MODELLING THE IMPACT OF PERCEIVED CONNECTIVITY ON THE INTENTION TO USE SOCIAL MEDIA: DISCOVERING MEDIATING EFFECTS AND UNOBSERVED HETEROGENEITY

Samuel Fosso Wamba, NEOMA Business School, Rouen, France, Samuel.fosso.wamba@neoma-bs.fr

Shahriar Akter, School of Management, Operations and Marketing, University of Wollongong, Wollongong, NSW, Australia, sakter@uow.edu.au

Eric Ngai, Department of Management and Marketing, Faculty of Business, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, eric.ngai@polyu.edu.hk

Imed Boughzala, Telecom Ecole de Management, France, imed.boughzala@telecom-em.eu

Abstract

Early research examined the direct effect of perceived connectivity (PC) on intention to adopt information systems. In this study, we extend that research stream by examining the mediating effects of perceived enjoyment (PE) and perceived playfulness (PP) on the relationship between PC and the intention to use social media within the workplace. To test our proposed model, we collected data from 2,556 social media users from Australia, Canada, India, the UK, and the US. We applied the REBUS-PLS algorithm, a response-based method for detecting unit segments in PLS path modelling and assessing the unobserved heterogeneity in the data sample. Based on the strength of effects, the algorithm automatically detected two groups of users sharing the same intentions to use social media. A post hoc analysis of each group was done using contextual and demographic variables including geographic location, country, age, education and gender. Implications for practice and research are discussed.

Keywords: Social Media, Perceived Connectivity, Perceived Enjoyment, Perceived Playfulness Unobserved Heterogeneity, REBUS PLS.

1. INTRODUCTION

The exponential growth of social media has given firms the opportunity to connect employees within workplace environments across organizations (Barnes and Lescault 2011; Hughes and Palen 2009; Nah and Saxton 2012; Thackeray et al. 2012). A recent study found that two-thirds of responding companies had either embraced social media already or planned to introduce it into the workplace (Gillan 2010). According to Culnan et al. (2010,p.243), "Web 2.0 social media applications such as Twitter and Facebook create new opportunities for firms to improve their internal operations and to collaborate in new ways with their customers, business partners, and suppliers". But what factors contribute to the use of social media in organizations? Is there any unobserved heterogeneity in the conceptualization of such factors? We address these questions by consulting the literature on information systems (IS) and cognitive psychology. We propose a research model to predict the intention to use (IU) social media within the workplace, modelling the impact of perceived connectivity (PC), perceived enjoyment (PE) and perceived playfulness (PP). In particular, we propose to study the direct and indirect effects of technology's PC, especially interactive technologies such as social media, on IU. In developing our theoretical model, we argue that social media's PC will have a positive impact on both PE and PP, which in turn will influence the intention to adopt social media. To empirically test the proposed relationships, we collected data from 2,556 respondents across various industries who rely on social media for their day-to-day operations and strategic management. The findings of the study suggest that PC has a significant positive impact on PE and PP, which in turn influence IU. In this relationship, PE and PP act as significant mediators.

Past research has largely focused on anecdotal evidence in proposing social media strategies and adoption (Gnyawali et al. 2010; Mangold and Faulds 2009). We contribute to this field by examining the practical relationships between PC and IU. Furthermore, this study seeks to extend this research by modelling the mediating effects of PE and PP in PC-IU relationships. Although research on IS has investigated the adoption and use of various innovative information technology (IT) platforms, empirical IS research has not shed much light on how people use social media in work environments. The literature has called for empirical research to enhance our understanding of the factors that facilitate the use of social media at work (Culnan et al. 2010; Zeisser 2010). Furthermore, as Becker et al. (2013) reported, very few studies using structural equation modelling (SEM) that were published in top IS journals over the last 20 years have examined "unobserved heterogeneity" in conceptualizing and testing models. As such, Becker et al. (2013) are calling for presenting forward methods and techniques that can examine unobserved heterogeneity. Overall, this study seeks to answer the following research questions: *(R1)* How do connectivity perceptions of social media determine critical use intentions? *(R2)* Are users' behaviours homogenous when they intend to use social media in a workplace? *(R3)* Is it possible to detect groups of users who engage in the same behaviours when they intend to use social media in the workplace? The answers to these research questions will clearly contribute to IS studies by framing the direct and indirect impact of PC on PE, PP and IU. The paper is organized as follows: The next section focuses on the conceptual model and hypothesis development. This is followed by a description of the method, analysis and findings. The last section presents the conclusion, sets out theoretical and practical contributions, and provides guidelines for future research.

