Performance measurement for knowledge management project: model development and empirical validation

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Abstract

Purpose – *This paper aims to propose a model for measuring the performance of knowledge management (KM) projects in enterprises. No such model has been proposed in the literature thus far. The activities, factors and outcomes of KM are the main constructs of the model. Their operationalization and interactions are investigated.*

Design/methodology/approach – *A survey was conducted of 120 respondents from SME firms in Morocco. A structural equation modeling (SEM) technique called partial least squares (PLS) was used to assess the validity of the constructs and verify the hypotheses. A performance index for KM projects was derived from the model constructs.*

Findings – *The results support the model designed for KM activities and related interactions. The effects of KM activities on its outcomes are significant as well. The results also confirm that KM factors are predictors of KM activities and that the effects of these are significant. Furthermore, a performance importance analysis (importance performance map analysis [IPMA]) was performed on the data to expand the results of the PLS-SEM by identifying under-performing KM drivers that require managerial action.*

Originality/value – *This paper is one of the first to propose a generic performance measurement model for KM projects. Additionally, it is a pioneering study in the use of IPMA for KM performance measurement.*

Keywords *Indicators, Knowledge management project, Performance measurement model*

Paper type *Research paper*

1. Introduction

Knowledge is an important organizational resource. The main concern for knowledge management (KM) is ensuring effective knowledge flow while furthering the performance of the organization (Oufkir *et al.*, 2016).

Undoubtedly, achieving high-performing KM is a key step toward the achievement of organizational performance objectives (Ragab and Arisha, 2013). Measuring KM performance is an important part of this.

Furthermore, due to the increased investment required by the cost of KM projects, companies should not only assess KM on the firm level but on the project level as well, to rationalize investments, control the achievement of objectives and secure the continuity of projects through a recovery action (Ragab and Arisha, 2013).

In fact, approaches to KM performance measurement proposed in the literature deal with many aspects. Some approaches consider that KM can be evaluated relative to process (Chang Lee *et al.*, 2005; Chen and Fong, 2015; Kuah *et al.*, 2012; Lee and Choi, 2003; Lee *et al.*, 2012), and many models of KM processes have been proposed to this end. Some

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authors focus on assessing both the drivers and results of KM while investigating their assumed interrelationships (Lee and Choi, 2003; Lee *et al.*, 2012; Mas-Machuca and Martínez Costa, 2012; Migdadi, 2008; Wong, 2005; Wu and Chen, 2014; Zack *et al.*, 2009). Other authors study design of specific assessment approaches for specific KM projects, while a few generic approaches are dedicated to performance measurement for KM projects. Overall, each approach provides a significant insight toward understanding the KM environment, even though they are mainly dedicated to KM performance measurement on the firm level.

In the literature, it is found that many challenges to the development of performance measurement for KM persist:

- It is still unclear how to characterize KM, and what to measure in it remains controversial. Globally, KM performance measurement centers on KM flow. However, the KM models reported in the literature are so diverse that the entire design of KM flow should be reviewed (Handzic, 2011; Nonaka *et al.*, 2000; Oztemel and Arslankaya, 2012; Wen, 2009).
- KM performance is closely linked to its organizational goals in much of the literature (Andreeva and Kianto, 2012; Chen and Fong, 2015; Choy *et al.*, 2006; Lyu *et al.*, 2016; Mas-Machuca and Martínez Costa, 2012; Tanriverdi, 2005; Wu and Chen, 2014; Zack *et al.*, 2009). Thus, KM outcomes in relation to company performance attributes should be identified and analyzed.
- The success of KM is conditioned by certain socio-technical factors that can act as success factors for KM (Akhavan *et al.*, 2006; Mas-Machuca and Martínez Costa, 2012). Other, related factors should be identified as well.

In addition to coping with these issues, well-designed performance measurement should also be actionable and could propose practical areas for improvement.

Beyond these constraints, assessing KM on the project level entails more complexity, due to the diversity of KM solutions driven by technological progress. Designing a unified and up-to-date model of performance measurement that could be used for different KM projects is more limiting.

Hence, this study produces a generic performance measurement model for KM projects that addresses reported issues in the design of an approach to the performance measurement of KM. The proposed model is based on the following three constructs: activities, drivers and outcomes of KM. With an empirical application, this study asserts that the indicators developed are consistent, and the theoretical assumptions are statistically significant and generalizable to a large population.

The article is structured as follows: Section 2 explores the KM literature. Section 3 presents our conceptual model and related research hypotheses. The methods and data sample are outlined in Section 4. Section 5 reports the results. Section 6 presents a discussion of the results. Finally, we present our conclusions in Section 7, together with the implications, limitations and directions for future research.

2. Background

The understanding of KM varies in scope and focus, depending on the target perspective. Regarding performance measurement, we consider that KM refers to socio-technical systems (composed of technologies and social mechanisms) that enable knowledge to flow toward achieving the organizational performance objectives (Oufkir *et al.*, 2016).

