Assessing Unobserved Heterogeneity in SEM Using REBUS-PLS: A Case of the Application of TAM to Social Media Adoption

Completed Research Paper

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Abstract

The present study applies the REBUS-PLS algorithm to handle unobserved heterogeneity in the context of the application of the technology acceptance model (TAM) to social media adoption and use within a workplace environment. Using data collected from 2556 social media users within their workplace from UK, US, Canada, India and Australia, the REBUS-PLS algorithm automatically detects three groups of social media users, each of them being characterized by different values for model parameters and manifest variable means. A post-hoc analysis of each group shows that metropolitan geographic location, postgraduate education level, country and ages range from 18 to 24 & 25 to 34 are the places where we can find main differences that depict the three discovered social media users groups. Finally, implications for research and practice are discussed.

Keywords

Technology Acceptance Model, TAM, perceived ease of use, perceived usefulness, social media, REBUS-PLS algorithm, unobserved heterogeneity.

Introduction

Recently, the importance of evaluating unobserved heterogeneity in structural equation models (SEM) has emerged as an important research area, including in marketing (Sarstedt et al. 2011; Sarstedt and Ringle 2010), and in information systems (IS) (Becker et al. 2013). For example, in a new study by Becker et al. (2013), the authors identified that very few articles from top IS journals using SEM over the last 20 years have "examined unobserved heterogeneity". Most IS studies assumed that empirical data are homogeneous and represent a single population, thus leading to potential bias when assessing SEM parameters. This situation may therefore conduct to invalid conclusions (Becker et al. 2013). In fact, when using SEM, "unobserved heterogeneity is not only a validity threat for the structural model but also for the measurement model regardless of whether the measures are reflective or formative"(Becker et al. 2013, p. 667). Therefore, they are calling for research on methods that investigate unobserved heterogeneity when using SEM, especially for mature theories (e.g. the technology acceptance model (TAM)). Consequently, this research is an initial effort towards bridging this knowledge gap in the literature. The main objective here is to apply the REBUS-PLS algorithm (Esposito Vinzi et al. 2008) to handle unobserved heterogeneity in the context of the application of the TAM to social media adoption and use within a workplace environment. More specifically, this study seeks to answer the following research questions:

RQ1: Are user's behaviors homogenous when applying the TAM to social media adoption and use in a workplace?

RQ2: Can we detect groups of users sharing the same behaviors (in terms of strength of the effects) when applying the TAM to social media adoption and use in a workplace?

In order to address these research questions, this research draws on the extant literature on the TAM as well as the emerging literature on social media. Also, we use the REBUS-PLS algorithm that offers a response-based procedure for detecting unobserved unit segments in PLS path modelling in our research model.

The rest of this paper is structured as follows. After the Introduction, Section 2 presents the literature review with a focus on the TAM and the research model. Section 3 presents the REBUS-PLS method. Section 4 presents the methodology. Section 5 presents the results and discussion. Finally, Section 6 provides the conclusion including limitations and future research directions.

The TAM and Research Model

"What causes people to accept or reject information technology [(IT)]?" (Davis 1989, p. 320). This question is at the core of research on the adoption and use of IT. Indeed, researchers and practitioners are seeking to know why a potential adopter resists or accepts a given IT, and at the same time they are striving to be able to "develop better methods for designing technology, for evaluating systems and for predicting how users will respond to new technology" (Morris and Dillon 1997, p. 58). In the extant literature, several models have been developed and proposed by researchers to answer the question. The TAM is one of these models (Davis 1989; Davis and Venkatesh 2004; Venkatesh and Bala 2008). The TAM was first developed and proposed by Davis to assess an individual's acceptance of an IT artifact (Davis 1989). Afterwards, the model has undergone many extensions (Venkatesh and Bala 2008; Venkatesh and Davis 2000; Venkatesh et al. 2003). The TAM is considered as one of the extensively used theoretical models in IS (Brown et al. 2010; Jeyaraj et al. 2006; Sun and Zhang 2008). At the core of all related TAM models, it appears that the behavioral intention of a potential adopter of an IT artifact is explained jointly by two interrelated beliefs, namely perceived usefulness—which is "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis 1989, p. 320)—and perceived ease of use or "the degree to which a person believes that using a particular system would be free of effort(Davis 1989, p. 320). The model also theorizes that perceived usefulness is influenced by perceived ease of use (Davis 1989, p. 320), because "other things being equal, the easier a technology is to use, the more useful it can be" (Venkatesh 2000, p. 343). In short, we have the following hypotheses (Figure 1):

