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Predictive and mediation model for decision-making in the context of dynamic capabilities and knowledge management

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Abstract

Purpose – Drawing on resource and capability theory, this study aimed to analyze the relationship between the dynamic capabilities (DC), the knowledge management (KM) process (KMP) and results in customers and people. More specifically, the study argues that the KM process mediates the relationship between DC and the results outlined above. In addition, a predictive analysis is carried out that demonstrates the relevance of the KM process in the model.

Design/methodology/approach – The study sample is made up of 118 Spanish organizations that have some kind of recognition of excellence awarded by the European Foundation for Quality Management (EFQM). Partial least squares methodology is used to validate the research model, the hypothesis testing and the predictive analysis.

Findings – The results show that organizations which leverage the DC through the KMP improve customer and people outcomes. Moreover, the predictive power is higher when the KMPmediates the relationship between the DC and the results.

Originality/value – There is no consensus in the literature on the relationship between DC, KM and performance. Moreover, there are also not enough papers that study KM or DC through the dimensions that define these constructs or variables. Given this need, this work considers the KMP according to the stages of knowledge creation, storage, transfer and application. Similarly, DC is dimensioned in sensing, learning, integrating and coordinating capabilities. These, as reconfigurators of knowledge assets, influence the KMP. Accordingly, the empirical model connects these knowledge domains and analyses their link to outcomes.

Keywords Dynamic capabilities, Knowledge management, Customer results, People results, PLS-SEM, Mediation analysis, Predictive modelling

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1. Introduction

Through the resource-based view (RBV), the literature argues that the firm's resources and capabilities are sources of competitive advantage (Helfat and Peteraf, 2003). To achieve such

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advantages, it is vital for the organization to know how to develop its dynamic capabilities (DC), to reconfigure its resources into new combinations of ordinary or operational capabilities (Eisenhardt and Martin, 2000). In this way, organizations can support their strategies in the face of environmental turbulence (Prahalad and Ramaswamy, 2004), contributing to revenue generation or improving organizational response efficiency (Chmielewski and Paladino, 2007). DC are seen as the main source for creating new knowledge and capabilities, which are crucial for coping with today's rapidly changing environment (Hong *et al.*, 2008). In this sense, while the frequency and speed in the environment is important, the prevailing degree of uncertainty is even more important (Teece, 2016). Thus, knowledge is fundamental to achieve uncertainty reduction in organizations, and for this reason, the RBV considers knowledge as a key asset that can be a source of competitive advantage (Argote and Ingram, 2000). According to Cegarra-Navarro *et al.* (2023), the peculiarities of this environment require organizations to integrate their knowledge resources and adopt a proactive view of the DC of their employees and other stakeholders. In fact, from the development of the knowledge-based view (Nonaka, 1994; Nonaka and Takeuchi, 1995; Grant, 1997), authors such as Santoro *et al.* (2018) argue that organizational competitive advantage lies in the ability of companies to apply new and existing knowledge to create new products and processes. In this regard, according to Bolisani and Oltramari (2012), the knowledge-based organization encompasses a set of intangible resources and DC that foster organizational learning in order to achieve a competitive advantage.

From the above, it appears that DC can explain the achievement of competitive advantage in dynamic environments, as does the efficient development of the knowledge management process (KMP). However, the literature is inconclusive in determining how DC behaves with respect to knowledge management (KM). Thus, authors such as Ambrosini and Bowman (2009) stress the need to establish empirical models to explain it. For Alegre *et al.* (2013), certain KM practices directly influence DC, but they do not rule out the possibility of the inverse relationship. Easterby-Smith and Prieto (2008) understand the learning process from a KM perspective, which contributes to the creation and renewal of DC. Nielsen (2006) considers knowledge development, knowledge recombination and knowledge use as DC that influence KM and facilitate knowledge creation or renewal. Cepeda and Vera (2007) indicate that dynamic knowledge-based capabilities influence operational capabilities. For Makkonen *et al.* (2014) value creation and DC capture are responsible for reorganizing and transforming static resources such as knowledge. According to Gold *et al.* (2001), knowledge, in addition to being a resource, enhances organizational routines through processes. They also stress the importance of developing knowledge process capability, thereby improving organizational effectiveness. Authors such as Khaksar *et al.* (2020) consider the KMP as a dynamic process capability that will be affected by higher order DC.

Similarly, both fields of study have analyzed the impact on organizational outcomes and/or performance. Sandhawalia and Dalcher (2011) studied the impact of DC on KM, as well as their effects on technological performance. Gary *et al.* (2012) found that managerial DC to establish knowledge schemas facilitates knowledge transfer in a more efficient way, impacting on the bottom line. Sher and Lee (2004) argue that KM influences DC and that DC, in turn, positively influences performance. For Wilkens *et al.* (2004) and Eisenhardt and Martin (2000), competitive advantage is a consequence of the impact of DC, enhanced by learning and KM. According to Hung *et al.* (2009), KMPs that manage learning and knowledge in organizations serve as a basis for improving DC and, subsequently, their performance.

As we can see, there is no consensus in the literature on the relationship between DC, KM and performance. That said, there are also not enough papers that study KM or DC through the dimensions that define these constructs or variables. Given this need, our work considers the KMP according to the stages of knowledge creation, storage, transfer, and application

(Chang and Lin, 2015; Alavi and Leidner, 2001). Similarly, DC is dimensioned in sensing, learning, integrating, and coordinating capabilities (Pavlou and El Sawy, 2011). These, as reconfigurators of knowledge assets, influence the KMP. Accordingly, our empirical model connects these knowledge domains and analyzes their link to outcomes. In this model, the four dimensions of DC would adopt a second-order categorization (Zollo and Winter, 2002) that would influence the KMP, whose stages would operate as first-order capabilities. In this sense, DC reconfigures and enhances KM capabilities (Criado-García *et al.*, 2020). KMP capabilities serve to organize, combine, and coordinate knowledge in a meaningful and structured way, improving knowledge usability (Gold *et al.*, 2001) and impacting on potential outcomes. In this context, the aim of our study is to advance the understanding of the relationships between DC - given that this field encounters a practical limitation (Helfat, 2007) – the KMP and outcomes. According to Schilke (2014), it is necessary to analyze not only the link between second-order DC and performance outcomes, but also to determine whether an improvement in outcomes is due to an indirect effect of DC linked to organizational processes. Cepeda and Vera (2007) invite us to analyze the indirect impact of DC on competitive advantage through the establishment of operational routines. For this purpose, we will examine the mediating effect of the KMP between DC and outcomes, particularly customers and employees. The analysis incorporates a predictive study of both models, which complements and enriches the mediation analysis and will determine the importance of the KMP in the effect of DC on outcomes.