2. THEORETICAL DEVELOPMENT

Drawing mainly on the diffusion of the innovation theory and the technology acceptance model, we argue in this study that the PC of social media will have a positive impact on both PE and PP, which in turn will influence the intention to adopt social media. These relationships are at the basis of the research hypotheses depicted in Figure 1. The constructs are defined in Table 1.

Construct and definition	Source
Perceived connectivity is defined as the ability of a social media platform to bring together people who share common interests or goals.	(Benbasat 2006)
Perceived enjoyment is defined as the extent to which the activity of using a social media platform is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use.	(Venkatesh and Bala 2008)
Perceived playfulness refers to users' degree of cognitive spontaneity in microcomputer interactions in the context of social media.	(Webster and Martocchio 1992)
Intention to use refers to a person's perceived likelihood or subjective probability of an individual to engage in a given behaviour.	(Venkatesh and Davis 1996)

Table 1. Constructs and Definitions.

Perceived connectivity is considered an important determinant of IT adoption, especially for interactive technologies such as the Internet, the enterprise instant messaging and social media (Luo et al. 2010; Strader et al. 2007). For example, in their study of the key determinants of user acceptance of enterprise instant messaging Luo et al. (2010) posit that "perceived connectivity in terms of the cognitive number of users interacting in the same technological context could explain the electronic communication of an individual with other involved parties" (p. 166). Similarly, Strader et al.'s (2007) study of acceptance of electronic mail (e-mail) and instant messaging (IM) systems confirmed that the unique feature of these tools is that their value to a potential user increases as the total number of users adopting the system increases: the so-called positive network externality. Since social media tools have similar characteristics to e-mail and IM, we argue here that a potential user's behavioural intention to adopt social media will increase if his or her network of friends is already using social media.

The constructs of *perceived playfulness* and *perceived enjoyment* were introduced by Davis et al. (1992) to study the role of intrinsic motivation. They are considered to be affect factors influencing user acceptance of technology (Sun and Zhang 2008). Prior studies have found strong evidence of relationships between PP and PE and the behavioural intention to adopt and use IT. For example, Luo et al. (2010) in their study of IM acceptance found that perceived enjoyment had a strong positive relationship with the adoption intention. Similarly, Yu et al. (2005) found that PE was among the most important factors affecting behavioural intention to use television commerce or t-commerce.

Emerging studies on social media adoption and use have confirmed the positive relationship between both PE and PP and behavioural IU. For example, in their study of the determinants of the intention to continue using Facebook, (Chang et al. 2014) found that PP can facilitate this intention. Likewise, (Park et al. 2014) found that the PE is an important determinant of player acceptance of mobile social network games.

Following on the above discussion, we propose the following hypotheses (see Figure 1):

H1: PC has a significant positive effect on the intention to use social media within workplace environments.

H2: PC has a significant positive effect on PE within workplace environments.

H3: PC has a significant indirect effect on the intention to use social media, which is mediated by a positive effect on PE within workplace environments.

H4: PC has a significant positive effect on PP within workplace environments.

H5: PC has a significant indirect effect on the intention to use social media, which is mediated by a positive effect on PP within workplace environments.