Hypothesis H1.: *Perceived ease of use (PEOU)has a positive effect on intention to use (IU).*
Hypothesis H2.: *Perceived ease of use (PEOU) has a positive effect on perceived usefulness (PU).*
Hypothesis H3.: *Perceived usefulness (PU) has a positive effect on intention to use (IU).*

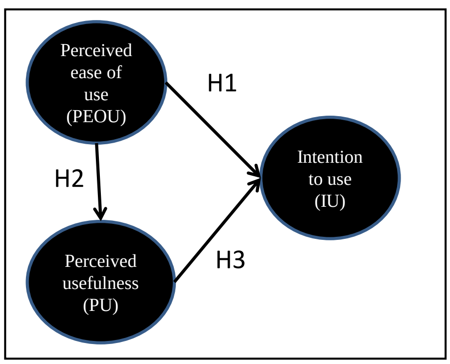

Figure 1: Research Model

The TAM has been used for theory testing in various research fields and settings including assessing consumer adoption of new IT artifact (Jeyaraj et al. 2006; Legris et al. 2003; Venkatesh et al. 2002), adoption of software measures (Wallace and Sheetz 2014), computer-based communication media adoption (Zhang et al. 2012), healthcare technology adoption (Moores 2012), smartphones adoption (Joo and Sang 2013), and general Internet users (Sun and Zhang 2008). All of this led to an important accumulation of strong empirical supports for the model (Venkatesh 2000). In addition, the TAM has been proven effective in predicting approximately 40% of an IT artifact's adoption and use (Legris et al. 2003). Furthermore, the TAM has been considered as a model that "can serve as a simple to use, and cost-effective tool for evaluating applications and reliably predicting whether they will be accepted by users" (Morris and Dillon 1997, p. 58). However, the TAM also holds some limits, including: (i) the lack of consideration of different user task environment and limits (Fu et al. 2006); (ii) the lack of assessment of the role of facilitating conditions; and (iii) the assumption of data homogeneity in empirical studies, which may lead to potential invalid conclusions (Becker et al. 2013).

Therefore, this study aims to assess unobserved heterogeneity in predictive SEM (Esposito Vinzi and Russolillo 2013) using REBUS-PLS in the case of the application of TAM to social media adoption and use within a workplace environment.

Social media (e.g., Facebook, Twitter) have recently captured the imagination of practitioners and scholars, mainly because of their high operational and strategic potential in creating business value and firm competitive advantage (Culnan et al. 2010). Indeed, social media tools and technologies offer tremendous benefits, including: (a) their ability to facilitate consumer shopping experiences, by aggregating for example consumer past experiences data with friends and relatives comments in real time during purchase activities, thereby facilitating final purchasing decisions (Fisher 2011; Zhou et al. 2011); (b) their capacity to allow real-time communication and collaboration between a focal organization with its key stakeholders (e.g., customers, suppliers)(Burke et al. 2010; Culnan et al. 2010); and (c) their extraordinary ability to create not only relationships based on trust among supply chain partners, but also to detect potential business partners in the context of B2B selling (Michaelidou et al. 2011).

Assessing Unobserved Heterogeneity in SEM: The Case of the REBUS-PLS Method

The assumption of homogenous behaviors is hard to meet in reality (Jedidi et al. 1997). Two different approaches can be used to deal with heterogeneity. The first one assumes the heterogeneity to be explained by well-known observed variables (such as gender, income levels, and education) or contextual factors (e.g., individualism, collectivism). Those variables serve as moderators and the groups whose definitions are based on such variables are supposed to share homogenous behaviors. The second approach assumes that heterogeneity in the data cannot be explained by one or several observed variables and that we should look for class of units showing similar behaviors. In this case, no information about group membership is available and the applied statistical method should be able to discover such groups in the data. We refer to this case as unobserved heterogeneity. According to Hahn et al. (2002) heterogeneity in the model will very rarely be captured by well-known observable variables playing the role of moderating variables. Moreover, McLachlan and Basford (1988) observe that all the available information should be used when looking for clusters in the data. Therefore, a response-based clustering method such as REBUS-PLS should be used, where the obtained classes are detected with respect to the postulated model (Trinchera 2007). Once the groups of units showing different model parameters have been identified, a post-hoc analysis can be performed to typify the detected groups in terms of contextual or demographic variables (e.g. culture, gender, experience, etc..).

REBUS-PLS, a response-based method for detecting unit segments in PLS path modeling, is being commonly used (Esposito Vinzi et al. 2008). "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, p. 185). It uses a closeness-measure to assess to which latent class each unit belongs and provides a final classification of each unit in a latent class. Compared to other methods for handling unobserved heterogeneity in PLS-PM, REBUS-PLS does not need to define a priori the number of latent classes to be detected or to test the goodness of fit of different solutions to define the best split of units in classes. This is a main advantage when no information about the existence of groups of users is available, as it is the case for the TAM model. Moreover, REBUS-PLS allows us to detect groups of users that may differ in terms of strength in the coefficients of both the measurement model and/or the structural model.

