NON-LINEAR AND LINEAR POSTULATIONS OF TECHNOLOGY ADOPTION DETERMINANTS

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ABSTRACT

Using polynomial regression and response surface analysis to examine the non-linearity between variables, this study demonstrates that better analytical nuances are required to investigate the relationships between constructs when the underlying theories suggest non-linearity. By utilising the Theory of Planned Behaviour (TPB), Ettlie's adoption stages as well as employing data gathered from 162 owners of Small and Medium-sized Enterprises (SMEs), our findings reveal that subjective norms and attitude have differing influences upon behavioural intention in both the evaluation and trial stages of the adoption.

Keywords: technology adoption, polynomial regression, response surface methodology, cloud ERP, SMEs.

INTRODUCTION

The topic of technology adoption has long been discussed within the IS domain and has supposedly reached the stage of a mature level of discussion [1]. However, those researches have always considered technology adoption as being a single action (i.e., a snapshot) rather than examining the manner in which combinations of two predictor variables relate to an outcome variable [2]. Such a myopic explanation prevents a holistic understanding of the adoption process, especially for business technology adoption, as the process is a far more complex phenomenon [3]. Use of sophisticated analytical techniques such as polynomial regression [4] and response surface analysis [5] allow researchers to examine the extent to which combinations of two predictor variables relate to an outcome variable [2]. Polynomial regression [4] together with response surface methodology [6] provides the basis required for testing and interpreting the features of surfaces corresponding to polynomial quadratic regression equations. The combination provides the degree of statistical sophistication required to examine the nuanced views of tripartite relationships by graphing the three variables in a three dimensional space so as to provide relationships between combinations of two predictor variables and an outcome variable [2]. Despite the fact that most theories used in IS are derived from social and behavioural sciences and predict non-linearity, the mainstream IS researchers have rarely used such techniques in their analysis. Rather, the focus predominantly stayed with linearity assumptions; hence the linear techniques. There are a few rare exceptions where researchers have relaxed linearity assumptions by staying true to the original theoretical assumptions (see [7, 8]) however such applications are few and far between.

The theoretical models used in technology adoption research have been primarily adopted from psychology and sociology theories (for a review, see [9]) and suggest non-linear relationships. For example, the most widely-used and cited model, Unified Theory of Acceptance and Use Technology (UTAUT), has resulted from the combination of theories/models of technology adoption. Further, the Theory of Planned Behaviour [10] and the Theory of Reasoned Action (TRA) [11] have been central components of that model. Both models, TPB and TRA have been used extensively not only in UTAUT models but in other models as well for the last two decades [8]. Three TPB major constructs include subjective norms, perceived behavioural control and attitude respectively [10] whilst subjective norms and attitude are two of the key constructs in TRA [11]. In addition, non-linear relationships have been observed in the extant empirical research. This research comprises both the information systems that study information technology acceptance as well as research from other fields that have used the subjective norms and attitude of the two constructs (see [8]). However, previous technology adoption research other than Titah and Barki [8] which largely employed subjective norms, perceived behavioural control and attitude as key constructs. They seldom considered non-linearity and hence largely overlooked the non-linear behaviour of the relationships. Titah and Barki [8] also have only examined the interplay between attitude and subjective norms where perceived behavioural control has been overlooked. Mainstream research using the constructs of subjective norms, perceived behavioural control and attitude has predominantly followed linear assumptions despite the existence of theories suggesting non-linear relationships. Thus, linearity assumptions not only hinder possible opportunities to understand the complex relationship existing between the constructs but also present a danger of understating or overstating the main effects. This could lead to incomplete, partial or erroneous interpretations of the findings [8, 12]. As such, the employment of non-linear postulations in analysis has the potential to uncover the complex and contingent relationship between the constructs that the theory originally suggests. Such analysis could offer finer detailed knowledge regarding the relationship between independent and dependent variables compared to the linear analysis.

Receiving motivation from the above gaps, we aim to discuss the tripartite relationships between subjective norms, perceived behavioural control and attitude against intention with both linear and non-linear assumptions. In doing so, our objective here is to demonstrate that it is possible to discover complex contingent relationships between constructs by relaxing the traditional linearity assumptions. This is especially relevant when the underlying theory assumes non-linearity. In this regard, we use the example of the adoption of cloud ERP by SMEs focusing on the interactions between subjective norms, behavioural control and attitude against intention in the adoption stage (prior to use). In particular, we investigate the following factors: (i) how issues of attitude, subjective norms, and perceived behavioural control in combination influence the decision-maker's intention, (ii) Do issues of perceived behavioural control, subjective norms and attitude impact differently on behavioural intention in different phases of the adoption process? (iii) Does polynomial regression, together with response surface methodology, provide a better analytical nuance to provide finer detailed knowledge concerning the aforementioned relationships compared to the linear analysis?