Accordingly, our paper is structured as follows. After the Introduction, a literature review is presented, and the research hypotheses are developed. In the next section, Method, the research methodology is described. Subsequently, the empirical analysis is carried out and the results are shown. Finally, the results are discussed, and the implications, conclusions, limitations, and future lines of research are set out.

2. Theoretical framework and hypotheses

2.1 Dynamic capabilities

Capabilities are divided into DC and operational capabilities (Helfat and Winter, 2011). Teece *et al.* (1997) defined DC as the firm's ability to integrate, build and reconfigure internal and external competencies to cope with rapidly changing environments. A work of Augier and Teece (2009) highlights the power of DC to detect and seize new opportunities. Moreover, such capabilities reconfigure and protect knowledge assets, competencies, and other assets in order to gain a competitive advantage (Loureiro *et al.*, 2021). Zollo and Winter (2002) emphasize the innovative character of DC, which modifies operational routines by making use of ordinary capabilities and organizational resources to improve processes. On the other hand, Eisenhardt and Martin (2000) conceive of DC as organizational processes of integration and reconfiguration of resources that favor the creation of knowledge in dynamic environments. DC are also necessary to harness, create, access and release ordinary - static - capabilities in response to environmental dynamism (Eisenhardt and Martin, 2000). Under this division, DC influence operational capabilities (Khaksar *et al.*, 2020). It is from this idea that the literature is enriched, and some researchers differentiate between first-order and higher-order capabilities (Zollo and Winter, 2002). In the higher order would be DC, which modifies the organization's resources and capabilities, improving processes and finding more innovative solutions (Savastano *et al.*, 2022). Clarifying through categorization the relationship between DC and ordinary DC, as well as the relationship between them, can facilitate organizational decision-making in dynamic environments (Suddaby, 2010). Winter (2003) makes a distinction between operational (zero-order or ordinary) and dynamic (first-level or order) capabilities. In this sense, DC modify the resource base of organizations and alter routines, reconfigure processes and impact on operational capabilities (Leemann and

Kanbach, 2022). Other authors. such as Ambrosini and Bowman (2009), distinguish between incremental, renewal and, finally, regenerative capabilities. For Zollo and Winter (2002), DC act as higher-order routines, shaping systematic methods in the organization that modify zero-order, i.e. operational, routines.

Research has enriched the study of capacity development by identifying several phases or dimensions that facilitate the interpretation of capacity development and give it a broader body. Li and Liu (2014) classified DC into three dimensions: strategic sense-making capacity, timely decision-making capacity and change implementation capacity. Tseng and Lee (2014) used two dimensions of capabilities: sensing and integration. Denford (2013) classified DC as creating, integrating, reconfiguring, replicating, developing, assimilating, synthesizing, and imitating. Inspired by the work of Teece *et al.* (1997) on the tasks of coordination/integration, learning and reconfiguration in organizational processes, and environmental sensing as a key activity to achieve a competitive advantage (Teece, 2007), Pavlou and El Sawy (2011) present a model of DC delimited by four phases or dimensions. First, the sensing capability, i.e. the ability to identify, interpret and find new opportunities. Second, the learning capability, which involves renewing knowledge and skills that will result in a renewal of capabilities. The third phase is the integration phase, i.e. connecting individual knowledge with collective knowledge. And, finally, the coordination phase emphasizes the need to plan new tasks, or resources. These dimensions encompass a set of ordered capabilities that contribute to reconfiguring operational capabilities. This model of Pavlou and Sawy would improve the KMP. It is our aim to analyze the relationship between the two.

2.2 Knowledge management process

Building on the seminal study of Alavi and Leidner (2001), whose conceptualization inspired the work of Lee and Choi (2003) and Lin and Huang (2008), we define the KMP as the structured coordination of effective KM, through mechanisms of knowledge creation-capture, storage, transfer-exchange and application-use. Understanding these mechanisms is critical for organizations wishing to take advantage of KM by being able to maximize the effectiveness and performance of knowledge assets (Chou *et al.*, 2005). According to Gold *et al.* (2001), mechanisms for knowledge creation, storage, transfer, and application allow knowledge and skills to be shared throughout the organization.

The theory of organizational knowledge creation, through the model of socialization, combination, externalization, and internalization explains the knowledge generated in the organization (Nonaka and Takeuchi, 1995). According to Nonaka *et al.* (2000), knowledge creation is a capability that helps the organization to continuously improve by updating the existing knowledge base. Similarly, knowledge is also identified, acquired, and accumulated in the organization (Gold *et al.*, 2001; Zahra and George, 2002), involving the creation as well as the sharing or dissemination of knowledge (Mills and Smith, 2011). However, creating or acquiring knowledge does not generate performance *per se* for the organization (Cohen and Levinthal, 1990). To have an impact on the bottom line, knowledge must be applied effectively and efficiently, with the application of knowledge being the key to success in achieving a sustainable competitive advantage (Dröge *et al.*, 2003). According to Gold *et al.* (2001), the actual use of knowledge is manifested in the application of knowledge, which is strategically important for the organization and its efficiency. This is made possible by knowledge transfer, which connects the sender of the knowledge transfer and the receiver, who will apply it according to his or her own purposes (Argote and Ingram, 2000). In order for this existing knowledge - which will be used for a future application - to be available, it will need to be stored and organized in an orderly manner, allowing for an efficient transfer of knowledge when needed (Alavi and Leidner, 2001). In short, through the generation, storage, transfer and utilization of knowledge, KM performance is enhanced and hence its impact on the organization (Zaim *et al.*, 2007).

2.3 Relationships between dynamic capabilities and customer–people results

Authors such as Wang *et al.* (2015), Lin and Wu (2014), Wilden *et al.* (2013), Drnevich and Kriauciunas (2011) and Zahra *et al.* (2006) argue how DC leads to improved performance. Some papers analyze the direct effect of DC on specific outcomes, such as on employees or customers. For Ferreira *et al.* (2020), DC has a positive impact on employee performance through creativity or innovation, and indirectly on the achievement of competitive advantages (Farzaneh *et al.*, 2021). Bieńkowska and Tworek (2020) study how DC directly and positively influence employee satisfaction and subsequently contribute to improving employee performance. On the other hand, in order to create customer value, Hubbard *et al.* (2008) propose that organizations develop and use DC to transform operational capabilities through learning. In this regard, Wang and Ahmed (2007) and Benner and Tushman (2003) emphasize the importance of setting up DC to foster management processes that have a direct impact on the customer and bring superior value to the organization.

From the above, DC contribute to an organization's reconfiguration of its resource base, adapting to changing demand and satisfying, among others, the customer, or employees (Zahra and George, 2002). However, more work is needed to help determine whether this contribution is direct. This leads to the formulation of the following hypotheses:

H1. DC relate positively to customer results.