Methodology

In this study, a web-based questionnaire was used to collect data from 2556 social media users within their workplace from UK, US, Canada, India and Australia in January 2013. The use of web-based survey in IS is considered as the best means of collecting original data that describe a population that is too large to be observed directly. More importantly, "surveys are also excellent vehicles for measuring attitudes and orientations in a large population" Babbie (2004, p. 238). Furthermore, the use of survey method is appropriate for research that involves hypotheses testing, populations description, theoretical models building and measurement scales development in research within various industry sectors (Lee and Shim

2007). All our constructs were adapted from prior studies, mainly from (Davis 1989; Luo et al. 2010). A 7-point Likert scale with anchors ranging from Strongly Disagree (1) to Strongly Agree (7) was used for all our items.

Data collection was conducted online by Survey Sampling International (SSI), a leading market research provider that offers sampling and data collection through various modes (e.g., face-to-face interview, postal or landline phones, mobile phones, and online via tablets and smartphones). Respondents were sourced from SSI's panels. Data analysis was realized using XLSTAT-PLS, version of 2013.6.04. XLSTAT-PLS is a statistical Excel add-in with advanced modeling tools including Partial Least Squares (PLS), Path Modeling and PLS Regression, which all are considered free from some constraints held by classical linear regression and analysis of variances such as the "non-colinearity of the explanatory variables and the minimal sample size that must be greater than the number of explanatory variables"[1]. In this study, the reliability and validity of the items were evaluated. All item loadings values higher than 0.70 are considered to be adequate. A composite reliability value higher than 0.70 is considered to be acceptable (Sun and Zhang 2008). For average variance extracted (AVE), a value higher than 0.50 is considered as acceptable measure justifying the use of a construct (Sun and Zhang 2008).

Results and Discussion

REBUS-PLS automatically detects 3 groups of social media users (G1, G2 and G3), each of them being characterized by different values for model parameters and manifest variable means.

Latent variable	Manifest Variables Or Items	GM		G1		G2		G3	
		Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Perceived ease of use	PEU1	4.806	1.792	5.242	1.414	5.214	1.337	**4.068*** **	2.138
	PEU2	4.935	1.697	5.052	1.475	5.189	1.409	**4.654*** **	2.020
	PEU3	4.946	1.777	5.333	1.399	5.396	1.356	**4.238*** **	2.124
Perceived usefulness	PU1	4.669	1.948	**5.518*** **	1.232	**5.190*** **	1.304	**3.392*** **	2.238
	PU2	3.562	1.948	**5.144*** **	1.298	**3.784*** **	1.071	**1.618*** **	1.036
	PU3	3.428	1.975	**5.168*** **	1.271	**3.546*** **	0.962	**1.364*** **	0.721
	PU4	3.504	1.969	**5.231*** **	1.209	**3.661*** **	0.932	**1.429*** **	0.815
	PU5	3.588	2.011	**5.280*** **	1.210	**3.866*** **	1.137	**1.484*** **	0.921
Intention to use Social Media	IU1	3.748	2.076	**4.978*** **	1.564	**3.929*** **	1.745	**2.231*** **	1.769
	IU2	4.597	2.011	**5.381* **	1.403	**5.154* **	1.531	**3.372*** **	2.242
	IU3	3.752	2.099	**5.123*** **	1.454	**4.018*** **	1.741	**2.025*** **	1.629
	IU4	4.598	1.989	5.326	1.417	5.179	1.500	**3.423*** **	2.235

Table 1. Descriptive Statistics of Measurement Manifest Variables (GM=Global Model). In bold mean values that are significantly different (*p<0.05, ***p<0.001)

Table 1 shows the descriptive statistics for all the manifest variables in the model. Mean values and standard deviations are presented for the overall dataset (Global Model) and for each of the detected groups. The three groups show different mean values for all the manifest variables, except for the items related to the Perceived ease of use. In particular, group 3 shows smaller mean values for all the manifest variables (values between 1.6 and 1.4 for the items PU2, PU3, PU4, PU5).

[1] http://www.xlstat.com/en/products-solutions/pls.html

From Table 2 and Table 3, we can see that all Cronbach's alpha, composite reliability and the average variance extracted (AVE) from all groups are respectively greater than the threshold of 0.7, 0.7 and 0.5, except α for 'PU' for G2; and AVE for 'PU' for G2 and G3. While all the loadings of items measuring our constructs exceed 0.707 for all constructs in GM and G1, those related to PU and IU3 in G2 and G3 are less than the threshold. Also, only the Cronbach's alpha of PU in G2 is less than the acceptable threshold of 0.7, suggesting for example that the percentage of the variance of our constructs that is explained by our observed variables varies between the groups identified.

