Information & Management 55 (2018) 120–130

Contents lists available at ScienceDirect

Information & Management

journal homepage: www.elsevier.com/locate/im

Evolution of the impact of e-business technology on operational competence and firm profitability: A panel data investigation

Jose Benitez[a,b,*], Yang Chen[c], Thompson S.H. Teo[d], Aseel Ajamieh[b,e]

[a] Rennes School of Business, Rennes, France
[b] Department of Management, School of Human Resource Management, School of Business, University of Granada, Granada, Spain
[c] School of Business Administration, Southwestern University of Finance and Economics, Chengdu, Sichuan, China
[d] School of Business, School of Computing, National University of Singapore, Singapore, Singapore
[e] College of Business Administration, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia

ARTICLE INFO

Keywords:
E-business technology capability
Operational capabilities
Firm profitability
Business value of IT
Partial least squares path modeling
Panel data

ABSTRACT

This study examines the evolution of the impact of e-business technology on operational competence and profitability using a panel dataset of 154 Spanish firms. We find that (1) e-business technology has a positive effect on operational competence that decreases over time and (2) the firm's proficiency in exploiting a portfolio of operational capabilities has a positive impact on profitability that becomes more substantial over time. The findings provide some insights on how the initial and subsequent IT investments affect operational competence and profitability over time. This study methodologically illustrates how to perform a partial least squares estimation using panel data.

1. Introduction

Firms invest millions of Euros in information technology (IT) to build process capabilities and increase their competitiveness [1–4]. However, not all IT investments generate the expected results [5]. This situation demands managers to carefully (re)assess all their IT investments [6,7].

The majority of past research focused on IT impact on the supply chain and manufacturing activities through a cross-sectional design [8–13]. It remains unclear that whether and how IT investments impact a broader set of operational capabilities and performance over time. Considering that IT and operational capabilities along with their relationship and effect on firm performance can be dynamic, there seems to be a significant gap that needs to be filled in research in our field.

The present research focuses on e-business technology (one type of IT capability investment/resource allocation) and on whether, how, and under what conditions this capability creates business value. E-business technology can improve the firm's operations management system by enabling the real-time interchange of information across the supply chain [9,12]. However, e-business technology has become commoditized and can be affordable for most large firms, which can reduce its potential to create operational advantages over time [5]. This leads to our first research question: How does the time of investment in e-business technology affect the firm's operations management system (specifically, operational competence comprising a portfolio of capabilities) over time? We believe that the Information Systems (IS) field needs to provide an answer to this critical research question. This is what we try to achieve in this research.

With regard to the firm's operations management system, we focus on the firm's operational competence, which refers to the firm's proficiency in exploiting its portfolio of operational capabilities [12,14]. This competence is related to the heart of the business model of a firm, which supposes a natural starting point in this research [15]. On the basis of the work of Tatikonda et al. [16], we focus on a portfolio of operational capabilities that determines operational competence: gross margin, employee productivity, operational talent management, and operational excellence. These operational capabilities are related to product margin control, productivity management, talent management, and manufacturing and service excellence; they are a good representation of the potential portfolio of operational capabilities that a contemporary firm may possess to be successful and survive in the long run [16].

The operational capabilities of the firm can be refined through time and experience. Early developers of operational capabilities through early investment in e-business technology can achieve greater competitiveness because of longer duration and experience in developing their operational capabilities. This leads to our second research question: Do initial and subsequent e-business technology investments result in

* Corresponding author.
E-mail addresses: jose.benitez@rennes-sb.com, joseba@ugr.es (J. Benitez), chenyang@swufe.edu.cn (Y. Chen), bizteosh@nus.edu.sg (T.S.H. Teo), aseelkhalil1987@hotmail.com (A. Ajamieh).

http://dx.doi.org/10.1016/j.im.2017.08.002
Received 28 September 2015; Received in revised form 18 April 2017; Accepted 4 August 2017
Available online 10 August 2017

differences in the operations management impact on the firm's competitiveness over time? We address the above two questions in this study. Specifically, by drawing on the IT-enabled organizational capabilities perspective [1,17–19], the operational capabilities-based theory [20,15], and the literature on the hierarchy of capabilities of the firm [8], the main goal of this study is to examine the evolution of the impact of e-business technology on operational competence and firm profitability over time. To achieve this goal, we use the structural equation modeling (SEM) technique with a panel dataset for the period 2008–2010 on a sample of 154 large firms in Spain. The empirical analysis suggests that the positive effect of e-business technology on operational competence decreases over time, while the positive effect of operational competence on firm profitability increases over time. The findings provide some insights on how the initial and subsequent IT investments affect operational competence and firm profitability over time. Early development of IT-enabled operational capabilities maximizes firm profitability because of the greater time and experience the firm has in developing its operational capabilities. Furthermore, this study methodologically illustrates how to perform a partial least squares (PLS) estimation using panel data.

2. Theory and hypotheses

2.1. Theoretical background

The IT-enabled organizational capabilities perspective has argued that one of the key mechanisms through which IT capability influences firm performance is by developing organizational/process capabilities, such as business flexibility, talent management, new product development, absorptive capability, and innovation capability [21–25]). This study builds on the IT-enabled organizational capabilities to conceptualize e-business technology and to theoretically link e-business technology to operational competence and firm profitability over time. We use a three-year panel data.

Operational routines are patterns of activities/processes that a firm performs at the operations level, which can lead to superior firm performance. Operational capabilities are the firm's proficiency in using a collection of interrelated operational routines to solve operational problems and implement the operations strategy [20,26,15]. The theory of operational capabilities provides a strong theoretical framework to conceptualize e-business technology and operational competence and to link these constructs both among themselves and to firm profitability.

This study also draws from the literature on the hierarchy of firm's capabilities (e.g., [27,8], which is consistent with the IT-enabled organizational capabilities perspective and the operational capabilities-based theory. In the hierarchy of capabilities, lower-order capabilities require other higher-order capabilities to affect business outcomes (firm profitability in this case). In this sense, e-business technology is considered as a lower-order capability that requires operational competence (a higher-order capability) to affect firm profitability [28,22].

2.2. Conceptualization of e-business technology, operational competence, and firm profitability

E-business technology capability is the firm's proficiency in leveraging its web-based technologies to interchange within and outside the firm for buying and selling activities with suppliers and customers [9,10,29–33]). Operational competence refers to the firm's proficiency in exploiting its portfolio of operational capabilities [14,12]. On the basis of the work of [16], we focus on a portfolio of operational capabilities that determines operational competence: gross margin, employee productivity, operational talent management, and operational excellence. Gross margin is the firm's proficiency in managing/estimating proper product margins. Employee productivity refers to the firm's proficiency in stimulating the personnel to achieve higher individual performance [34]. Operational talent management is the firm's proficiency in recruiting (sourcing, attracting, and selecting), getting on board, developing, and retaining operational talent [15]. Operational excellence refers to the firm's proficiency in developing and executing operational routines to manufacture/supply products agilely (in an excellent way) to the market [26,25]). This study focuses on firm profitability to assess the firm's business benefits. Fig. 1 presents the conceptual model showing the interrelationships among e-business technology, operational competence, and firm profitability over time.

2.3. E-business technology and operational competence

E-business technology can enable the development of operational competence by facilitating the improvement of gross margin, employee productivity, operational talent management, and operational excellence. E-business technology can enable the firm's proficiency in managing successful product margins. Web-based technology enables the firm to have real-time interchange of accurate and timely information on product cost and demand with upstream suppliers and downstream customers, thereby enabling the firm to better manage its product margins [9,10,22]. Similarly, e-business technology can also be leveraged to increase employee productivity [35]. The firm's web-based communication networks (e.g., email, Intranet) enable the employees to access and share more heterogeneous/diverse knowledge (e.g., information about the manufacturing process/other employees) and learn to perform multiple tasks, which increase employee productivity [36,37].