NON-LINEARITIES BETWEEN ATTITUDE, SUBJECTIVE NORMS AND PERCEIVED BEHAVIOURAL CONTROL

TPB posits that an individual's intention to perform various kinds of behavior can be predicted by, namely: (1) high precision of attitudes towards the behaviour; (2) subjective norms; and (3) perceived behavioural control [13] TPB and TRA research explicitly discusses the interaction effects between the constructs [10] and has been extensively investigated in a variety of non-IS contexts [8]. For example, the relationship between attitude and subjective norms has been used to examine behaviours in, specifically: smoking and drinking [14], adult alcohol consumption [15] as well as switching of behaviour patterns [16]. In addition, TPB has been extensively used to explain the variance seen in, namely: technology adoption intention in the household [17], employee compliance in organizations [18], physicians' acceptance of telemedicine technology [19], the process of e-commerce adoption by consumers [20], and the ability to predict a small business executive's decision to adopt IT [21] in the IS context. In addition, the key studies that investigated behavioural intention also used the processes of Technology Acceptance (TAM) and Expectation Confirmation Theory (ECT) as their theoretical perspectives.

IS research has traditionally examined the linear effect of attitude, subjective norms and perceived behavioural control on intentions and behaviours. As evident in Table 1, such studies predominantly followed traditional linearity assumptions and have used linear analytical tools such as linear regression, LISREL and PLS. However, some researchers have investigated the non-linear moderation effects of demographical characteristics such as age, sex, income and marital status on social influence and the intention to adopt [e.g., 17]. Some other researchers have investigated the negative synergy between attitude and subjective norms on intention using TPB with non-linear postulations and polynomial regression together with response surface methodology [8]. In addition, a few other studies have relaxed such linearity assumptions and have employed sophisticated analytical techniques such as polynomial regression and response surface methodology to study non-linear behaviour of intention using TAM and ECT [22, 23] (see Table-1 for a summary). However, one should not be under the erroneous impression that polynomial regression is a non-linear regression. Rather, it is a form of linear regression and has been used to describe non-linear phenomena [24, 25]. As Shanock *et al.* [2] explain the combination of response surface methodology and polynomial regression technique has more explanatory power compared to the traditional moderated regression analyses or difference scores. Further, it has the potential to apply for a wide range of research questions. This combination has been widely applied to study the outcomes of self-observer rating discrepancies in multisource feedback instruments. In this procedure, the research demonstrated the relationship between congruence and discrepancies between self- and other-ratings as well as related dependent variables in tripartite relationships [2]. As they further explain, in particular, this technique can be used for any instance where researchers are interested in investigating how combinations of two predictor variables relate to an outcome. For example, in IS research this technique has been used to study technology adoption [e.g., 22, 23].

Table-1. Key literature of technology adoption focusing on behavioural intention, main focus of the study and method of analysis.

Reference	Focus of the study	Method of analysis
Pavlou and Fygenson (2006)	This study investigates the process of e-commerce adoption by consumers using TPB. The longitudinal study conceptualises perceived behavioural control as a higher-order factor formed by self-efficacy and controllability.	Analysis of longitudinal survey data using the PLS method in structural equation modelling with non-linearity assumptions.
Titah and Barki (2009)	This study tests the non-linear relationship between attitude and subjective norms. In particular, the study explores the negative synergy between attitude and subjective norms in organisational IT use contexts using the economic theory of complementarities.	Polynomial regression and response surface methodology with non-linearity assumptions.
Venkatesh and Goyal (2010)	A study of individual-level information systems adoption using expectation confirmation theory. Further, the study presents insights from cognitive dissonance, realistic job preview and prospect theory to present a polynomial model of expectation–disconfirmation in information systems.	Polynomial regression and response surface methodology with non-linearity assumptions.
Brown et al. (2012)	This study discusses expectation confirmation in technology use based on the assimilation-contrast model and prospect theory using the TAM primary construct of perceived usefulness.	Analysis of survey data using polynomial quadratic equations and response surface methodology with non-linear assumptions.