H1II. DC relate positively to people results.

2.4 Relationships between the knowledge management process and customer–people results

Several papers highlight how the KMP can help organizations to improve performance and enhance their competitive advantage (Xue, 2017). Our study focuses on customer and employee outcomes.

First, for the organization to deliver better customer outcomes, it is necessary to analyze, evaluate and update the company's knowledge about the customer. In this respect, knowledge sharing between the organization and the customer is essential to identify specific needs that, if met, will improve customer expectations and satisfaction (De Vries *et al.*, 2006). In this sense, KM is a strategic source that creates value for the customer (Migdadi, 2021), improving the performance of customer services (Xue, 2017). Through the KMP, better services are offered to customers, improving customer satisfaction, and achieving a more competitive organization (Vorakulpipat and Rezgui, 2008). Finally, authors such as Cepeda-Carrion *et al.* (2017) and Zack *et al.* (2009) confirm that KM practices contribute to improved customer outcomes.

Similarly, KM is conceived by different authors (Meher and Mishra, 2022; Chou *et al.*, 2005) as an innovative organizational practice that contributes to employee satisfaction. According to Singh and Sharma (2011), KM practices have a positive effect on the work environment and task content, fostering knowledge worker performance. According to Jimenez-Jimenez and Sanz-Valle (2012), organizations generate knowledge that is transmitted among employees, who have the ability to learn and share such knowledge among their peers. Zack *et al.* (2009) argue that generating knowledge and transferring it among workers is key to acquiring new individual and group skills that lead to improved outcomes for the employees themselves. If provided to the right employees at the right time, knowledge has great value (Chou *et al.*, 2007). In this sense, the manager must enable knowledge to flow successfully among employees and improve organizational performance (Butt *et al.*, 2022). Thus, the following hypotheses are proposed:

H2. KMPs relate positively to customer results.

H2II. KMPs relate positively to people results.

2.5 Mediating effect of knowledge management on the relationship between dynamic capacity and customer–people results

Although in principle Teece (2007) and Teece *et al.* (1997) establish a direct relationship between DC and organizational performance, authors such as Helfat (2007) disassociate the direct relationship and argue that DC do not inevitably lead to competitive advantage. Researchers argue that although DC can change the resource base, they cannot by themselves create valuable, rare, inimitable, and non-substitutable resources (VRIN) (Helfat, 2007; Zahra *et al.*, 2006). In the same vein, Eisenhardt and Martin (2000) disassociated the direct relationship and postulated that, by themselves, DC do not achieve a competitive advantage, arguing for an indirect relationship between DC and performance. Pavlou and El Sawy (2011) found that DC indirectly influence performance through the reconfiguration of (ordinary) operational capabilities. Indeed, authors such as Zahra *et al.* (2006) claim that DC transform substantive capabilities as well as the firm's knowledge base, affecting organizational performance. Authors such as Laaksonen and Peltoniemi (2018) argue that DC do not alter organizational performance directly, but act through ordinary capabilities or their resource base, aided by the dynamic environment (Ambrosini and Bowman, 2009). DC will explain changes in performance, not performance *per se* (Wilden *et al.*, 2013). Drnevich and Kriauciunas (2011) argue that DC positively affect organizational performance, though, for example, the development of new processes. Furthermore, the changing environment requires organizations to continuously adapt, and DC play a key role, reconfiguring and enhancing KM capabilities (Criado-García *et al.*, 2020). Gold *et al.* (2001) underline in their work that dimensions such as knowledge acquisition, conversion, application, and protection are process capabilities. According to Criado-García *et al.* (2020), DC reconfigure and enhance the KM operational capability, helping to improve organizational outcomes. This leads to the formulation of the following hypotheses:

H3. DC relate positively to KMPs.

H4. KMPs positively mediate the relationship between DC and customer results.

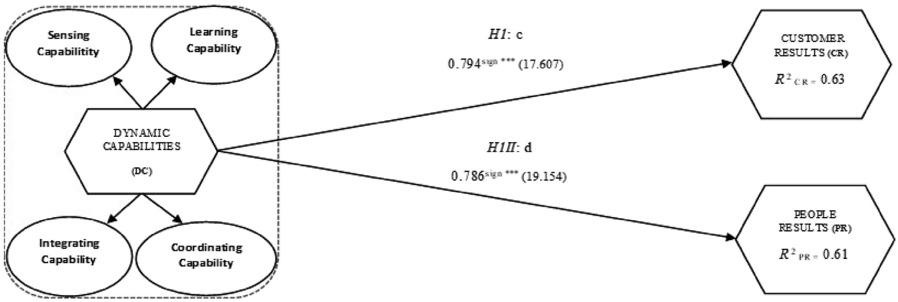
H4II. KMPs positively mediate the relationship between DC and people results.

Given the current environment, its competitiveness and dynamism, it is key to demonstrate how DC activate the KMPs' mediating effects, positively influencing customer and employee outcomes. DC will enable the organization to create new knowledge that it can leverage efficiently. Through the dimensions of sensing, learning, integration, and coordination, the KMP is fostered in the way knowledge is acquired, stored, transferred and applied. Through DC, the organization will implement better KM routines, impacting on staff and customer outcomes.

This study presents a research model (Figure 1) that relates DC to the KMP and the outcomes for customers and people.

In summary, the theoretical assumptions revolve around the significance of DC and KMPs in attaining competitive advantages, adapting to dynamic environments, and enhancing outcomes for both customers and employees. The convergence of these two fields of study not only complements each other but also enriches our understanding of how organizations should enhance a critical intangible asset for their survival. In this context, knowledge, which does not inherently generate performance, requires an efficient mechanism that is stimulated by DC. Therefore, our primary contribution lies in advancing knowledge in these two domains.

The economic assumptions supported by the existing literature are based on the premise that effective KM and the exploitation of DC can generate economic value and enhance organizational performance, ultimately leading to the attainment of competitive advantages. These assumptions significantly contribute to the advancement of our understanding of the relationships among DC, KMPs, and outcomes for both customers and employees.



Source(s): Authors' own creation

Figure 1.
Research model with total effect

3. Method

3.1 Data collection and sample

The study population consists of national organizations that have been awarded a European seal of excellence by the European Foundation for Quality Management (EFQM). These organizations are committed to knowledge, innovation, and capacity development and improvement as strategic drivers to achieve competitive advantages in their respective markets. According to information on its website (www.clubexcelencia.org), as of December 2020 there were 582 organizations with some form of EFQM Recognition. These organizations form the target population for this study. The EFQM self-assessment methodology is supervised by certifying bodies such as AENOR, SGS and Bureau Veritas, among others, to ensure the correct application of the procedures.

