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INTELLECTUAL CAPITAL, ORGANIZATIONAL LEARNING CAPABILITY, AND ERP IMPLEMENTATION FOR STRA-TEGIC BENEFIT

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Research paper

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Abstract

Despite extensive research, the degree to which organizations are successful in creating strategic advantage with ERP systems, and the factors that distinguish successful and unsuccessful ERP implementations are still equivocal. Using a lens of the Resource-Based View of the firm, and following studies that suggest that IT become valuable over time when they interact with other organizational resources and capabilities, we hypothesize that the creation of the intellectual capital (IC) that can lead to strategic advantage is related to the scope of ERP implementation. We examine how ERP implementation can be used to create IC, moderated by the presence of organizational learning capability (OLC). We find clear relationships between OLC and IC, and between ERP implementation scope and IC, and ambiguous moderating effects from OLC.

Keywords: ERP Implementation scope, Organizational Learning Capability, Intellectual Capital, Resource-Based View.

1 Introduction

Organizations implement enterprise resource planning (ERP) systems to gain benefits, such as more efficient business processes, inventory reduction, improved decision-making, improvements to customer services, and business growth (Panorama 2015; Shang et al. 2002). Many organizations hope to achieve strategic advantage as a result. Nevertheless, achievement of the benefits from an ERP investment is equivocal. Research has found that on average, 53% of organizations achieved less than 50% of the benefits they expected (Panorama 2015). Understanding and measuring the benefits of ERP (or other ICT investment) can be measured from a number of different perspectives: operational, managerial, strategic, IT infrastructure, and organizational benefits (Shang et al. 2002). We concentrate on strategic benefits and competitive advantage, using the lens of the resource-based view of the firm (RBV). RBV tells us that organizations have sustainable competitive advantage when they own resources that are valuable, rare, inimitable, and cannot be substituted (Barney 1991). Since ERP systems are commercial IT products that can be bought and implemented if firms have sufficient financial resource (Carr 2005), they are not rare or inimitable, so ERP implementation alone is unlikely to create benefits that result in strategic advantage. However studies of other IT resources have found that *when they interact with other organizational resources and capabilities* (Melville et al. 2004), IT resources become strategically valuable over time (Piccoli et al. 2005). In this study, learning is treated as an organizational capability and intellectual capital (IC) is an outcome of ERP implementation that can lead to strategic advantage. Following this logic, we examine how the interaction between ERP implementation and organizational learning capability (OLC) can increase the ability of an ERP to create unique IC that can lead to competitive advantage. We suggest that ERPs can create significant IC as a strategic resource, but this is not a guaranteed result. Organizations with higher levels of OLC at the outset (or that are able to quickly acquire OLC as their ERP implementation is in progress) are both more likely to succeed with their implementation *and* more likely to be able to leverage their ERP implementation into the creation of strategic IC. Thus, we argue that organizations hoping to gain strategic benefit from ERP implementation should lift their collective capabilities in organizational learning.

2 Literature Review and Model Development

2.1 ERP Implementation

ERP systems typically contain many modules that span a large number of business processes. Varying numbers of modules may be implemented, and varying numbers of business processes may be changed as a result. Similarly, ERP implementation may occur in a number of geographic sites or divisions of an organization. These differences are captured in the concept of the *scope* of ERP implementation (Barki et al. 2005; Karimi et al. 2007), which reflects the extent to which the ERP system is diffused within an organization and its business processes (Barki et al. 2005). The scope of ERP implementation is decomposed into: implementation depth (the extent to which ERP implementation and business process reengineering (BPR) is diffused vertically in an organization; implementation magnitude (the extent to which BPR changes the work of people involved in ERP implementation and business processes become more automated); and implementation breadth (the extent to which implementation of the system, including hardware, and software, is diffused horizontally in an organization. (Barki et al. 2005). Typically, ERP implementation takes some time to deliver the anticipated benefits. We therefore concentrate on organizations that have a mature ERP implementation, to minimize the possibility that expected benefits have not yet accrued.

2.2 Organizational Learning Capability

Organizational learning capability controls the extent to which the organization accumulates knowledge (McElyea 2002; Vera et al. 2003). Learning capability comprises the *pre-conditions* for effective organizational learning, such as managerial commitment, systems perspective, openness and experimentation, and knowledge transfer and integration (Jerez-Gómez et al. 2005). Managerial commitment refers to the role of the management team in creating a culture of learning. Managers should hold a view that learning is of fundamental value. They should participate and encourage employees to participate in learning. A systems perspective denotes the ability to think broadly about the interdependency of organizational factors (Nevis et al. 1995). It is associated with creating a shared vision and mental models in an organization. Openness and experimentation are necessary for the organization to welcome new ideas (Senge 2006), and are also associated with the notion of "unlearning" which is vital for organizational change (Sinkula et al. 1997). Finally, knowledge transfer and integration ability represent the extent to which the organization is able to spread and integrate knowledge among its members (Jerez-Gómez et al. 2005). If a firm has these capabilities, or can develop them, the learning required (for example, to generate strategic benefits from ERP implementation) is more likely to occur easily and effectively (DiBella et al. 1998).