E-business technology can also improve the management of operational talent. Through e-business technology, the firm acquires/provides accurate and timely information from/to the market to recruit and get on board outstanding operational talent to design and integrate its talent base. For example, Cortefiel (an apparel manufacturer in Spain) uses web-based social media tools such as LinkedIn, Facebook, and Twitter to recruit operational managerial talent that fits the profile needed in designing its talent base [38]. Web-based technology enables the firm to implement scheduling and workplace flexibility activities to retain operational talent and to provide reliable information on goal completion, performance appraisal, and career planning to develop and retain operational talent [15]. Finally, leveraging web-based business applications (e.g., operational module of an enterprise resource planning) enables better execution of operational routines and agility in manufacturing/supplying products to the markets to pursue operational excellence [39,25]). We therefore hypothesize that

H1a. *E-business technology has a positive effect on operational competence.*

Firms may not need to invest substantially in IT every year/period. For example, Air Canada (the largest airline firm in Canada) invested in 2007 in its web-based technology to be the first airline in offering its customers the online boarding pass and self-service IT applications to save costs (increase gross margin) and improve operational excellence. After its initial investments in e-business technology, Air Canada did not need substantial additional investments in e-business technology to retain its operational development in the subsequent periods [40].

We also predict that the positive effect of e-business technology on operational competence can decrease over time for two reasons. First, additional investments in e-business technologies (after investments in prior periods) can diminish the operational marginal returns [37]. Second, e-business technology has been commoditized and can be affordable for most firms. Consequently, follower firms can learn to invest in e-business technology and develop e-business technology capability, which can convert e-business technology into a non-unique/imitable capability, and its effect on operational competence can decrease over time [5,41]. We therefore hypothesize that

H1b. *The effect of e-business technology on operational competence decreases over time.*

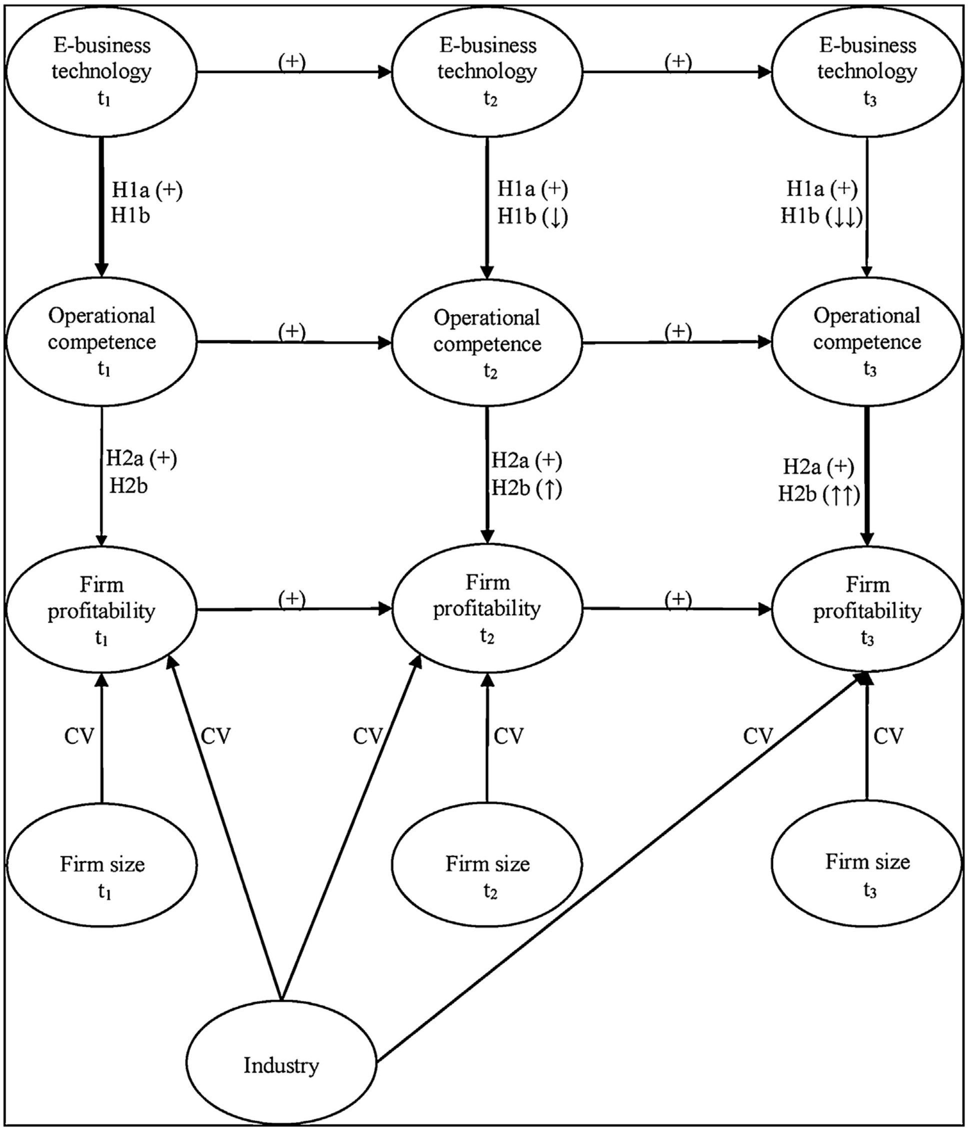

Fig. 1. Conceptual model (CV = Control variable). Note: While H1a and H2a refer to a positive effect, H1b and H2b refer to a change (decreasing and increasing, respectively) in the effects over time. H1b (↓) (↓↓) and the decreasing thickness of arrows show decreasing effect over time. H2b (↑) (↑↑) and the increasing thickness of arrows show increasing effect over time. CV indicates control variable.

2.4. Operational competence and firm profitability

We also argue that operational competence has a positive impact on firm profitability. Since firms can develop different proficiencies in managing/estimating product margins, this operational capability can generate differences in firm's benefits and profitability [16], thus indicating that it is rational to expect a positive impact of gross margin capability on firm profitability. Higher employee productivity and better firm's proficiency in recruiting, getting on board, developing, and retaining operational talent reduce costs and increase revenues, which in turn increase business benefits and profitability [42,43]. For example, Mercadona (a leading retailer) is a top employer firm in Spain that offers excellent working conditions and an attractive career plan to develop and retain shop talent, which has enabled Mercadona to be the most profitable retailer of Spain [44,15]. Finally, by developing operational routines to achieve operational agility, operational excellence can increase profitability [45–47]. Thus, we hypothesize that

H2a. *Operational competence has a positive impact on firm profitability.*

Because the firm's proficiency in exploiting its portfolio of operational capabilities is the heart of the firm's business model [20,14] and because this proficiency can be refined through time and experience, we expect the positive impact of operational competence on firm profitability to increase over time. Therefore, we propose the following hypothesis:

H2b. *The effect of operational competence on firm profitability increases over time.*

Although not stated as a formal hypothesis, we expect that e-business technology, operational competence, and firm profitability in one period affect the same construct in the subsequent periods [48]. For example, since current business benefits are affected by prior business benefits, we can also expect that firm profitability in the prior period affects that in the subsequent periods [49,50,22]. Firm sizes in t_1, t_2, and t_3 were considered as exogenous variables, and they were not subsequently linked among themselves.

Firm profitability could be affected by the type of industry. We thus controlled for industry effect on firm profitability [51,18,52].

3. Research methodology

3.1. Sample and data

The proposed model was tested with a secondary dataset collected from a sample of 154 large manufacturing and service firms in Spain for the period 2008–2010. A panel of data from three subsequent years was sufficient to investigate the evolution of effects that we pursued in this research [53]. Our sample was obtained from the Monitor Empresarial de Reputacion Corporativa (MERCO) database (http://www.merco.info/es/), which includes ranking and evaluation of corporate reputation and employer brand of firms in Spain and Latin America. Our sample was representative of the large manufacturing and service firms located in Spain because large firms in Spain participate in the annual MERCO evaluation and were included in the MERCO database.