According to Hair *et al.* (2011), PLS-SEM recommends estimating the sample size effect considering the model and the data itself. Therefore, we performed a statistical power analysis using G*Power software that determined, for an error probability of 5%, effect size 0.15 and Power 0.8, a Total Sample Size of 43. We also met the standards of Hair *et al.* (2019), with a probability of error of 5%, a Power of 0.80 and according to the maximum number of independent variables that are related to any construct of the structural model. Also, as an instrument for data collection, a questionnaire was sent by email and post to senior executives such as quality managers, general managers and other area managers. The first questionnaires were sent out in December 2020, while the last ones were received in December 2021 and 118 surveys were validated with a response rate of 20.27%. The organizations in the sample can be classified according to different criteria:

(1) *Level of excellence*: In the data collection period, the EFQM had four levels of awards depending on the organization's score after the self-assessment and external evaluation processes (between 0 and 1000 points): 200+ (Commitment to Excellence) and European Seals of Excellence 300+ (3-star), 400+ (4-star) and 500+ (5-star). The 2013 and 2020 versions of the European model coexisted until mid-2021. Thus, organizations had the option to be assessed by either of them. Consequently, there is still insufficient data on experiences and results in the application of the EFQM 2020 model. In this respect, 24.57% of the organizations have Committed to Excellence (200+), 21.19% obtained a Recognized for Excellence (300+), 27.12% had a 400+ recognized, and finally, 27.12% had the top 500+ seal of excellence. The recognition level seals are valid for a period of two years during which the organizations must develop and improve their management. After this time, they must demonstrate that changes and improvements have been made, in order to progress to a higher level of recognition.

(2) *Company Size*: where micro enterprises (6.87%), small enterprises, between 10 and 49 employees (30.75%), medium-sized organizations, between 50 and 249 employees (35.89%), and, finally, enterprises with more than 249 employees (26.49%) were surveyed.

(3) *Sector:* According to the classification established by the Club of Excellence of EFQM in Spain for the type of sector of activity, we have the data and their frequency (approximate percentage): Service Sector (39.8%), Public Administration (17.84%), Education (19.49%), Health (16.94%), Others (5.93%).

From the above, according to the sample obtained in our research (118 subjects), PLS estimates structural models with smaller sample sizes. Chin (2010) and Reinartz *et al.* (2009) argue that a model with reflective measures can be analyzed with at least 100 observations and reach acceptable levels of statistical power.

3.2 Measures

The data were obtained through a questionnaire, divided into four parts. The first part contains contextual variables such as number of employees and EFQM Level of excellence. The remaining three parts refer to the variables that make up the research model, measured on a seven-point Likert scale (1 being a high level of disagreement and 7 being a high level of agreement). First, for DC we used 19 items from the work of Pavlou and El Sawy (2011). DC is a higher multidimensional construct that has been constituted by the dimensions sensing, learning, integration, and coordination under a reflective approach. These dimensions, established in our model as first-order constructs, form a second-order construct estimated in Mode A. According to Hair *et al.* (2019) and Chin (2010), Mode A in PLS-SEM obeys a composite created to model reflective measurement constructs. On the other hand, 16 items were used to measure the dimensions of the KMP construct. This is a second-order construct that was estimated in Mode A as the correlations between the dimensions of the constructs were expected to be high. The dimensions that make up the KMP construct are first-order reflective, and shape the phases of the process: creation, storage, transfer, and application. Works such as that of Gold *et al.* (2001) have served as a reference for defining the items of the questionnaire. To conclude, the constructs referring to the customer results (CR) and people results (PR) measures have a single dimension, estimated in Mode A. The indicators and measurement scales have been obtained from the MS results sub-criteria (EFQM, 2012).

3.3 Data analysis

The constructs in our study represent a composite measurement model (Rigdon, 2012). This is why we use the partial least squares (PLS) technique, a variance-based structural equation modeling to test the research model. Among other reasons justifying the use of PLS, the model has been estimated in Mode A, using correlation weights (Becker *et al.*, 2013). According to Rigdon (2012), the selection of PLS is also motivated by its use of component scores in the subsequent analysis to model multidimensional constructs using a two-stage approach. The main disadvantage of a small sample is that it may not accurately represent the population. However, in this case, the population is controlled and also small. Our sample ($n = 118$) is smaller than 250 (Reinartz *et al.*, 2009). In this regard, according to what the authors indicate, PLS can estimate structural models with small samples, which is an advantage, given that the target population is also small. Finally, as in our study we conducted a predictive analysis, according to Shmueli *et al.* (2016), the use of PLS is equally favorable. These circumstances justify the use of PLS, using the software SmartPLS 3.3.5 (Ringle *et al.*, 2015).

4. Results

Next, we evaluate the research model using PLS-SEM. Firstly, we analyze the external model, which will consider the relationships between the latent variables and their respective manifest variables. Secondly, we analyze the internal model of the latent variables.

4.1 Measurement model

All first and second-order constructs established in the model are of a reflective nature (Mode A). Thus, the correlation of indicators and composite dimensions is relied upon, as the constructs were designed as tools. Therefore, we can apply the reliability measures and validate the internal consistency, according to Henseler *et al.* (2016) (Table 1), first, assessing the indicator loadings and their significance. Following Henseler *et al.* (2014), the external loadings of the indicator show values above 0.707. This indicates that the construct explains more than 50% of the variance of the indicator, suggesting a satisfactory level of reliability of the indicator (Hair *et al.*, 2019). According to Nunnally and Bernstein (1994), regarding internal consistency, each of the first and second-order reflective constructs demonstrates high and satisfactory levels of internal consistency reliability, exceeding 0.7. Consequently, the variables meet the requirement for construct reliability (composite reliability) (Hair *et al.*, 2019).

As for the study of convergent validity, the average variance extracted (AVE) was analyzed. In this regard, as the values of all constructs and dimensions exhibit AVEs greater than the threshold of 0.5, this criterion is satisfied, and, therefore, more than 50% of the variance in the reflective indicators is explained by the latent variable (Fornell and Larcker, 1981). Finally, to analyze the discriminant validity, we applied the Fornell–Larcker and HTMT criteria (Henseler *et al.*, 2014) (Table 2). Through the Fornell–Larcker criterion we compare the square root of the AVE with the correlations. In this respect, the discriminant validity is satisfactory because the diagonal (bold) items are significantly higher than the off-diagonal items in the corresponding rows and columns (Fornell and Larcker, 1981). Therefore, all constructs are valid measures of specific concepts. Likewise, as for the heterotrait-monotrait correlations ratio (HTMT), which assesses the average of the heterotrait-heteromethod correlations (Henseler *et al.*, 2015), discriminant validity is also achieved, presenting values equal to or below 0.85.