2.3 Intellectual Capital

Intellectual Capital (IC) is often defined as the sum of human capital (the knowledge and capabilities of its people), organizational capital (the institutionalized knowledge residing in databases, structures and processes), and social or relational capital (the knowledge and value of its relationships) (Youndt et al. 2004). IC has been widely highlighted as an organizational resource and it is said to be essential for the attainment of high organizational performance (Bontis 1999; Youndt et al. 2004). Scholars have agreed that the strategic resources of a contemporary organization often derive from the collective knowledge resources available to the organization (Winter 1998). The IC of each organization is inherently unique, because it represents the knowledge of the organization, and it is something absolutely peculiar to each and every company (Bontis et al. 1999).

2.4 Organizational Learning Capability as a Moderator of the Benefits of IT Investment

In the context of ERP implementation, it has been argued that organizational learning is essential for the success and the effectiveness of the system (Robey et al. 2000). While the relationship between ERP and IC has not been studied explicitly (some previous studies have been conducted which evaluate the relationship between ERP and strategic advantage, without separating out IC in particular), previous literature has shown that IT investment in general can be associated with intangible capital in general and IC in particular. Brynjolfsson et al. (2002) remarked that investment in computerization is associated with other intangible assets and collectively create a firm's market value. Youndt et al. (2004) found that organizations with higher levels of investment in IT display higher overall levels of IC. Accordingly the interplay between ERP and OLC seems to offer potential insights on the development of IC. The research questions are: (1) To what extent is the scope of ERP implementation associated with greater intellectual capital? (2) What is the interaction effect of OLC on the relationship between the scope of ERP implementation and the enhancement of intellectual capital?

2.5 Research Model and Hypothesis Development

The conceptual model is shown in Figure 1. Using the idea that IT resources can produce strategic advantage for firms when they are supported by organizational capabilities or when they interact effectively with other organizational resources, we propose a research model that links the scope of ERP implementation with the creation of IC, moderated by OLC. We posit that the scope of ERP implementation, which includes breadth, depth, and magnitude (Barki et al. 2005), has a positive effect on IC. A broader scope, involving more modules, business processes, and business units will create more opportunities for the firm to create IC. Accordingly, it is hypothesized that:

H1a: the breadth of ERP implementation scope has a positive effect on IC

H1b: the depth of ERP implementation scope has a positive effect on IC

H1c: the magnitude of ERP implementation scope has a positive effect on IC

In addition, the organization must have the ability to learn in order maximize the IC created. Therefore the presence of OLC (the conditions that facilitate organizational learning) will moderate the relationship between ERP scope and IC. It is hypothesized that:

H2a: The relationship between the breadth of ERP implementation and IC is moderated by OLC

H2b: The relationship between the depth of ERP implementation and IC is moderated by OLC

H2c: The relationship between the magnitude of ERP implementation and IC is moderated by OLC

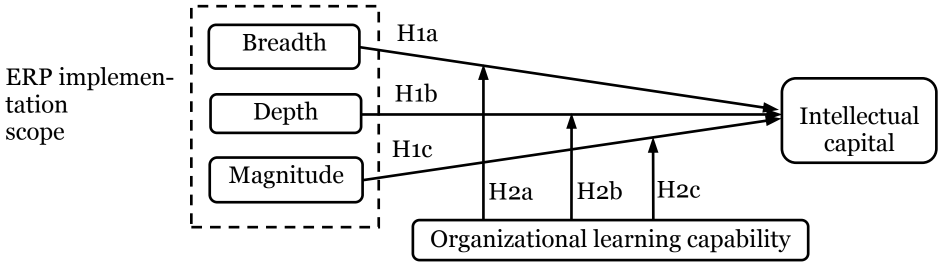

Figure 1. The Conceptual Model

3 Methodology

3.1 Measurement

The model was operationalized using existing measures, but with modifications informed by recent understandings of construct operationalization (MacKenzie et al. 2011). We adapted the scale developed by Youndt et al. (2004) reflects the "state of being" of IC (Isaac et al. 2010). IC is operationalized as reflective first-and formative second-order constructs. IC has three facets: human capital (HC), organizational capital (OC), and social capital (SC). Depending on the research purpose, prior studies have examined these dimensions either separately (e.g. Bontis et al. 2000; Cabrita et al. 2008) or in a combined form (e.g. Hsu et al. 2012). This study examines IC in a combined form. IC has previously been modelled as reflective first-and reflective second-order construct (Hsu et al. 2012), but because; the three sub-dimensions of IC describe unique aspects of the construct; they are not interchangeable; and if one dimension is dropped the conceptual domain of IC may be altered (Jarvis et al. 2003) we modelled the higher-level concept of IC as formative. For the measure of OLC, this study applied the measures established in the study of Jerez-Gómez et al. (2005). The operationalized OLC as a focal construct with four dimensions: managerial commitment (MC); systems perspective (SP); openness and experimentation (OP); and knowledge transfer and integration (KW). OLC in this study is also modelled as reflective-formative construct. Prior studies have specified these four dimensions as either reflective (e.g. Jerez-Gómez et al. 2005; Liao et al. 2009) or formative (López-Cabrales et al. 2011) to the focal construct. Once again, we point out that these sub-dimensions of OLC are not interchangeable, and each of properties features a different aspect of the totality of all facilitators for organizational learning. Therefore, in the same manner of López-Cabrales et al. (2011), the study views these four properties as formative measures of the focal construct OLC. The measures developed by Barki et al. (2005), including breadth (BRE), depth (DEP), and magnitude (MAG) were used to gauge the scope of ERP implementation. The questionnaire also included information about the time frame that the firm has been using their ERP system; general information about the ERP package; respondent's job title, respondent's time in the job, a self-evaluation on ERP implementation knowledge of the respondent; ERP package name, ERP modules used; operating industry, and number of employees of the firm.