However, three basic conditions must be satisfied in order to be able to use this technique. First, the two predictors (independent variables) should be proportionate or represent the same conceptual domain [26]. Thus, any incongruence or congruence on the two predictor variables is interpretable in a meaningful manner with respect to the dependent variable [2]. Second, the two predictor variables must be measured on the same numeric scale [26] or the scale needs to be transformed to a standardized scale so as to place them in a common metric [27]. This will enable their degree of correspondence to be determined. Third, all the usual assumptions of multiple regression (see [28] for a listing of assumptions) must be met as polynomial regression is a method of moderated regression that provides information about combinations of variables but with greater potential to provide deeper insights about the relationships [2]. The technique of polynomial regression together with response surface methodology allow researchers to examine the agreement (i.e., the theoretical match between the two variables, or when both predictor variables are similar) between two predictor variables relative to an outcome. Next, the technique allows researchers to investigate the manner in which the mis-match of predictor variables (divergence, degree of discrepancy, or the extent to which the two predictor variables differ from each other) relate to an outcome. Finally, this technique allows researchers to investigate how the direction of the discrepancy between two predictor variables (which predictor variable is higher than the other) relates to an outcome. In other words, with this technique one could determine the level of the dependent (outcome) variable when one predictor variable is higher (lower) than the other predictor variable. In addition, the three dimensional response surface extrapolation technique allows researchers to analyse the non-linear relationships that the underlying theory posits. Also, this technique resolves the problems inherent to the use of difference scores (the algebraic, squared, or absolute differences between the values of two variables or the absolute or squared differences between the two variables) in analysing the effect of discrepancies on a dependent variable [26, 29]. For example, as difference scores combine distinct measures into one measure, the effect of individual scores on the outcome variable is compounded. Thus, the difference scores neither have the ability to explain the extent to which each of the individual (component) measures contribute to the outcome variable, nor would be able to divulge which variable is better for the outcome variable [2]. As such, the use of polynomial regression together with response surface methodology eliminates limitations such as ambiguous interpretations and confounded effects. Further, it allows researchers to examine the extent to which each predictor variable (i.e., each component measure) contributes to the variance in the dependent variable (outcome) in a three-dimensional examination as opposed to the two-dimensional view in traditional regression analyses. We take TPB to investigate the adoption by SMEs of cloud ERP and demonstrate the advantages of response surface analysis compared to the traditional analysing methods such as moderated regression and partial least square (PLS) analysis. In this paper, we have used TPB to investigate the role of attitude, subjective norms and perceived behavioural control on adoption intention during the early stages of cloud ERP adoption in SME's. In doing so, we treat the adoption as a multi-stage decision-making process. This involves investigating whether perceived behavioural control, subjective norms and attitude behave differently on the outcome variable behavioural intention in different stages of the adoption process using three analytical techniques; namely: traditional moderated regression, PLS and polynomial regression

PROCESS VIEW TECHNOLOGY ADOPTION IN SME'S

In general, the decision of technology adoption is a cognitive activity where an individual makes a positive (or negative) disposition (termed attitude in TPB) prior to making the choice of action (i.e., behavioural intention) [10]. Engagement or dis-engagement of behaviour such as the decision for technology adoption is also influenced by the perceived social pressure exerted on individuals created by the expectations of important referents (termed subjective norms in TPB) [10]. In addition, behavioural intention is also influenced by the perceptions of one's ability to perform a given behaviour (termed perceived behavioural control in TPB) [10]. The decision-making in SMEs are influenced by three determinants; namely: (1) the decision-makers' cognitive disposition (attitude); (2) influence of competitors, regulatory bodies, the government, customers, vendors and employees (subjective norms); and (3) the perceptions of the key stakeholders (e.g., CEO, senior managers, employees) regarding their ability to utilize the technology effectively (perceived behavioural control). This ultimately defines the SME's eventual choice of action (behavioural intention / intention to adopt). We recognize that the three determinants of behavioural intention are vital for the decision of cloud ERP adoption in SME's. However, we argue here that a better comprehension of how the influence of such determinants varies during the adoption process (a multi-stage phenomenon) is even more important for the complete understanding of the adoption.

Our idea of treating adoption as a multi-stage decision-making process is well supported by previous research [e.g., 30, 31]. Rogers [32, p.163] suggests that adoption is "a decision process from the initial knowledge of a new technology [innovation], to forming a favourable or unfavourable attitude toward it, to a decision to use, and to finally seeking reinforcement of the adoption decision made". Conversely, Fichman [33, p.3] declared that [technology] adoption is a "series of stages, flowing from the innovation through persuasion, decision, implementation and confirmation". Furthermore, technology adoption can be viewed as a process of spanning from a firm's awareness of technology to its widespread deployment [34]. Some studies refer to the process as pre-adoption, adoption and post-adoption [e.g., 30, 31] while others have perceived it as being initiation, adoption decision and implementation respectively [e.g., 32, 35, 36]. Considering that the firm makes the most important decisions in the pre-adoption stage, we confine our discussion to this initial phase of adoption. During this phase, the firm evaluates and selects the most suitable technology through a sequence of activities [37] in order to arrive at either the acceptance or rejection decision. Past literature studies have discussed the pre-adoption phase with the number of stages ranging from five [e.g., 38, 39] to seven [e.g., 40]. Distillation of aforementioned studies provides us with five common stages, specifically: awareness → interest → evaluation → trial → commitment.