4.2 Structural model results

The R^2 values presented in Table 3 indicate, for the two models under study, the variance explained in the endogenous variables and the path coefficients. Model I is a model with direct relationships; on the contrary, model II presents a mediating effect. According to Chin (1998), the R^2 values for customer results (0.67) and people results (0.68) are substantial when we consider the KMP construct as a mediator of the relationships. In contrast, they are moderate when the relationship is direct, with a lower coefficient of determination for Customer Outcomes (0.630) and for People Outcomes (0.617). From the above it can be seen that the model that considers KMP as a mediator presents a substantial improvement in its ability to explain the variance of the dependent variables (CR and PR) compared to the previous one. Regarding the collinearity statistics (VIF), in both models they present data below 3.3 (Diamantopoulos and Siguaw, 2006), which indicates a positive assessment of collinearity in the antecedent variables. Following Hair *et al.* (2019), bootstrapping (5000 resamples) was performed using SmartPLS software to obtain standard errors and *t*-values, thus demonstrating the significance of the hypothesized relationships in our study. In this respect, there is significance for all the direct effects presented in Model 1 b (Model with an indirect effect).

Construct/*Dimension*/Indicator	Loadings	Weights	CR	AVE
KM Process (MC)			0.959	0.855
Knowledge creation (composite Mode A)				
GC1. Units or departments interact with senior management to acquire new knowledge	0.755	0.263		
GC4. Other areas are visited for information or communication	0.795	0.257		
GC8. New opportunities to serve customers are quickly identified	0.812	0.231		
GC10. Changes in our customers' tastes are quickly analyzed and interpreted	0.852	0.245		
GC11. The consequences of market changes on new services are routinely considered	0.794	0.253		
Knowledge storage (composite Mode A)				
GC12. Employees retain and archive new information for future use	0.825	0.352		
GC31. Storing and organizing knowledge	0.938	0.384		
GC32. Replacing obsolete knowledge	0.900	0.389		
Knowledge transfer (composite Mode A)				
GC23. Incorporating knowledge into the implementation of new products and services	0.866	0.409		
GC28. Incorporating the knowledge of other companies into the company	0.850	0.334		
GC29. Distributing knowledge throughout the company	0.902	0.401		
Knowledge application (composite Mode A)				
GC34. Applying the lessons learned from experience	0.895	0.243		
GC37. Quickly finding the kind of knowledge needed to solve each problem	0.909	0.224		
GC39. Using knowledge to adapt strategic plans	0.878	0.216		
GC40. Locating and applying the knowledge needed to change competitive conditions	0.911	0.223		
GC43. Quickly applying the necessary knowledge in urgent and/or critical competitive situations	0.871	0.213		
Dynamic capabilities (DC)			0.963	0.868
Sensing capability (composite mode A)				
CDd1. Frequently explores the environment to identify new business opportunities	0.876	0.249		
CDd2. Regularly reviews the effect of changes in its business environment on clients	0.927	0.277		
CDd3. Reviews product/service development efforts to ensure that they are in line with what the customer wants	0.932	0.288		
CDd4. Spends time implementing new product/process ideas and improving existing ones	0.910	0.282		
Learning capability (composite mode A)				
CDa5. Has effective processes and routines for identifying, assessing and importing new information and knowledge	0.881	0.214		
CDa6. Has appropriate processes and routines for assimilating new information and knowledge	0.895	0.220		
CDa7. Is effective in transforming existing information into new knowledge	0.906	0.239		
CDa8. Is effective in using knowledge in new products/processes	0.867	0.227		
CDa9. Is effective in developing new knowledge that has the potential to influence product/process development	0.923	0.218		
Integrating capability (composite mode A)				
CDi10. Employees are willing to contribute their individual efforts to the organization	0.751	0.176		
CDi11. There is a comprehensive understanding of the tasks and responsibilities of each employee	0.905	0.215		

(*continued*)

Table 1.
Measurement model

Construct/*Dimension*/Indicator	Loadings	Weights	CR	AVE
CDi12. Is aware of who has specialized skills and knowledge relevant to the job	0.883	0.233		
CoI13. Carefully interrelates his or her actions to adapt to changing conditions	0.885	0.259		
CDi14. You get your employees to successfully interconnect their activities	0.921	0.257		
Coordinating capability (composite Mode A)				
CDc15. It is ensured that the output of each employee's work is synchronized with that of others	0.875	0.223		
CDc16. Ensures appropriate allocation of material and immaterial resources	0.869	0.220		
RQ17. Assigns tasks to employees commensurate with their skills and abilities	0.859	0.204		
CDc18. Ensures that there is compatibility between employees' expertise and work processes	0.912	0.235		
RQ19. Overall, it is well coordinated	0.926	0.242		
Customer results (composite Mode A)			0.934	0.740
CR1. Increased customer value for products and services	0.860	0.242		
CR2. Improving the distribution of products and services	0.845	0.216		
CR3. Increased customer loyalty and commitment	0.898	0.245		
CR4. Improved service, attention and support to the customer	0.835	0.222		
CR5. Involvement of customers in the design of products, processes and/or services	0.863	0.237		
People results (composite Mode A)			0.943	0.769
PR1. Increased employee satisfaction	0.892	0.236		
PR2. Increased employee motivation	0.905	0.235		
PR3. Acquisition of skills and improvement of staff training	0.859	0.223		
PR4. Improving communication between workers	0.848	0.223		
PR5. Improving working conditions	0.880	0.222		

Note(s): CR: composite reliability; AVE: average variance extracted; MC: multidimensional construct
Source(s): Authors' own creation

Table 1.

Fornell–Larcker criterion					Heterotrait-monotrait ratio (HTMT)				
	CR	DC	KMP	PR		CR	DC	KMP	PR
CR	**0.860**				CR				
DC	0.790	**0.932**			DC	0.846			
KMP	0.772	0.809	**0.925**		KMP	0.829	0.818		
PR	0.805	0.784	0.781	**0.877**	PR	0.832	0.835	0.825	

Note(s): CR: customer results; DC: dynamic capabilities; KMP: knowledge management process; PR: people results
Fornell–Larcker criterion: diagonal elements (bold) are the square root of the variance shared between the constructs and their measures (AVE). Off-diagonal elements are the correlations among constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements
Source(s): Authors' own creation

Table 2.
Discriminant validity

For the first model (Figure 1 Model with total effect), there is a positive direct effect of DC relationships on CR (path coefficient c = 0.79; *t*-value = 17.60), and PR (path coefficient d = 0.79; *t*-value = 19.15). However, when we include the mediating variable KMP in the model (hypotheses H4 and H4II), the direct relationships DC-CR and also DC–PR remain