3.2 The Survey

The study was carried out in Vietnam and the measures translated into the Vietnamese language. We note that the business practices of large Vietnamese manufacturing firms with regard to the use of ERP systems are not markedly different to those of large manufacturing organizations in other national and cultural contexts. To provide the sample, a list of companies was compiled from two sources: business customers of ERP providers, and companies identified from the Vietnam business directory. The search was confined to Ho Chi Minh City and surrounds, and Da Nang province, which is where much of the economic activity in Vietnam is concentrated. From this list 2000 companies were randomly chosen. The companies were contacted by phone to check if they had used ERP package for at least one year. Finally, 627 companies remained. A mail questionnaire was used to collect the responses (Neuman 2011). This was followed up by telephone calls. Eventually, 242 responses were received giving a response rate of 38.6%. After performing necessary data checking, 226 usable questionnaires were retained for data analysis. Consideration was given to the choice of multiple informant or key informant approaches (Wagner et al. 2010). We selected the key informant approach as most suitable for our study, as providing more accurate and privileged access to insights about the constructs in our study. The questionnaire in this study was designed with two parts: (A) the scope of ERP implementation, (B) information about IC and OLC. It required selection of appropriate, expert, informed responses; therefore, key informants were used to collect data: an IT manager (for part A) and another executive manager (for part B).

3.3 Data Analysis Techniques

We used partial least squares (PLS) to evaluate the model, due to the presence of formative measures, the complexity of the research model, and the conditions of non-normal distribution for some items (Chin et al. 1999). A SEM analysis is performed through two major steps: analysis of the measurement model, and analysis of the structural model. The research model has two second-order constructs with formative dimensions and three moderating relationships. A redundancy analysis technique was used to assess the convergent validity of two formative constructs (Hair et al. 2014). To evaluate the structural model and moderating effects, the repeated indicator approach and latent variables scores (Hair et al. 2014), and the approaches for moderation analysis suggested by Henseler et al., (2010) were used.

4 Data Analysis Results

4.1 Descriptive Statistics

A very wide range of industries was represented, including agriculture, chemicals, construction, food, textiles, plastic and paper. All of the respondents had been using their ERP system for more than one year; most had used their system for between 2 and 3.5 years; and more than 94% claimed to have "finished" their ERP implementation. The typical surveyed organization was a limited liability or joint-stock company, more than 50% of which had 300 or more employees, and 93% had more than 100 staff. All the key respondents for part A were senior IT staff, at team-leader level or above, and two-thirds had been in their current organization for between three and 10 years. All had a good or expert knowledge of ERP systems based on a self-evaluation. The second source of information for the study (part B) is from people at managerial level identified as knowledgeable about OLC and IC of their firms. These respondents came from a wide variety of functional areas including finance, engineering, human resources, sales and marketing. Approximately two-thirds of respondents had been in the organization for between three and ten years and all rated their knowledge of the organizational factors they were evaluating as good-to-excellent. We are very satisfied that our sample is highly representative of our target population, and includes respondents and organizations with the desired characteristics.

4.2 Evaluating the Data

Fifteen cases with missing values in the descriptive part of the questionnaire were kept because they had no effect on the regression results. The variables involved in regression analysis also had incomplete items that accounted for less than 10% on any single variable. According to Hair et al. (2010) if the proportion of missing responses was low, any of the imputation methods can be applied. This study used the mean substitution method.

Selection and non-response are potential risks for this study, as it may be influenced by the absence of potential respondents who are not willing to answer the questionnaire (Bryman 2003). In order to check the presence of non-response bias, a “time trend extrapolation test” (Armstrong et al. 1977) was performed. The sample of this study was divided into three sub-groups according to early and late responding time. The late responding companies were assumed to be similar to non-response companies. The three sub-groups were compared in pair using an independent sample t-test at 5% significant level. The results show that there are no significant differences on any of the measurement items of the scope of ERP implementation, IC, and OLC (p-values were ranged from 0.058 to 0.992), strongly suggesting that non-response bias is not a risk.