KM is introduced into enterprises by the implementation of KM projects that refer to a whole or a part of a socio-technical system. KM projects, also termed KM initiatives, constitute an attempt to structure the technology and knowledge of individuals and firms to ensure knowledge flow and accomplish organizational objectives (Oufkir and Kassou, 2018). Accordingly, this may range from a purely social practice (such as a lunch and learn session) to a completely integrated IT system (such as a knowledge portal).

This view of KM projects is illustrated in Figure 1.

In line with this vision, the performance of a KM project is measured in relation to the effectiveness of knowledge flow, achievement of KM objectives and adherence to contextual factors.

In this section, we consider that KM activities, KM factors and KM outcomes are the main constructs for our research model of KM project performance measurement.

2.1 Knowledge management activities

Building on previous study of the design of a KM flow model (Oufkir and Kassou, 2018), it is accepted that a knowledge flow model entails a cyclic sequence of KM activities. In fact, within firms, four forms of knowledge exist (tacit individual knowledge, explicit individual knowledge, tacit collective knowledge and explicit collective knowledge). It follows that KM activities are the conversions from those four identified forms of knowledge (Nonaka *et al.*, 2000). They are also the responses to the four recurring problems of knowledge identified in the enterprise: knowledge location, knowledge preservation, knowledge valuation and actualization of knowledge (Grundstein, 2008). Accordingly, Knowledge identification (KI) is a response to problems of knowledge location. Knowledge acquisition (KA), knowledge modeling (KMO) and knowledge storage (KS) are all responses to problems of knowledge preservation. Knowledge retrieval (KR), knowledge transfer (KT), knowledge internalization (KIT) and knowledge utilization (KU) address problems of valuation. Finally, knowledge updating (KUP) is a response to problems of the actualization of knowledge.

In this vein, we propose that a KM model should include the following activities, as described in Figure 2.

KI relies on the analysis of tacit organizational knowledge to identify knowledge gaps and locate crucial knowledge and competencies (Al-hawary and Alwan, 2016).

KA refers to how knowledge is obtained from different tacit sources. Two tacit sources in particular were specified by Do Rosário *et al.* (2015): dyadic knowledge sources and group knowledge. The former refers to knowledge captured from direct contact between a provider and receiver. Group knowledge is obtained from interactions among a group's members through conversation or Q&A.

KMO comes into play once knowledge is acquired from tacit sources, when it must be represented in models to make it usable. KMO relies essentially on methods of knowledge

Figure 1 KM project view

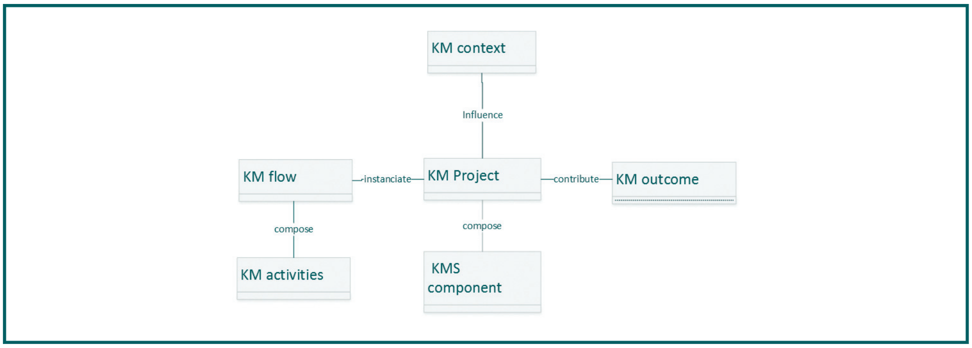
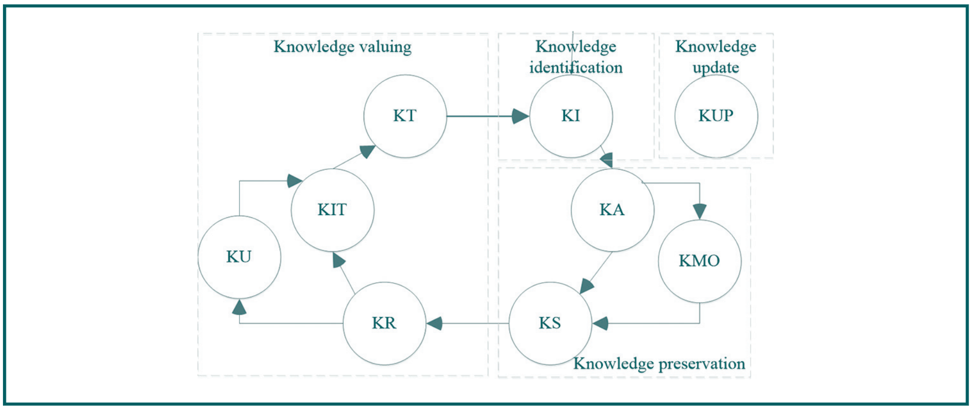


Figure 2 KM flow model



engineering to produce a knowledge book per knowledge area (Bimba *et al.*, 2016; Boughzala and Ermine, 2007).