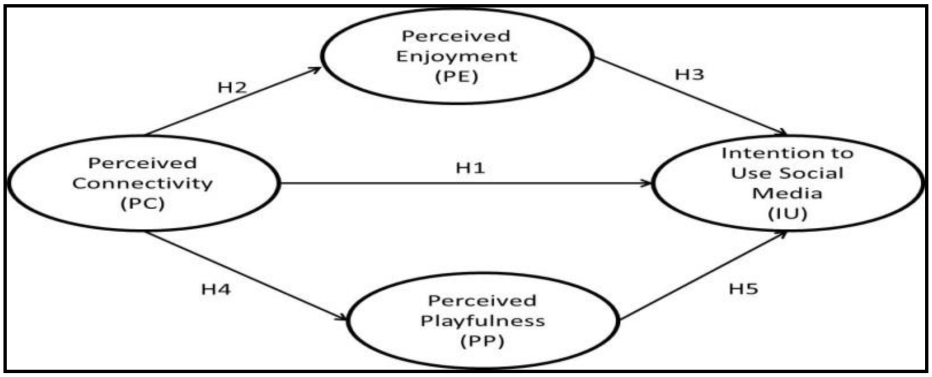


Figure 1. Research Model.

3. RESEARCH METHODOLOGY

The study employed a web-based survey to collect data from 2,556 social media users within their workplaces in Australia, Canada, India, the UK, and the US in January 2013; the survey was conducted by a market research firm called Survey Sampling International (SSI). All constructs used were adapted from (Davis 1989; Luo et al. 2010) to fit the context of social media. A 7-point Likert scale with anchors ranging from Strongly Disagree (1) to Strongly Agree (7) was used for all our items.

To test the unobserved heterogeneity in the data sample, the study used the response-based procedure (REBUS) partial least squares (PLS) or REBUS-PLS, which is a response-based method for detecting unit segments in PLS path modelling (Esposito Vinzi et al. 2008). Unlike similar techniques (e.g., the finite mixture partial least squares or FIMIX-PLS method), the REBUS-PLS is a distribution-free method that allows the simultaneous estimation of both the unit memberships in latent classes and the class-specific parameters of the local models (Trinchera 2007). In addition, the REBUS-PLS does not have to define a priori the number of latent classes to be identified or to test the goodness of fit of different solutions to define the best split of units in classes. Multigroup comparisons and permutation tests were performed to identify differences between segments in the path coefficients.

4. ANALYSIS

XLSTAT-PLS (version of 2013.6.04), a statistical Excel add-in with advanced modelling tools, was used for the data analysis. In addition, the SPSS-based macros developed by Preacher and Hayes (2004) were used to assess the mediation effects.

5. RESULTS AND DISCUSSION

Table 2 reports the descriptive statistics of our manifest variables for the pooled sample (Global model: GM) and the two detected groups (G1 and G2). These groups display different mean values for all the manifest variables. For example, the item values of PP1 and PP2 have minimum values of 1 in the GM and G2, while they are respectively 3 and 2 in G1.

Table 3 presents all factor loadings, Cronbach's alpha values, composite reliability and average variance extracted (AVE) of the GM, G1 and G2. All reported values in the table meet the acceptable threshold values—respectively, 0.6, 0.7, 0.7 and 0.5 (Guadagnoli and Velicer 1988)—and thus justify the use of all our constructs.

For the mediation testing, we followed an approach used by prior studies (Gerow et al. 2013). First, we looked at the significance of the direct effect of PC on IU, PE and PP. The results showed a significant direct effect at the 0.001 level. Then, using the SPSS-based macros developed by Preacher and Hayes (2004) with number of bootstrap samples set at 1000 and level of confidence for all confidence intervals at 95%, we found that PE and PP mediate the relationship between PC and IU. We therefore concluded that PC has an indirect effect on IU.