Common method bias refers to a bias in the dataset that is attributed to the measurement method rather than to the constructs the measurement items represent (Podsakoff et al. 2003). Because all measurement items were presented in the same questionnaire, correlations among these variables may be relatively high. We followed Zhuang et al. (2003) in using Harman’s single-factor test to check for common method bias. The assumption of this technique is that if a considerable value of common method variance exists, either (a) a single factor will appear from the factor analysis or (b) one general factor will represent the majority of the covariance among the measures. This study used two sources for data collection (i.e. an IT manager and another manager). The different sources can help to mitigate common method bias (Podsakoff et al. 2003), however the problem of common method bias could happen for each part of the questionnaire. To examine the possibility of this problem, this study used three exploratory factor analysis (EFA) tests: the first test only used the items measuring ERP implementation scope (i.e. part A of the questionnaire), the second test only used the items measuring IC and OLC (i.e. part B of the questionnaire), and the third used all items of ERP implementation scope, IC, and OLC. All three EFA tests show that there are at least three “unrotated” factors, of which no single factor is found to explain more than 50 percent of the variance. Therefore, the tests suggested that no significant common method variance is present in the dataset.

Overall, we were satisfied that we had a high quality data-set; that we had made all reasonable attempts to minimize bias in the design and execution of the survey; and that tests we conducted for bias on the final dataset indicated that no significant bias was present.

4.3 Assessment of Measurement Models

4.3.1 Reflective Variables

Cronbach’s Alpha was used as a reliability coefficient indicating how well the items are positively correlated to one another. The generally agreed upon lower limit for this coefficient is 0.7 (Hair et al. 2014). Composite reliability can be used as a better alternative of Cronbach’s Alpha, while Cronbach’s Alpha assumes that all indicators are equally reliable, composite reliability takes into account that indicators have different loadings (Chin 1998). The composite reliability of the study data was evaluated using confirmative factor analysis. Composite reliability with a value above 0.7 for exploratory research and values above 0.8 or 0.9 in more advanced stages of research are considered as satisfactory (Nunnally et al. 1994). For this study, except for two items, all items had loadings on their constructs greater than 0.7 and greater than their loadings on any other constructs. After these two items were excluded the composite reliability for all items was above 0.88.

In addition to the internal consistency reliability of latent variables, the reliability of each indicator should be examined. Indicator reliability refers to the extent to which an indicator or set of indicators is consistent regarding what it intends to measure. Indicator reliability is assessed using indicator loadings. Indicator loadings should be significant at least at the 0.05 level and greater than 0.7 (Chin 1998). An indicator is considered for removal only if its reliability is low and its elimination will lead to a substantial increase in composite reliability (Henseler et al. 2009). In this study, all indicator loadings were above 0.7 and the majority were above 0.8.

Convergent validity assesses the degree to which a set of indicators represent one and the same underlying concept. High correlations among indicators suggest that the scale is measuring its intended concept (Hair et al. 2010). Fornell et al. (1981) suggest using the average variance extracted (AVE) as a criterion of convergent validity. An AVE value of at least 0.5 indicates that a latent variable is able to explain more than half of the variance observed, thus it satisfies convergent validity. All constructs of the study had an AVE above 0.6 (see Table 1).

Discriminant validity represents the degree to which a construct is distinct from other constructs (Hair et al. 2010). Measures of discriminant validity include the Fornell-Larcker criterion and the cross-loadings. The Fornell-Larcker criterion (Fornell et al. 1981) requires a latent variable to share more variance with its assigned indicators that with any other latent variable, meaning the AVE of each latent variable should be greater than the latent variable's highest squared correlation with any other latent variable. For the second measure using the cross-loadings, it is required that the loading of each indicator on its designated latent variable is expected to be greater than all of its cross loadings (Chin 1998). In this study, the square root of EVA of each construct was greater than its highest correlation with any other construct, thus the Fornell-Larcker criterion was satisfied (Table 1). Each indicator had a higher loading on its designated latent variable than any of its cross loadings, also demonstrating discriminant validity.

	AVE	CR	BRE	DEP	MAG	HC	OC	SC	MC	SP	OP	KW
BRE	0.795	0.886	0.891									
DEP	0.820	0.901	0.246	*0.906*								
MAG	0.757	0.904	0.126	0.364	*0.870*							
HC	0.653	0.882	0.279	0.325	0.348	*0.808*						
OC	0.671	0.890	0.478	0.437	0.307	0.466	*0.819*					
SC	0.678	0.894	0.380	0.404	0.278	0.506	0.558	*0.823*				
MC	0.671	0.911	0.480	0.392	0.333	0.448	0.514	0.376	*0.819*			
SP	0.715	0.882	0.419	0.321	0.228	0.363	0.508	0.435	0.545	*0.845*		
OP	0.714	0.909	0.434	0.367	0.331	0.394	0.519	0.334	0.558	0.446	*0.845*	
KW	0.712	0.908	0.385	0.400	0.256	0.548	0.535	0.386	0.571	0.489	0.496	*0.844*

Note: Diagonal values are square root of construct's AVE.

