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Technological reflectiveness from a managerial capability perspective

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ABSTRACT

The purpose of this research is to analyze how managers reflect on technological shifts when they recognize opportunities to innovate in their organizations. We conceptualize that a deliberated reflection of technological shifts enhances the manager's disposition for promoting the use of new technological releases in the development of innovation processes. We obtain evidence supporting that reflection on technological shifts mediates the relationship between managerial perception and their subsequent intentions to accept a new technology. We test our hypotheses using the Partial Least Squares method in a sample of 161 interviewees with a technological background. Our results suggest that when managers reflect on technological shifts, they enhance the individual's capacity to sense opportunities in technological environments, such as Internet-based channels.

1. Introduction

The innovation management literature suggests that innovation processes lie in the ability to associate different resources in ingenious ways in order to generate products, sources of supply, manufacturing procedures and different forms of structure at both the organizational and individual levels (Wisse et al. 2015). The adoption of a new technology is a result of personal beliefs about the attributes conferred to a given technology, which create an attitude towards it. Managerial reflection on the benefit and threats of a new technology is highly influenced by prior experiences involving similar technologies (Schweitzer et al. 2015). Such experiences trigger reflections that form the way in which subjects understand how technology works. When subjects receive feedback from technology implementation, they can reinforce their beliefs or modify their prior understanding (Boud et al. 1985). The complexity of analyzing technology reflection lies in the fact that two people do not perceive technological phenomena equally (Hammedi et al. 2011). Two subjects could receive the same technology information but can perceive and interpret it differently because they may exhibit a limited understanding of the feedback effects (e.g., certain subjects assume linear, rather than causal, thinking) and a lack of consideration of the temporal dimensions when analyzing strategic issues (Torres et al. 2017).

Technology acceptance research explains how people accept, adopt and use new technologies (Davis 1989) and the processes of analyzing their intention to use such technologies (Hess et al. 2014). Technology acceptance research also explores the cognitive processes of people who analyze the impact of new technological releases on their communities and organizations (Schweitzer et al. 2015).

Despite the importance of the cognitive characteristics of decision makers in the technology acceptance literature, the process of how managers analyze new technology releases remains an unexplored issue in Internet research. We develop a framework, which connects the concepts of the perception of ease of use and perception of usefulness (Davis 1989) with technological reflectiveness (Schweitzer et al. 2015) to assess the impact of the intentions to promote new technological releases. We obtain evidence supporting that technological reflections mediate the relationship between managerial perception and managers' subsequent intentions of accepting a new Internet-based technology.

This research extends our knowledge of technology acceptance by showing that when managers reflect on technological shifts, they enhance the individual capacity to sense opportunities in technological environments. This managerial capability for sensing opportunities is a key issue in the innovation management and entrepreneurship literature (Biemans and Langerak 2015; Roberts et al. 2016; Teece 2007).

Another key strength of this study is the use Partial Least Squares (PLS)-Structural Equation Modeling (SEM) to validate our hypotheses in Internet research. PLS-SEM allowed us to analyze the effect of contingent variables on the technology acceptance process when managers face new technological releases on the Internet.

This paper is structured as follows: first, we develop a literature review of technological reflectiveness, managerial technological acceptance and the disposition towards promoting the use of new technological releases. Next, we explain the methodology and the validation processes of the PLS-SEM model. In this study, we evaluated PLS-SEM results based on a two-stage evaluation criterion. Stage 1 includes the

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following components for analysis: (1) indicator reliability, (2) internal consistency, (3) convergent validity and (4) discriminant validity (Sarstedt et al., 2017). To evaluate the structural model, we analyzed (1) collinearity, (2) R^2 explanation of endogenous latent variables, (3) predictive relevance Q^2, (4) significance and relevance of path coefficients and (5) f^2 and q^2 effect sizes (Sarstedt et al., 2017). We also perform a robustness check of unobserved heterogeneity and an Importance-Performance Map analysis (Ringle and Sarstedt 2016). This mapping analysis highlights the relative importance of manifest variables (Items) on specific target constructs, such as Technological Reflectiveness and Disposition, towards promoting knowledge of the use of technological innovations. Lastly, the final sections discuss results, outline implications and present concluding remarks for theory and practice.

2. Theoretical background

2.1. Technological reflectiveness in managerial decisions

Technological reflectiveness is "*the tendency of an individual to think about the impact of a technological product on its users and on society in general. Technologically reflexive individuals analyze the past effects of technological products on society, contemplate the potential effects of technological solutions in society, and can develop an advanced understanding of the socio-technical relationships involved*" (Schweitzer et al. 2015: p. 848). Technological reflectiveness is related to a cognitive, inquisitive and introspective effort using experiences and reflections for an understanding, judgment and evaluation of the impact of a novel artifact or a new technological release. Technological reflectiveness encompasses the perception of a new framework when rethinking the situation for its users or for society, extrapolating personal experiences or perceptions, and evaluating and reflecting on the pertinence and utility of its adoption, as well as the ease of use of the new technology by the members of that society.

Caniëls et al., (2015) suggest that managerial capabilities and managers' perception of the strategic value of Internet technologies affect the adoption of those technologies within companies. Certain elements related to reframing managerial activities have been significant predictors of the acceptance of Internet technologies, such as management commitment/support and managers' perceived benefits (Ifinedo 2011), managerial skills and concerns about the competitive position of the firm (Slade and Van Akkeren 2002), and the perceived relative advantage of Internet technology adoption (Lee 2004). In this sense, technological reflectiveness is a path-dependent managerial cognitive capability that contributes to heterogeneity in organizational performance because of the potential advantages of the superior detection of emerging opportunities and threats and the proper, suitable and even profitable use of new technologies within a given social context (Martin 2011).

2.2. Technological reflectiveness, perception and disposition

The technological reflectiveness concept involves three main facets in a unidimensional construct: (1) the individual's motivation for reasoning about technology-society associations and his/her enjoyment of it when thinking about its potential implications; (2) the ability to be included in the individual's thinking about personal product usage and its applicability to other publics; and (3) the individual's capabilities required to produce inferences regarding a technology's potential implications (Schweitzer et al. 2015: 851–853). To infer conclusions on the use of any technological product in a community for economic exploitation, a manager develops beliefs about the technological product's convenience and the advantageousness of its use in two processes: a perceptual process and a reflective process. The perceptual process has been investigated within the framework of the technology acceptance model (Davis 1989; Karahanna et al. 1999; Venkatesh and Davis 2000). The technology acceptance model suggests that individuals are actors who accept, adopt and use technological innovations. Hence, one of the key issues within the perceptual process is people's ability to identify the attributes of technological products and to create an attitude towards using it. Conversely, the reflective process refers to a cognitive, inquisitive and introspective endeavor to understand, judge, and evaluate the impact of novel, specific artifacts.

Perceptions of and reflections on new technologies trigger motivations for the cognitive adaptations of decision makers, and they have an influence on the dispositions towards their use in new technological releases. Managerial perception serves as a guide that inclines managers to act or to believe in one specific way or another (Caniëls et al. 2015). The interpretation of the term 'dispositions' suggests that new experiences, information and knowledge modify the cognitive structures created by the technological reflective process. Dispositions differ in strength and stability, depending in part on the regularity with which those mental structures are actualized in different contexts and circumstances (Lahire 2003). Hence, the perception of a new technology and its consequent reflective thinking has an impact on the dispositions towards the use of new technologies in new product releases for economic exploitation.