		Global Model				G1				G2			
Latent variable	Items	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD
PC	PC1	1.000	7.000	5.154	1.685	1.000	7.000	5.422	1.477	1.000	7.000	4.640	1.926
	PC2	1.000	7.000	5.047	1.755	1.000	7.000	5.372	1.508	1.000	7.000	4.422	2.010
	PC3	1.000	7.000	5.162	1.693	1.000	7.000	5.416	1.507	1.000	7.000	4.674	1.910
	PC4	1.000	7.000	5.565	1.557	1.000	7.000	5.493	1.548	1.000	7.000	5.704	1.563
IU	IU1	1.000	7.000	3.748	2.076	1.000	7.000	4.646	1.773	1.000	7.000	2.018	1.418
	IU2	1.000	7.000	4.597	2.011	1.000	7.000	5.561	1.277	1.000	7.000	2.740	1.857
	IU3	1.000	7.000	3.752	2.099	1.000	7.000	4.615	1.837	1.000	7.000	2.092	1.481
	IU4	1.000	7.000	4.598	1.989	1.000	7.000	5.553	1.247	1.000	7.000	2.760	1.854
PP	PP1	1.000	7.000	4.629	1.963	3.000	7.000	5.730	1.041	1.000	7.000	2.511	1.539
	PP2	1.000	7.000	4.523	2.016	2.000	7.000	5.696	1.059	1.000	7.000	2.265	1.409
PE	PE1	1.000	7.000	4.434	1.992	1.000	7.000	5.545	1.163	1.000	6.000	2.296	1.436
	PE2	1.000	7.000	4.376	1.994	1.000	7.000	5.503	1.172	1.000	6.000	2.207	1.355
	PE3	1.000	7.000	4.496	2.001	1.000	7.000	5.622	1.132	1.000	6.000	2.328	1.453

Table 2. Descriptive Statistics of Measured Manifest Variables.

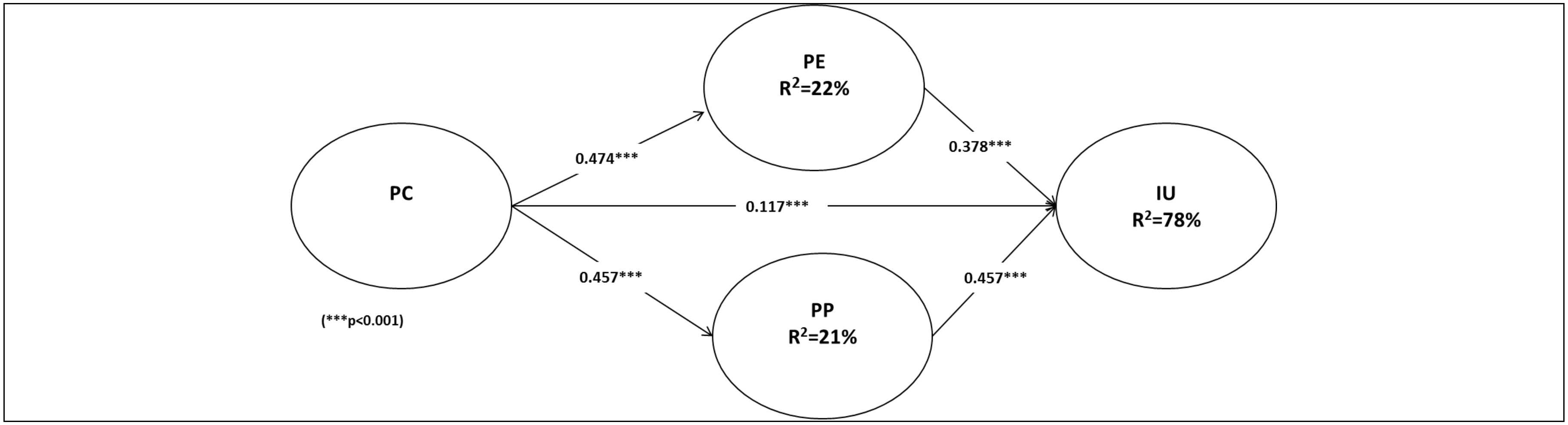
		Standardized loadings			Cronbach's alpha			D.G.'s ρ			AVE		
Latent variable	Items	GM	G1	G2	GM	G1	G2	GM	G1	G2	GM	G1	G2
PC	PC1	0.949	0.935	0.945	0.888	0.903	0.879	0.925	0.934	0.919	0.751	0.780	0.740
	PC2	0.913	0.899	0.898									
	PC3	0.943	0.929	0.941									
	PC4	0.615	0.756	0.610									
IU	IU1	0.839	0.670	0.743	0.903	0.788	0.856	0.933	0.863	0.903	0.775	0.608	0.699
	IU2	0.925	0.879	0.914									
	IU3	0.834	0.661	0.782									
	IU4	0.920	0.880	0.893									
PP	PP1	0.987	0.973	0.956	0.973	0.944	0.911	0.987	0.973	0.957	0.974	0.947	0.918
	PP2	0.987	0.974	0.960									
PE	PE1	0.982	0.947	0.961	0.980	0.941	0.952	0.987	0.962	0.969	0.962	0.895	0.913
	PE2	0.979	0.943	0.948									
	PE3	0.981	0.948	0.958									