As discussed in Rogers [32], in the awareness stage the SME realizes that they have a need for a technology solution. The state of being aware could also happen by coincidence without the problem or need actually being realized. Being aware will then create interest and that subsequently leads to the next stage: finding and searching for information. At this stage, the firm starts to gather information on the procedures that are important for them to be able to evaluate the technology. As such, at this stage, the firm's decision-makers start to familiarise themselves with the technology, pay attention to the promotional material, and find the most appropriate vendor of the technology. Once the overall consensus is made on the relative advantages and disadvantages of the cloud technology (functional and technical) and vendor through the evaluation process, the firm will then go through a trial prior to committing to adopt the technology. Trial is the stage where the firm has the chance to use the technology on a limited basis in order to determine its utility in a full-scale implementation. Once the firm has achieved the level of satisfaction adequate to commit to the technology (i.e., cloud ERP), the firm and vendor will then pledge for relational continuity. As a result, the pre-adoption (i.e., prior to use) process will end at this point. It is then necessary to attempt to achieve our objectives, specifically: (1) to understand how attitude, subjective norms and perceived behavioural control in combination influence the decision-maker's intention, (2) to see whether the aforementioned three predictor variables behave differently in different phases of the adoption process, and (3) to see the advantages of the combination polynomial regression analysis and response surface methodology in comparison to the traditional methods of linear analysis. We must now examine the evaluation and trial stages of pre-adoption using TPB as our theoretical lens.

HYPOTHESIS DEVELOPMENT

In this section, we aim to elucidate the SME's intention of cloud ERP adoption through the lens of TPB [10]. Here we hypothesise that, in the context of SME's, the intention of cloud ERP adoption is first determined by the decision-maker's (owner, CEO or a senior manager) attitude towards the cloud ERP technology. Thus, the decision-maker's overall positive or negative evaluation becomes one of the most significant predictors of behavioural intention of an SME's adoption of cloud ERP technology. As studies have demonstrated [e.g., 41] , the positive attitudes would then drive the SME's intention towards cloud ERP adoption. Thus, we hypothesise: H1: The decision-maker's optimistic attitude towards the adoption of new cloud ERP positively affects the SME's intention of cloud ERP adoption.

Second, as posited in TPB, subjective norms - opinions expressed by others, perceived social pressure created by the expectations of important referents - would influence the behavioural intention of cloud ERP adoption. In the context of our discussion, such referents could comprise their competitors, large customers, software vendors, legislative bodies, the government or within the SME itself. Thus, we hypothesise: H2: The subjective norms that support cloud ERP adoption positively affect the SME's intention towards cloud ERP adoption.

Further, as described in TPB, behavioural intention is also determined by the extent to which a person believes that he or she has control over the factors (personal or external) that may facilitate or restrain the behavioural performance [42]. Perceived behavioural control also refers to the perception of how easy or difficult performing the behaviour of interest would be [10, 42]. In the context of SMEs, resource availability, size of the firm, and their capabilities could possibly hinder the decision-maker's intention to adopt technology. In the case of cloud ERP, the cloud solution is comparatively less complex, requires lesser resources and hence the decision-maker could believe that the adoption is well within his control. Thus, we hypothesise: H3: The decision-maker's perceived behavioural control over the adoption of cloud ERP positively influences the SME's intention towards cloud ERP adoption.

As we have hypothesised above, the attitude, subjective norms and perceived behavioural control are positively related to behavioural intention. Thus, the three determinants of behavioural intention attitude, subjective norms and perceived behavioural control respectively, should generate a positive synergistic effect on behavioural intention in order for the SME to go ahead with the adoption decision. As such, knowing the right proportions (optimum combination) of the three aforementioned determinants is vital for better understanding of cloud ERP adoption in SMEs. As Pavlou and Fygenson [20] demonstrated, the level of influence each predictor variable could have on intention can be different in different stages of the adoption using perceived behavioural control in an e-commerce adoption context. Further, Karahanna et al. [31], in their study of pre-adoption and post-adoption belief, assert that a potential adopter's intention to adopt a technology is solely determined by normative pressures (i.e.; pre-adoption stage), whereas a user's intention (i.e. post-adoption stage) is solely determined by attitude. Thus, a clear comprehension of the interplay between the three predictor variables and behavioural intention is even more significant for holistic understanding of cloud ERP adoption. This is especially so if the impact of each predictor variable varies between the stages of the adoption process.