Latent variable	Items	Standardized loadings				D.G.'s ρ				AVE			
		GM	G1	G2	G3	GM	G1	G2	G3	GM	G1	G2	G3
Perceived ease of use	PEOU1	0.933	0.933	0.914	0.920	0.933	0.940	0.918	0.929	0.820	0.840	0.790	0.813
	PEOU2	0.841	0.880	0.833	0.848								
	PEOU3	0.940	0.936	0.916	0.934								
Perceived usefulness	PU1	0.772	0.838	0.739	0.758	0.955	0.942	0.738	0.838	0.808	0.763	0.347	0.490
	PU2	0.920	0.852	0.553	0.706								
	PU3	0.927	0.889	0.370	0.663								
	PU4	0.937	0.911	0.527	0.683								
	PU5	0.929	0.876	0.682	0.687								
Intention to use Social Media	IU1	0.845	0.787	0.643	0.758	0.933	0.926	0.866	0.900	0.776	0.759	0.614	0.692
	IU2	0.918	0.918	0.888	0.929								
	IU3	0.845	0.856	0.675	0.689								
	IU4	0.913	0.917	0.892	0.925								

Table 2. Factor Loadings Composite Reliability and AVE: GM: Global model, Gi=group i

		GM	G1	G2	G3
Latent variable	#Items	Cronbach's alpha	Cronbach's alpha	Cronbach's alpha	Cronbach's alpha
Perceived ease of use	3	0.891	0.905	0.866	0.885
Perceived usefulness	5	0.939	0.922	0.557	0.758
Intention to use Social Media	4	0.903	0.893	0.792	0.849

Table 3 Cronbach's Alpha Values

Dependent latent variables	Indipendent latent variables	Value (***p<0.001)			
		GM	G1	G2	G3
Perceived usefulness	Perceived ease of use	0.576***	0.813***	0.782***	0.561***
Intention to use Social Media	Perceived ease of use	0.363***	0.47***	0.642***	0.403***
	Perceived usefulness	0.592***	0.409***	0.133***	0.422***

Table 4 Structural Model

Table 4 shows that the standardized path coefficients for all models are significant at a level of 0.001: all our hypotheses are supported for all models. However, the strength of the relationship PEOU and PU is higher in G1(0.813) and G2(0.782) than in G3(0.561). For the relationship strength of PEOU and IU, the highest value is with G2(0.642), followed by G3(0.403), then G1(0.470). Finally, the highest relationship strength of PU and IU is in G3(0.422), then G1(0.409), and finally G2(0.133).

Dependent latent variables	Indipendent latent variables	Contribution to R^2 (%)				R^2			
		GM	G1	G2	G3	GM	G1	G2	G3
Perceived usefulness	Perceived ease of use	1	1	1	1	0.332	0.661	0.620	0.387
Intention to use Social Media	Perceived ease of use	0.650	0.540	0.850	0.510	0.729	0.697	0.556	0.567
	Perceived usefulness	0.350	0.460	0.150	0.490				

Table 5. Coefficients of Determination R^2

From Table 5, we can see that the coefficient of determination, R^2 of IU social media is 0.729 in GM, 0.697 in G1, 0.556 in G2 and 0.567 in G3. Thus, PEU and PU jointly explain a rate of respectively 73% and 70% for the variance of IU social media in GM and G1. In parallel, the same variables moderately explain the rate of respectively 56% and 57% for the variance of IU social media in G2 and G3. With regard to the dependent latent variable PU, the percentages of respectively 33% and 39% of PU variance in GM and G3 are weakly explained by the independent latent variable PEU, while the same variable moderately explain 66% and 62% of variance of PU in G1 and G2. Differences between groups arise also into the contribution to R^2 expressed as the percentage of the explained variability due to each independent variable. In particular, for group G2, PEU is the most relevant driver for IU social media, while for the others 2 groups the two independents variables PEU and PU have quite the same impact on explaining the IU social media. We can conclude that G2 is composed by users for which the IU social media is mostly due to their PEU than to PU.

	GM	G1	G2	G3
	GoF	GoF	GoF	GoF
Absolute	0.65	0.73	0.57	0.55
Relative	0.91	0.99	0.95	0.96

Table 6. Goodness of Fit Values

The analysis of Table 6 shows that all our models seem to fit well enough the data. Indeed, an absolute GoF greater than 0.5 is considered satisfactory. While a value of the relative that is equal to or higher than 0.90 illustrates a great fit of the model (Rahimnia and Hassanzadeh 2013).