KS meets the need for codified knowledge to be recorded and stored to provide further access to knowledge workers (Wong *et al.*, 2013).

KR consists of making explicit knowledge available to all organizational knowledge users by providing appropriate search mechanisms and making knowledge sources available (Oufkir *et al.*, 2016).

KU is the application of explicit knowledge without acquiring or learning it. Examples include solving problems, adopting best practices and troubleshooting. Ultimately, knowledge is only valuable when it is put in practical use (Lee and Wong, 2015). KU is mainly supported by intelligent technologies (Wong *et al.*, 2013).

KIT happens at the individual level; thus, for each knowledge worker, explicit knowledge is by this process embodied into its tacit knowledge, re-contextualized and processed, and it becomes subject to inductive and deductive reasoning, resulting in reworked tacit individual knowledge (Sarrasin and Ramangalahy, 2007).

KT is the sharing of individual tacit knowledge with a target group (Oufkir *et al.*, 2016).

KUP recognizes that knowledge is distributed among individuals and systems, which makes it vulnerable to vanishing and being outdated, so sources of knowledge must be updated on a regular basis such that new knowledge is incorporated and obsolete knowledge is removed (Al-hawary and Alwan, 2016).

2.2 Knowledge management factors

The success factors for KM are the contextual elements that, when addressed, enhance KM activities (Wong, 2005) and bring about KM success (Davenport *et al.*, 1998). The literature proposes multiple success factors (Lee and Choi, 2003), fundamentally suggesting that socio-technical systems such as KM projects are influenced by two types of factors: social enablers related to people, organizational culture and structure and technical factors. Those socio-technical factors can be categorized according to their soft and hard aspects: cultural factors could be considered soft KM factors, while concrete structural, strategic and technological factors are considered hard factors (Rouse, 2016). After their empirical study on Malaysian ICT companies Chong *et al.* (2007) conclude that three categories of success factors may enhance or impede KM activities: KM culture, KM technology and firm leadership. Theriou *et al.* (2011) propose that KM factors be categorized into five categories, which they also empirically validate: organizational culture, KM strategy, management support, technology and human factors.

2.3 Knowledge management outcomes

Although multiple approaches have been developed to quantify KM success, the means of doing so that foreground that KM success refers to the achievement of KM outcomes and benefits appear to be the most prevalent (Choy *et al.*, 2006; Mas-Machuca and Martínez Costa, 2012; Migdadi, 2008; Milovanovi, 2011). The benefits KM brings are understood differently in different contexts and in relation to different implied stakeholders (Choy *et al.*, 2006).

Analysis of prior studies of KM outcomes leads to the identification of some common measures. Business performance is the dominant short-term outcome identified. In both theoretical and empirical works related on KM, three additional performance outcomes that are indicative of non-financial and long-term performance are identified: customer satisfaction, competency development and innovation.

In fact, financial success is a direct and tangible observed result of KM success, and using it to measure KM is a trend in management studies. From this perspective, successful KM streamlines KM activities. Consequently, productivity is enhanced, customer needs are better addressed, and competitive advantage is reached that is reflected positively in organization benefits (Lyu *et al.*, 2016).

Customer satisfaction is another KM outcome that is a candidate for assessment. Better handling of customer knowledge through effective KM activities enhances client interactions and increases customer satisfaction.

Employees are a critical force for an organization because its knowledge is held in them. To sustain its KM, organizations should satisfy their employee's needs by leveraging and developing their competencies. Pursuing this increases employee loyalty and satisfaction, which is reflected positively in their productivity (Chen and Fong, 2012; Chen *et al.*, 2009; Mas-Machuca and Martínez Costa, 2012).

Innovation is another KM outcome: this denotes an abstract human process that is closely tied to knowledge creation. It generates and implements new or modified results (products, processes or services) for the purpose of creating new value for the firm (Mortensen and Carter, 2005; Roper and Hewitt-Dundas, 2011).