2.3. Hypothesis development

The acceptance and adoption of technological innovations on the Internet are procedures of exploration, perception and learning that lead to a decision of approval or rejection of the technological object under scrutiny (Venkatesh and Davis 2000). The innovation diffusion literature highlights that the attitude towards adopting a new developed technology is primarily generated by the individual's beliefs about the consequences of adopting that technology and the cost of these consequences at different levels (Karahanna et al. 1999). The adoption of a new technology is a consequence of personal beliefs, and it creates an attitude towards the given technology (Ajzen and Fishbein 1977). Karahanna et al. (1999) state that adoption can be disaggregated into the following attributes: perceived usefulness, image, compatibility and perceived ease of use, trialability, visibility and result demonstrability. Nonetheless, perceived ease of use and perceived usefulness were conclusive for the adoption of technologies in several meta-analyses (King and He 2006; Ma and Liu 2004) and, more recently, in the meta-analysis of e-learning technologies conducted by Šumak et al., (2011).

Davis (1989: 25) defines "Perceived ease of use" as "*the degree to which a person believes that using a particular system would be free of physical and mental effort*". Two different factors affect the perceptions of ease of use of a system: knowledge/self-efficacy and the environment (Venkatesh 2000). The knowledge/self-efficacy control type refers to personal beliefs regarding the ability to perform a specific task using a particular technology (Venkatesh and Davis 1996). The environment control type refers to the perception of the resources available that might be helpful in overcoming any given situation that could represent a barrier to the use of a new system, such as consultant support or user guides (Bhattacherjee and Premkumar 2004). The knowledge/self-efficacy control type is related to a reframing situation, where the evaluation of the 'effort-free' nature of a system is associated with the perception that the manager has of his/her own abilities and capacities compared to those that people in any given community might have. Another facet in the technological reflectiveness construct is environmental control. A technologically reflective manager has the ability to adapt a new technology to the community, assuming potential supports to help new users overcome the barriers and hurdles that arise in the use of a new technological release (Venkatesh 2000: p.348).

To analyze the ease of use of any technological product, the manager should develop his/her beliefs about the proximity of using a technological product, form a deeper understanding of it, and change his/her perception of it from generalized and abstract to a more concrete cognitive setting grounded in similar closer experiences (Venkatesh 2000).[1] Next, the manager makes conjectures regarding the ease of the adoption and use of the new technology by members of the community by repeating the perception process outside of the community (Schweitzer et al. 2015). Hence, the higher the perceptions are of the technologies' appropriateness with respect to whether perceived ease of use matches the self (needs and realities), the higher the reframing process is of the experience or beliefs involving the requirements and realities of the social group in which the innovation is intended to be implemented (Venkatesh and Davis 2000). Hence:

Hypothesis 1. Perceived ease of use is positively related to technological reflectiveness.

Davis (1989: 320) defines perceived usefulness as "*the degree to which a person believes that using a particular system would enhance his or her job performance*". Venkatesh (2000: 348) finds that technological utility relates to the determination to implement new technological releases to achieve goals/rewards. The aim of implementing any technology should go beyond the use of that technology. Deci and Ryan (1987) state that the focus on better results can be motivated by extrinsic or intrinsic elements, depending on whether the behavior is performed out of inherent satisfaction (intrinsic) or whether it is performed to reach a separable goal (extrinsic). For example, when a manager reflects on the potential implications of his or her decisions involving a new technology, an intrinsic motivation can be triggered. Nevertheless, an extrinsic motivation can be triggered when a manager in a rival firm performs a similar job. While closer similarities are observed from people performing similar tasks, the stimulus to create new mental structures based on the motivation for reasoning about the technology-society association is stronger. Both intrinsic and extrinsic motivations affect the manager's perception of the potential performance of using any new technology (Venkatesh and Davis 1996). Hence:

Hypothesis 2. Perceived usefulness is positively related to technological reflectiveness.

Davis (1989) conducts several experiments to validate the causality of the perceived ease of use and perceived usefulness of a new technology. The basic assumption is that a technology that is easier to use will reduce the physical or mental content of any given job using this technology. The lower complexity of cognitive structures allows managers to be prone to liberalize time in other activities. Further evidence in different meta-analyses supports that perceived ease of use is a causal antecedent of perceived usefulness, since a system of high-perceived utility is one for which a user believes in the existence of a positive relationship between use and performance (Ma and Liu 2004; Šumak et al. 2011). Therefore:

Hypothesis 3. Perceived ease of use is positively related to perceived usefulness.

The manager's dispositions towards promoting a new technology can vary according to new experiences, information, and knowledge (Lahire 2003). New information modifies the cognitive structures that form managerial decision rules (Sterman, 1989). For example, when managers discover a new technology (new information), they reflect on whether the new technology has potential benefits for their organizations. Managers modify their cognitive structures before making decisions, such as promoting the advantages of this new technology. Thus:

Hypothesis 4. Technological reflectiveness is positively related to the disposition towards promoting knowledge of the use of technological innovations of new technological releases in the manager's working group.

One of the main assumptions in technology acceptance research is that managers are willing to accept a new technology if they understand its use and its potential consequences in the current business (Karahanna et al. 1999). The manager's willingness to follow extrinsic objectives, such as firm growth and survival, reinforces the needs to identify and promote new technologies to compete within a market (Deci and Ryan 1987; Schweitzer et al. 2015). The promotion of new technology is a consequence of a reflective process, where managers make sense of whether the new technology will lead to a strategic advantage within the organization and beyond it. Therefore:

Hypothesis 5. Technological reflectiveness will mediate the relationships between perceived ease of use and perceived usefulness and the disposition towards promoting knowledge of the use of technological innovations of new technological releases.

Fig. 1 shows the theoretical model of managerial technological reflectiveness capability. We suggest that managers who promote new Internet-based technologies first perceive the ease of use of these technologies and then reflect on their usefulness for business performance. However, the central process that mediates these relationships is the manager's technological reflectiveness.

3. Research method

3.1. Instrument development

The study was conducted in two Spanish-speaking countries. Hence, we translated all scales used in this research and then validated the analysis in three steps: we used the double-back translation method suggested by Craig and Douglas, (2005) followed by the Douglas and Craig (2007) complementation for cross-cultural adaptation. We formally translated using a focus group comprising six doctoral candidates in business who are teaching fellows in business or engineering schools and two technological-expert facilitators. Both facilitators are research professors at local universities (Chile and Colombia) with Ph.D. degrees from an American business school. We followed up the validation process by developing two different concurrent think-aloud interviews with four technology managers from Colombia and Chile.

3.2. Sample and procedure

We use a convenience sampling procedure with middle managers enrolled in executive education in Colombia and Chile, as well as doctoral and master's students in a business area with a technological background. We received authorization from two local universities to send students the questionnaires randomly via email. We included a link that sent the respondents to an online platform called Qualtrics, which automatically collected all responses. We adhered to the high standards of compliance with ethical aspects of Internet research with human beings (Ess 2002). We used a letter to invite people to participate voluntarily in the survey and included specific information about the respondents' rights and other useful information that could shed light on the specific objectives that this research was pursuing. We also provided the participants with the researchers' emails for further questions. In addition, we sent the students an informed consent form concerning using the information confidentially for scientific purposes

[1] Fazio and Zanna (1981) and Karahanna (1999) demonstrate that there is a direct relationship between attitudes towards a technology and experience. However, they also show that there is a stronger relationship between attitudes and experience when the experiences are direct rather than indirect. The difference in magnitude of both experiences per se is not the focus of this research, which, instead, focuses on the causality of reflectiveness and, subsequently, of dispositions, which can be associated with attitudes as behavioral dispositions (see Campbell 1963).