Table 3.
Structural model results

Model I								
$R^2_{CR} = 0.630$ $R^2_{PR} = 0.617$			Model II $R^2_{CR} = 0.675$ $R^2_{PR} = 0.677$ $R^2_{KMP} = 0.654$					
				Percentile		Bias corrected		
Relationships	*Path coefficient*	*Support*	*Path coefficient*	Bootstrap lower	95% CI upper	Lower bias corrected	Upper bias corrected	Support
H1: DC→CR	0.794*** (17.607)	Yes	0.478*** (6.525)	0.36	0.599	0.36	0.599	Yes
H1II: DC→ PR	0.786*** (19.154)	Yes	0.439*** (5.195)	0.301	0.579	0.3	0.577	Yes
H2: KMP→ CR			0.385*** (5.116)	0.264	0.509	0.261	0.506	Yes
H2II: KMP→ PR			0.426*** (5.300)	0.292	0.555	0.292	0.555	Yes
H3: DC→ KMP			0.809*** (18.621)	0.73***	0.871	0.732***	0.873	Yes

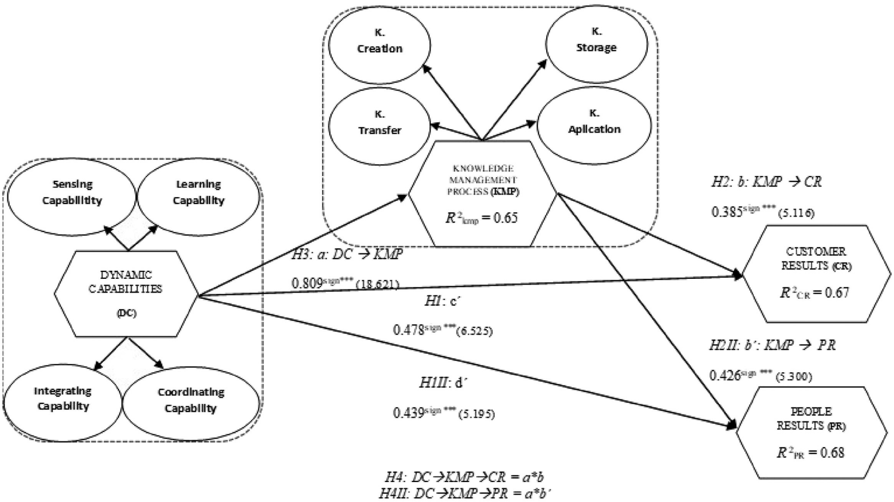
Note(s): DC: dynamic capabilities; CR: customer results; PR: people results; KMP: knowledge management process
t Values in parentheses: t (0.05, 4999) = 1.645; t(0.01, 4999) = 2.327; t(0.001, 4999) = 3.092
*$p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
Source(s): Authors' own creation

positive but decrease. When we look at the direct relationships in model 2 (Figure 2 Model with an indirect effect) we can confirm that the mediation hypotheses are fulfilled. Specifically, for DC on CR (path coefficient c' = 0.478; *t*-value = 6.525) and for DC on PR (path coefficient d' = 0.439; *t*-value = 5.195). The results demonstrate that KMP functions as a critical factor in facilitating the transmission of the effects of DC on both customer outcomes and organizational staff outcomes. By acting as a mediating variable, KMP becomes a key mechanism through which DC indirectly influence these strategically important outcomes.

In our study we have collected the indirect effect of DC on CR and DC on PR, by means of the mediating construct KMP. The indirect effects reflected (Table 3) are consistent, positive and increase through the KMP. The confidence interval, with a bootstrapping of 5000 resamples, at 95% for the indirect effect, is greater than 0 (Hair *et al.*, 2019), which indicates that there is statistical evidence of a significant indirect effect. Following Hayes and Scharkow (2013), we also include the bias-corrected bootstrap CI. According to Nitzl *et al.* (2016), the current findings confirm the presence of partial mediation, whereby the KMP variable acts as a mediator in the relationship between the constructs of DC and CR, as well as between the constructs of DC and PR. Following Williams and MacKinnon (2008), our study applied the bootstrapping technique in order to evidence the mediating effect. According to Chin (2010), we used the specific model, incorporating direct as well as indirect paths. Then, we perform an N-bootstrap resampling (5000 resamples for our study) and finally, we multiply the direct paths, which make up the indirect paths, the object of our analysis. The resampling also includes, for the mediator construct, its 95% confidence intervals (percentile). In summary, the results obtained support the presence of a significant indirect effect mediated by the KMP variable on the relationships between DC, CR and PR.

4.3 Predictive model assessment

According to Shmueli *et al.* (2019), the predictive power of a statistical model is crucial to assess the theory and practical relevance of our analysis. The present study explores the predictive power of the presented models (Figure 1; Figure 2). Both models contain two equal endogenous constructs (customer results and people results) that are theoretically related to



Source(s): Authors' own creation

Figure 2.
Research model with an indirect effect

the other constructs, either directly or indirectly, depending on the study streams. In the direct model, DC is linked to these results. On the other hand, in the model in Figure 2, the KMP is the construct that mediates the relationship between DC and the dependent constructs CR and PR. Therefore, our study aims to answer the following questions: first, to what extent DC predicts customer results and people results. Secondly, whether the KMP as a mediating construct improves or worsens the initial prediction. Following Hair *et al.* (2019), we assess the out-of-sample predictive power of models with total effect and indirect effect to analyze how they can predict unseen data (Danks and Ray, 2018). To do so, we turn to PLSpredict, under the holdout sample-based approach, developed by Shmueli *et al.* (2016). According to Danks and Ray (2018), this approach makes it possible to test the extent to which it is possible to generalize a model to other populations. The PLS prediction was first performed by k-fold cross-validation, setting k = 4 subgroups for each subgroup to meet the required minimum sample size (N = 30) for the holdout sample. This procedure was repeated 10 times. Next, following the steps outlined by Shmueli *et al.* (2019), a PLSpredict analysis was performed for both models (Table 4 and Table 5).