We used the name of firms selected from the MERCO database to collect additional information from the firm's websites, Sistema de Analisis de Balances Ibericos (SABI), Actualidad Economica, and COMPUSTAT databases. SABI is a database produced by Bureau van Dijk that contains abundant financial information on firms in Spain and Portugal (https://sabi.bvdinfo.com/) [22]. Actualidad Economica is a premier Spanish business magazine that develops annual rankings depending on sales and innovation to compose a database with rich information on the most admired firms in Spain (http://www.actualidadeconomica.com/) [15].

3.2. Measures

We measured all our constructs with secondary panel data for the period 2008–2010, which were obtained from five different sources. Table 1 provides the name, measure definitions, and data sources for all constructs. Consistent with prior IS research (e.g., [54,55,18], we measured e-business technology through the accumulated number of e-business technology services that each firm possesses to interact with its suppliers and customers with information collected from the firm's website.

Measurement models can be specified as factor or composite models [56,57]. Factor models use reflective constructs and assume that the variance of a set of indicators can be perfectly explained by the existence of one unobserved variable and individual random error. They are the standard models of behavioral research [57,58]. In contrast, composite models/constructs are formed as linear combinations of their respective indicators. A composite construct serves as a proxy for the concept under investigation (i.e., the recipe) that is composed of a mix of indicators (i.e., the ingredients) [59]. As an example, consider bread. Bread is constituted from wheat, water, salt, and yeast. If we were to examine the correlations among the amount of wheat, water, salt, and yeast in a sample of bread loaf, the correlations are likely to be high. However, such correlations do not mean that bread is a reflective construct and that bread causes wheat, water, salt, and yeast. Rather, bread is a composite construct where wheat, water, salt, and yeast are the simple entities (i.e., the ingredients), which are combined to form the composite concept we call bread. Clearly, the temporal precedence of the ingredients also suggests that bread cannot be the common cause of the ingredients [60]. The composite model does not impose any restrictions on the covariances among indicators of the same construct, thereby relaxing the assumption that all the covariations among a block of indicators are explained by a common factor. Emergent and strong concepts should be modeled as composite constructs [61]. Consequently, the model of this study is composite.

Operational competence is defined as a composite first-order construct composed of gross margin, employee productivity, operational talent management, and operational excellence [16]. Gross margin and employee productivity were measured from gross margin and operating revenues per employee with information collected from the SABI database. These measures are also used by business executives to evaluate gross margin and employee productivity in the real world [44]. We measured operational talent management through the score (from 0 to 10000) achieved by each firm in employer brand/reputation [15] with information collected from the MERCO database. Employer brand/reputation is a good proxy for operational talent management because top employers are also leading firms in recruiting, getting on board, developing, and retaining talent [43,38].

Operational excellence was measured through the rate of sectoral excellence (RSE) in sales with information collected from the Actualidad Economica database [17]. We assumed that excellent firms in operations also lead in sales [62]. RSE in sales has a value between 0 and a value very close to 1 (termed the industry's maximum value). The closer the RSE is to the maximum value for the industry, the better is the operational excellence of the firm [22]. Firm profitability was measured through the return on assets with information from the SABI database. We controlled for firm size and industry. We measured firm size through the natural logarithm of number of employees [63] using information collected from the SABI and Actualidad Economica databases. We classified firms into manufacturing (0) or services (1) to control for industry [18]. All variables were measured for the years 2008 (t_1), 2009 (t_2), and 2010 (t_3).

Prior to data collection, we arranged two informal meetings with four executives (two came from IT and two from business areas) and asked for their opinion about the congruence between the measures and constructs employed in the study [15,52]. They indicated that there

Table 1
Construct name, measure definitions, and data sources.

Construct name	Measure definition	Source
E-business technology	Accumulated number of e-business technology services that each firm possesses on the following list of 26 e-business technology services: website, online catalog, online ordering, banner, online order tracker, site map, search engine, bulletin subscription, e-mail, discussion forum, online calendar/agenda, repository of documents, tools to provide recommendations to customers, invoice system, customer service management solution, shopping cart solution, payment system, website advertising, Intranet for employees, supplier management solution, shareholder solution, social media usage, frequently asked questions, online visitor counter, and customer loyalty solution. This measure ranges from 0 to 26	Proprietary content analysis of the firm's website
Profit margin	Profit margin (%) = (Earnings before taxes/Operating revenues) × 100	SABI
Employee productivity	Operating revenues per employee (in thousands of Euros) = Operating revenues/Number of employees	SABI
Operational talent management	Score from 0 to 10000 given by the MERCO to the firm in employer brand/reputation	MERCO
Operational excellence	RSE in sales = 1 − (Ranking position of firm in sales/Total number of firms in the industry). RSE ranges from 0 to 1	Actualidad Economica
Firm profitability	Return on assets (%) = (Earnings before taxes/Total assets) × 100	SABI
Firm size	Natural logarithm of the number of employees	SABI and Actualidad Economica
Industry	Dummy variable (0 = Manufacturing, 1 = Service firm)	SABI, Actualidad Economica, and COMPUSTAT
Advertising spending	Advertising expenditure per employee (in thousands of Euros) = Advertising expenditure/Number of employees	SABI and COMPUSTAT (only for 2009 and 2010, see Section 4.3)

Table 2
Results of the PLS estimation.

Relationship	Beta coefficient	f^2 value	Effect size
Hypothesized relationship			
E-business technology$_{t1}$ → Operational competence$_{t1}$ (H1a)	0.306*	0.103	Medium
E-business technology$_{t2}$ → Operational competence$_{t2}$ (H1b)	0.023	0.002	Very weak
E-business technology$_{t3}$ → Operational competence$_{t3}$ (H1b)	0.005	0	Zero
Operational competence$_{t1}$ → Firm profitability$_{t1}$ (H2a)	0.199*	0.043	Weak
Operational competence$_{t2}$ → Firm profitability$_{t2}$ (H2b)	0.209*	0.067	Weak-medium
Operational competence$_{t3}$ → Firm profitability$_{t3}$ (H2b)	0.473**	0.333	Large
Control variables			
Firm size$_{t1}$ → Firm profitability$_{t1}$	−0.170*	0.031	Weak
Firm size$_{t2}$ → Firm profitability$_{t2}$	0.034	0.002	Very weak
Firm size$_{t3}$ → Firm profitability$_{t3}$	−0.042	0.003	Very weak
Industry → Firm profitability$_{t1}$	0.095*	0.010	Very weak
Industry → Firm profitability$_{t2}$	0.026	0.001	Very weak
Industry → Firm profitability$_{t3}$	−0.091	0.012	Weak
Nonhypothesized relationships (between time periods)			
E-business technology$_{t1}$ → E-business technology$_{t2}$	0.477***	0.294	Large
E-business technology$_{t2}$ → E-business technology$_{t3}$	0.620***	0.625	Large
Operational competence$_{t1}$ → Operational competence$_{t2}$	0.850***	2.530	Very large
Operational competence$_{t2}$ → Operational competence$_{t3}$	0.518*	0.361	Large
Firm profitability$_{t1}$ → Firm profitability$_{t2}$	0.558***	0.472	Large
Firm profitability$_{t2}$ → Firm profitability$_{t3}$	0.273*	0.110	Medium

Note: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, one-tailed test.

was a very good conceptual proximity between the measures and constructs. Overall, this shows satisfactory content validity for our constructs.

4. Empirical analysis

We used the variance-based SEM technique and the PLS method of estimation to test the hypotheses and examine the indirect effects involved in the proposed model. We used the statistical software package Advanced Analysis for Composites (ADANCO) Professional (http://www.composite-modeling.com/) [64]. ADANCO is a modern statistical software package that enables the execution of a modern approach for variance-based SEM technique, including the PLS method of estimation. ADANCO is particularly useful to estimate models that contain composite constructs, as in our study [61].