Finally, a post-hoc analysis of each group shows that metropolitan geographic location, postgraduate education level, country and ages range from 18 to 24 & 25 to 34 are the places where we can find main differences that depict the three discovered social media users groups (Table 7). The first four columns in Table 7 show the proportion of each category of the socio-demographical variables in each of the groups as well as in the GM (i.e., for each group, the sum over the categories of a given variable is 1). The last four columns show the percentage of each category present in each group (i.e., for each category of a given variable, the sum over the groups equals 100%). For instance, according to these results, most of Indians (73%) belong to G1, or the older users (>55 years) belong to G3.

Table 8 shows that the difference in path coefficients of all groups' pairwise comparison are significant. More importantly, those coefficients are significant at a level of 0.001 (i) (Perceived ease of use -> Perceived usefulness) for G2 vs G1, G3 vs G1 (with the highest difference: 0.342) and G3 vs G2; (ii) (Perceived ease of use -> Intention to use Social Media) for G3 vs G2 (with the highest difference: 0.319); and (iii) (Perceived usefulness -> Intention to use Social Media) for G3 vs G1 and G3 vs G2 (with the highest difference: 0.539). All of this suggests an excellent ability of the REBUS-PLS to detect distinct groups that highlight the presence of unobserved heterogeneity within our sample.

Variable	Categories	Relative frequency per category (%)							
		GM	G1	G2	G3	GM	G1	G2	G3
Geographic Location	Metropolitan	0.51	0.58	0.48	0.44	100%	**47.8%**	20.2%	32.0%
	Regional	0.30	0.27	0.32	0.32	100%	**38.0%**	23.3%	**38.8%**
	Rural	0.19	0.15	0.20	0.24	100%	32.9%	21.5%	**45.5%**
Education	No formal education	0.01	0.01	0.00	0.00	100%	**70.0%**	10.0%	20.0%
	Primary school	0.03	0.03	0.03	0.03	100%	**44.7%**	22.4%	32.9%
	Secondary school	0.26	0.20	0.28	0.33	100%	31.3%	22.5%	**46.2%**
	Technical	0.23	0.19	0.24	0.27	100%	35.4%	22.4%	**42.2%**
	Undergraduate	0.27	0.28	0.28	0.25	100%	**43.5%**	22.4%	34.1%
	Postgraduate	0.20	0.29	0.16	0.12	100%	**60.5%**	17.6%	21.9%
Country	Australia	0.20	0.16	0.22	0.24	100%	32.6%	23.6%	**43.8%**
	Canada	0.20	0.19	0.21	0.22	100%	38.8%	21.7%	**39.4%**
	UK	0.20	0.15	0.20	0.26	100%	31.2%	21.2%	**47.6%**
	USA	0.20	0.18	0.23	0.22	100%	36.5%	23.7%	**39.8%**
	Indian	0.19	0.33	0.14	0.06	100%	**73.1%**	16.1%	10.8%
Age	18 to 24	0.15	0.20	0.17	0.08	100%	**56.1%**	24.6%	19.3%
	25 to 34	0.19	0.24	0.23	0.10	100%	**54.1%**	25.9%	19.9%
	33 to 44	0.20	0.17	0.21	0.19	100%	**41.7%**	23.2%	35.1%
	45 to 54	0.17	0.17	0.13	0.20	100%	41.2%	16.3%	**42.5%**
	> 55	0.30	0.20	0.26	0.43	100%	28.0%	18.6%	**53.4%**

Table 7. Descriptive Statistics of Categorical Variables

Conclusion, implications and future research directions

This study makes a number of contributions to the IS research streams applying the TAM. First, it is a response to the call by (Becker et al. 2013) for studies that investigate unobserved heterogeneity when using SEM, especially for mature theories (e.g., technology acceptance model (TAM)). Second, it addresses the issue of the vast majority of studies using TAM investigating mainly and only the direct effect of PEOU and PU on IU and of PEOU on PU, as well as the moderating and mediating variables of PU and PEOU (Poirier and McCollum 2006), without exploring the unobserved heterogeneity within the data sample (Becker et al. 2013). In this study, we chose to use the REBUS-PLS algorithm to handle unobserved heterogeneity in the context of the application of TAM to social media adoption and use. The results of the global model provided strong support to the TAM. As expected, both PEOU (0.363***) and PU (0.592***) had significant effect on the behavioral intention to use social media. In addition, PEOU (0,576***) had a significant effect on PU. PEOU and PU, which together substantially explained the rate of 73% for the variance of IU social media in the global model. These results are consistent with prior studies using TAM (Figure 2) (Venkatesh and Davis 2000; Wang et al. 2011; Wu and Wang 2005). Therefore, the TAM could be used to explain acceptance of social media in a research framework on user behavior. However, our results offer stronger relationships between PEOU and PU on IU as well as PEOU on PU, as compared to studies by (Venkatesh and Davis 2000) and (Wu and Wang 2005). Our research follows the footsteps (Wang et al. 2011), who identified stronger relationships between PEOU(0.399**) and IU, and between PEOU(0.693**) and PU, both at 0.01 level, with however a lower explained percentage of the variance of IU (41.8%) and a weaker relationship between PU(0. 302*) and IU. For example, (Wu and Wang 2005) found that while PEOU(0.33**) and PU(0.33**) had respectively a direct effect on PU and IU, such a direct effect of PEOU on IU does not exist (Figure 2).