Table 3. Factor Loadings. Cronbach's Alpha, Composite Reliability and AVE for GM, G1 and G2.

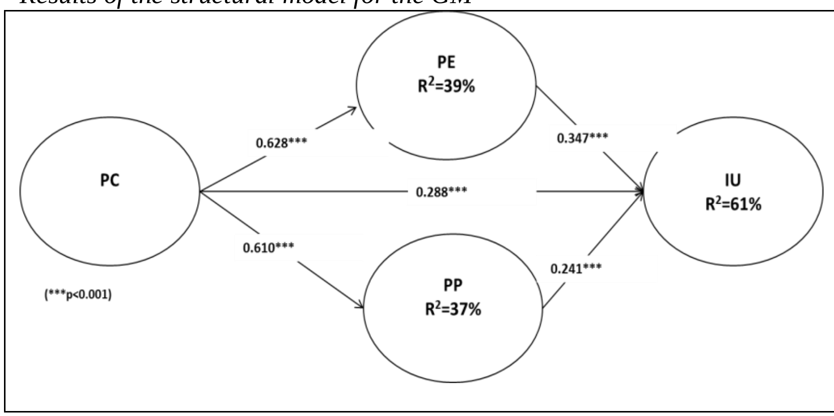
The analysis of Table 4 shows that all our models appear to fit the data sample for the GM and G1 well, as an absolute goodness of fit (GoF) greater than 0.5 is considered satisfactory. Relative GoF with a value equal to or higher than 0.90 demonstrates an excellent fit for the model (Rahimnia and Hassanzadeh 2013), and thus all three models have an excellent fit. Our post hoc analysis shows that we have an equal distribution of gender at the GM. However, G1 is dominated by females (53.6%), metropolitans (55%) and Indians (25.4%), while G2 has more males (56.8%). This latter group also has the highest percentage of respondents aged 55+ (46.0%) and who have a secondary school education (33.2%).