3. Conceptual model and research hypotheses

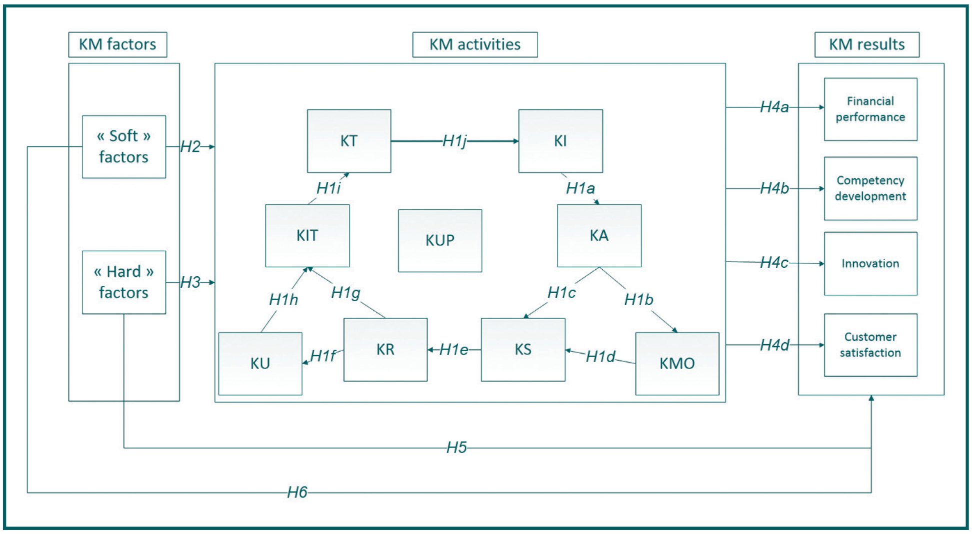
This study develops a research model to measure performance of KM projects by drawing on key constructs: activities, outcomes and factors of KM. Figure 3 presents the proposed research model and its underlying assumptions.

3.1 Knowledge management activities

KM activities are the building blocks for KM measurement. They can be classified into four sequential categories that carry out nine knowledge activities: KI, which responds to the knowledge location problem, and knowledge preservation, which deals with the retention of knowledge through KA, KMO and KS. Knowledge valuation deals with how to benefit from available knowledge by accessing it, applying it, internalizing it and eventually transferring it. This category covers KR, KU, KIT and KT. Last, KUP that deals with the actualization of knowledge by incorporating new knowledge and removing obsolete knowledge.

In accordance with the cyclic nature of knowledge flow, we assume that the KM activity model will behave in a sequential way, with a point of departure in the identification activity. In fact, the intention of KI is to analyze organizational knowledge to locate critical

Figure 3 Research model for KM project performance measurement



considerations and identify knowledge and competencies (Soulignac, 2012). Subsequent KM activity in the KM cycle includes the KA of identified knowledge in an explicit form, using capturing techniques (Hubert and Trees, 2014). Because knowledge cannot be captured unless it is identified, the intensity of the KA depends on the intensity of the KI.

The acquired knowledge is unprocessed in its explicit form. It must be organized and structured through KMO so it can be used and evaluated. Similarly, because KMO requires prior KA (King, 2009; Wiig, 1999), we can assume that KMO is positively associated with KA.

In the same vein, KMO generates a considerable amount of codified, structured knowledge that could benefit from KS (King, 2009). In fact, codified knowledge is unavailable to a worker unless it is stored in a common repository. Thus, we propose that KMO is positively associated with KS.

The more knowledge is stored, the more likely it is to be retrieved, and the more intensive is the knowledge retrieval (Kuah *et al.*, 2012).

Once knowledge is retrieved, there are two possibilities: either the knowledge worker attempts to assimilate it through internalization or uses it in a KU solution.

In certain specific contexts, the knowledge worker may wish to develop the internalized knowledge further through re-contextualization, induction and deduction reasoning. This operation may generate elaborated tacit knowledge, which would continue to evolve, following the knowledge cycle (Nonaka *et al.*, 2000).

Individual, (interiorized) tacit knowledge is converted to organizational knowledge through KT (Davenport *et al.*, 1998; Nonaka *et al.*, 2000). The more knowledge that is internalized, the more it is likely to be transferred, and the higher is the intensity of KT (Chen and Fong, 2015).

Following these observations, we develop the following hypotheses for testing:

H1a. KI is positively related to KA.

H1b. KA is positively related to KMO.

H1c. KA is positively related to KS.

H1d. KMO is positively related to KS.

H1e. KS is positively related to KR.

H1f. KR is positively related to KU.

H1g. KR is positively related to KIT.

H1h. KU is positively related to KIT.

H1i. KIT is positively related to KT.

H1j. KT is positively related to KI.

3.2 Knowledge management factors and activities

The role that KM factors play in enabling KM activities has been widely discussed in the literature. The positive effects it can have are supported in various theoretical and empirical studies. Thus, Lee and Choi (2003), Lee *et al.* (2012) and Chen and Fong (2015) empirically confirm that cultural values have a positive impact on the entirety of the knowledge flow. Davenport *et al.* (1998), Wong (2005) and Mas-Machuca and Martínez Costa (2012) find that the adoption of proper structure ensures better participation in knowledge activities. Tanriverdi (2005) and Kamhawi (2012) show that efficient technological infrastructure is a key driver to the effectiveness of knowledge activities.

Studies on the individual effects of KM factors on KM activities are missing in the literature.

To fill this gap, we propose to verify the following hypotheses:

H2. Soft factors affect some KM activities to some extent.

H3. Hard factors affect some KM activities to some extent

3.3 Knowledge management activities and outcomes

A KM project attempts to achieve organizational objectives through the promotion of knowledge flow. The literature of KM outcomes indicates that they can be divided into four dimensions: competency development, innovation, financial performance and customer satisfaction. The precise ways in which KM activities affect KM outcomes are discussed below.

