more meaningful insights. Finally, future study may also test and control for confounding variables during hypotheses testing.

6. Conclusion

In this study, we have theoretically developed and empirically validated a research model that extends the models proposed by Kwon et al. (2015) and Santhanam and Hartono (2003) and integrates intrinsic and extrinsic factors into IT acceptance to predict the adoption and use of social media within a given workspace. We assessed the unobserved heterogeneity in our SEM to detect the homogeneity of users' behaviors within the model. Not only do our results provide support for the proposed model, but they also highlight the existence of three distinctive subgroups of homogenous user behavior within our sample, particularly concerning the strength of induced effects. This study furthers research on both the adoption of IT at the individual level and the identification of unobserved heterogeneity within our research sample.

Appendix. : Survey instrument.

a. Perceived Usefulness

	Strongly Disagree	Moderately Disagree	Slightly Disagree	Undecided	Slightly Agree	Moderately Agree	Strongly Agree
Using social media tools helps me connect with others instantaneously	1	2	3	4	5	6	7
Using social media tools improves the efficiency of my decision making	1	2	3	4	5	6	7
Using social media tools increases my work productivity	1	2	3	4	5	6	7
Using social media tools improves my work effectiveness	1	2	3	4	5	6	7
I find social media tools to be useful in my work	1	2	3	4	5	6	7

b. Perceived Ease of Use.

	Strongly Disagree	Moderately Disagree	Slightly Disagree	Undecided	Slightly Agree	Moderately Agree	Strongly Agree
My interaction with social media tools is clear and understandable	1	2	3	4	5	6	7
Interacting with social media tools does not require a lot of mental effort	1	2	3	4	5	6	7
I find social media tools easy to use	1	2	3	4	5	6	7

c. Intention to Use

	Strongly Disagree	Moderately Disagree	Slightly Disagree	Undecided	Slightly Agree	Moderately Agree	Strongly Agree
If I have to temporarily use a computer without social media tool(s), I intend to install it (them).	1	2	3	4	5	6	7
If I own a computer with social media tool(s), I intend to use it (them).	1	2	3	4	5	6	7
Given that I have a computer with social media tool(s), I predict that I will use it (them) at work.	1	2	3	4	5	6	7
I plan to use social media tools in the near future.	1	2	3	4	5	6	7

d. Perceived Enjoyment

	Strongly Disagree	Moderately Disagree	Slightly Disagree	Undecided	Slightly Agree	Moderately Agree	Strongly Agree
I have fun using social media tools.	1	2	3	4	5	6	7
Using social media tools provides me with a lot of enjoyment	1	2	3	4	5	6	7
Overall, I enjoy using social media tools	1	2	3	4	5	6	7

e. Perceived Playfulness

	Strongly Disagree	Moderately Disagree	Slightly Disagree	Undecided	Slightly Agree	Moderately Agree	Strongly Agree
I think social media tools are interesting	1	2	3	4	5	6	7
Overall, using social media tools interests me	1	2	3	4	5	6	7

f. Image

	Strongly Disagree	Moderately Disagree	Slightly Disagree	Undecided	Slightly Agree	Moderately Agree	Strongly Agree
People who use social media tools have a high profile	1	2	3	4	5	6	7
People who use social media tools have more prestige than those who do not	1	2	3	4	5	6	7

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