	GoF		
	GM	G1	G2
Absolute	0.58	0.60	0.46
Relative	0.94	0.99	0.95

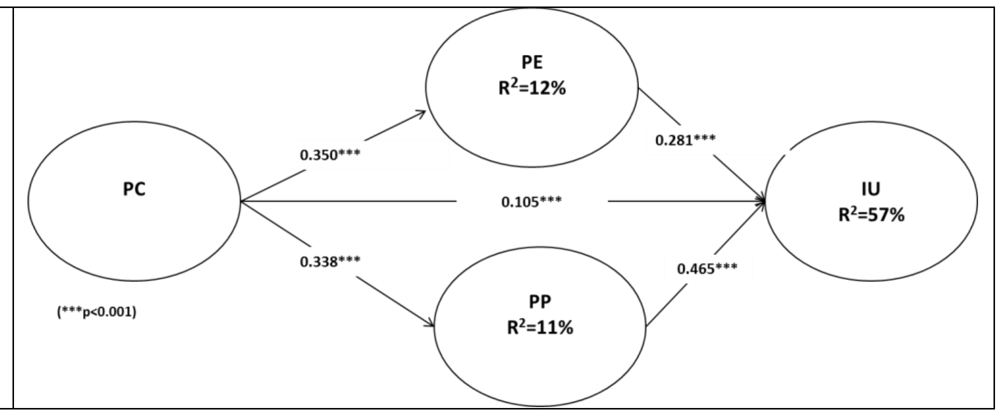
Table 4. Goodness of Fit Values.



Results of the structural model for the GM



Results of the structural model for G1



Results of the structural model for G2

Figure 2. Results of the Structural Model.

Variable	Categories	Relative frequency per category (%)		
		GM	G1	G2
Geographic Location	Metropolitan	51	55	44
	Regional	30	28	32
	Rural	19	17	23
Education	No formal education	0.8	1.0	0.5
	Primary school	3.0	3.0	3.0
	Secondary school	26.5	23.0	33.2
	Technical	23.0	21.4	26.1
	Undergraduate	27.0	28.5	24.0
	Postgraduate	19.8	23.2	13.3
Country	Australia	20.2	17.8	24.8
	Canada	20.3	19.5	22.0
	UK	20.3	17.7	25.4
	USA	20.3	19.6	21.5
	India	18.9	25.4	6.3
Age	18 to 24	14.6	17.4	9.3
	25 to 34	18.9	24.1	8.7
	33 to 44	19.7	21.4	16.5
	45 to 54	17.3	16.1	19.6
	> 55	29.5	20.9	46.0
Gender	Male	50.0	46.4	56.8
	Female	50.0	53.6	43.2

Table 5. Descriptive Statistics of Categorical Variables.

Figure 2 presents the structural model results for all three models. We can see that all the standardized path coefficients are significant (p-value=0.000), thus supporting all of our hypotheses for all the models. However, the strongest relationships between PC and PE, PP and IU are found in G1, while the strongest relationship between PE and IU is in the GM; finally, the strongest relationship between PP and IU is in G2. Regarding R-square values for the GM, G1 and G2, the R-square values for IU are 0.78, 0.61 and 0.57. Those for PE are 0.22, 0.39 and 0.12, and the values for PP are 0.21, 0.37 and 0.11, respectively. IU is better explained in the GM, while PE and PP are better explained in G1.

Groups	Difference	t (Observed value)	p-value	Significant
Path coefficient (PC -> PP):				
2 vs. 1	0.272	8.585	0.000	Yes
Path coefficient (PC -> PE):				
2 vs. 1	0.278	9.048	0.000	Yes
Path coefficient (PC -> IU):				
2 vs. 1	0.183	4.546	0.000	Yes
Path coefficient (PP -> IU):				
2 vs. 1	0.224	4.191	0.000	Yes
Path coefficient (PE -> IU):				
2 vs. 1	0.066	1.097	0.273	No

Table 6. The Difference in Path Coefficient Testing.

Table 6 shows the difference in path coefficient testing of all groups' pairwise comparisons. The values exhibited in this table clearly show that all our path coefficients are significant (p-value=0.000) (except for the path coefficient (PE -> IU)), highlighting the REBUS-PLS method's ability to detect distinctive groups of users within our sample data.