It is appropriate to use PLS as the method of estimation for the following reasons. First, PLS is a full-fledged SEM method of estimation that can conduct exact test of model fit [61]. Second, the construct operational competence is identified as a composite, and PLS is a suitable method for estimating models with this type of constructs [56,57]. Third, the use of PLS SEM is advisable to estimate models that use secondary data like our model [65,17]. Fourth, prior research in the Marketing domain has proven that PLS estimation is useful for testing models that use panel data (e.g., [48]). Finally, PLS is a variance-based SEM technique that has been used and highlighted in prior IS research [8,66]. To estimate the level of significance of weights, loadings, and path coefficients, we ran the bootstrapping algorithm with 200 subsamples.

Prior to data collection, we performed a prior statistical power analysis. The maximum number of predictors in the proposed model was four (i.e., comprising the composite indicators of the constructs' operational competence in t_1, t_2, and t_3). Assuming a medium effect size ($f^2 = 0.150$), the proposed model required a minimum sample size of 84 to achieve a power of 0.800 and an alpha level of 0.05 [67,3]. Our sample size was 154, which is adequate to estimate the proposed model. This analysis suggested that our study had sufficient statistical power to detect the effects of interests. After estimating the proposed model, we also conducted a post-hoc statistical power analysis by using the GPower 3.1.9.2 software [68,69].[1] The average effect size for the relationships included in the proposed model was 0.278, which with an alpha level of 0.05 and four predictors provided a statistical power of 0.999, well above of the accepted threshold of 0.800. The results of the prior and post-hoc statistical power analyses confirm that the non-significant effects of the empirical analysis are not because of the sample size [68].

4.1. Hypotheses testing

We tested the proposed model by performing a PLS estimation and analyzing the evolution of the effect size (f^2) for the hypothesized relationships. f^2 values of 0.020, 0.150, and 0.350 indicate a weak, medium, or large effect size of adding a link between an exogenous and endogenous variable [70]. Thus, we examined the evolution of beta coefficients, level of significance, and f^2 values to test the hypotheses. Table 2 and Fig. 2 present the results of the PLS estimation. The empirical analysis gave good support to the hypotheses. E-business technology had a positive effect on operational competence that decreased over time even becoming nonsignificant. The portfolio of operational capabilities had a positive impact on firm profitability, which became more substantial over time. The firm size effect on firm profitability was significant only in t_1. The effect of industry on firm profitability was significant at 0.05 level in t_1. All the constructs were affected by the same construct in the prior period (significant at 0.05 level).

The values of the beta coefficients, their level of significance, the f^2 values, and the R^2 values are individual measures of the explanatory power of the model. Beta coefficients around 0.200 were considered economically significant, and R^2 values higher than 0.200 indicate good explanatory power of the endogenous variables of the model [71,22]. The beta coefficients of the hypothesized relationships in our model ranged from 0.199* to 0.473**. The f^2 values for the six endogenous variables involved in the hypothesized relationships ranged from 0.043 to 0.333. The R^2 values for these relationships ranged from 0.091 to 0.732. Overall, this analysis suggests a good explanatory power for the proposed model.

4.2. Overall model fit evaluation

We evaluated the overall goodness of model fit for the proposed model by examining the standardized root mean squared residual (SRMR), unweighted least squares (ULS) discrepancy (d_{ULS}), and geodesic discrepancy (d_G) [57]. All these measures of goodness of fit

[1] GPower 3.1.9.2 is a free general power analysis program [68].

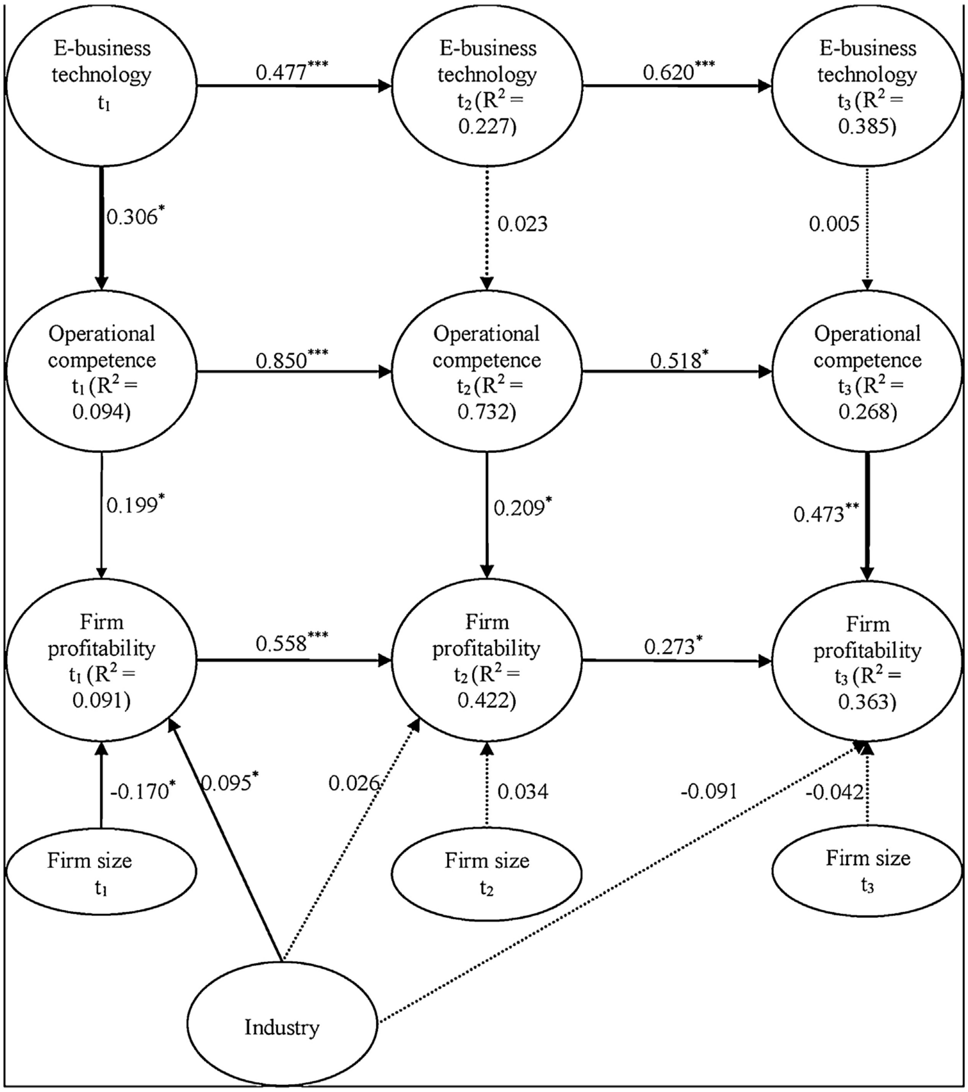

Fig. 2. PLS estimation of the proposed model.
Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, one-tailed test.

evaluate the discrepancy between the empirical correlation matrix and the model-implied correlation matrix [59]. The lower the SRMR, d_{ULS}, and d_G, the better is the fit of the theoretical model [64]. All discrepancies were below the 95% quantile of the bootstrap discrepancies (see Table 3), which implies that the model should not be rejected based on an alpha level of 0.05 and that the model provides a good explanation of the business world with a probability of 5% [60].

Table 3
Model fit evaluation.

Discrepancy	Value	HI_{95}	Conclusion
SRMR	0.163	0.454	Supported
d_{ULS}	6.751	52.044	Supported
d_G	2.916	52.806	Supported

4.3. Effect of advertising spending on the proposed model

The firm's advertising spending can increase firm profitability and can affect the operational competence impact on firm profitability [7]. These effects may also occur over time. Because of missing data for a significant number of firms of the sample for t_1 in the SABI and COMPUSTAT databases, we did not control for advertising spending on firm profitability in the proposed model. As a robustness check, we estimated an alternative model in which we controlled for advertising spending on firm profitability in t_2 and t_3 for which we have available data. The beta coefficients of these two effects were not significant (-0.084 and -0.017), while all other results were similar.