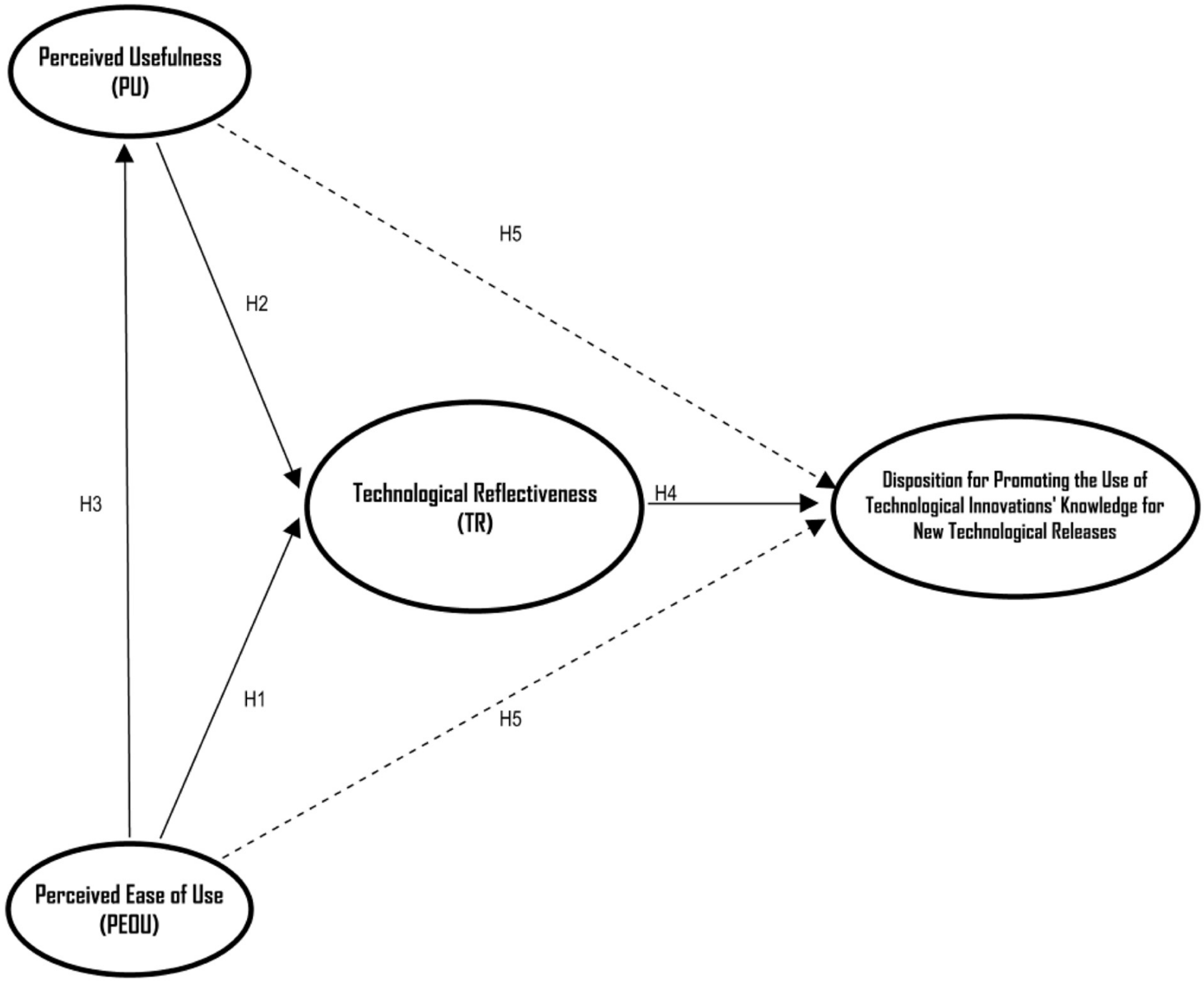

Fig. 1. Proposed model of managerial technological reflectiveness capability to internet-based technology adoption.

twice: once before the development of the questionnaire in the invitation letter and then at the end of the self-administered survey (Corbin and Morse 2003).

We received 197 completed forms out of 557 invitations over 30 days. Ten participants did not give permission to use their information in this research; thus, their data were removed from the analysis and the participants were notified of this procedure via email. The application of the Reynolds (1982) procedures for scoring social desirability allowed us to eliminate eight questionnaires, thus avoiding biased responses. The remaining questionnaires retained for analysis correspond to 86 questionnaires from Colombia and 75 questionnaires from Chile (161 questionnaires). The average age of the respondents in the sample was 35.6 years old (33.6% were 21–30 years old followed by 35.6% who were 31–40 and 30.8% who were older than 40). The sample has 55.2% female participants and 44.8% male participants. 66.4% of the participants were senior managers with technology experience and 33.6% were young managers and Ph.D./master's students with formal training in technology and operations.

3.3. Measures

We used validated scales (internal psychometric properties) published in prior research. Appendix A presents the list of measurement items. We assessed all items with a 7-point Likert-type scale ranging from “totally disagree” to “totally agree” using the rescaling procedure employed by Dawes (2002). We made this choice to avoid early test retirements and respondent fatigue due to the length of the entire questionnaire, making it look shorter and easy to complete (Steenkamp and Baumgartner 1995). We chose to randomize the questions to eliminate order bias (Schwab 2005).

The reported Cronbach's α values of the scales used in this research ranged from 0.86 to 0.98 in the case of the perceived usefulness and perceived ease of use constructs (Venkatesh and Davis 2000). In the case of technological reflectiveness, the reported Cronbach's α values ranged from 0.88 to 0.93 in four studies, as reported by Schweitzer et al. (2015). The Social Desirability Scale developed by Fischer and Fick (1993), adapted into Spanish (Ferrando and Chico 2000), was included in the questionnaire, aiming to find response-biased items.

We created a single item construct to measure disposition towards promoting knowledge of the use of technological innovations of new technological releases (DU), following the suggestion by Bergkvist and Rossiter (2007), who state that there is no difference in the predictive validity of multiple-item and single-item measures when the construct consists of a concrete singular object and a concrete attribute. We asked the respondent to consider a scenario where he/she had researched a new technology and finally concluded that its implementation in new technological releases would also have a positive impact on society, as well as on the revenue of his/her firm. Next, we asked the following:

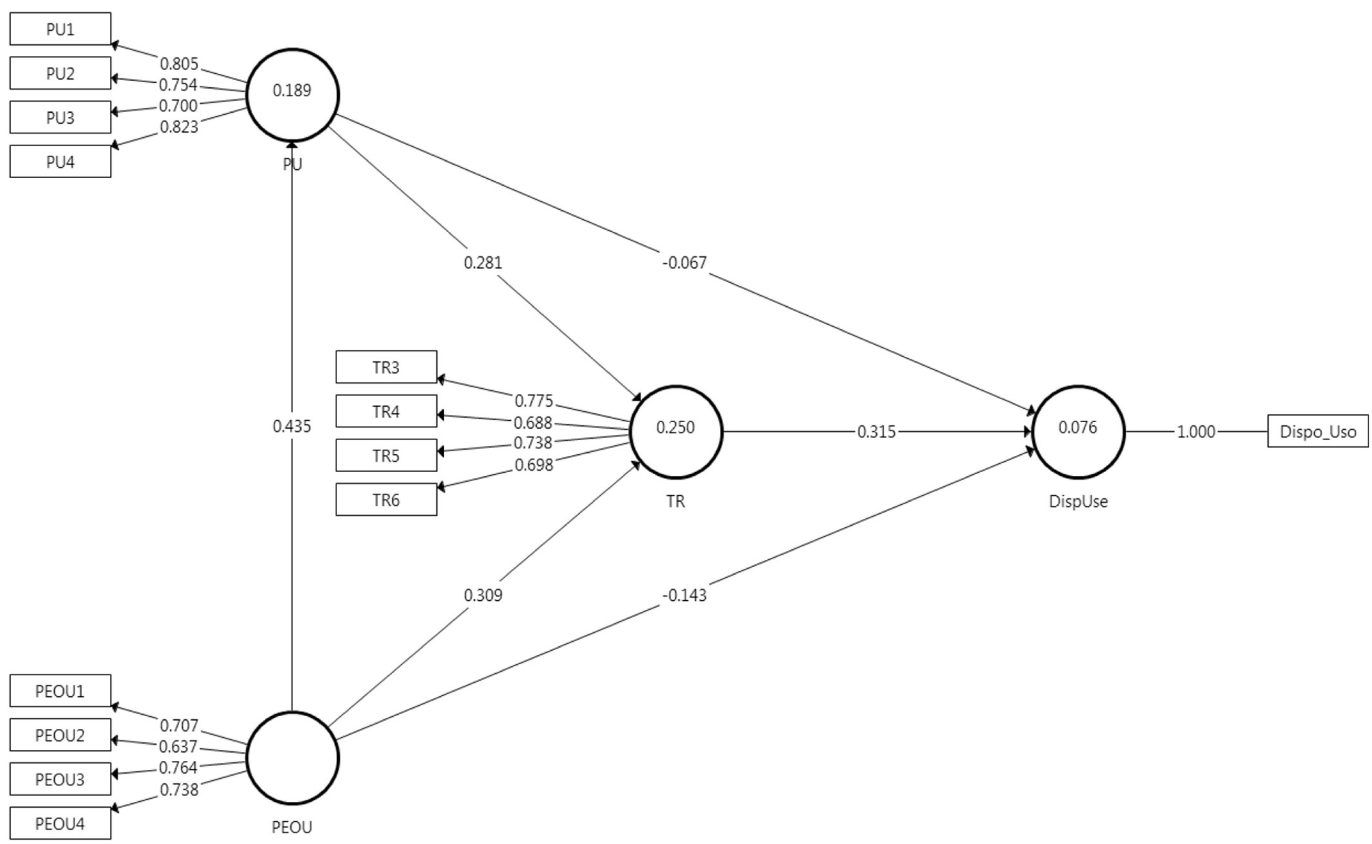

Fig. 2. PLS path models results.

"How much would you be disposed to promote your findings in your working group for the exploration of new business prospects?" The answers were rated with a 7-point Likert-type scale ranging from 1 (definitely will not) to 7 (definitely will).

4. Data analysis and results

There are two main approaches to validating hypotheses in structural equations. We used Variance-based SEM through a Partial Least Squares (PLS) estimation procedure to assess the relationships among constructs and to determine the predictive power of the research models (Fornell and Bookstein 1982; Wold 1982). We selected this approach for the following reasons. Falk and Miller (1992) and Chin (1998) demonstrate that PLS avoids restrictive assumptions that are essential to the use of covariance-based SEM techniques, such as larger sample sizes, greater demands on measurement scales, and assumptions of multivariate normality. As our sample reached only 161 questionnaires, PLS-SEM model predictions tend to be more accurate than covariance-based SEM techniques (Richter et al. 2016). Ainuddin et al., (2007) comment that the use of "PLS-SEM is especially suited to exploratory studies where […] (relationships) have not been previously tested." The nature of our research is an exploratory study because we related the Technological Reflectiveness concept to the original Technological Acceptance Model (TAM). In fact, Gefen et al. (2000) suggests the use of PLS-SEM when two validated concepts are used within the same theoretical model.

Other advantages of PLS methods relate to PLS generating useful and robust equations even when the number of 'independent variables', or coefficients to be evaluated, vastly exceeds the number of experimental observations compared to covariance-based SEM techniques (Cramer 1993). PLS-SEM models are considerably more stable when the sets of independent variable values are correlated rather than orthogonal, which is the most common situation in structure-activity studies (Becker et al. 2013). Predictions from PLS-derived models tend to be more accurate compared with those from Multiple Regression-derived models (Cramer 1993). In recent years, PLS-SEM methodology has received increased attention from different fields, such as management and business (Jensen and Clausen 2017), marketing (Rezaei 2015), information systems (Ge et al. 2016), and environmental sciences (Benmoussa et al. 2017), as well as oncology (Hedegaard et al. 2010), chemistry (Cheng and Sun 2017) and pharmacology (Ghafghazi et al. 2017). We used SmartPLS version 3.2.7 software (Ringle et al., 2015) and SPSS version 17.0 to perform our partial least squares-structural equation model and validation procedures.

4.1. PLS path model estimation

We compared mean difference in the Technological Reflectiveness construct using an independent-samples *t*-test between Colombian and Chilean samples. Next, we tested the assumption of normality and homogeneity of variances. The Chilean sample show skewness of −0.6 (SD = 0.28) and kurtosis of 0.64 (SD = 0.55). The Colombian sample presents skewness of −0.11 (SD = 0.26) and kurtosis of −0.31 (SD = 0.51). These results suggest that both distributions are sufficiently normal for the purposes of conducting a t-test (Schmider et al. 2010). We tested the homogeneity of variances via Levene's F test, (F = 0.01, p = 0.91), which indicates that the variances between both samples are not significantly different. The *t*-test also shows that the Colombian t-test scores (M = 34.53; SD = 9.46) are not significantly different from the Chilean sample (M = 34.99; SD = 9.81), t

(159) = 0.30, p = 0.77, d = 0.05. Moreover, p-values from three different tests (the Welch-Satterthwait test, the Parametric tests and the Non-parametric significance test) from a 95% two-tail testing Bias-corrected and Accelerated confidence intervals, derived from bootstrapping 10,000 samples in the PLS Multi-group Analysis (PLS-MGA), are not statistically significant. These results show that both samples can be considered to be not significantly different.

Following Cohen's (1992) recommendations, the minimum sample size for multiple OLS regression analysis should be 103 observations to detect R^2 values of approximately 0.10, assuming a significance level of 5% and a statistical power of 80%. Hence, a sample size of 161 participants is adequate. With this evidence, we proceed using a joint database for both countries.

We use SmartPLS version 3.2.7 software to develop the PLS path model estimation (Ringle et al., 2015). The model estimation uses the basic PLS-SEM algorithm by Lohmöller (1989), a maximum of 10,000 iterations, a stop criterion of 1×10^{-7}, and equal indicator weights for the initialization (see Streukens and Leroi-Werelds 2016). The presence of unidimensional constructs in the nomological network suggests that a centroid-weighting scheme is suitable for measurements using PLS-SEM (Ringle et al., 2012; Evermann and Tate 2016).

Wong (2013) suggests an item elimination process for all analyzed constructs. We considered the Colombian sample for item elimination because it was the sample with the highest number of questionnaires. We used the Chilean observations for holdout sample validation (Sarstedt et al. 2016). In this instance, we eliminate items 1, 2, and 6 in the Technological Reflectiveness construct. After item elimination, we performed a principal component factor analysis, obtaining a Kaiser-Meyer-Olkin test value of 0.69, and the Bartlett's test of sphericity was statistically significant. Fig. 2 shows the results from the PLS algorithm.

PEOU, Perceived Ease of Use; TR, Technological Reflectiveness; DispUse, Disposition for Promoting the Use of Technological Innovations' knowledge of New Technological Releases. The coefficient of determination, R^2, of each construct is shown inside the circle; Path coefficients are shown in the arrows between the circles; Outer loadings are shown between the circles and the items.

Fig. 2 reports the following preliminary observations: (1) the coefficient of determination R^2 is 0.08 for the DU endogenous latent variable. Technological Reflectiveness (TR), Perceived Usefulness (PU), and Perceived Ease of Use (PEOU) explain approximately 8% of the variance in disposition towards promoting knowledge of the use of technological innovations of new technological releases (DU). PEOU and PU together explain 25% of the variance of TR, and PEOU explains approximately 19% of the variance in PU. (2) The inner model suggests that TR has the strongest effect on DU (0.315). Nonetheless, the effects of PEOU and PU on DU are lower than 0.2, which reveals a lack of statistical significance. PEOU has the strongest effect on TR (0.309) followed by PU (0.281). Finally, the effect of PEOU on PU is 0.435.