Table 1. Average Variance Extracted, Correlation, and Composite reliability of Constructs

4.3.2. Formative Variables

To assess the convergent validity of a second-order construct, one global item measuring the essence of the construct was included in the questionnaire (Hair et al. 2014). Since the second-order formative constructs are expressed as a function of their dimensions (the first-order reflective constructs), the dimensions should not necessarily be highly correlated. Hair et al. (2014) propose a procedure to evaluate second order formative measurement models, using a repeated indicator approach and latent variable scores (Hair et al. 2014).

In this procedure, a redundancy analysis model is established (see Figure 2). In the model, all indicators of the first-order constructs (or components) are assigned to the corresponding second-order construct and a link between the second-order construct and a criterion item is established. The criterion item or global item is added to test whether the formatively measured construct is highly correlated with a reflective measure of the same construct. If the structural path coefficient is above 0.8, the formative construct's convergent validity is supported (Chin 1998; Hair et al. 2014).

This procedure was applied to the OLC and IC constructs. The PLS algorithm was implemented to obtain the structural path coefficient. The analysis showed the path coefficients of 0.874 and 0.824 for OLC and IC construct respectively. These values are above the threshold of 0.8, thus providing support for the formative construct's convergent validity.

The second criterion for the assessment of a formative measurement model is multicollinearity. Formative dimensions of the focal construct should be relatively independent of one another (Chin 1998) because a high collinearity among formative dimensions makes it difficult to ascertain the unique contribution from each dimension (Diamantopoulos et al. 2001). The multicollinearity of the formative dimensions are assessed using variance inflation factor (VIF): the value of VIF should be lower than 5 to reach the conclusion that there is no potential collinearity problem (Hair et al. 2011).

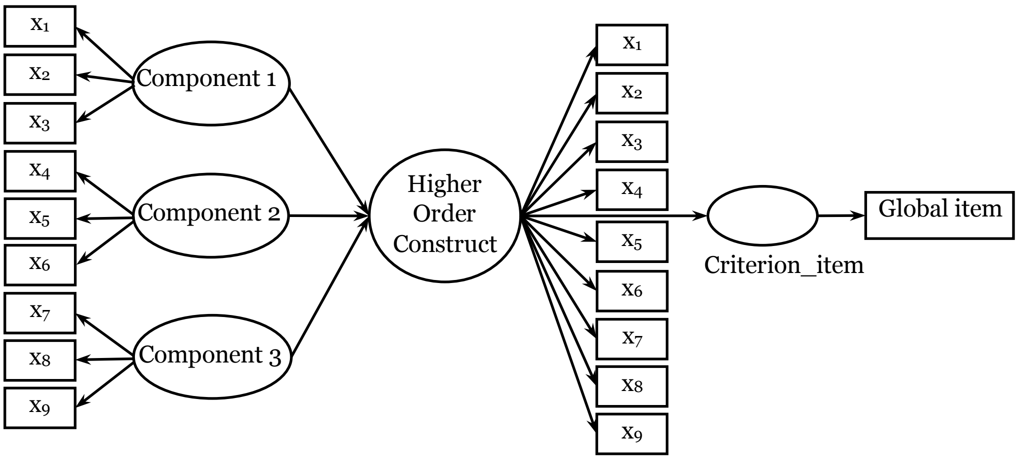

Figure 2. Redundancy Analysis Model

The last rule for the evaluation of a formative measurement model is the significance of the paths linking the formative dimensions and the focal construct. The significance of path coefficients were assessed using the bootstrapping technique, the minimum number of bootstrap samples was 5,000 and the number of cases for bootstrapping was equal to the number of observations in the original sample, i.e. 226. (Hair et al. 2011). To calculate the value of VIF and the coefficients of first-order factors, a repeated indicators approach was used (Hair et al. 2014; Lohmöller 1989). In the model, two second-order constructs OLC and IC were measured by the indicators of their first-order constructs, and then the PLS algorithm was implemented to obtain the regression coefficients and latent variables scores of formative dimensions of the second-order constructs. The latent variables scores were used to calculate the value of VIF. As shown in Table 2, the VIF values for the first-order constructs of each second-order construct vary from 1.439 to 1.915. All values are not higher than 5, therefore there is no multicollinearity among the first-order constructs of OLC and IC. All path coefficients of first-order dimensions were found to be significant. The results support the formation of second-order constructs OLC and IC by their first-order constructs.

Second-order construct	First-order construct	VIF	Coefficient
IC	Human capital (HC)	1.439	0.381**
	Organizational capital (OC)	1.554	0.410**
	Social capital (SC)	1.636	0.426**
OLC	Managerial commitment (MC)	1.915	0.392**
	Systems perspective (SP)	1.557	0.221**
	Openness and experimentation (OP)	1.594	0.303**
	Knowledge transfer and integration (KW)	1.669	0.326**

*Note: ** Significant at 0.01*

Table 2. Path Coefficients and Multicollinearity of Formative Dimensions

4.4 Assessment of the Structural Model

The structural model of the study has three independent variables (breadth, depth, and magnitude of ERP implementation scope), one dependent variable (IC), and one moderating variable (OLC). According to Henseler et al. (2010) moderating effects in a structural model can be evaluated by two approaches: group comparison and product term.