4.4. Mediation analysis

On the basis of the works of Zhao et al. [72] and Nitzl et al. [73], we performed a mediation analysis to examine the more critical mediation effects involved in the proposed model. Specifically, to the proposed model, we added a link between: (1) e-business technology$_{t1}$ and firm profitability$_{t1}$, (2) e-business technology$_{t1}$ and operational competence$_{t2}$, and (3) e-business technology$_{t1}$ and operational competence$_{t3}$. Because the proposed model has many potential indirect effects involved in the analysis, we selected the more critical mediation effects for parsimony and to provide the simplest explanation [59]. The direct effects of these three links were not significant, while the indirect effects were significant (0.05 level), which suggests a full mediation of operational competence$_{t1}$ in the relationship between e-business technology$_{t1}$ and firm profitability$_{t1}$, a full mediation of operational competence$_{t1}$ in the relationship between e-business technology$_{t1}$ and operational competence$_{t2}$, and a full mediation of operational competence$_{t1}$ in the relationship between e-business technology$_{t1}$ and operational competence$_{t3}$. This mediation analysis reinforces the results obtained in the test of hypotheses and suggests that the impact of early investments in e-business technology on the development of operational capabilities over time is substantial.

4.5. Additional analysis for the significance of the evolutions over time

We performed a multigroup PLS analysis as described by Roemer [74] to conduct an additional test to examine whether the trends of the beta coefficients involved in H1b and H2b are statistically significant.[2] In this analysis, we removed the carry-over effects (e.g., e-business technology$_{t1}$ → E-business technology$_{t2}$) from the model to avoid the appearance of "noise" in the analysis. Different groups were interpreted as different points in time, and we examined whether the beta coefficient of the effect of X on Y in t (e.g., e-business technology$_{t1}$ → Operational competence$_{t1}$) is inside the bootstrapping confidence interval of the effect of X on Y in t_{+1} (e.g., e-business technology$_{t2}$ → Operational competence$_{t2}$) and vice versa. Table A2 (in the Appendix A) presents the results of this analysis. This additional analysis indicated that the change in effect of e-business technology on operational competence in t_1 and t_3 was statistically significant. The analysis also showed that the change in effect of operational competence on firm profitability in t_1 and t_2 and in t_1 and t_3 were statistically significant. Considering these results together with the results from the effect size analysis gives some support to H1b and full support to H2b.

5. Discussion

5.1. Main findings

Although IT capability investments can develop and improve the firm's process capabilities and competitiveness [62,25]), not all IT capability investments generate the expected results. This study focused on e-business technology and examined the evolution of the impact of e-business technology on operational competence and firm profitability by performing a panel data investigation on a sample of 154 large firms in Spain. We revealed that (1) e-business technology has a positive effect on operational competence that decreases over time even becoming nonsignificant and (2) the firm's proficiency in exploiting a portfolio of operational capabilities has a positive impact on profitability that becomes more substantial over time.

5.2. Implications for research

This study has several implications for research. First, the findings provide some insights on how the initial and subsequent IT investments affect operational competence and firm profitability over time. This study differentiates from past studies (e.g., [35,10,12] by performing a panel data investigation on the impact of e-business technology on operational competence and firm profitability. Our results suggest that early developers of operational capabilities through early investments in e-business technology maximize profitability because of a longer time and experience in developing their operational capabilities.

We found that the firm's proficiency in leveraging its web-based technologies has a positive effect on the firm's proficiency in exploiting a portfolio of operational capabilities (i.e., operational competence). We focused on a portfolio of operational capabilities that determines operational competence composed of gross margin, employee productivity, operational talent management, and operational excellence. We argued that this sample of operational capabilities is a good representation of the potential portfolio of operational capabilities that a contemporary firm may possess to be successful and survive in the long run [16]. The empirical analysis supports our theory. Web-based technology enables the firm to perform real-time interchange of accurate and timely information on product cost and demand with upstream suppliers and downstream customers to improve gross margin management. E-business technology also enables the firm to (1) acquire/provide information from/to the market to recruit and get on board outstanding operational talent, (2) implement scheduling and workplace flexibility activities to retain operational talent, and (3) provide reliable information on goal completion, performance appraisal, and career planning to develop and retain operational talent. Finally, e-business technology also facilitates better execution of operational routines and greater agility in manufacturing/supplying products to markets. However, the positive effect of e-business technology on operational competence decreases over time even becoming nonsignificant. This result suggests that firms can imitate IT investments from their competitors and learn to develop an e-business technology capability over time, which may convert e-business technology into a nonunique (i.e., lower order in the hierarchy of capabilities) capability to enable operational competence. This implies that early investors/developers of e-business technology are the firms that mainly achieve e-business technology-based operational development.

We found that operational competence has a positive impact on profitability that becomes more substantial over time. Through a better management/estimation of product margins, greater employee productivity, an appropriate recruitment, the development and retention of operational talent, and a higher product manufacturing/supply chain agility, the firm can increase its profitability. Since the firm's operational competence is the heart of the business model and can be refined through time and experience, the operational competence impact on firm profitability increases over time. This result suggests that the timing of e-business technology investment for the operational development is critical to maximize firm profitability over time.

Prior IS research [75] has proposed the virtuous cycle argument to explain a firms' IT investments over time. This argument suggests that firms that invest in IT in t_1 reap benefits and then invest more in IT in the subsequent periods. Over time, these effects become magnified, leading some firms to continue investing more in IT than in their historical investment and that of their competitors [7]. Is this IT behavior economically rational? Our results are not only consistent with the virtuous cycle argument [beta (e-business technology$_{t1}$ → E-business technology$_{t2}$) = 0.474***] but also suggests two new interesting insights that extend the virtuous cycle argument: (1) firms continue investing in IT in subsequent periods although they do not see immediate benefits [beta (e-business technology$_{t2}$ → Operational competence$_{t2}$) = 0.025] and (2) firms may be investing in IT in subsequent periods although they do not really need it, which is not economically rational. This trend may also be due to capturing "low hanging fruits" (i.e., easy benefits compared to cost) through initial IT investment, with subsequent IT investments being more difficult to have a similar impact.

Second, the findings also provide theoretical implications on the impact of IT on the development of operational capabilities. Past research has explored the effects of IT on the following manufacturing capabilities: just-in-time manufacturing and supplier and customer participation programs [35], supply chain information integration [9], organizational collaboration [10], and operational absorptive capability [12]. In a different way, we focused on the impact of e-business technology on a different set of operational capabilities: gross margin, employee productivity, operational talent management, and operational excellence. The results suggested that e-business technology has a positive effect on the development of operational capabilities, which is consistent those of past studies (e.g., [35,12]. However, a key insight from our results is that the effect of e-business technology on operational development decreases over time at least in the subsequent periods.

Third, this study also has methodological implications because it illustrates how to perform a panel data investigation focusing on the evolution of effects by using SEM and the PLS method of estimation. Few studies have performed this type of analysis [74]). In this sense, we developed and extended Johnson et al.'s [48] study (in the Marketing domain) that uses the method of estimation of PLS to examine the evolution of loyalty intentions. While Johnson et al. used a three-year

[2] We thank an anonymous reviewer for this suggestion.

survey dataset, we used a three-year secondary dataset. We also showed that this method could be applied to IS research for examining the evolutionary impact of e-business technology on operational competence and firm profitability. In addition, we showed that the analyses of effect size and the confidence intervals are a useful tool to examine the evolution of effects on this type of dynamic models. Drawing from the Roemer's (74) methodological work, this paper provides an illustration of how to test whether the trends over time in a business value of IT domain are significant.

Finally, this study also has theoretical implications for the literature on the hierarchy of firm's capabilities (e.g., [27,8]. In the hierarchy of capabilities, lower-order capabilities require other higher-order capabilities to affect firm performance. This research extends our understanding on the hierarchy of capabilities by finding and explaining the role of timing in the effect of e-business technology (a lower-order capability) on firm profitability (the business outcome variable) through operational competence (a higher-order capability). In this sense, timing has a critical role in the relationship between lower-order and higher-order capabilities and business gains.