6. CONCLUSION, IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

How does intention to use social media differ from other IT artefacts in organizations? Given the hype around social media adoption and use in work environments and increasing employee-driven demand, perceived connectivity dynamics has become a critical concept in answering this question, as it manifests at the individual level of analysis and affects individual behaviour. Our findings on the intention to use social media in work environment are significant. Based on the empirical support of our research model, the study makes the following theoretical contributions. First, it addresses the research gap concerning intention to use social media in organizations by modelling PC-PE-PP using theories from the fields of IS, technology diffusion, cognitive psychology and critical mass. In this regard, (Whetten 1989, p.493) states that "the common element in advancing theory development by applying it in new settings … that is, new applications should improve the tool, not merely reaffirm its utility". Second, the study found that PC, PE and PP are significant predictors of IU. The study adds further theoretical rigour by analysing the indirect impacts of PE and PP in modelling the effects of PC on IU. In this context, (Iacobucci 2009, p.673)) says that "if mediation clarifies the conceptual picture somewhat, with the insertion of just one new construct—the mediator—imagine how much richer the theorizing might be if researchers tried to formulate and test even more complex nomological networks". Methodologically, our study extends PLS path modelling by applying REBUS-PLS to handle unobserved heterogeneity in social media use in workplace environment. The results of the global model provide strong support for the hypothesized impact of PC (0.117***), PE (0.378***) and PP (0.457***) on IU; together, they explained 78% of the variance. In addition, the application of REBUS-PLS allowed us to identify two groups of social media users (G1, G2), each of which is characterized by distinct model parameters. For example, in terms of the explained variance of social media use intention, G1 explained 61% of variance whereas G2 explained 57% of variance. The strength of the relationship between PC, PE and IU is relatively higher in G1, whereas the relationship between PP and IU is relatively higher in G2. This application extends PLS path modelling by accommodating unobserved heterogeneity. It suggests that social media platforms should be designed to focus on distinct clusters. The findings of the study have significant implications for IT managers who are responsible for creating social-media-based communication inside firms. As a matter of fact, these findings will help in designing personalized training for each group according to their characteristics and needs. Practically speaking, the findings of the study will help in implementing social media within a firm with the goal of supporting knowledge sharing among employees. However, the study suggests that this kind of implementation must be handled carefully because of the potential amount and nature of the changes in work practices and interpersonal relationships—always a focus for strong resistance.

Future studies might take into account various intrinsic and extrinsic factors of social media use intentions within the work environment for better modelling. Moreover, our study did not focus on a specific social media platform; thus, more in-depth research should be conducted in future focusing on a particular platform and its contextual factors. Furthermore, the data were collected under a cross-sectional design, so the study contains the typical limitations associated with this kind of research methodology. For example, the model represents the static nature of service evaluation and the findings are confined to a single point in time. To gain a deeper understanding, a longitudinal study should be conducted to evaluate intentions to use social media over time. Overall, an increasing number of firms are using or planning to use social media platforms to gain business value. However, simply creating an online presence will not create value unless perceived connectivity, enjoyment and playfulness are taken into account. The findings of this study will help firms of all sizes to understand such dynamics and enhance intentions to use social media platforms.

References

Barnes, N. G. and Lescault, A. M. (2011). Social media adoption soars as higher-ed experiments and reevaluates its use of new communications tools. Center for Marketing Research. University of Massachusetts Dartmouth, North Dartmouth, MA.

Becker, J.-M., Rai, A., Ringle, C. M. and Völckner, F. (2013). Discovering Unobserved Heterogeneity in Structural Equation Models to Avert Validity Threats. MIS Quarterly, 37(3), 665-694.

Benbasat, I. (2006). A program of studies to improve the communication between customers and online stores. In D. F. Galletta & P. Zhang (Eds.), Human-computer Interaction and Management Information Systems: Applications: Advances in Management Information Systems.

Chang, C.-C., Hung, S.-W., Cheng, M.-J. andWu, C.-Y. (2014). Exploring the intention to continue using social networking sites: The case of Facebook. Technological Forecasting and Social Change, doi: http://dx.doi.org/10.1016/j.techfore.2014.03.012

Culnan, M. J., McHugh, P. J. and Zubillaga, J. I. (2010). How large US companies can use Twitter and other social media to gain business value. MIS Quarterly Executive, 9(4), 243-259.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

Davis, F. D., Bagozzi, R. P. and Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. Journal of Applied Social Psychology (14), 1111.