When KM activities are effectively implemented, open communication and knowledge exchange are fostered between knowledge workers, and this affects their learning and enhances their competencies and skills (Wu and Chen, 2014). Likewise, work performance improves, and productivity is increased (Andreeva and Kianto, 2012; Lee and Choi, 2003; Palacios Marqués and José Garrigós Simón, 2006; Zack *et al.*, 2009). This also affects the firm's customers that sow their needs better addressed.

Another benefit of KM is that it allows the new knowledge to be generated that results from KIT and KT (Nonaka *et al.*, 2000). In this way, innovation is reinforced (Al-Sa'di *et al.*, 2017; Santoro *et al.*, 2017; Xu *et al.*, 2011).

Past studies assert that KM activities globally influence KM outcomes (Al-Sa'di *et al.*, 2017; Chen and Fong, 2015; Kim *et al.*, 2014). This conclusion is widely discussed in the literature and is repeatedly verified in empirical studies. However, the effects of KM activities on the dimensions of KM results have not yet been determined.

We assume that the intensity of knowledge activities is associated with each of the KM results dimension to some extent. Five related hypotheses are posited:

H4. The intensity of KM activities is associated with the effectiveness of KM outcomes to some extent.

H4a. KM activities are positively associated with competency development outcome.

H4b. KM activities are positively associated with financial performance outcome.

H4c. KM activities are positively associated with innovation outcome.

H4d. KM activities are positively associated with customer satisfaction outcome.

3.4 Knowledge management factors and outcomes

Globally, the effects that KM factors have on KM results are attributed to those KM activities that play a mediating role. However, some studies have concluded that KM factors may have a direct effect on KM outcomes (Chen and Fong, 2012, 2015; Gold *et al.*, 2001; Theriou *et al.*, 2011).

In relation to these studies and taking into consideration that KM success is measured against KM outcomes, this study argues that KM factors have a direct effect on KM outcomes.

The following hypotheses are proposed:

H5. Hard factors positively affect KM outcomes.

H6. Soft factors positively affect KM outcomes.

4. Research methodology

4.1 Instrument development

Our research model consisted of 16 multi-item constructs that measure three main concepts: KM activities, KM factors, and KM outcomes. The items in the survey were measured using a five-point Likert scale ranging from 1 (strongly disagree/poor) to 5 (strongly agree/excellent), and they are presented below in 4.3.

The survey design adapted prior survey research and the literature on KM. Some of the measurement scales for each of the KM constructs were directly taken from the literature, while others were modified. Additional items were developed, following the author’s considerations.

To ensure the content and face validity of the survey instrument, four subject matter experts (two practitioners and two academics) were asked to evaluate the survey questions. The questionnaire was revised based on their feedback; some items were rewritten, and the parts of the survey were also reorganized for ease of comprehension.

4.2 Data collection and sample

A cross-sectional survey study was undertaken to investigate KM project performance. The studied population was Moroccan medium-sized and large enterprises that implement KM projects. Judgment sampling and convenience sampling were used. The sampling frame included some selected qualified respondents (for which we had current contact details), coupled with respondents recruited with convenience sampling. Both groups were composed entirely of individuals working in a medium-sized or large company, operating mostly in the technology services sector. Such firms work closely with KM because they operate in the turbulent and dynamic technology services market. The target respondents were professionals in positions with KM responsibilities: KM staff (if such exists in the organization) and middle and top-level managers in different functional areas.

Data collection was performed through an online survey that was available in French and English. Emphasis was placed on pre-identified professional group networks. Additionally, other potential participants were identified and contacted via e-mail. Hence, three waves of e-mails were sent, and multiple recall phone calls were made. Furthermore, some respondents required phone assistance to complete the survey. For the judgment and convenience sampling methods, the response rate is not computed according to the recommendations of Schonlau *et al.* (2002). A total of 800 responses were received, but 680 were judged invalid due to incomplete data for key constructs. The remaining 120 responses were used to test the proposed research model.

The sampling frame included 120 respondents. Among these, 86 were young managers between 25 and 35 years old. This slant is the result of the recent infusion of technology in the third world and developing countries; accordingly, the youth constitute the local IT staff (both managerial and functional) in such countries. Moreover, the dominance of multinational firms in the computing technology sector offer attractive compensation packages, so employee retention rates are generally high and employees often remain long in the same company. Detailed demographic information for the respondents is shown in Table I.

4.3 Measures

4.3.1 Knowledge management activities construct. The literature reports many KM flow models, using various designations and measures for KM. To select the most relevant measures for our proposed model, a literature review was performed, and measures of KM activities were categorized according to the target KM model. Then, a screening was carried out for each category to retain only relevant measures.

KI allows employees to locate where knowledge in a company resides and to find what is available. Two measures were adopted by Heisig (2003), Atwood (2009) and Al-hawary and Alwan (2016) and retained for this activity:

1. contributors learn from each other who knows what (KI1); and
2. we know how to find available knowledge (KI2).