4.2. Model evaluation

To validate the PLS algorithm results, we performed a two-stage valuation criterion that assess (1) the measurement model and (2) the structural model (Sarstedt et al., 2017). Stage 1 includes the following components for analysis: (1) indicator reliability, (2) internal consistency, (3) convergent validity, and (4) discriminant validity. Stage 2 shows the following components for analysis: (1) collinearity, (2) R^2 explanation of endogenous latent variables, (3) predictive relevance Q^2, (4) significance and relevance of path coefficients, and (5) f2 and q2 effect sizes (Sarstedt et al., 2017).

4.2.1. Stage 1. Measurement model evaluation

Sarstedt et al., (2017) state that the evaluation of PLS-SEM results begins with an assessment of the measurement models. Table 1 shows the basic PLS-SEM algorithm results.

All three reflective measurement models meet relevant assessment criteria (for criteria evaluation outcomes, see Sarstedt et al., 2017). All of the outer loadings are above 0.7, which indicate a sufficient level of reliability. Even when the PU2 was slightly lower than this threshold, its inclusion did not significantly affect the PU reliability construct. All AVE scores are above 0.5, which suggest a convergent validity.

Internal consistency reliability was measured using Cronbach's α, Rho A, and Composite Reliability. Table 1 shows that the Cronbach's α values range between 0.66 and 0.75, which are acceptable values for exploration analysis. Rho A values meet the minimum level of 0.7. Lastly, Composite Reliability is above the 0.7 threshold. These results provide support for internal consistency reliability.

Next, we conducted a Heterotrait-Monotrait (HTMT) procedure for discriminant validity. Table 2 reports that all values are lower than 0.9 in the HTMT matrix. This matrix confirms that there is enough evidence in the proposed nomological network to confirm that the technological reflectiveness construct has discriminant validity (Henseler et al. 2015).

Table 3 shows correlation values among constructs. The Fornell and Larcker (1981) criterion suggests that the AVE of each construct should be above of 0.5; CR values should be higher than 0.7, and the square root of the AVE of each construct greater than the correlations among the constructs. Our results confirm the nomological validity of the model. For information on the correlations regarding the utilized items and constructs, see Appendix B.

4.2.2. Stage 2. Structural model evaluation

The Variance Inflation Factors (VIF) for the outer and inner models are lower than 5, which is the maximum standard threshold criteria for collinearity (VIF [1.16; 1.59]). Table 4 reports the significance and relevance of the structural model relationships (Streukens and Leroi-Werelds 2016).

Table 4 shows that the confidence intervals do not contain zero, which indicates statistical significance of the effects among the constructs. PEOU shows the strongest effects on PU (0.44) and TR (0.31 and 0.43 on Total Effects). TR has the strongest effects on DU (0.32 and 0.31 on Total Effects). The relationships between PEOU-DU and PU-DU are not statistically significant, measured using path relationships and Total Effects. However, there is a significant indirect effect between PEOU-DU, PEOU-TR and PU-DU.

Table 5 reports the in-sample and out-of-sample predictive power (Shmueli et al. 2016). We use the R^2, the R^2 adjusted and the f^2 effect to perform the in-sample predictive power (Rigdon 2012, 2016). The out-of-sample predictive power is estimated by the cross-validated redundancy (as a measure of Q^2) running the blindfolding procedure with an omission distance of 8 and by the calculated q^2 effect size.

Table 5 displays the Q^2 values from the blindfolding procedure with an omission distance of 8 ($Q^2 > 0$). The explained variance of the endogenous constructs in the structural model is measured by R^2. In our model, R^2 suggests a low intermediate value, but still satisfactory for exploratory behavior research (Hair et al. 2017, p. 197). In addition, the impact of omitted constructs, measured by the f^2 and q^2 effect sizes ranging between 0.04 and 0.23, represent small to medium effects (Cohen 1992).

Table 6 shows the PLS Predict procedure with 10 folds and 10 repetitions. We report error-based metrics, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The RMSE for the latent variables (LV) range from 0.12 to 0.47, and the MAE score is between 0.06 and 0.37, respectively. Roy et al., (2016) states that RMSE values lower than 0.4 reveal an acceptable predictive power. We also report individual error-based metrics for each item for future comparisons.

Table 1
PLS-SEM assessment results of measurement models.

Latent variable	Indicators	Mean	SD	Corrected item-total correlation	Convergent validity		Internal consistency reliability		
					Loadings	AVE	Cronbach's α	Rho A	CR
					> 0.70	> 0.50	0.70–0.90	> 0.70	> 0.70
Perceived usefulness (PU)	PU1	5.41	2.48	0.57	0.71	0.57	0.75	0.78	0.84
	PU2	5.17	2.49	0.55	0.64				
	PU3	5.38	2.4	0.47	0.76				
	PU4	5.03	2.44	0.60	0.74				
Perceived ease of use (PEOU)	PEOU1	5.04	2.4	0.36	0.81	0.57	0.66	0.70	0.79
	PEOU2	4.5	2.29	0.42	0.75				
	PEOU3	5.32	2.3	0.48	0.70				
	PEOU4	5.14	2.11	0.52	0.82				
Technological reflectiveness (TR)	TR1*	5.39	2.25	–	–	0.52	0.69	0.75	0.81
	TR2*	4.73	2.14	–	–				
	TR3	5.01	2.23	0.51	0.78				
	TR4	5.01	2.32	0.45	0.69				
	TR5	4.96	2.18	0.49	0.74				
	TR6*	5.04	2.18	–	–				
	TR7	4.92	2.17	0.44	0.70				
Disposition towards promoting knowledge of the use of technological innovations (DU)	DU1	5.72	1.44	–	1	–	–	1	–

* Items eliminated in the analysis due to low factor loadings - AVE, average variance extracted; CR, composite reliability; SD, standard deviation.

Table 2
Heterotrait - monotrait ratio (HTMT).

	DU	PEOU	PU
DU			
PEOU	0.19		
PU	0.04	0.56	
TR	0.27	0.56	0.53

PEOU, Perceived ease of use; TR, Technological Reflectiveness; DU, Disposition for Promoting the Use of Technological Innovations' knowledge of New Technological Releases.

Table 3
Correlations between variables for the Fornell and Larcker (1981) criterion analysis for checking discriminant validity.

	DU	PEOU	PU	TR
DU	**1.00***			
PEOU	−0.06	**0.71***		
PU	−0.01	0.41	**0.76***	
TR	0.22	0.39	0.39	**0.72***

* Average Variance Extracted (AVE) square root in **bold**. PEOU, Perceived ease of use; TR, Technological Reflectiveness; DU, Disposition for Promoting the Use of Technological Innovations' knowledge of New Technological Releases.

Regarding the model fit measurement, we utilized the standardized root mean square residual (SRMR) criterion because "*Initial simulation results suggest that the SRMR…is capable of identifying a range of model misspecifications*" (Hair et al. 2017). This criterion assumes that values lower than 0.1 demonstrate a good fit (Henseler et al. 2014). The SRMR of the model is 0.09, which demonstrates a good model fit.

4.3. Robustness check: unobserved heterogeneity

To analyze unobserved heterogeneity, we followed the procedure proposed by Hair et al., (2018). First, we ran the Finite Mixture procedure (FIMIX-PLS) using SmartPLS 3 software (Ringle et al., 2015) to identify the number of segments to retain from the data. This procedure is the most common approach to latent class analyses (Ringle and Sarstedt 2016). We used 10,000 samples bootstrapping with 10 folds and 10 repetitions, stop criterion of 1×10^{-5} from one to five segments, and casewise deletion.