5.3. Limitations and future research opportunities

This research has two key limitations. First, the results of this study may be generalized only to large firms in Spain. Future research can explore whether these results remain under other environmental conditions, in other countries and/or specific industries. Second, IT investments may take some time to fruition. The findings of this study should be viewed within a context of a three-year panel data. We were unable to extend our analysis to a longer duration panel data because of the unavailability of data for some variables (e.g., e-business technology). Nevertheless, even with a three-year panel data, our results suggest that the effect of e-business technology on operational competence decreases over a three-year period even becoming nonsignificant. Future research can explore whether this result remains valid over a longer duration panel data (e.g., 10 years) period.

5.4. Implications for practice

Our findings also provide important managerial implications. First, this study shows how managers can develop e-business technology and operational competence to maximize firm profitability. Second, our findings suggest IT managers to control IT investments over time. Early e-business technology investments provide more time and experience to refine the firm's portfolio of operational capabilities, thus improving the operations management system and increasing the firm's profitability in the long run. In other words, early investment in IT can enhance operational competence and result in an increase in profitability over time. Thus, clearly deciding when the firm should allocate IT resources is critical for operational development and maximizing firm profitability. This lesson learned seems to have been institutionalized in the past by firms such as Air Canada that invested in 2007 in its web-based technology to be the first airline in offering its customers the online boarding pass and self-service IT applications to save costs and improve operational excellence. After its initial investments in e-business technology, Air Canada did not seem to need substantial additional investments in e-business technology to retain its operational development in the subsequent periods [40].

Financial analysts should pay attention to the firm's IT allocation decisions over time because these decisions can provide early signals about subsequent operational development and firm profitability over time [7]. Finally, our results also provide some empirical evidence to managers that investment in e-business technology enhances operational competence and firm profitability. Such evidence can help managers to better justify investments in e-business technology.

6. Concluding remarks

This study examined the evolution of the impact of e-business technology on operational competence and firm profitability by performing a panel data investigation on a sample of 154 large firms in Spain. We found that e-business technology has a positive effect on operational competence that decreases over time even becoming nonsignificant and that the firm's proficiency in exploiting a portfolio of operational capabilities has a positive impact on profitability that becomes more substantial over time. One key implication of the findings is that early IT investment is critical for the operational development and effect on firm profitability over time. Early development of IT-enabled operational capabilities maximizes firms' profitability because of a longer time and experience in developing their operational capabilities.

Acknowledgments

This research was sponsored by the European Regional Development Fund (European Union) and the Government of Spain (ECO2013-47027-P), the Regional Government of Andalusia (Research Project P11-SEJ-7294), and the COVIRAN-Prodware Chair of Digital Human Resource Strategy at the School of Human Resource Management of the University of Granada. This manuscript has benefited from the comments of Andres Navarro and the overall support of Ana Castillo and Jessica Braojos.

Appendix A

See Table A1

Table A1
Correlation matrix.

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13
1. E-business technology$_{t1}$	1												
2. E-business technology$_{t2}$	0.477	1											
3. E-business technology$_{t3}$	0.376	0.620	1										
4. Operational competence$_{t1}$	0.306	0.250	0.138	1									
5. Operational competence$_{t2}$	0.297	0.235	0.114	0.856	1								
6. Operational competence$_{t3}$	0.138	0.085	0.064	0.364	0.518	1							
7. Firm profitability$_{t1}$	0.137	0.152	0.104	0.218	0.306	0.213	1						
8. Firm profitability$_{t2}$	0.026	0.115	0.051	0.171	0.377	0.208	0.618	1					
9. Firm profitability$_{t3}$	−0.143	0.007	0.050	0.054	0.124	0.535	0.372	0.367	1				
10. Firm size$_{t1}$	0.113	0.108	0.147	−0.113	−0.180	−0.106	−0.209	−0.126	−0.077	1			
11. Firm size$_{t2}$	0.150	0.140	0.186	−0.125	−0.155	−0.131	−0.210	−0.122	−0.087	0.863	1		
12. Firm size$_{t3}$	0.208	0.189	0.251	−0.059	−0.100	−0.102	−0.144	−0.114	−0.104	0.815	0.874	1	
13. Industry	0.038	−0.170	−0.177	0.007	0.094	−0.011	0.126	0.109	−0.058	−0.178	−0.217	−0.194	1

Table A2
Results of test of significance on the changes in beta coefficients.

Time	Effect	Beta coefficient	Size of the change	Bias-corrected CI	Comparison of beta $coefficient_{t+1}$ with CI_t and of beta $coefficient_t$ with CI_{t+1}	Beta $coefficient_{t+1}$ inside CI_t?/Beta $coefficient_t$ inside CI_{t+1}?	Significant change?
t_1	E-business $technology_{t1}$ → Operational $competence_{t1}$ (H1b)	0.317^{***}	−0.291	[0.190, 0.463]	0.026 < 0.190	No	No
t_2	E-business $technology_{t2}$ → Operational $competence_{t2}$ (H1b)	0.026		[−0.286, 0.404]	−0.286 < 0.317 < 0.404	Yes	
t_2	E-business $technology_{t2}$ → Operational $competence_{t2}$ (H1b)	0.026	−0.013	[−0.286, 0.404]	−0.286 < 0.013 < 0.404	Yes	No
t_3	E-business $technology_{t3}$ → Operational $competence_{t3}$ (H1b)	0.013		[−0.082, 0.141]	−0.082 < 0.026 < 0.141	Yes	
t_1	E-business $technology_{t1}$ → Operational $competence_{t1}$ (H1b)	0.317^{***}	−0.304	[0.190, 0.463]	0.013 < 0.190	No	Yes
t_3	E-business $technology_{t3}$ → Operational $competence_{t3}$ (H1b)	0.013		[−0.082, 0.141]	0.141 < 0.317	No	
t_1	Operational $competence_{t1}$ → Firm $profitability_{t1}$ (H2b)	0.197^{*}	0.350	[−0.004, 0.420]	0.420 < 0.547	No	Yes
t_2	Operational $competence_{t2}$ → Firm $profitability_{t2}$ (H2b)	0.547^{***}		[0.211, 0.787]	0.197 < 0.211	No	
t_2	Operational $competence_{t2}$ → Firm $profitability_{t2}$ (H2b)	0.547^{***}	0.117	[0.211, 0.787]	0.211 < 0.664 < 0.787	Yes	No
t_3	Operational $competence_{t3}$ → Firm $profitability_{t3}$ (H2b)	0.664^{***}		[0.345, 0.851]	0.345 < 0.547 < 0.851	Yes	
t_1	Operational $competence_{t1}$ → Firm $profitability_{t1}$ (H2b)	0.197^{*}	0.467	[−0.004, 0.420]	0.420 < 0.664	No	Yes
t_3	Operational $competence_{t3}$ → Firm $profitability_{t3}$ (H2b)	0.664^{***}		[0.345, 0.851]	0.197 < 0.345	No	

Note: CI = Confidence interval.