The degree of KA depends on two parameters: how frequently knowledge collection is performed (García-Fernández, 2015) and how good the KA process is (Zaied, 2012). Hence, the following measurement items were adopted:

1. is knowledge collected from employees on regular basis (KA1); and
2. is a KA process specified by the enterprise (*KA2*).

Table I Demographic information

Demographic information	*Valid (%)*
Personal background	
Age	
Under 25	5.8
25-35	71.7
36-45	21.7
Over 46	0.8
Experience	
Less than 5 years	7
More than 5 years	65
More than 10 years	28
Position	
KM role	17.5
Middle and high management	58.4
Senior professional staff member	17.1
Firm background	
Sector	
Telecommunication and technology	68.30
Headcount	
More than 250	70

To measure KMO, two items were developed, following Boughzala and Ermine (2007) and Bimba *et al.* (2016); these concern the presence of a knowledge book per domain area and the regular update of this book. The selected items were:

1. we have a knowledge book for the knowledge area related to our project (KMO1); and
2. the knowledge book is a living object and subject to regular updates, sharing and integration (*KMO2*).

KS depends on the storage policy for the firm, which determines the nature of the knowledge to store and the rules and instructions for KS (Heisig, 2003; Zaied, 2012). KS activity is therefore operationalized with three items:

1. we all agree on what knowledge should be stored (*KS1*);
2. we know how and where we can store our knowledge (*KS2*); and
3. we have assigned roles and responsibilities regarding it (*KS3*).

In line with Chang Lee *et al.* (2005), KR was measured using following four items:

1. knowledge sources are available (KR1);
2. we have search mechanisms that facilitate access to available knowledge (*KR2*);
3. employees search knowledge from various knowledge sources administered by the organization (*KR3*); and
4. the provided search mechanisms are relevant (*KR4*).

The scales for KU were drawn from Wong *et al.* (2003), which stated that KU depends on the effective application of accessed knowledge and the availability of supporting systems and technologies. The measurement items were:

1. employees apply frequently the accessed knowledge (*KU1*); and
2. we have systems that make it easier to use available knowledge (*KU2*).

Zaied (2012) identified three measures for KIT activity. These were:

1. our organization provides process for absorbing knowledge (*KIT1*);
2. needed time is allocated to collaborators to absorb internalized knowledge (*KIT2*); and
3. our organization provides systems to support knowledge absorption (*KIT3*).

KT was assessed by the mean of three items:

1. the organization possesses formal mechanisms ensuring KT (*KT1*) (Lauren and Darcy, 2015);
2. organization possesses informal mechanisms ensuring KT (*KT2*) (Lauren and Darcy, 2015); and
3. collaborators possess needed communication capabilities (*KT3*) (Ahn and Chang, 2004).

4.3.2 Knowledge management factors construct. Three broad categories have been empirically identified as success factors for KM initiatives: culture, structure and technology (Chong *et al.*, 2007; Lee and Wong, 2015; Migdadi, 2008).

Culture refers to the set of shared beliefs and values within communities. Trust (*Cult1*), collaboration (*Cult2*), professionalism (*Cult3*) and transparency (*Cult4*) are the four basic soft values that are indicative of a friendly culture that both values and preserves knowledge (Mas-Machuca and Martínez Costa, 2012).

The structure of KM is the organizational structure assigned the role to plan, decide, follow, monitor and act on KM activities. Management support (*Org1*) along with a clearly aligned KM strategy (*Org2*) is crucial elements for providing continual support and sustaining KM activities (Lee and Wong, 2015). Additionally, a dedicated KM structure (*Org3*) and integrating KM activities within business processes (*Org4*) may help support and enhance KM performance (Chen and Fong, 2015; Mas-Machuca and Martínez Costa, 2012).

The technological factor refers to the systems, platforms and solutions that facilitate knowledge flow. It is identified as an important factor in KM enhancement, which is gaining more and more importance, thanks to technological progress and the introduction of new forms of KM technologies. The following three items are indicative of an efficient technological infrastructure (Chong *et al.*, 2007): reliability (*Tech1*), flexibility (*Tech2*) and responsiveness (*Tech3*).

4.3.3 Knowledge management outcomes construct. As with many KM studies, four groups of outcomes have been identified for KM, such as financial performance outcome (FinOut), competency development outcome (CompetOut), performance outcome from the customer perspective (CustOut) and innovation outcome (InovOut).

A measurement scale for each of these outcomes was obtained from prior empirical studies of KM.

In line with Chen *et al.* (2009), Zaied (2012) and Chen and Fong (2015), financial performance was measured using three items: growth in sales revenue (*Fin1*), cost reduction (*Fin2*) and increased productivity (*Fin3*).