In addition, in this study, the execution of the REBUS-PLS allowed us to identify 3 groups of social media users (G1, G2 and G3), each of them being characterized by different values for model parameters. This therefore allowed us to improve our model for it to accommodate this unobserved heterogeneity; this may facilitate the design of the IT artifact that is suitable for each identified user group (Becker et al. 2013). For example, in terms of explained variance of IU social media, each of the detected groups explained the percentage of 56% to 70% for the variance of IU social media. These values are higher than those from comparable IS studies using TAM (e.g., (Venkatesh and Davis 2000), (Wang et al. 2011)). Furthermore, the strength of the relationship between PEOU and PU is higher in G1(0.813) and G2(0.782) than in G3(0.561). For the relationship strength of PEOU and IU, the highest value is with G2(0.642), followed by G3(0.403), then G1(0.470). Finally, the highest relationship strength of PU and IU is in G3(0.422), then in G1(0.409), and lastly in G2(0.133), thereby suggesting that, for users in G1 and G3, PU and PEOU will have a comparable strong effect on their intension to use social media. While for users in G2, PEOU will have the strongest effect (as compared to PU) on the intention to use (IU) social media. At the same time, for both G1 and G2, the PEOU of social media had a strong effect on PU of social media. Such information may allow IS practitioners to better design IT artifact that fits each user group's requirements, and which therefore facilitates its adoption and extended use. Our results also have an important implication for CIO and IT project managers, mainly those who are in charge of providing training during the implementation and adoption process of ITs. Indeed these results may facilitate not only the design of more personalized training for each group identified by REBUS-PLS, but also the adoption and extended use of ITs.

Groups	Difference	t (Observed value)	t (Critical value)	DF	p-value	Significant
Path coefficient (Perceived ease of use -> Perceived usefulness):						
G2 vs G1	0.205	7.333	1.961	1618	0.000	Yes
G3 vs G1	0.342	15.817	1.961	2008	0.000	Yes
G3 vs G2	0.137	6.867	1.962	1480	0.000	Yes
Path coefficient (Perceived ease of use -> Intention to use Social Media):						
G2 vs G1	0.183	2.825	1.961	1618	0.005	Yes
G3 vs G1	0.136	2.907	1.961	2008	0.004	Yes
G3 vs G2	0.319	6.225	1.962	1480	0.000	Yes
Path coefficient (Perceived usefulness -> Intention to use Social Media):						
G2 vs G1	0.179	2.138	1.961	1618	0.033	Yes
G3 vs G1	0.360	5.293	1.961	2008	0.000	Yes
G3 vs G2	0.539	6.063	1.962	1480	0.000	Yes

Table 8. The Difference in Path Coefficient Testing

Future studies may consider taking into account the intrinsic and extrinsic motivations for user behavioral intention to use social media before applying the REBUS-PLS. In addition, in this study, we did not focus on a specific type of social media tool. (Fosso Wamba and Carter 2013) argue that the geographic location has a significant impact on Twitter adoption by SMEs, but not on the adoption of Facebook Events Page by SMEs. These results suggest that the type of social media tool may have different adoption determinants. Therefore, future studies should focus on a specific type of social media tool when applying the TAM. Similarly, a seven-point Likert scale anchored ranging from "strongly disagree"(1) to "strongly agree"(7) was used to assess our items. This may introduce the so-called "acquiescence bias" related to the "respondents' tendency to respond to items positively without much regard for its true content" (p. 697) (Chin et al. 2008). Future studies may rather use the nine-point scale fast form items with the two-anchor points ranging from -4 to +4 as suggested by (Chin et al. 2008) or use the C-OAR-SE-based single-item measures as proposed by (Rossiter and Braithwaite 2013). Indeed, for (Rossiter and Braithwaite 2013), PEOU and PU are beliefs, which are "single, concrete, conscious thoughts that are salient in the potential user's mind or the actual user's mind when the individual confronts the new product [or IT artifact] and considers how often to use it" (p. 30). Therefore, they recommended that "a doubly concrete" construct, each belief, PEOU and PU, is most validly measured with one good single item" (p. 30).