Table 4. PLSpredict assessment of indicators in the direct model

PLSpredict assessment of indicators in the direct model

Indicator	PLS RMSE	PLS MAE	PLS Q^2*predict*	LM RMSE	LM MAE	LM Q^2*predict*	PLS – LM RMSE	PLS – LM MAE	PLS – LM Q^2*predict*
CR1	0.826	0.607	0.561	0.832	0.606	0.555	−0.006	0.001	0.007
CR2	1.045	0.736	0.321	1.047	0.774	0.318	−0.002	−0.038	0.003
CR3	0.885	0.654	0.473	0.923	0.681	0.427	−0.037	−0.028	0.046
CR4	0.774	0.566	0.440	0.807	0.594	0.390	−0.033	−0.028	0.049
CR5	1.069	0.824	0.448	1.089	0.815	0.427	−0.020	0.009	0.021
PR1	0.926	0.717	0.537	0.932	0.725	0.531	−0.006	−0.008	0.006
PR2	0.943	0.723	0.506	0.932	0.727	0.517	0.011	−0.003	−0.011
PR3	0.856	0.652	0.442	0.891	0.676	0.395	−0.035	−0.023	0.047
PR4	0.907	0.696	0.379	0.948	0.714	0.321	−0.042	−0.018	0.058
PR5	0.986	0.762	0.434	0.983	0.784	0.438	0.003	−0.023	−0.004

Note(s): RMSE: root mean squared error. MAE: mean absolute error. PLS: partial least squares path model. LM: linear regression model. PR: people results. $K = 4$ subgroups, number of repetitions = 10
Source(s): Authors' own creation

Table 5. PLSpredict assessment of indicators in the indirect model

PLSpredict assessment of indicators in the model mediated by the KMP construct

Indicator	PLS RMSE	PLS MAE	PLS Q^2*predict*	LM RMSE	LM MAE	LM Q^2*predict*	PLS – LM RMSE	PLS – LM MAE	PLS – LM Q^2*predict*
CR1	0.823	0.606	0.560	0.829	0.606	0.554	−0.006	0.000	0.006
CR2	1.042	0.733	0.325	1.060	0.782	0.302	−0.018	−0.049	0.023
CR3	0.882	0.652	0.471	0.917	0.677	0.429	−0.035	−0.025	0.043
CR4	0.769	0.564	0.444	0.802	0.587	0.396	−0.032	−0.022	0.047
CR5	1.064	0.818	0.449	1.079	0.808	0.433	−0.016	0.010	0.016
PR1	0.917	0.710	0.537	0.931	0.721	0.523	−0.014	−0.011	0.014
PR2	0.937	0.719	0.505	0.939	0.731	0.503	−0.001	−0.012	0.001
PR3	0.860	0.653	0.437	0.906	0.685	0.375	−0.046	−0.032	0.062
PR4	0.909	0.696	0.374	0.942	0.712	0.328	−0.033	−0.016	0.047
PR5	0.980	0.755	0.433	0.986	0.786	0.426	−0.006	−0.031	0.007

Note(s): RMSE: root mean squared error. MAE: mean absolute error. PLS: partial least squares path model. LM: linear regression model. PR: people results. $K = 4$ subgroups, number of repetitions = 10
Source(s): Authors' own creation

First, our models have predicted Q2 values greater than 0 for all the indicators of the constructs or endogenous variables. Therefore, the first condition is fulfilled, according to Shmueli *et al.* (2019). Second, in order to evaluate the prediction error of the PLS-SEM analysis, the prediction error summary statistic values were compared to naive values, obtained using a linear regression model (LM). Compared to the LM results, the PLS SEM results should have a lower prediction error, e.g. in terms of root mean square error (RMSE) or mean absolute error (MAE) values. Also, the skewness values for the prediction errors of the outcome indicators are, as a whole, less than 1 for both the PLS-SEM and LM analyses. From the above, the RMSE was selected as the basis for the assessment of predictive power (although we also show the MAE statistics).

Following Shmueli *et al.* (2019), Table 4 shows that PLS-SEM analyses (compared to LM) generated lower prediction errors in terms of RMSE for most indicators, thus presenting a medium predictive power. However, Table 5 shows that PLS-SEM analyses presented a high predictive power for all the indicators. According to Hair *et al.* (2019), we confirm the high predictive power of the model mediated by the KMP construct, as opposed to the direct model. The incorporation of the mediating construct KMP into the model reveals a substantial improvement in its predictive efficacy in contrast to the direct model. These results corroborate the importance of incorporating mediation in the study and provide convincing evidence of the influence and relevance of KMP in predicting study outcomes.

The PLS-SEM analysis of the KMP construct evidences the relationship of the endogenous variable KMP with respect to the exogenous variable DC. In this sense, the PLS-SEM analyses (compared to the LM) generated lower prediction errors in terms of RMSE for all indicators, thus presenting high predictive power. The dimensions of DC sensing, learning, integrating, and coordinating capabilities strongly predict the KMP (Table 6).

5. Discussion

The results provided by the research support the hypotheses H1, H1II, H2, H2II, H3, H4, H4II. Regarding hypotheses H4, H4II, the analysis of the values obtained for the model shows that the KMP exerts a strong influence on the results on clients and staff. In fact, Table 3 suggests the existence of partial mediation (Hair *et al.*, 2019). This seems to indicate that, although higher-order DC influences customer and people results, it needs a mediating construct, in this case the KMP, with which to enhance its effects indirectly. This is not to say that without the mediation of the KMP, the DC have an influence on the results, which they do (H1, H1II), but the incorporation of the KMP variable improves the model (H2, H2II). This confirms that higher-order DC indirectly influence customer and people results, but a mediating construct, in this case the KMP, enhances their effects. In this line, works such as those of Drnevich and Kriauciunas (2011) and Ambrosini and Bowman (2009) support our results when they state that the possession of DC is an insufficient, but necessary, condition to achieve superior performance (Wilden *et al.*, 2013). Thus, the KMP, through its dimensions of creation, storage, transfer, and application, improves customer relations in terms of loyalty, commitment, communication . . . or increases employee satisfaction and motivation (Singh *et al.*, 2021) through training, communication, and skills acquisition, for example.

In line with the above, the results evidently also support hypothesis H3, which indicates a significant relationship between DC and the KMP. The literature concerning these fields of knowledge is still expanding and there is a plurality of ideas and models that make their understanding more complex (Kaur, 2022; Hung *et al.*, 2009; Easterby-Smith and Prieto, 2008; Nielsen, 2006). Undoubtedly, there is a positive relationship between DC and the KMP, which is extremely important for the success of the organization because, if these capabilities are properly managed, our study shows significant improvements in customer and employee outcomes. Focusing on the R2 values, we see that, in the model with a total effect, CR has an

Table 6.
PLSpredict assessment of indicators KMP construct

Indicator	PLS RMSE	PLS MAE	PLS Q^2*predict*	LM RMSE	LM MAE	LM Q^2*predict*	PLS – LM RMSE	PLS – LM MAE	PLS – LM Q^2*predict*
Creation K	620.997	503.175	0.572	647.235	520.487	0.535	−26.237	−17.312	0.037
Storage K	715.254	579.718	0.468	716.967	561.269	0.465	−1.713	18.449	0.003
Transfer K	684.028	532.263	0.538	703.292	537.693	0.512	−19.264	−5.430	0.026
Apply K	668.485	461.061	0.538	694.093	480.112	0.501	−25.608	−19.051	0.036

Note(s): RMSE: root mean squared error. MAE: mean absolute error. PLS: partial least squares path model. LM: linear regression model. $K = 4$ subgroups, number of repetitions = 10
Source(s): Authors' own creation

$R2 = 0.63$; and a $PR = 0.61$. The effect, however, is substantially larger (Chin, 1998), in the indirect effect model as $CR = 0.67$ and $PR = 0.68$.