In the context of the adoption of cloud ERP by SMEs, decision-makers first form perceptions on the benefits that they aim to attain through the opinion of others (e.g., opinions from experts, consultants, vendors, clients, business partners) during the evaluation stage; thus, subjective norms act as the key determinant of adoption intention. Next, in the trial stage, the decision-maker will be given an opportunity to use (trial) a cloud ERP package for a limited basis. Unlike stages that lead to trial, in this stage the decision-makers receive a hands-on opportunity to use the systems and gain a better sense of the technology. Hence, in this stage, the perceptions and beliefs developed by experiencing the software hands-on (i.e. attitude) can operate as the key determinant of adoption intention. Thus, we hypothesise: H4: The subjective norms of the decision-maker related to the adoption of cloud ERP are more significant than attitude and perceived behavioural control in the evaluation stage of the adoption; and H5: The decision-maker's attitude towards adoption of cloud ERP is more significant than subjective norms and perceived behavioural control in the trial stage of the adoption.

METHODOLOGY

Instruments development and data collection

To test our hypothesised relationship above, we first referred to the existing constructs and measures available in the extant literature. They were then adapted to the context of this study using standard psychometric instrument development procedures specified in Boudreau et al. [43]. Three different sources have been used for the distillation of measurement instruments. For the individual items, a study by Harrison et al. [21] has been used. We then referred to studies from Ettlie [38] as well as Fichman and Kemerer [44] to adapt our instruments for different stages. In this question, respondents were asked to tick at which stage their firm was currently positioned in relation to cloud ERP adoption (each stage have an appropriate definition).

The answers provided through this question enabled the total sample to be divided into different stages (i.e., evaluation and trial). For new measures and those that required significant changes, we followed the standard scale development procedures stipulated in Mackenzie et al. [45]. We then conducted a pre-test and pilot study to assess the reliability and validity of our measures. Subsequent follow-up discussions with a subset of pilot respondents then created sufficient confidence in the scales to be able to proceed with the full-scale survey administration. Our final instrument comprising six components, namely: intention, attitude, subjective norms, normative belief, control belief and perceived behavioural controls were then used for the full-scale survey administration. We administered an anonymous survey off-line from a sample consisting of decision-makers of SMEs in Southeast Asia (Malaysia). From 210 surveys distributed, our exercise yielded a total of 162 respondents (with over 80% response rates). We received a very high response rate as the questionnaires were distributed and collected during an event where one of our research members was the speaker. The respondents were from different industry backgrounds including: automotive-2%, construction-10%, design consultancy-16%, electrical-36%, financial services-21%, manufacturing-12% and others-4%.

Reliability tests

Following Barclay *et al*. [46] we examined individual measurement item reliability, discriminant and convergent validity using the partial least square (PLS) technique of structural equation modelling in Smart PLS 2.0 [47]. Our examination of individual item reliability confirmed sufficient reliability as all of the measurement items were loaded within the ideal tolerance threshold of 0.70 [46, 48]. Moreover, the test of convergent validity by average variance extracted (AVE) measures affirms the reliability with the values being greater than the recommended threshold level of 0.5 [49]. Results of our test of composite reliability for each reflective construct to examine the internal consistency all met the suggested tolerances of above 0.70 [49]. All latent constructs were given as the square root of each construct's AVE was greater than the latent-variable correlation between each construct and its comparing construct thereby lending support to the discriminant validity [50]. (Table-2).

Table-2. Test for discriminant validity.

Latent Construct	1	2	3	4	5	6
1. Attitude	**0.815**					
2. Control Belief	0.2713	**0**				
3. Intention	0.4479	0.2792	**0.827**			
4. Normative Belief	0.1611	0.2358	0.2895	**0**		
5. Perceived Beh. Control	0.0889	0.1371	-0.0933	-0.075	**0.841**	
6. Subjective Norm	0.2666	0.3022	0.3994	0.3891	0.1239	**0**

Note: The diagonal (bold and coloured) shows the construct's square root of AVE

Testing hypothesis

In order to test the first three hypothesized relationships, we analysed: (1) the subset of respondents who represent the evaluation stage of adoption (47 respondents), and (2) the subset of respondents who represent the trial stage of adoption (115 respondents). We used the PLS technique of SmartPLS software to examine the standardized path coefficients, path significances and variance explained (R^2) to test the predictive power of the structural model and the relationships between the constructs using three different samples as mentioned above (Figure-1).