References

[1] Y. Chen, Y. Wang, S. Nevo, J. Benitez, G. Kou, IT capabilities and product innovation performance: the roles of corporate entrepreneurship and competitive intensity, Inf. Manag. 52 (6) (2015) 643–657.
[2] T. Cui, H. Ye, H. Teo, J. Li, Information technology and open innovation: a strategic alignment perspective, Inf. Manag. 52 (3) (2015) 348–358.
[3] Y. Wang, Y. Chen, J. Benitez, How information technology influences environmental performance: empirical evidence from China, Int. J. Inf. Manag. 35 (2) (2015) 160–170.
[4] A. Ajamieh, J. Benitez, J. Braojos, C. Gelhard, IT infrastructure and competitive aggressiveness in explaining and predicting performance, J. Bus. Res. 69 (10) (2016) 4667–4674.
[5] N. Carr, IT doesn't matter, Harv. Bus. Rev. 81 (5) (2003) 1–8.
[6] B. Shao, W. Lin, Technical efficiency analysis of information technology investments: a two-stage empirical investigation, Inf. Manag. 39 (5) (2002) 391–401.
[7] S. Mithas, A. Tafti, I. Bardhan, J. Goh, Information technology and firm profitability: mechanisms and empirical evidence, MIS Q. 36 (1) (2012) 205–224.
[8] A. Rai, R. Patnayakuni, N. Seth, Firm performance impacts of digitally enabled supply chain integration capabilities, MIS Q. 30 (2) (2006) 225–246.
[9] S. Devaraj, L. Krajewski, J. Wei, Impact of ebusiness technologies on operational performance: the role of production information integration in the supply chain, J. Oper. Manag. 25 (6) (2007) 1199–1216.
[10] N. Sanders, An empirical study of the impact of e-business technologies on organizational collaboration and performance, J. Oper. Manag. 25 (6) (2007) 1332–1347.
[11] S. Ayabakan, I. Bardhan, Z. Zheng, The impact of IT-enabled manufacturing capabilities on plant profitability: new models and evidence, Proceedings of the 33rd International Conference on Information Systems, Orlando, Florida, USA, 2012, pp. 1–19.
[12] P. Setia, P. Patel, How information systems help create OM capabilities: consequents and antecedents of operational absorptive capacity, J. Oper. Manag. 31 (6) (2013) 409–431.
[13] B. Huo, C. Zhang, X. Zhao, The effect of IT and relationship commitment on supply chain coordination: a contingency and configuration approach, Inf. Manag. 52 (6) (2015) 728–740.
[14] S. Wu, S. Melnyk, B. Flynn, Operational capabilities: the secret ingredient, Decis. Sci. 41 (4) (2010) 721–754.
[15] J. Benitez, J. Llorens, V. Fernandez, IT impact on talent management and operational environmental sustainability, Inf. Technol. Manag. 16 (3) (2015) 207–220.
[16] M. Tatikonda, S. Terjesen, P. Patel, V. Parida, The role of operational capabilities in enhancing new venture survival: a longitudinal study, Prod. Oper. Manag. 22 (6) (2013) 1401–1415.
[17] J. Benitez, R. Walczuch, Information technology, the organizational capability of proactive corporate environmental strategy and firm performance: a resource-based analysis, Eur. J. Inf. Syst. 21 (6) (2012) 664–679.
[18] J. Braojos, J. Benitez, J. Llorens, Impact of IT infrastructure on customer service performance: the role of micro-IT capabilities and online customer engagement, Proceedings of the 19th Pacific Asia Conference on Information Systems, Singapore, Singapore, 2015, pp. 1–17.
[19] J. Benitez, A. Castillo, J. Llorens, J. Braojos, IT-enabled knowledge ambidexterity and innovation performance in small U.S. firms: the moderator role of social media capability, Inf. Manag. (2016) 1–41 (in press).
[20]. D. Peng, R. Schroeder, R. Shah, Linking routines to operations capabilities: a new perspective, J. Oper. Manag. 26 (6) (2008) 730–748.
[21] P. Pavlou, O. El Sawy, From IT leveraging competence to competitive advantage in turbulent environments: the case of new product development, Inf. Syst. Res. 17 (3) (2006) 198–227.
[22] J. Benitez, G. Ray, Introducing IT-enabled business flexibility and IT integration in the acquirer's M & A performance equation, Proceedings of the 33rd International Conference on Information Systems, Orlando, Florida, USA, 2012, pp. 1–21.
[23] J. Dong, C. Yang, Information technology and organizational learning in knowledge alliances and networks: evidence from US pharmaceutical industry, Inf. Manag. 52 (1) (2015) 111–122.
[24] D. Palacios, P. Soto, J. Merigo, Online social networks as an enabler of innovation in organizations, Manag. Decis. 53 (9) (2015) 1906–1920.
[25] Y. Chen, Y. Wang, S. Nevo, J. Benitez, Kou. G, Improving strategic flexibility with information technologies: Insights for firm performance in an emerging economy, J. Inf. Technol. 32 (1) (2017) 10–25.
[26] P. Huang, S. Pan, T. Ouyang, Developing information processing capability for operational agility: implications from a Chinese manufacturer, Eur. J. Inf. Syst. 23 (4) (2014) 462–480.
[27] R. Grant, Prospering in dynamically-competitive environments: organizational capability as knowledge integration, Organ. Sci. 7 (4) (1996) 375–387.
[28] P. Pavlou, O. El Sawy, Understanding the elusive black box of dynamic capabilities, Decis. Sci. 42 (1) (2011) 239–273.
[29] T. Teo, C. Ranganathan, Adopters and non-adopters of business-to-business electronic commerce in Singapore, Inf. Manag. 42 (1) (2004) 89–102.
[30] P. Soto, A. Merono, Analyzing e-business value creation from a resource-based perspective, Int. J. Inf. Manag. 28 (1) (2008) 49–60.
[31] J. Xin, T. Ramayah, P. Soto, S. Popa, T. Ping, Analyzing the use of web 2.0 for brand awareness and competitive advantage: an empirical study in the Malaysian hospitability industry, Inf. Syst. Manag. 31 (2) (2014) 96–103.
[32] D. Palacios, P. Soto, J. Merigo, Analyzing the effects of technological, organizational and competition factors on web knowledge exchange in SMEs, Telemat. Inform. 32 (1) (2015) 23–32.
[33] S. Soto, D. Popa, E-business, organizational innovation and firm performance in manufacturing SMEs: An empirical study in Spain, Technol. Econ. Dev. Econ. 22 (6) (2016) 885–904.
[34] G. Pan, S. Pan, C. Lim, Examining how firms leverage IT to achieve firm productivity: RBV and dynamic capabilities perspectives, Inf. Manag. 52 (4) (2015) 401–412.
[35] R. Banker, I. Bardhan, H. Chang, S. Lin, Plant information systems, manufacturing capabilities, and plant performance, MIS Q. 30 (2) (2006) 315–337.
[36] G. Bock, R. Zmud, Y. Kim, J. Lee, Behavioral intention formation in knowledge sharing: examining the roles of extrinsic motivators, social-psychological forces, and organizational climate, MIS Q. 29 (1) (2005) 87–111.
[37] S. Aral, E. Brynjolfsson, M. Van Alstyne, Information, technology, and information worker productivity, Inf. Syst. Res. 23 (3) (2012) 849–867.
[38] J. Benitez, J. Llorens, V. Fernandez, The relationship between IT infrastructure leveraging, talent management and operational sustainability, and their effects on the business value of the operations strategy, Proceedings of the 19th Americas Conference on Information Systems, Chicago, Illinois, USA, 2013, pp. 1–8.
[39] C. Law, E. Ngai, ERP systems adoption: an exploratory study of the organizational factors and impacts of ERP success, Inf. Manag. 44 (4) (2007) 418–432.
[40] F. Karimi, S. Rivard, Air Canada : Flying high with information technology, HEC Montreal Centre for Case Studies, 2014, pp. 1–20 HEC045.
[41] A. Dutta, H. Lee, M. Yasai, Digital systems and competitive responsiveness: the dynamics of IT business value, Inf. Manag. 51 (6) (2014) 762–773.
[42] S. Ahmad, R. Schroeder, The impact of human resource management practices on operational performance: recognizing country and industry differences, J. Oper. Manag. 21 (1) (2003) 19–43.
[43] G. Stahl, I. Bjorkman, E. Farndale, S. Morris, J. Paauwe, P. Stiles, J. Trevor, P. Wright, Six principles of effective global talent management, MIT Sloan Manag. Rev. 53 (2) (2012) 24–32.
[44] Z. Ton, S. Harrow, Mercadona Harvard Business School Case 9-610-089 (2010) 1–25.
[45] R. Beach, A. Muhlemann, D. Price, A. Paterson, J. Sharp, A review of manufacturing flexibility, Eur. J. Oper. Res. 122 (1) (2000) 41–57.
[46] M. Malhotra, A. Mackelprang, Are internal manufacturing and external supply chain flexibilities complementary capabilities? J. Oper. Manag. 30 (3) (2012) 180–200.
[47] Y. Chen, Y. Wang, S. Nevo, J. Jin, L. Wang, W. Chow, IT capability and organizational performance: the roles of business process agility and environmental factors, Eur. J. Inf. Syst. 23 (3) (2014) 326–342.
[48] M. Johnson, A. Herrmann, F. Huber, The evolution of loyalty intentions, J. Market. 70 (2) (2006) 122–132.
[49] A. Bharadwaj, A resource-based perspective on information technology capability and firm performance: an empirical investigation, MIS Q. 24 (1) (2000) 169–196.
[50] R. Santhanam, E. Hartono, Issues in linking information technology capability to firm performance, MIS Q. 27 (1) (2003) 125–153.
[51] T. Teo, A. Bhattacherjee, Knowledge transfer and utilization in IT outsourcing partnerships: a preliminary model of antecedents and outcomes, Inf. Manag. 51 (2) (2014) 177–186.
[52] J. Braojos, J. Benitez, J. Llorens, How do small firms learn to develop a social media competence? Int. J. Inf. Manag. 35 (4) (2015) 443–458.
[53] M. Serva, H. Kher, J. Laurenceau, Using latent growth modeling to understand longitudinal effects in MIS theory: a primer, Commun. Assoc. Inf. Syst. 28 (1) (2011) 213–232.
[54] K. Zhu, K. Kraemer, E-commerce metrics for net-enhanced organizations: assessing the value of e-commerce to firm performance in the manufacturing sector, Inf. Syst. Res. 13 (3) (2002) 275–295.
[55] A. Merono, P. Soto, External web content and its influence on organizational performance, Eur. J. Inf. Syst. 16 (1) (2007) 66–80.
[56] E. Rigdon, Rethinking partial least squares path modeling: in praise of simple methods, Long Range Plann. 45 (5–6) (2012) 341–358.
[57] J. Henseler, T. Dijkstra, M. Sarstedt, C. Ringle, A. Diamantopoulos, D. Straub, D. Ketchen, J. Hair, G. Hult, R. Calantone, Common beliefs and reality about PLS: comments on Ronkko & Evermann (2013), Organ. Res. Methods 17 (2) (2014) 182–209.
[58] T. Dijkstra, J. Henseler, Consistent partial least squares path modeling, MIS Q. 39 (2) (2015) 297–316.
[59] J. Henseler, Is the Whole More than the Sum of Its Parts? On the Interplay of Marketing and Design Research, Enschede, The Netherlands, University of Twente, 2015, pp. 1–40.
[60] J. Benitez, J. Henseler, A. Castillo, Development and update of guidelines to perform and report partial least squares path modeling in Information Systems research, Proceedings of the 21st Pacific Asia Conference on Information Systems, Langkawi, Malaysia, 2017, pp. 1–15.
[61] J. Henseler, G. Hubona, P. Ray, Using PLS path modeling in New Technology research: updated guidelines, Ind. Manag. Data Syst. 116 (1) (2016) 1–23.
[62] J. Benitez, R. Walczuch, IT, proactive environmental strategy and firm performance: a resource-based analysis, Proceedings of the 17th Americas Conference on Information Systems, Detroit, Michigan, USA, 2011, pp. 1–10.
[63] Q. Zhu, J. Sarkis, Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises, J. Oper. Manag. 22 (3) (2004) 265–289.
[64] Henseler, J., & Dijkstra, T. (2015). ADANCO Professional. Kleve, Germany : Composite Modeling, http://www.compositemodeling.com.