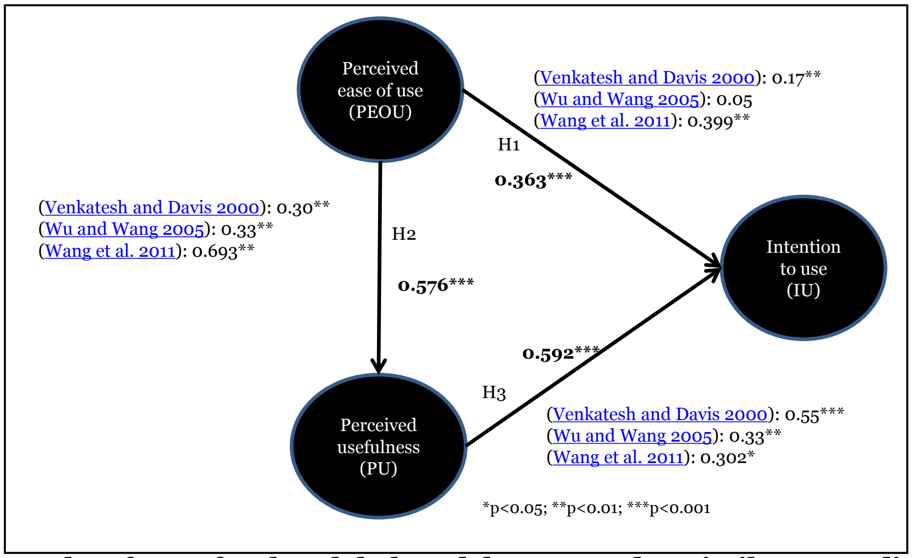

Figure 2: The results of TAM for the Global Model Compared to Similar IS Studies with Direct Effect from PU and PEOU on IU

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REFERENCES

Babbie, E. 2004. *The Practice of Social Research*. Belmont, CA: Thomson Wadsorth.

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), pp. 665-694.

Brown, S., Dennis, A., and Venkatesh, V. 2010. "Predicting Collaboration Technology Use: Integrating Technology Adoption and Collaboration Research," *J. Manage. Inf. Syst.* (27:2), pp. 9-54.

Burke, W.Q., Fields, D.A., and Kafai, Y.B. 2010. "Entering the Clubhouse: Case Studies of Young Programmers Joining the Online Scratch Communities," in: *Journal of Organizational and End User Computing*. p. 21+.

Chin, W.W., Johnson, N., and Schwarz, A. 2008. "A Fast Form Approach to Measuring Technology Acceptance and Other Constructs," *MIS Q.* (32:4), pp. 687-703.

Culnan, M.J., McHugh, P.J., and Zubillaga, J.I. 2010. "How Large U.S. Companies Can Use Twitter and Other Social Media to Gain Business Value," *MIS Quarterly Executive* (9:4), pp. 243-259.

Davis, F.D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* (13:3), pp. 319-340.

Davis, F.D., and Venkatesh, V. 2004. "Toward Preprototype User Acceptance Testing of New Information Systems: Implications for Software Project Management," *Engineering Management, IEEE Transactions on* (51:1), pp. 31-46.

Esposito Vinzi, V., and Russolillo, G. 2013. " Partial Least Squares Algorithms and Methods," *WIREs Comp Stat* (5), pp. 1-19.

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), pp. 439-458.

Fisher, L. 2011. "The Key Trends in Social Commerce." Retrieved June 27, 2011, from http://thenextweb.com/socialmedia/2011/03/08/the-key-trends-in-social-commerce/

Fosso Wamba, S., and Carter, L. 2013. "Twitter Adoption and Use by Smes: An Empirical Study," *The 46 Hawaii International Conferences on System Sciences (HICSS)*, Maui, Hawaii, US.

Fu, J.-R., Farn, C.-K., and Chao, W.-P. 2006. "Acceptance of Electronic Tax Filing: A Study of Taxpayer Intentions," *Information & Management* (43:1), pp. 109-126.

Hahn, C., Johnson, M., Herrmann, A., and Huber, F. 2002. "Capturing Customer Heterogeneity Using a Finite Mixture Pls Approach," *Schmalenbach Business Review*:54), pp. 243-269.

Jedidi, K., Jagpal, H.S., and DeSarbo, W.S. 1997. "Finite-Mixture Structural Equation Models for Response-Based Segmentation and Unobserved Heterogeneity," *Marketing Science* (16:1), pp. 39-59.