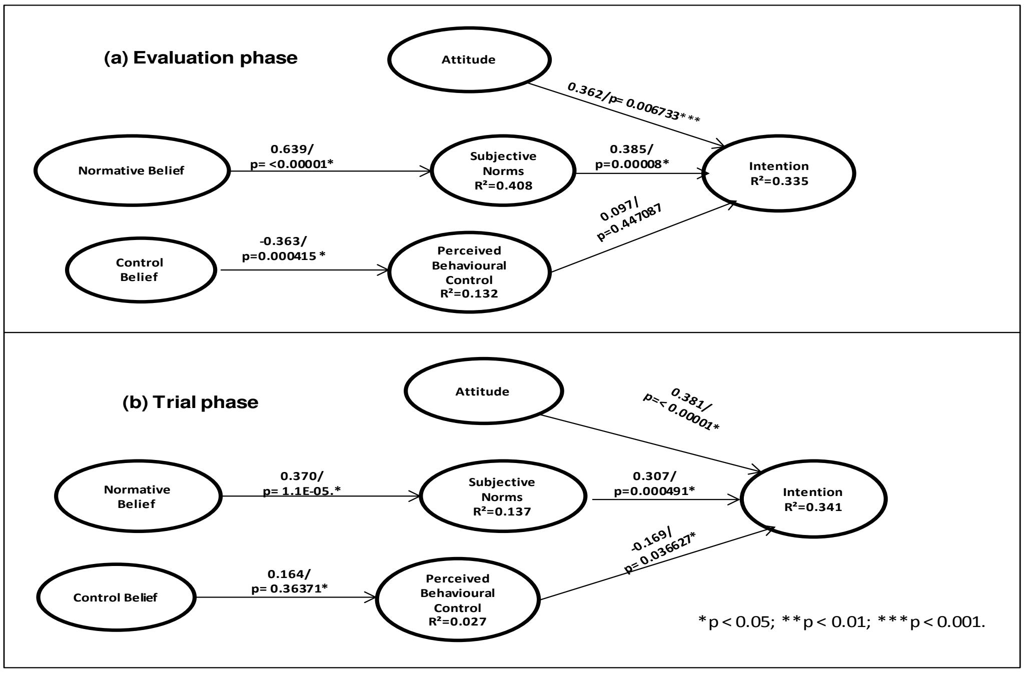

Figure-1. The assessment of structural model using PLS method for (a) evaluation and (b) trial stages.

Testing hypothesis 1:

To test our first hypothesised relationship, we refer back to the structural model illustrated in Figures 1a and 1b. These structural models support our hypothesised relationship where models concerning evaluation and trial (Figures 1a and 1b) also confirm significant positive relationships between attitude-intention (evaluation → β=0.369, p<0.001, trial → β=0.381, p<0.001) thereby lending support to our first hypothesis.

Testing hypothesis 2:

To test our second hypothesised relationship, we refer to the structural models presented in Figures 1a and 1b. Structural models in both models showed a significant positive relationship between subjective norms and intention (i.e., evaluation stage →β=0.397, p<0.001, and trial stage → β=0.307, p<0.001) thereby lending support to our second hypothesised relationship.

Testing hypothesis 3:

To test our third hypothesised relationship, we refer to the path coefficients and the significance of the relationship between perceived behavioural control and intention, as shown in models 1a and 1b. Although we predicted a positive relationship between perceived behavioural control and intention, the results show a negative relationship for the complete data set and trial stage. Similarly, a positive relationship in the evaluation stage (i.e., evaluation stage → β=0.087, p<0.001, and trial stage → β= - 0.169, p<0.001) challenges the relationship that we have hypothesised.

Testing hypothesis 4 and 5:

To test our fourth and fifth hypothesised relationships, we first refer back to the two structural models in Figure 1. As seen in Figure 1a, the evaluation stage (the path coefficient between subjective norm and behavioural intention) shows a much stronger and significant relationship compared to the other two predictor variables' attitude and perceived behavioural control (attitude-intention, β=0.369, p<0.001, subjective norms-intention β=0.397, p<0.001, and perceived control-intention β=0.087, p<0.001) with three predictor variables, namely, attitude, subjective norms and perceived behavioural control explaining 34.3% of the variance in behavioural intention (R^2). As shown in Figure 1a, the path coefficient between subjective norms and intention shows a much more powerful and significant relationship compared to the other two predictor determinants (i.e., attitude and perceived behavioural control) (attitude-intention, β=0.369, p<0.001, subjective norms-intention β=0.397, p<0.001, and perceived control-intention β=0.087, p<0.001). This comprises three predictor determinants' attitudes, subjective norms and perceived behavioural control explaining 34.3% of the variance in behavioural intention (R^2). Next, we refer to Figure 1b for our fifth hypothesized relationship. As seen therein, the attitude displays a much stronger relationship to intention than subjective norms and perceived behavioural control in the trial stage (attitude-intention, β=0.381, p<0.001, subjective norm-intention β=0.307, p<0.001, perceived control-intention β=-0.169, p<0.001), with the three predictor determinants' attitudes, subjective norms and perceived behavioural control explaining 34.1% of the variance in behavioural intention (R^2).