Finally, we confirm that the KMP, as a process capability, improves the prediction of the outcome constructs and makes the model more robust. The evaluation of PLSpredict at the indicator level ensures, for both models, how these models could be used to predict the outcome variables, either through new data or in a future study. Specifically, the outcome assessments of the dependent variables of customers and employees, from the construct-level prediction, show that the best predictive model is with the KMP indirect effect. This model has a high predictive power. The model with a direct effect has a medium predictive power. In more detail, it is in the dependent variable person outcomes where the predictive power is medium (in the model with a total effect). However, the predictive power is high when we incorporate the KMP variable as a mediator between the outcomes and the exogenous variable DC.

6. Implications and conclusions

6.1 Theoretical implications

Our study examines the indirect impact of DC on outcomes, specifically customer and employee outcomes, through the creation of KMP operational routines. In doing so, we extend and empirically enrich this field of study, in line with Cepeda and Vera (2007), who express this need. Empirical support is provided by works such as those of Laaksonen and Peltoniemi (2018), Pavlou and El Sawy (2011), and Ambrosini and Bowman (2009), who claim that DC indirectly influences outcomes through the reconfiguration of operational capabilities. Recent research points in this direction, although our work demonstrates this with concrete outcome measures - customers and employees - and not just firm performance. Similarly, our model finds a high predictive power in the KMP mediating the relationship between DC and outcomes. Specifically, our work enriches the investigation of DC and the KMP in the predictive study (Suárez *et al.*, 2017). To this end, we have built a valid, stable predictive model that links DC, the KMP and customer and employee outcomes. In turn, we have conducted a comparative prediction study on a mediated and an unmediated model. In this respect, the KMP construct explains the model through its dimensions and strongly predicts it.

On the other hand, unlike the literature, which establishes relationships between DC and KM eminently, we delve deeper into these phases of the process and how they are affected by DC, also dimensioned according to the model proposed by Pavlou and El Sawy (2011).

In summary, our research contributes significantly to the fields of KM and DC. It advances our understanding of how DC stimulate KMPs, which ultimately positively impact customer and employee outcomes. Our study highlights the critical role of DC as a driver for KM, providing organizations with the ability to respond effectively to changes in the environment and seize opportunities to improve the creation, storage, transfer, and application of knowledge. Finally, our findings provide compelling evidence that organizations that adopt a shared framework for performance improvement through quality management and the pursuit of excellence achieve remarkable results.

6.2 Implications for business management

In terms of practical implications, DC depend on knowledge, and KMPs are essential for assessing improved performance. DC is necessary, but it is not sufficient, and to increase performance the processes in place to manage knowledge need to be efficient. Dynamic sensing capabilities explore the environment and help knowledge creation by generating new ideas. In this sense, knowing what the customer wants, and how we can provide it, are fundamental objectives for business success. The learning capability helps the KMP to identify and analyze new information and knowledge, to transform it, and finally to apply it in new products/processes. It is a fundamental capability that synergizes with the KMP phases. The integration capability allows the organization to know how involved its employees are, their responsibilities and their suitability for their tasks. Managers who have access to this information, through knowledge transfer and application, will establish improvements in the conditions of their employees, implement training, and skills development programs. The aim of all this is to improve the satisfaction of their work teams. The ability to co-ordinate matches the experience and knowledge of employees to their jobs. This allows for improved product and service development, which in turn satisfies customers. The management must be able to transfer between departments the appropriate matching of jobs and tasks to each employee. Finally, the managers must be able to implement changes and improvements. In this sense, managers must put into action DC that reconfigure their KMPs. By realizing improvements and facilitating the flow of knowledge, employee satisfaction will be higher, as will the customer's perception of value towards the company and its products/services. Also, their involvement will be greater, consolidating a strategic *customer-organization-customer* feedback and improvement channel.

Moreover, out-of-sample prediction as an integral evaluation of the model in PLS-SEM serves as an evaluation of its practical relevance in predicting outcomes (Shmueli *et al.*, 2019). Specifically, managers who properly implement DC in their organization will reshape KMPs, positively impacting the outcomes of their employees and also their customers. In competitive and changing markets, increasing employee satisfaction, as well as customer value, is key. Likewise, reducing risk is within the organization's reach if it is able to properly manage a strategic asset such as knowledge.

7. Conclusions

This study contributes significantly to the fields of KM and DC. It enriches our understanding of how KM and KM impact organizational outcomes for customers and employees. The main objective of this work was to empirically confirm that KM *per se* does not have the same impact on customer and employee outcomes as when it mediates the relationship with KMP. Through a comparative analysis, the model in which the KMP mediates the relationships between CD and CR and PR predicts and improves outcomes more strongly than when KMP is absent. Moreover, KMP as a mediating variable increases the model's predictive power. Undoubtedly, the KMP is a critical component that aids in developing and implementing DC, essential in turbulent and rapidly changing environments to which organizations need to adapt and ensure their survival and which drive improvements in employee satisfaction and generate customer value. The results of our empirical study have provided strong support for our argument. In addition, we demonstrate that organizations committed to the search for continuous improvement, based on the EFQM model of excellence, show a synergy between the implementation of dynamics and solid KMPs, which translates into better results. As we move forward, we envisage a deeper integration of these concepts. Thus, we hope the present study will inform future research looking at integrated models that include DC, KMPs, and outcomes.

8. Limitations and directions for future research

The limitations of our research stem, firstly, from the lack of consensus in the literature when it comes to determining the role played by DC with respect to the KMP. In this sense, PLS-SEM interprets the relationships between variables as linear and one-way. For the models presented, it would be extremely interesting to address the behavior of the model in inverse relationships for future research.

With respect to the sample, this is made up of organizations operating in Spain, so there is a geographical limitation that prevents the results of the research from being generalized. The organizations follow the EFQM quality self-assessment framework, whose criteria are standardized at an international level. Given this particularity, factors limiting the sample have to be taken into account. Not all organizations undergo self-assessments to improve quality, given the existence of other models and certifying bodies such as the Malcolm Baldrige or the Ibero-American models. Future research can be enhanced by comparative studies between companies that are covered by different certifying bodies, or simply operate in other countries. Studies can also be carried out by segmenting according to the level of certification the sector in which they operate or the size of the organization. In this paper it has not been possible to test the moderating effects of these contextual variables. According to Sarstedt *et al.* (2011), it is necessary to segment the sample into equitable groups to allow for a consistent study. This would enhance the understanding of the relationships between DC and KMP in relation to the outcomes and the attainment of competitive advantages as the outcomes can be subject to diverse contextual factors such as organizational size, sector, or other moderating factors.

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