Jeyaraj, A., Rottman, J.W., and Lacity, M. 2006. "A Review of the Predictors, Linkages, and Biases in It Innovation Adoption Research," *Journal of Information Technology* (21:1), pp. 1-23.

Joo, J., and Sang, Y. 2013. "Exploring Koreans' Smartphone Usage: An Integrated Model of the Technology Acceptance Model and Uses and Gratifications Theory," *Computers in Human Behavior* (29:6), pp. 2512-2518.

Lee, C.-P., and Shim, J.P. 2007. "An Exploratory Study of Radio Frequency Identification (Rfid) Adoption in the Healthcare Industry," *Eur J Inf Syst* (16:6), pp. 712-724.

Legris, P., Ingham, J., and Collerette, P. 2003. "Why Do People Use Information Technology? A Critical Review of the Technology Acceptance Model," *Information & Management* (40:3), pp. 191-204.

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), pp. 155 -181.

McLachlan, G.J., and Basford, K.E. 1988. *Mixture Models: Inference and Applications to Clustering*. New -York: Marcel Dekker.

Michaelidou, N., Siamagka, N.T., and Christodoulides, G. 2011. "Usage, Barriers and Measurement of Social Media Marketing: An Exploratory Investigation of Small and Medium B2b Brands," *Industrial Marketing Management* (40:7), pp. 1153-1159.

Moores, T.T. 2012. "Towards an Integrated Model of It Acceptance in Healthcare," *Decision Support Systems* (53:3), pp. 507-516.

Morris, M., and Dillon, A. 1997. "How User Perceptions Influence Software Use," *IEEE Software* (14:4), pp. 58-65.

Poirier, C., and McCollum, D. 2006. *Rfid Strategic Implementation and Roi: A Practical Roadmap to Success*. J. ROSS Publishing.

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), pp. 240-247.

Rossiter, J.R., and Braithwaite, B. 2013. "C-Oar-Se-Based Single-Item Measures for the Two-Stage Technology Acceptance Model," *Australasian Marketing Journal (AMJ)* (21:1), pp. 30-35.

Sarstedt, M., Henseler, J., and Ringle, C. 2011. "Multi-Group Analysis in Partial Least Squares (Pls) Path Modeling: Alternative Methods and Empirical Results," *Advances in International Marketing* (22), pp. 195-218.

Sarstedt, M., and Ringle, C.M. 2010. "Treating Unobserved Heterogeneity in Pls Path Modelling: A Comparison of Fimix-Pls with Different Data Analysis Strategies," *Journal of Applied Statistics* (37:8), pp. 1299-1318.

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), pp. 1252-1263.

Trinchera, L. 2007. "Unobserved Heterogeneity in Structural Equation Models: A New Approach to Latent Class Detection in Pls Path Modeling " in: *Dipartimento di Matematica e Statistica*. Napoli: Universit a degli Studi di Napoli Federico II, p. 338.

Venkatesh, V. 2000. "Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model," *Information Systems Research* (11:4), pp. 342-365.

Venkatesh, V., and Bala, H. 2008. "Technology Acceptance Model 3 and a Research Agenda on Interventions," *Decision Sciences* (39:2), pp. 273-315.

Venkatesh, V., and Davis, F.D. 2000. "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies," *Management Science* (46:2), pp. 186-204.

Venkatesh, V., Morris, M.G., Davis, G.B., and Davis, F.D. 2003. "User Acceptance of It User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (vol. 27:no. 3), pp. pp. 425-478.

Venkatesh, V., Speier, C., and Morris, M.G. 2002. "User Acceptance Enablers in Individual Decision Making About Technology: Toward an Integrated Model," *Decision Sciences* (33:2), pp. 297-316.

Wallace, L.G., and Sheetz, S.D. 2014. "The Adoption of Software Measures: A Technology Acceptance Model (Tam) Perspective," *Information & Management* (51:2), pp. 249-259.

Wang, W., Hsieh, J.J.P.-A., and Song, B. 2011. "Understanding User Satisfaction with Instant Messaging: An Empirical Survey Study," *International Journal of Human-Computer Interaction* (28:3), 2012/03/01, pp. 153-162.

Wu, J.-H., and Wang, S.-C. 2005. "What Drives Mobile Commerce? An Empirical Evaluation of the Revised Technology Acceptance Model," *Inf. Manage.* (42:5), pp. 719-729.

Zhang, P., Li, T., Ge, R., and Yen, D.C. 2012. "A Theoretical Acceptance Model for Computer-Based Communication Media: Nine Field Studies," *Computers in Human Behavior* (28:5), pp. 1805-1815.

Zhou, L., Zhang, P., and Zimmerman, H.-D. 2011. "Call for Papers for a Series of Special Issues: Social Commerce," *Electronic Commerce Research and Applications*).