Even though our analysis using the PLS method of structural equation modelling provides support to our fourth and fifth hypothesised relationships, it does not explain the degree of dominance that subjective norms and attitude have in two respective stages of adoption. As such, we use polynomial regression together with response surface methodology to demonstrate how the combination provides nuanced views of the tripartite relationship between attitude, subjective norms and intention and supports our hypothesised relationship. We decided to restrict our discussion to comparing the relationship between attitude, subjective norms and intention using only two stages of adoption. This was done for two reasons: the first being for the simple reason of simplicity. Even though we can have many combinations of tripartite relationships between two predictor variables and intention based on TPB, we deemed that it is not necessary to present all of these in order to send the message – polynomial regression and response surface methodology together can produce richer and deeper insights into the relationships. Second, we chose attitude, subjective norms and intention for the comparison between evaluation and trial because the path model results suggest that attitude and subjective norms are the two variables that show the most significant relationships with intention. Thus, we next used the following polynomial equations to discuss the tri-partite relationship between attitude-subjective norms-intention in the evaluation and trial stages. We then followed the procedure outlined by Atwater et al. [51] to perform the polynomial regression analysis to obtain the coefficients. Although the resultant of higher order of polynomial is often difficult to interpret [26], the response surface methodology [6] nevertheless provides the basis required for testing and interpreting the features of surfaces corresponding to polynomial quadratic regression equations. In this procedure, the response surface is considered a visual aid so as to acquire a richer and more meaningful understanding of complex polynomial equations. The combination provides the sophisticated statistical degree required to examine the extent to which the combination of two predictor variables relates to an outcome variable, in particular when the discrepancy (or match) between the two predictor variables is a fundamental consideration [2]. We repeated the polynomial regression procedure using two data sets (i.e., evaluation and trial stage) to further investigate our fourth and fifth hypothesised relationships. Figures 2a and 2b provide the two response surfaces for attitude, subjective norms and intention in the evaluation and trial stages.

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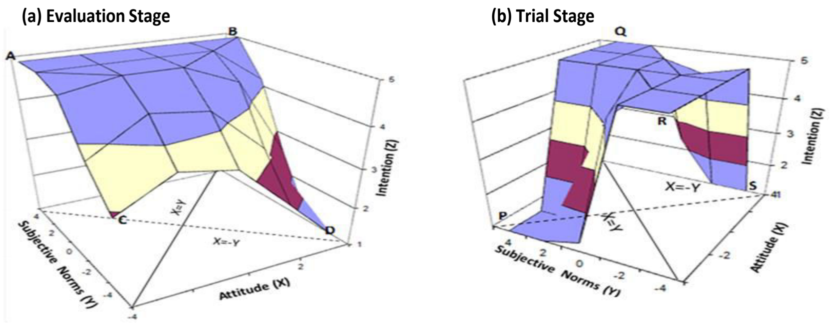

Figure-2. Response surfaces between attitude, subjective norms an intention for evaluation and trial stages.

Following this, to test our fourth hypothesis, we refer to Figure-2a. As the response surface depicts, when the subjective norm is at its lowest point, attitude influences the intention (surface along the X axis, C through D along the surface). However, when subjective norms are at the maximum point, the influence of attitude on intention does not become evident as intention does not change with the increased levels of attitude (surface along the X axis when subjective norm is at its maximum = +4, A through B along the surface). This explains the concept that, when subjective norms are present, they tend to dominate the influence of attitude on the intention to adopt, thus lending a better explanation of our fourth hypothesised relationship. In relation to our fifth hypothesis, we refer to Figure 2b. As the response surface depicts in the evaluation stage, when subjective norms are at their lowest point, attitude influences the intention of adoption (surface along the X axis, R through S along the surface). In contrast to diagram 2a in Figure-2b, when the level of significant of attitude increases, the behavioural intention also increases despite the subjective norm being at its maximum point (surface along the X axis when the subjective norm is at its maximum = +4, P through Q along the surface). This explains that, in the trial stage, even with the existence of subjective norms, attitude presents a dominating influence on the intention to adopt, thus lending a better explanation to our fifth hypothesised relationship.