4.4.1 Group Comparison Approach

In this approach, the data set is divided into two groups: high and low value of moderating variable (M), and then the same model is assessed using these two subsets of data. In case the moderating variable has formative dimensions, the latent variable scores are used for the dichotomization by the following rule (Henseler et al. 2010):

- If the moderating variable's latent variable score of an observation lies within the upper third, the grouping value is set to "high".
- If the moderating variable's latent variable score of an observation lies within the lower third, the grouping value is set to "low".
- Otherwise, the observation is not assigned to any group

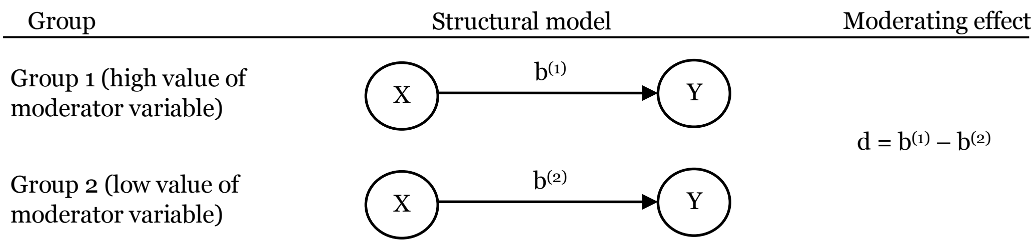

Figure 3. Moderating Effect Using Group Comparison Approach

After two groups are determined, a regression technique is used to estimate the parameters of the model for each group. Then the parameters are compared between two groups for the conclusion on the moderating effect (Henseler et al. 2010). As shown in Figure 3, two groups of data are determined based on the value of the moderating variable, then the direct relationship b between independent variable (X) and dependent variable (Y) is estimated for each group. The difference in b is interpreted as being caused by moderating effects.

4.4.2 Product Term Approach

In this approach, an additional variable representing the product of the independent variable and the moderating variable is included in the structural model. The product terms are built by multiplying the indicators of the latent independent variable and the indicators of the latent moderating variable, and these product terms are used as indicators of the interaction variable in the structural model (Henseler et al. 2010). While the formation of the product terms is feasible for reflective constructs, it is not if the independent variable or moderating variables is formative. In that case, a two-stage PLS approach should be used (Hair et al. 2014; Henseler et al. 2010):

Stage 1: In this stage, the main effect PLS path model is run in order to obtain estimates for the latent variable scores. The latent variable scores (LVS) are calculated and saved for further analysis.

Stage 2: In this stage, the interaction term is built up as the pair multiplication of the latent variable scores of independent variable (X) and moderating variable (Z). This interaction term and the latent variable scores of X and Z are used as independent variables in a multiple linear regression on the latent variable scores of the dependent variable (Y).

An example of the two-stage approach is illustrated in Figures 4 adapted from Henseler et al. (2010). A structural model is estimated with three variables: independent variable X, moderating variable Z, and dependent variable Y. At least one construct has formative indicators (e.g., Z). In Stage 1, the main effects model without the interaction variable is estimated to obtain the latent variable scores for X, Z, and Y (i.e., LVS(X), LVS(Z), and LVS(Y)). Then the product term is built between the latent variable scores of X and Z and is used as the indicator for the interaction variable X×Z. In Stage 2, the interaction variable X×Z is included in the model. Each of variables in Stage 2 is measured with a single item of the latent variable scores from Stage 1.

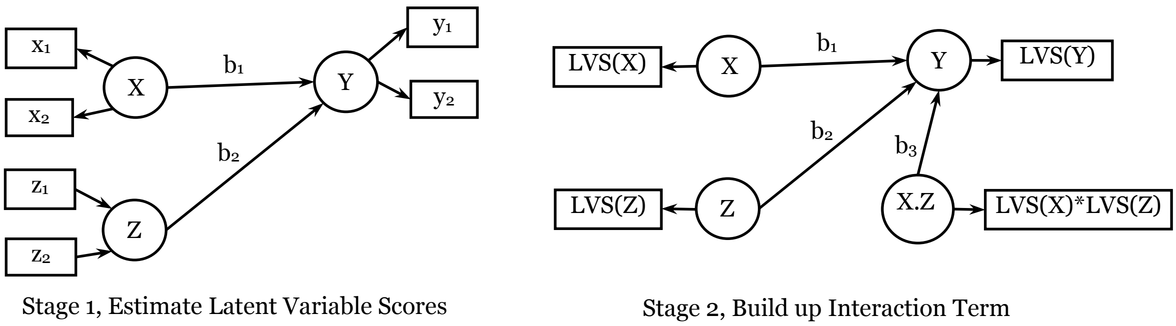

Figure 4. Moderating Effect Using Product Term Approach

4.4.3 Analysis Results Using Group Comparison Approach

The dataset was divided into two groups. After the latent variable scores of the moderator variable (OLC construct) were calculated, observations whose moderator LVSs lie within the upper third were specified as the high OLC group; observations whose moderator LVSs are within the lower third were specified as the low OLC group; the remaining observations are not assigned to any group. The size of each sub-sample was 75 observations. The direct relationships between the dimensions of ERP implementation scope and IC are illustrated in Figure 5. The path coefficients were calculated for the whole data set (baseline) and then for the two groups: Low OLC and High OLC. The calculation was performed using the PLS algorithm and bootstrap technique (Hair et al. 2014). The results are depicted in Table 3. As can be seen in Table 3, for the *whole* sample all three dimensions of ERP implementation scope have positive significant effects on IC. However while two dimensions breadth and magnitude positively significantly affected IC for the group representing high OLC (β=0.2 and β=0.268 respectively), none of the ERP implementation scope dimensions showed any significant effects on IC for organizations featuring low OLC. The observed results support the main hypotheses (H1a, H1b, and H1c) and two of three moderating hypotheses (H2a and H2c).