Table 7 shows all criteria to select the number of segments. Hair et al., (2018) states that if AIC3 and CAIC indicate the same number of segments, choose the solution. Alternatively, jointly consider AIC_3 and BIC. Also consider the segment number as indicated by AIC_4 and BIC. Our pair-results show that the number of segments is between 1 and 2. Therefore, we analyzed the minimum sample size requirements for a Partial Least Squares procedure (Cohen 1992). Cohen (1992) suggests a

Table 4
Significance analysis of direct and indirect effects.

	Path coefficients			Total effects			Total indirect effects		
	Original sample	2.5%	97.5%	Original sample	2.5%	97.5%	Original sample	2.5%	97.5%
PEOU - > DU	−0.14	−0.31	0.09	−0.04	−0.22	0.24	0.11	0.01	0.22
PEOU - > PU	0.44	0.26	0.56	0.44	0.26	0.57			
PEOU - > TR	0.31	0.17	0.46	0.43	0.24	0.56	0.12	0.05	0.21
PU - > DU	−0.07	−0.26	0.11	0.02	−0.16	0.21	0.09	0.03	0.18
PU - > TR	0.28	0.12	0.41	0.28	0.14	0.42			
TR - > DU	0.32	0.1	0.49	0.31	0.11	0.49			

Results from 95% two-tail testing bias-corrected and accelerated confidence intervals derived from bootstrapping 10,000 samples, using the no sign changes option (see Streukens and Leroi-Werelds 2016). PEOU, Perceived ease of use; TR, Technological Reflectiveness; DU, Disposition for Promoting the Use of Technological Innovations' knowledge of New Technological Releases.

Table 5
Predictive power.

	R^2	R^2 Adj.	[a]Cross validated redundancy Q^2			f^2 effect size			[a]q^2 effect size		
						Endogenous constructs			Endogenous constructs		
			SSO	SSE	Q^2	DU	PU	TR	DU	TR	PU
DU	0.08	0.06	161,000	152,251	0.05						
PEOU			644,000	644,000		0.02	0.23	0.10	0.01	0.04	0.12
PU	0.19	0.18	644,000	578,666	0.10	0.01		0.09	0.01	0.03	
TR	0.25	0.24	644,000	569,039	0.12	0.08			0.07		

PEOU, Perceived ease of use; TR, Technological Reflectiveness; DU, Disposition for Promoting the Use of Technological Innovations' knowledge of New Technological Releases.
[a] Results from blindfolding procedure with an omission distance of 8.

sample of 103 participants with a maximum number of three arrowheads in the endogenous construct, a 5% significance level, and R^2 ranging from 0.10 to 0.25. Hence, the sample is homogenous because the consideration of > 1 segment is not reasonable.

5. Results

We observed that the four constructs in our proposed model appear highly interrelated. The results indicate that taken together, technological reflectiveness, perceived usefulness, and perceived ease of use can explain approximately 8% of the variance in disposition towards promoting knowledge of the use of technological innovations of new technological releases. This evidence is strengthened by the statistically significant values from the standardized path coefficients and total effects (Table 3) in the TR-DU relationship. These results provide support for Hypothesis 4. Moreover, the results also support that the variances of the technological reflectiveness construct are explained by the perceived ease of use and perceived usefulness constructs by 25.0%. This evidence suggests that the values obtained from the standardized path coefficients and total effects in Table 3 and Fig. 2, which are significant, support Hypotheses 1 and 2.

Table 3 shows a strong effect between perceived ease of use (PEOU) and technological reflectiveness (TR) (Hypothesis 1), between perceived usefulness (PU) and technological reflectiveness (TR) (Hypothesis 2), between perceived ease of use (PEOU) and perceived usefulness (PU) (Hypothesis 3), and between technological reflectiveness (TR) and disposition towards promoting knowledge of the use of technological innovations of new technological releases (DU) (Hypothesis 4). Neither the relationship between Perceived ease of use (PEOU) and Disposition towards promoting knowledge of the use of technological innovations of new technological releases (DU), nor that between Perceived usefulness (PU) and disposition towards promoting knowledge of the use of technological innovations of new technological releases (DU), was significantly correlated. Hence, the technological reflectiveness (TR) construct has mediation effects among PEOU, PU and DU. The values of the Sobel (1982) test for significance of the mediation effects of TR among PEOU, PU and DU are above 1.96 and significant (PEOU-Sobel test statistic: 2.35, $p = 0.02$; PU-Sobel test statistic: 2.19, $p = 0.03$).

The in-sample measurements of the predictive power show that even when the relationships are significant (Table 3), its effects expand from small to moderate (see Hair et al. 2013). The predictive power of the out-of-sample model reported in Tables 4 and 5 shows that all the constructs are relevant in their predictions, according to Stone-Geisser's Q^2 statistics, which are greater than zero (Fornell and Cha 1994). The q^2 and f^2 predictive relevance and effect sizes between constructs measure the impact when a specified exogenous construct is omitted in the endogenous variables. Both show that these measures are positive (and above the threshold), ranging from small to medium (Cohen 1992; Hair et al. 2013), meaning that the model has acceptable predictive relevance.

5.1. Importance performance map analysis

We performed an Importance Performance Map Analysis (IPMA) to extend our findings. This IPMA analysis highlights the relative importance of each construct and manifest variables on specific target constructs (Hair et al., 2018). We analyzed three target constructs: Technological Reflectiveness, Disposition towards promoting knowledge of the use of technological innovations, and Perceived Usefulness.

Table 6
PLS predict procedure results.

PLS predict latent variables (LV)			PLS predictmanifest variables (MV)				
Construct	RMSE	MAE	Item	RMSE	MAE	MAPE	Q^2
DU	0.12	0.06	DU	1.37	0.98	28.56	0.03
PU	0.47	0.37	PU1	1.85	1.68	46.61	0.13
			PU2	1.91	1.75	50.46	0.08
			PU3	1.81	1.60	45.05	0.09
			PU4	1.83	1.62	46.22	0.12
TR	0.46	0.35	TR4	1.87	1.54	54.63	0.03
			TR5	1.71	1.44	45.48	0.07
			TR6	1.74	1.44	48.69	0.09
			TR3	1.65	1.38	41.52	0.20

TR, Technological Reflectiveness; DU, Disposition for Promoting the Use of Technological Innovations' knowledge of New Technological Releases.
Calculations are based on the PLS Predict procedure with 10 number of folds and 10 number of repetitions.

Table 7
Results of the FIMIX-PLS procedure, from one to five segments.

Fit indices	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
AIC(Akaike's Information Criterion)	1294.18	1270.87	1264.61	1261.18	**1240.93**
AIC_3 (Modified AIC with Factor 3)	1303.18	**1289.87**	1293.61	1300.18	1289.93
AIC_4 (Modified AIC with Factor 4)	1312.18	**1308.87**	1322.61	1339.18	1338.93
BIC (Bayesian Information Criteria)	**1321.92**	1329.42	1353.97	1381.36	1391.92
CAIC (Consistent AIC)	**1330.92**	1348.42	1382.97	1420.36	1440.92
HQ (Hannan Quinn Criterion)	1305.44	**1294.65**	1300.897	1309.98	1302.24
MDL_5 (Minimum Description Length with Factor 5)	**1504.85**	1715.61	1943.42	2174.06	2387.88
LnL (LogLikelihood)	−638.09	−616.44	−603.31	−591.59	−571.46
EN (Entropy Statistic (Normed))		**0.51**	0.68	0.76	0.61
NFI (Non-Fuzzy Index)		0.59	0.70	0.72	0.54
NEC (Normalized Entropy Criterion)		78.67	52.13	38.63	62.10
Relative segment size (number required of observations per segment)					
Number of segments	1	2	3	4	5
2		104.49	30.51		
3		100.85	19.98	14.18	
4		95.58	21.47	9.32	8.78
5		67.64	41.45	13.91	7.16

Calculations are based on 10,000 iterations and 10 numbers of repetitions with a stop criterion of 1 × 10–5 from one to five segments, (list-wise deletion) using SmartPLS version 3.2.7 (Ringle et al., 2015). We multiplied the segment-specific values and the sample size to compute the relative segment size (Hair et al., 2018).