Esposito Vinzi, V., Trinchera, L., Squillacciotti, S. and Tenenhaus, M. (2008). REBUS-PLS: A response-based procedure for detecting unit segments in PLS path modelling. Applied Stochastic Models in Business and Industry, 24(5), 439-458.

Gerow, J. E., Ayyagari, R., Thatcher, J. B. and Roth, P. L. (2013). Can we have fun @ work? The role of intrinsic motivation for utilitarian systems. European Journal of Information Systems, 22(3), 360-380.

Gillan, P. (2010). The New Conversation: Taking Social Media from Talk to Action. Harvard Business Review.

Gnyawali, D. R., Fan, W. and Penner, J. (2010). Competitive actions and dynamics in the digital age: an empirical investigation of social networking firms. Information Systems Research, 21(3), 594-613.

Guadagnoli, E. and Velicer, W. (1988). Relation of sample size to the stability of component patterns Psychological Bulletin, 103, 265-275.

Hughes, A. L. and Palen, L. (2009). Twitter adoption and use in mass convergence and emergency events. International Journal of Emergency Management, 6(3), 248-260.

Iacobucci, D. (2009). Everything you always wanted to know about SEM (structural equations modeling) but were afraid to ask. Journal of Consumer Psychology, 19(4), 673-680.

Luo, X., Gurung, A. and Shim, J. P. (2010). Understanding the Determinants of User Acceptance of Enterprise Instant Messaging: An Empirical Study. Journal of Organizational Computing and Electronic Commerce, 20(2), 155 -181.

Mangold, W. G. and Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix. Business horizons, 52(4), 357-365.

Nah, S. and Saxton, G. D. (2012). Modeling the adoption and use of social media by nonprofit organizations. New Media & Society.

Park, E., Baek, S., Ohm, J. and Chang, H. J. (2014). Determinants of player acceptance of mobile social network games: An application of extended technology acceptance model. Telematics and Informatics, 31(1), 3-15.

Preacher, K. J. and Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. Behavior Research Methods, Instruments, & Computers, 36(4), 717-731.

Rahimnia, F. and Hassanzadeh, J. F. (2013). The impact of website content dimension and e-trust on e-marketing effectiveness: The case of Iranian commercial saffron corporations. Information & Management, 50(5), 240-247.

Strader, T. J., Ramaswami, S. N. and Houle, P. A. (2007). Perceived network externalities and communication technology acceptance. European Journal of Information Systems 16(1), 54-65.

Sun, H. and Zhang, P. (2008). An exploration of affective factors and their roles in user technology acceptance: Mediation and causality. Journal of the American Society for Information Science and Technology (JASIST), 59(8), 1252-1263.
Thackeray, R., Neiger, B. L., Smith, A. K. and Van Wagenen, S. B. (2012). Adoption and use of social media among public health departments. BMC public health, 12(1), 242.
Trinchera, L. (2007). Unobserved Heterogeneity in Structural Equation Models: a new approach to latent class detection in PLS Path Modeling Doctoral Thesis in Statistics, Universit a degli Studi di Napoli Federico II, Napoli.
Venkatesh, V. and Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. Decision Sciences, 39(2), 273-315.
Venkatesh, V. and Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. Decision sciences, 27(3), 451-481.
Webster, J. and Martocchio, J. J. (1992). Microcomputer Playfulness: Development of a Measure with Workplace Implications. MIS Quarterly, 16(2), 201-226.
Whetten, D. A. (1989). What constitutes a theoretical contribution? Academy of Management Review, 14(4), 490-495.
Yu, J., Ha, I., Choi, M. and Rho, J. (2005). Extending the TAM for a t-commerce. Information & Management, 42(7), 965-976.
Zeisser, M. (2010). Unlocking the elusive potential of social networks. McKinsey Quarterly, 3, 28-30.