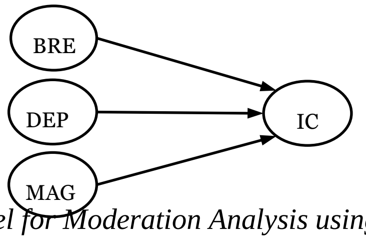

Figure 5. Structural Model for Moderation Analysis using Group Comparison Approach

Path	Path coefficient (β)		
	Baseline (n=226)	Low OLC (n=75)	High OLC (n=75)
BRE → IC	0.361**	-0.057 n/s	0.200*
DEP → IC	0.307*	0.018 n/s	0.163 n/s
MAG → IC	0.220**	0.091 n/s	0.268*
R-square (IC)	0.396	0.013	0.168

*Note: * Significant at 0.05 ** Significant at 0.01 n/s not significant*

Table 3. Moderation Effect Analysis Using Group Comparison Approach

4.4.4 Analysis Results Using Product Term Approach

In the product term approach, an additional variable is added to the structural model. In the first stage, the structural model was analysed in which two second-order constructs OLC and IC were measured by the indicators of their first-order constructs, and then the PLS algorithm was implemented to obtain the latent variables' scores (LVS) for the main constructs (BRE, DEP, MAG, OLC, and IC). In the second stage, LVSs obtained in stage 1 were used to estimate the parameters of structural model. In the second stage, to assess the contribution of OLC as a moderator, two models were used (see Figure 6).

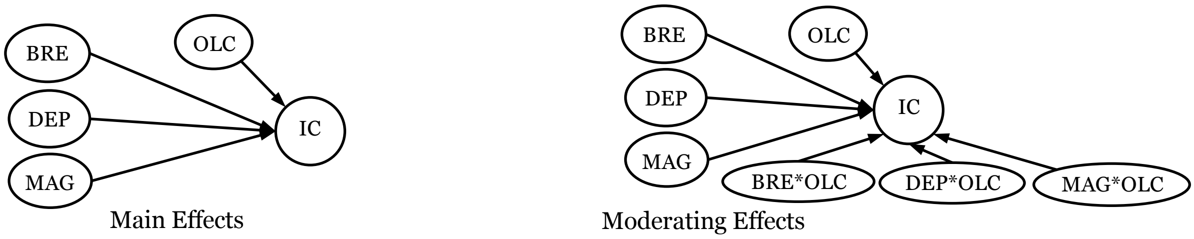

Figure 6. Structural Model for Moderation Analysis using Product Term Approach

The first model only included the direct effect of BRE, DEP, MAG, and OLC on IC. The second model included product terms (i.e., BRE*OLC, DEP*OLC, and MAG*OLC). The product terms are the products of the scores of OLC with the scores of BRE, DEP, and MAG. The path coefficients were calculated for the paths in the two models. The calculation was performed using the PLS algorithm and bootstrap technique with bootstrap samples of at least 5000, each sample contains 226 observations to determine the coefficients' significance (Hair et al. 2014). The results in Table 4 show that for the Model 1 all dimensions of ERP implementation scope and OLC had significant effects on IC. However, in Model 2 the results depict substantial differences in the patterns of interaction of ERP implementation scope with the organizational learning level. With the presence of the moderation effects, only the magnitude of ERP implementation has a significant moderation effect with OLC on IC. Therefore, while the results support all the main hypotheses (H1a, H1b, and H1c) only one of three moderating hypotheses (H2c) is supported by the results. For the strength of moderating effect, the overall effect size f^2 was .0432[1].

Path	Path coefficient	
	Model 1 (main effects)	Model 2 (moderation effects)
BRE → IC	0.155 **	0.144 **
DEP → IC	0.175 **	0.164 **
MAG → IC	0.124 *	0.156 **
OLC → IC	0.466 **	0.492 **
BRE*OLC → IC		0.043 n/s
DEP*OLC → IC		0.027 n/s
MAG*OLC → IC		0.117 *
R-square (IC)	0.517	0.537

*Note: * Significant at 0.05 ** Significant at 0.01 n/s not significant*

Table 4. Moderation Effect Analysis Using Product Term Approach

5 Discussion

Interestingly, despite strong theoretical support for our model, strong psychometric properties; a highly representative sample; and a strong response rate, our hypothesized moderating effects received fairly weak support. While the various dimensions of scope of ERP implementation *and* organizational learning capability all had significant effects on intellectual capital, the moderating effect of OLC at 0.432 was small[2], and only existed where there was a high magnitude of ERP implementation