DISCUSSION AND CONCLUSIONS

This paper was motivated by the assertion that attitude, subjective norms and perceived behavioural control respectively exhibit a relationship that explains the influence of each of the variables on behavioural intention. There is also the concept that it neither stays constant nor does the same variable stay dominant in the technology adoption process. Thus, this study investigated the influence of three determinants of TPB on cloud ERP adoption by SMEs, and the varying degree of influence that each predictor variable exercises on intention in the evaluation and trial stages. Further, motivated by the original underlying non-linearity assumptions of TPB in this study, we used the polynomial regression technique together with response surface methodology to better explore the varying degrees of influence that two key determinants - attitude and subjective norms - impose on adoption of cloud ERP by SMEs, specifically in the evaluation and trial stages.

Our discussion highlights the need to re-visit the concept of technology adoption with unconstrained open-minded approaches such as relaxed linearity assumptions and alternative viewpoints. This includes, notably, treating the adoption process as resembling a multi-stage phenomenon. First, we investigated how three predictors in combination relate to the outcome variable (i.e., behavioural intention of SMEs towards cloud ERP adoption). As hypothesised, attitude and subjective norms both displayed a significant positive relationship between behavioural intentions towards the adoption of cloud ERP by SMEs. Despite a positive relationship having been predicted between perceived behavioural control and the adoption intention of cloud ERP in SME's, our findings predict a negative relationship. A possible reason for this discrepancy could be the enormous pressure that the government and other regulatory bodies exert on SMEs to have an ERP (i.e. compliance). As such, even though the decision-maker believes that the firm has less control over the adoption of cloud ERP; their intention to adopt is nevertheless high due to the overriding influence of subjective norms.

Next, following our second objective, we analysed our data for any variance regarding the impact of adoption determinants on behavioural intention to adopt cloud ERP during the evaluation and trial stages. The two key determinants of behavioural intention that we have used in this analysis - specifically, attitude and subjective norms, demonstrated that their relative influence on behavioural intention of cloud ERP adoption does vary across both stages. Our employment of the PLS method of structural equation modelling (SEM) and the use of polynomial regression, together with response surface methodology, both explained this variance but with contrasting richness. Our non-linearity assumptions and the use of polynomial regression and response surface methodology in fact explained the dominant roles that subjective norms play in the evaluation stage and attitude in the trial stage respectively. It affirms our basic premise that polynomial regression, together with response surface methodology, could provide a better analytical nuance. It also has the potential to provide finer detailed knowledge concerning the relationships between constructs, especially when the underlying theories suggest non-linearity. As Titah and Barki [8] state, theoretically, non-linearities promote new propositions between the conditional relationship displays within key constructs in a theory or a study model. Thus, the use of analytical approaches that support non-linear assumptions can provide alternative explanations that are unique to different contexts without understating or overstating the main effects. As such, our study views the omission of non-linear postulations in model testing and the employment of only linear assumption to be possibly hindering the full potential of the underlying theory. It could therefore be considered as a possible limitation. As such, we believe that this study will encourage researchers to relax traditional linearity assumptions and to carefully consider the use of non-linear postulations to uncover potential non-linear relationships that might present between the key constructs in their research models. Further, we hope that this paper will stimulate the interest of the IS research community towards pursuing research questions that resemble non-linearities using techniques similar to polynomial regression together with response surface analysis to push the limits of our current theoretical knowledge.

We acknowledge that this discussion has several limitations. First, our focus on evaluation and trial stages limited a fuller understanding of complex technology adoption issues as we omitted a series of other stages of the adoption process such as awareness, interest and commitment. Second, the use of attitude and subjective norms in the evaluation and trial stages as the only example to demonstrate the application of polynomial regression and response surface methodology also limited our ability to fully demonstrate the full explanatory potential of the technique and the non-linear postulations. Third, in reference to TPB, all the constructs in the proposed model reflect the assessment of cloud ERP adoption. Consequently, this prevents the generalisation of the findings to other types of complex technology adoption. Therefore, additional research that could capture a general construct pertaining to other types of corporate-wide systems could be undertaken in the future. Fourth, the use of TPB (individual adoption theory) for organisation technology adoption only applied for organisations where the important decision is made by an individual and his/her decision represents the voice of the entire firm. However, for organisations with multiple decision-makers, the result from the finding cannot be generalized.

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