For competency development, improvement in skills and learning is a good indicator of effective KM benefits (Lyu *et al.*, 2016; Migdadi, 2008). This improvement increases employee loyalty and generates satisfaction. Items selected to measure this specific construct are: level of employee satisfaction (*Compet1*), skills increase (*Compet2*) and improvement in staff retention (*Compet3*) (Chen and Fong, 2012; Chen *et al.*, 2009; Mas-Machuca and Martínez Costa, 2012).

Customer satisfaction perspective was measured with a single-item, following Chen *et al.* (2009), referring to the level of customer satisfaction (*Custo1*).

Innovation performance was operationalized using a scale developed by Mortensen and Carter (2005). Two measurement items were selected: technological innovation by the mean of product and process innovation (*Inov1*), non-technological innovation related to new organizational or marketing method (*Inov2*).

4.4 About partial least square–structural equation modeling

We used structural equation modeling (SEM), particularly partial least square (PLS) (a variance-based SEM method), to assess our research model in both its psychometric properties and its hypotheses (Hair *et al.*, 2014). PLS is the most fully developed variance-based SEM method, and it is in common use in information systems research for its ability to handle both factor and composite models. It is also appropriate for situations where theory is less developed and the aim of a study is explaining target constructs (Henseler *et al.*, 2016). Common criticisms of the PLS-SEM method include the following: a lack of consistency when estimating common factors, a limited local model assessment and limited development functionalities. These drawbacks are all neutralized with the extended consistent partial least squares algorithm (PLSc), which enables this method to be used to obtain our research objectives (Dijkstra and Henseler, 2015). SmartPLS 3 software was used to run the analysis (Ringle *et al.*, 2005).

5. Results

The assessment of the PLS path modeling for explanatory research has two steps, as stated by Hensler *et al.* (2016): the overall model assessment and the local assessment.

This section gives the results of the verification of common method bias; then, the results of the model assessment are reported in four parts. First, the overall model assessment is discussed. Next, the measurement model assessment is presented for common factor, composite and hierarchical constructs (HCs). The third part deals with the assessment of the structural model. Then, advanced analysis, including the reciprocal causation assessment and the development of the KM project performance index, is presented. The last part provides the results of the importance performance analysis.

5.1 Common method bias

Because the data were collected using a self-administered questionnaire, a full collinearity test was used to rule out concerns over common-method bias, as advised by Kock (2015). The procedure consists of checking the non-existence of vertical and lateral collinearity in the model through the verification of the VIF value for each latent variable of the model. A higher threshold value of 5 is used when algorithms that incorporate measurement error (such as the PLSc) are used. The results (shown in Table II) indicate that all constructs possess a VIF value below the threshold. Thus, common method bias does not appear to be a concern in this study.

5.2 Overall model assessment

The overall model assessment relies on bootstrap methods to check the fit between the empirical and the model-implied correlation matrix. It is recommended to use 5000 bootstrap samples because this number is sufficiently close to infinity for ordinary use. If more than 5 per cent of the bootstrap sample is below the implied model value, the model is assumed to be correctly specified. Indeed, three criteria are required to test the overall model fit:

1. the geodesic discrepancy d_G;
2. the unweighted least square discrepancy d_{ULS}; and
3. the standardized root mean square residual SRMR.

Table II Common method bias verification

Constructs	*VIF*
Customer outcome	1.32
Financial outcome	1.13
Innovation outcome	1.57
Knowledge acquisition	3.07
Knowledge internalization	2.04
Knowledge identification	1.76
Knowledge modeling	2.15
Knowledge retrieval	3.66
Knowledge storing	3.00
Knowledge transfer	2.89
Knowledge utilization	4.96
Knowledge update	2.78
Learning outcome	2.01
Organizational factors	2.27
Soft factors	2.81
Technological factors	1.73

Note: VIF: variation inflation factor

The results of PLS and the execution of bootstrapping with a bootstrap subsample of 5000 show that the d_G, d_{ULS} and SRMR are below the 95 per cent bootstrap quantile of respective indicators. Accordingly, the implied correlation matrix does not significantly differ (at the 5 per cent level) from the empirical one. Additionally, the SRMR value of 0.069 (which is below the cutoff value of 0.08) provides evidence for a correct model fit. Table III presents the results of this assessment.

5.3 Measurement model assessment

The measurement model should demonstrate the minimum requirements for validity and reliability to assess the structural model. The factors, composites and HCs are assessed in different ways:

5.3.1 For the factor model. As recommended by Hair *et al.* (2014), construct reliability, convergent validity and discriminant validity can be used to assess the properties of a measurement model. In this vein, Henseler *et al.* (2016) provided updated guidelines for how to use, interpret and report those criteria. Hence, reliability is measured with ρA, while the minimum value of 0.7 indicates an acceptable amount of random error.

The average variance extracted (AVE) is a dominant measure for validity. The cutoff value of 0.5 for this factor indicates the unidimensionality of the construct, with no systematic measurement error.