[65] D. Gefen, D. Straub, R. Rigdon, An update and extension to SEM guidelines for Administrative and Social Science research, MIS Q. 35 (2) (2011) iii–xiv.
[66] J. Benitez, J. Henseler, J. Roldan, How to address endogeneity in partial least squares path modeling, Proceedings of the 22nd Americas Conference on Information Systems, San Diego, California, USA, 2016, pp. 1–10.
[67] J. Cohen, Statistical Power Analysis for Behavioral Sciences, 2nd edition, Erlbaum, Hillsdale, New Jersey, USA, 1988.
[68] S. Mayr, E. Erdfelder, A. Buchner, F. Faul, A short tutorial of GPower, Tutor. Quant. Methods Psychol. 3 (2) (2007) 51–59.
[69] M. Aguirre, M. Ronkko, Sample size determination and statistical power analysis in PLS using R: an annotated tutorial, Commun. Assoc. Inf. Syst. 36 (3) (2015) 33–51.
[70] J. Henseler, G. Fassott, Testing moderating effects PLS path models: an illustration of available procedures, in: V. Esposito, W. Chin, J. Henseler, H. Wang (Eds.), Handbook of Partial Least Squares: Concepts, Methods and Applications, Springer, Berlin, Germany, 2010, pp. 713–735.
[71] W. Chin, How to write up and report PLS analyses, in: V. Esposito, W. Chin, J. Henseler, H. Wang (Eds.), Handbook of Partial Least Squares: Concepts, Methods and Applications, Springer, Berlin, Germany, 2010, pp. 655–690.
[72] X. Zhao, J. Lynch, Q. Chen, Reconsidering Baron and Kenny: myths and truths about mediation analysis, J. Consum. Res. 37 (2) (2010) 197–206.
[73] C. Nitzl, J. Roldan, G. Cepeda, Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models, Ind. Manag. Data Syst. 116 (9) (2016) 1849–1864.
[74] E. Roemer, A tutorial on the use of PLS path modeling in longitudinal studies, Ind. Manag. Data Syst. 116 (9) (2016) 1901–1921.
[75] S. Aral, E. Brynjolfsson, D. Wu, Which came first, IT or productivity? The virtuous cycle of investment and use in enterprise systems, Proceedings of the 27th International Conference on Information Systems, Milwaukee, Wisconsin, USA, 2006, pp. 1819–1840.

Jose Benitez is a Full Professor of IS at Rennes School of Business, France. Jose is also Visiting Professor of IS at the University of Twente, Enschede, The Netherlands, and Instructor of PLS Path Modeling at the PLS School. His research interests cover the study of how the firm's portfolio of IT capabilities affects organizational capabilities and firm performance, and the development of PLS path modeling in the field of IS. His research has been published in leading IS journals such as *MIS Quarterly, Information & Management, European Journal of Information Systems, Journal of Information Technology,* and *Journal of Business Research.* He currently serves as Associate Editor for *Information & Management,* and *European Journal of Information Systems,* as Guest Editor of *Decision Sciences,* and as a Guest Associate Editor for *Decision Support Systems.* Jose got a Ph.D. in Business Administration (with concentration in IS) from University of Granada, Spain. Jose can be contacted at jose.benitez@rennes-sb.com.

Yang Chen is a Professor of IS in the School of Business Administration, Southwestern University of Finance and Economics, China. His research has been published in *Information & Management, Journal of Information Technology, European Journal of Information Systems, Communications of the Association for Information Systems, Human Resource Management, International Journal of Human Resource Management,* and *Journal of Business Ethics*.

Thompson Teo is an Associate Professor in the School of Business and the School of Computing (by courtesy), National University of Singapore, Singapore. He has published more than 250 papers in leading journals and conferences. Thompson has served as Senior Associate Editor for the *European Journal of Information Systems* and is currently serving on the Editorial Boards of *Information & Management, Communications of the Association for Information Systems, MIS Quarterly Executive, and Omega*. He is also the Regional Editor (Pacific Asia) for the *International Journal of Information Management*. Thompson has co-edited four books on IS and is a four-time winner of the Society for Information Management Paper Competition.

Aseel Ajamieh is an Assistant Professor of IS at the College of Business Administration, Princess Nourah bint Abdulrahman University, Saudi Arabia. She got a Ph.D. in Business Administration (with concentration in IS) from University of Granada, Spain. In her research, she examines the effects of IT on the development of operational capabilities to create business value. Her research has been published in the *Journal of Business Research* and presented in the Decision Sciences Institute Annual Meeting.