Fig. 3 shows that "Perceived Ease of Use (PEOU)" has a higher impact on Technological Reflectiveness (TR). The total effect score suggests that one unit of PEOU score increases TR scores in 0.46 units in the Likert-scale, which ranges from 1 to 7. In fact, the manifest variables that have the strongest influence on TR are the degree of understanding of the interaction with the new technology (PEOU1) and its ease of use (PEOU3). Appendix A shows all latent variables (constructs) and their manifest variable (items).

Fig. 4 shows that "technological reflectiveness (TR)" has a higher impact on Disposition towards promoting knowledge of the use of technological innovations (DU). The total effect score suggests that one unit of TR score increases DU scores in 0.35 units. The most significant manifest variable on DU is the reflection on whether the participant has new ideas about how this new technology can be used to reduce a social problem (TR3), and whether the participant reflects the market consequences that this technology may have for society (TR5).

Lastly, Fig. 5 shows that one unit of Perceived Ease of Use (PEOU) score increases "Perceived Usefulness (PU)" scores in 0.53 units. The manifest variable with the strongest influence on PU is the degree of understanding of the interaction with the new technology (PEOU1).

6. Discussion

This research provides a highly valuable contribution to management and technological forecasting research by showing the behavioral aspects of Internet-based technology adoption. Our results suggest that technological reflectiveness acts as an individual and managerial capability when managers adopt new technologies. The proposed model highlights that companies should invest in training managers to develop reflections on technologies and their impacts on business growth before investing in new Internet-based technologies. Lin et al., (2007) suggest that technology experimentation is a strong driver of reflective thinking that facilitates technology adoption. We show that the development of a formal reflection allows managers to reflect on and make sense of new technologies that could enhance the organizational response to new technological trends (Helfat and Peteraf 2015; Teece 2007). We supplement the technological acceptance model (Joo and Sang 2013; King and He 2006) by showing that managerial perceptions of the usefulness and ease of use of technologies increase managerial dispositions towards promoting new technologies in organizations.

Our results also confirm that two facets of the technological reflectiveness construct affect an understanding of the use of new

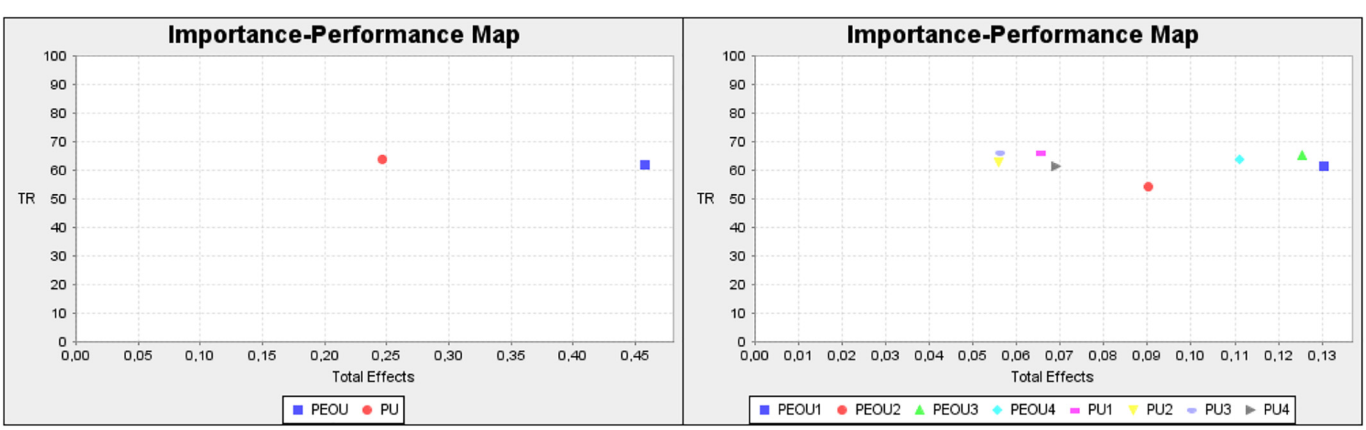

Fig. 3. Importance performance matrix - technological reflectiveness. Left: Latent variable level analysis; right: Indicator level analysis. Source: Images from SmartPLS version 3.2.7 (Ringle et al., 2015).

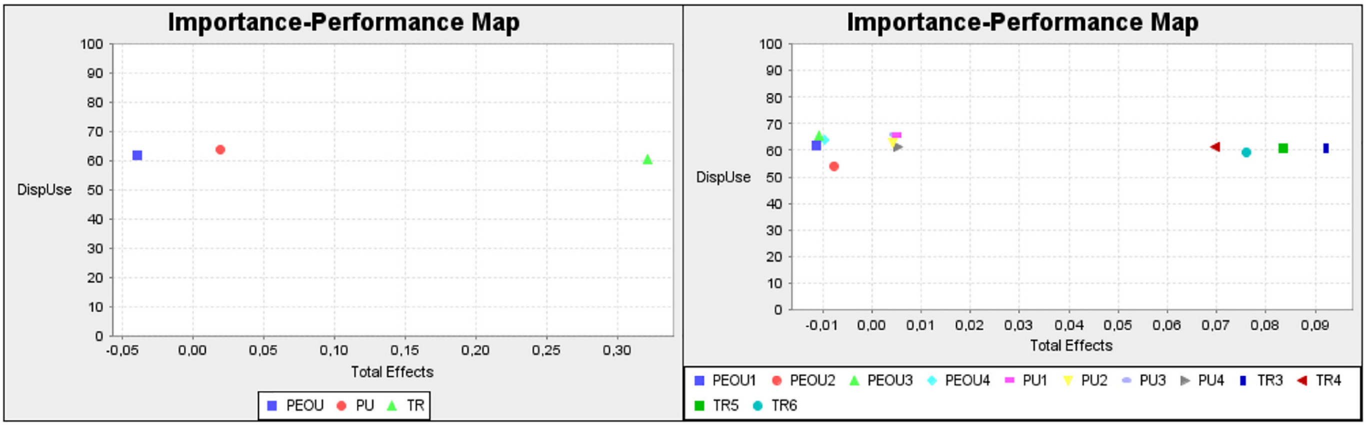

Fig. 4. Importance performance matrix - disposition towards promoting knowledge of the use of technological innovations. Left: Latent variable level analysis; right: Indicator level analysis. Source: Images from SmartPLS version 3.2.7 (Ringle et al., 2015).

technologies. These two facets reflect managers' ability to think beyond personal use and to analyze the potential implications of a technology for the future of their business (Schweitzer et al. 2015: 851–853). Nonetheless, we observed that the facet related to the manager's motivation to consider the interaction between technology and society was not a good predictor of technological reflectiveness in our cultural environment (Chile and Colombia). The cultural dimensions of individualism may explain why managers in Colombia and Chile are not aware of the potential impacts that technological innovation can have on others (McMillan and Chavis 1986: 12, Jariego 2004: 193).

7. Conclusions

This research suggests that the concept of technological reflectiveness is a dynamic managerial capability of opportunity detection (Teece 2007) that enables a firm to use new technologies for business growth. We suggest that the cognitive process of technological adoption is based on the manager's personal beliefs, reflective orientation and disposition towards promoting actions to evaluate observed economic opportunities of new technologies. Technological reflectiveness, as a sensing managerial dynamic capability, includes both technology and market surveillance processes, which enable managers to understand the current and latent trends in industries and markets (Teece 2007).