A possible explanation is that on the one hand, firms need a certain level of learning capability in advance to acquire the new knowledge necessary to carry out the implementation; on the other hand the outcomes of the adoption of the new IT system and its integration into the firm's business processes (Robey et al. 2002) also enhance the firm's knowledge stock. Furthermore, organizations vary in their initial learning capability, and their ability to acquire it, which can explain the varying degrees of success of an IT implementation (Lee et al. 2007; Lin 2008). It may be that the relationship between the scope of ERP implementation and IC is a dynamic process of knowledge interaction and ERP implementation, enabled by the firm's organizational learning capabilities. Some level of OLC is a precondition for the ability to change and improve business processes, and the scope of ERP implementation can be measured (among other things) in the number of business processes changed. In turn, as ERP implementation is completed, the learning ability to carry out process improvement is supported, reinforced and embedded by the ERP. A continuation of this cycle leads to the ERP improving IC as knowledge is encoded and disseminated through the organization. Therefore the strategic benefits of ERP implementation cannot be explained by the ERP alone, but by the ERP *in the presence* of OLC, – a virtuous circle of ERP implementation.

[1] Calculated as $f^2 = \frac{R^2_{\text{interaction model}} - R^2_{\text{main effect model}}}{1 - R^2_{\text{interaction model}}} = \frac{0.537 - 0.517}{1 - 0.537} = 0.043$

[2] where effect sizes (f^2) of 0.02, 0.15, and 0.35 are suggested as small, moderate, and large respectively (Cohen 1988).

Another possible explanation for our weak effect if that we sampled only organizations who were well into, or had completed, their ERP implementation process. They already possessed, or had developed during their ERP implementation process, the necessary capabilities for organizational learning. Measuring OLC *before* ERP implementation might show stronger effects on the likely outcome for the organization in the future. Organizations need to be able to rapidly create, integrate, synthesize and disseminate a blend of their own unique organizational history, processes, and knowledge (IC) with the ‘best practices”, and capabilities for standardization and dissemination embedded in ERP systems. This blend is a unique and strategic resource in the way that ERP technology is not. It seems that most organizations with “mature” ERP implementations (>1 year old) are achieving this to varying degrees, as all paths between the dimensions of ERP implementation scope and IC were significant. Some aspects of the presence of OLC are therefore already captured in measures of the scope of ERP implementation. High OLC is likely to improve *both* the likelihood of successful implementation and the extent to which the implementation generates strategic benefits. An important implication of this research is that the magnitude of ERP implementation can be used as an indicative proxy for the likely success of the ERP system in creating the IC that leads to strategic advantage.

Nevertheless, this study had some limitations. It was a cross-sectional study of a dynamic process that takes place over a period of 1-3 years. Longitudinal studies are recommended to provide richer insights into the dynamic interactions involved. Also, it was confined to a particular geographic region, although we have no reason to believe that businesses in the region are not analogous to other similar companies in terms of their approach to ERP implementation.

6 Conclusion

This study makes several contributions to the understanding of strategic ERP implementation. 1) As expected, IT investment alone does not lead to the creation of strategic resources (Carr 2003) this only occurs in the presence of other organizational resources and capabilities (Piccoli et al. 2005). 2) We identified the organizational conditions that should be present as a pre-condition to rapid and effective ERP implementation and creation of valuable IC. These are: managerial commitment, a systems perspective, a culture of openness and experimentation, and the ability to carry out knowledge transfer and integration. These capabilities can be used as proxies for “ERP readiness”. 3) We find that many aspects of OCL post implementation are captured in measures of ERP scope, especially ERP magnitude. This simplifies the ability of organizations to evaluate whether their ERP implementation is progressing as expected, and to diagnose problems if it is not. If an ERP implementation is not progressing as expected, attention to the conditions associated with OLC should improve the progress and overall success of implementation. 4) We present a way forward for remediating ERP implementations that are faltering or failing to achieve the desired benefits through careful attention to organizational conditions, rather than technical solutions. 5) We show that simply rolling out an ERP (achieving depth and breadth) without engaging in process change may not require the same levels of OLC but may not yield the expected strategic benefits. 6) We apply contemporary understandings of construct conceptualization and measurement to widely cited constructs. This provides further confidence in their continuing use. We commend our re-specification of IC and OLC as higher order formative constructs to future researchers. Overall, organizations should not treat ERP implementation simple as a technical challenge and assume that strategic benefits will follow in a natural cycle, even from “successful” implementation projects. The major conclusion of our study is that having (or rapidly acquiring) OLC is a pre-condition for effective iteration of the “virtuous circle” of ERP implementation. This in turn leads to the ability to change processes (magnitude of implementation in our study), create and capture new organizational knowledge, and finally create new IC for competitive advantage. This is likely to be true for other major IT initiatives as well, suggesting that organizations that master the challenge of effectively integrating new IT with their unique organizational capabilities are most likely to see strategic benefits flowing from their IT investment.

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