One of our key contributions is that we show that technological reflectiveness is significantly related to the individual willingness to promote new technologies. Although the technology reflectiveness represents a low degree of variance (8%) on disposition for promoting the use of technology innovations, perceptions of technology usefulness and ease of use are significantly related to technological reflectiveness, explaining 25% of its variance. We argue that managers' perception of the potential uses of new technologies facilitates the reflective process of making sense of the benefits of a new technology.

This study has several limitations. For example, the respondents are middle managers and postgraduate students with limited experience of corporate decision-making. Future research should test our nomological model with top manager who are responsible for selecting and implementing new technologies. It is important to note that the variances in all constructs suggest that there are other factors that must be considered when explaining how managers reflect on technological issues and their disposition towards using new technologies. Therefore, this study is a call to explore new items to supplement the suggested constructs. Lastly, this study makes a unique contribution to the current body of knowledge by showing the technological reflectiveness process as a capability. Nonetheless, our study does not consider the role of environmental factors, such as stress conditions under uncertainty, increments of conflicts when participants acquire new technologies, and compensation mechanisms when participants implement projects that involve new technologies. Further research is warranted to explore the effects of these environmental factors within industries or countries.

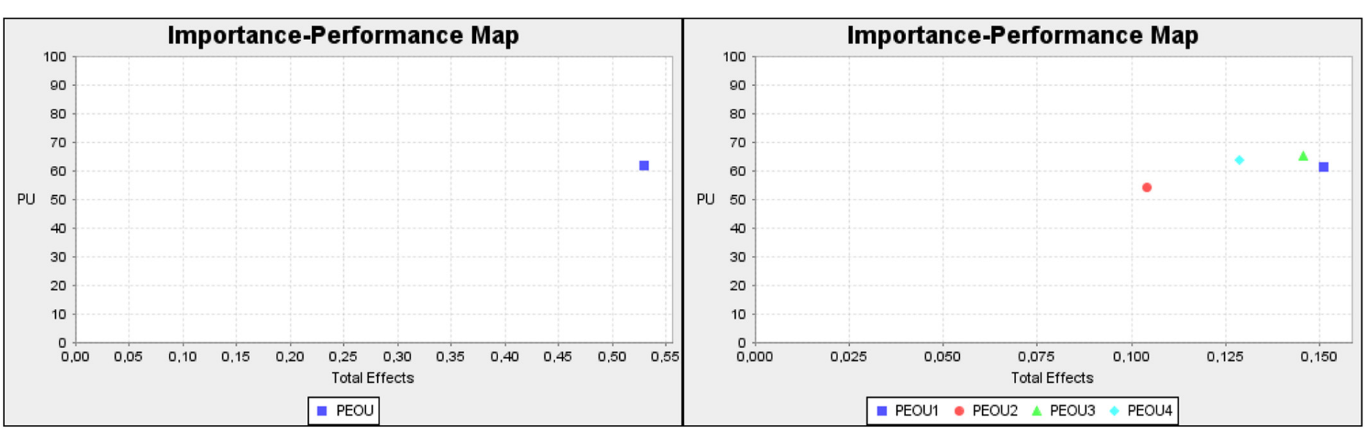

Fig. 5. Importance performance matrix – Perceived usefulness. Left: Latent variable level analysis; right: Indicator level analysis. Source: Images from SmartPLS version 3.2.7 (Ringle et al., 2015).

Appendix A

Table A
Constructs, measurement items, and authors.

Construct	Item	Author
Perceived usefulness (PU)	PU1. If I were to adopt new technology, it would enable me to accomplish my tasks more quickly. PU2. If I were to adopt new technology, the quality of my work would improve. PU3. If I were to adopt new technology, it would enhance my effectiveness on the job. PU4. If I were to adopt new technology, it would make my job easier.	Venkatesh and Davis (2000)
Perceived ease of use (PEOU)	PEOU1. My interaction with the new technology will be clear and understandable. PEOU2. Interacting with the new technology will not require a considerable amount of my mental effort.[a,b] PEOU3. I will find the new technology easy to use. PEOU4. I will find it easy to get the new technology to do what I want it to do.	Venkatesh and Davis (2000)
Technological reflectiveness (TR)	TR1. I enjoy thinking about the chances and risks that a new technology might provide and harbor for society.[a] TR2. I am very interested in studying the impact that new technical products have on society.[a] TR3. When I hear about a new technological product, I spontaneously have ideas on how this product can be used to reduce social problems. TR4. I enjoy thinking about the impact that new technological products have on different social groups (e.g., the elderly, the young, and the chronically ill). TR5. When I hear that a new technological product is on the market, I immediately reflect on the consequences that this product may have for society. TR6. I enjoy thinking about the ways in which future technology could change our society.[a] TR7. I often think about how technological products could impact the autonomy and self-determination of individuals and social groups.	Schweitzer et al. (2015)
Social desirability (SD)	SD1. Sometimes, I like to gossip a little. SD2. I once took advantage of someone. SD3. When I make a mistake, I'm always willing to admit it. SD4. Sometimes, I try to take revenge instead of forgiving and forgetting what they have done to me. SD5. Sometimes, I insist on doing things my way. SD6. I never get irritated when people express ideas that are very different from my own. SD7. I have never deliberately said anything that could hurt someone's feelings.	Fischer and Fick (1993); Ferrando and Chico (2000)
Disposition towards Promoting knowledge of the use of technological innovations (DU)	DU1. How much would you be disposed towards using, or promoting its use in your working group, for the exploration of new business prospects?	Authors' elaboration

[a] Items eliminated in the analysis due to low factor loadings.
[b] Reversed item score.

Appendix B

Table B
Item descriptions and correlations.

	MEAN	SD	PU1	PU2	PU3	PU4	PEOU1	PEOU2	PEOU3	PEOU4	TR1	TR2	TR3	TR4	TR5	TR6	TR7	DU
PU1	5.41	2.48	1															
PU2	5.17	2.49	0.42*	1														
PU3	5.38	2.4	0.33**	0.38**	1													
PU4	5.03	2.44	0.52**	0.41**	0.4**	1												
PEOU1	5.04	2.4	0.31**	0.30**	0.20**	0.33**	1											
PEOU2	4.5	2.29	0.16*	0.02	0.19**	0.18*	0.3	1										
PEOU3	5.32	2.3	0.35**	0.22**	0.27**	0.19*	0.27**	0.28**	1									
PEOU4	5.14	2.11	0.25**	0.17*	0.15*	0.28**	0.23**	0.36**	0.53**	1								
TR1	5.39	2.26	0.06	0.11	0.23**	0.12	0.09	−0.09	0.17*	0.19**	1							
TR2	4.73	2.14	0.22**	0.12	0.15*	0.24**	0.34**	0.02	0.2**	0.35**	0.29**	1						
TR3	5.01	2.23	0.26**	0.24**	0.20**	0.20**	0.24**	0.15	0.37**	0.42	0.26**	0.32**	1					
TR4	5.01	2.32	0.32**	0.27**	0.15*	0.29**	0.21**	0	0.17*	0.11**	0.37**	0.29**	0.37**	1				
TR5	4.96	2.18	0.24**	0.12	0.17*	0.30*	0.14	0.11	0.23**	0.31	0.34**	0.22**	0.37**	0.35**	1			
TR6	5.04	2.19	0.20**	0.1	0.23**	0.19**	0.23**	0.11	0.34**	0.25**	0.28**	0.33**	0.26**	0.24**	0.31**	1		
TR7	4.92	2.18	0.11	0.05	0.1	0.18*	0.14	0.18*	0.30**	0.24**	0.26**	0.29**	0.39**	0.29**	0.38**	0.39**	1	
DU	5.72	1.44	−0.06	0	0.03	0.01	−0.13	−0.17*	0.03	0.12	0.29**	0.04*	0.17*	0.16*	0.19**	0.08	0.14	1

Two-tailed P-values: *p < 0.05; **p < 0.01; ***p < 0.001.

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