The discriminant validity contributes to evidence that each pair of factors stand in for theoretically different concept. In fact, two criteria are both informative about discriminant validity: heteotrait-montrait ratio (HTMT) and the Fornell–Larcker criterion that checks that each factor's AVE is higher than its correlation, with remaining factors in the model.

The results of the measurement model assessment show that all constructs have a value of ρA between 0.764 and 0.943 and an AVE higher than 0.754. Those values exceed the threshold for acceptable reliability and convergent validity, as presented in Table IV.

Table V shows that discriminant validity is met for all constructs, with an HTMT significantly smaller than 1.

5.3.2 For the composite model. Our theoretical model contains two composite constructs: the technological factor and the organizational factor. For this type of construct, validity is checked with the model fit of saturated model. The relevance and significance of the weights assess how significant and substantial the indicators are for the composite model. Collinearity is a major issue for the composite models; it refers to high correlation between two composites. It is verified where the variance inflation indicator (VIF) is much higher than 1.

In our case, validity is confirmed with a good model fit of the saturated model (checking d_G, d_{ULS} and SRMR for saturated model). Examining the outer weight significance using the bootstrap procedure shows that *Tech1* and *Tech3* are not significant. According to Van Riel *et al.* (2017), the rule of thumb for these cases is to check the relevance of the outer loading: an outer loading value greater than 0.5 shows that the indicator is absolutely important, so it would be retained in the analysis. The highest VIF value for the entire model is 2.4, which means that multicollinearity is not an issue.

Table III Overall model fit (estimated model)

	Value	*HI95*
SRMR	0.072	0.073
d_{ULS}	4 0.726	4.789
d_G	3.004	6.903

Note: HI95: 95% bootstrap quantile

Table IV Convergent validity and reliability

	Cronbach's alpha	ρA	Composite reliability	AVE
Financial outcome	0.736	0.773	0.750	0.604
Innovation outcome	0.763	0.764	0.763	0.617
Knowledge acquisition	0.800	0.829	0.805	0.585
Knowledge internalization	0.844	0.867	0.846	0.652
Knowledge identification	0.752	0.754	0.753	0.604
Knowledge modeling	0.936	0.937	0.936	0.880
Knowledge retrieval	0.899	0.903	0.899	0.690
Knowledge storing	0.867	0.869	0.865	0.682
Knowledge transfer	0.788	0.824	0.801	0.671
Knowledge utilization	0.767	0.787	0.774	0.633
Knowledge update	0.817	0.817	0.817	0.691
Competency outcome	0.791	0.824	0.788	0.562
Soft Factors	0.806	0.815	0.804	0.581

Notes: AVE: average variance extracted; ρA: factor reliability

Table V Discriminant validity

	1	2	3	4	5	6	7	8	9	10	11	12	13
Customer outcome													
Financial outcome	0.035												
Innovation outcome	0.075	0.131											
Knowledge acquisition	0.024	0.136	0.163										
Knowledge internalization	0.175	0.061	0.157	0.100									
Knowledge identification	0.173	0.137	0.098	0.153	0.222								
Knowledge modeling	0.011	0.150	0.162	0.539	0.377	0.222							
Knowledge retrieval	0.150	0.080	0.037	0.099	0.502	0.324	0.272						
Knowledge storing	0.059	0.163	0.146	0.605	0.193	0.214	0.382	0.339					
Knowledge transfer	0.039	0.049	0.110	0.115	0.597	0.217	0.207	0.556	0.193				
Knowledge utilization	0.048	0.160	0.142	0.063	0.529	0.421	0.266	0.769	0.348	0.654			
Knowledge update	0.072	0.135	0.355	0.352	0.256	0.265	0.428	0.131	0.438	0.259	0.077		
Competency outcome	0.119	0.127	0.199	0.212	0.131	0.237	0.078	0.161	0.071	0.163	0.057	0.217	
Soft factors	0.307	0.189	0.344	0.087	0.240	0.287	0.065	0.098	0.093	0.180	0.054	0.327	0.600

The results of the composite model assessment are shown in Table VI.

5.3.3 For the hierarchical construct. HCs are measured by means of other constructs instead of being measured directly by manifest variables. Their use in complex modeling is very common because thereby model complexity is reduced and parsimony is improved.

Following the operationalization presented in Section 2, the outcomes and hard factors of KM were assumed to be represented by HCs. As illustrated in Figure 3, higher-order construct of KM outcomes is explained by the lower-order constructs: competency development, financial, innovation and customer satisfaction outcomes. The construct for hard factors of KM is explained by lower-order constructs: technological and organizational factors.

HC estimation should be manually computed because it is not integrated into conventional PLSc analysis. Several approaches have been proposed in the literature for HC estimation: Van Riel *et al.* (2017) state that the "three stage approach" has advantages over extant approaches because it can provide consistent estimation of path coefficients and outer weights. It also includes a model fit assessment to demonstrate the usefulness of high-order construct consideration. The efficacy and consistency of the approach have also been demonstrated through simulated data.

Table VI Composite assessment			
Model	*Value (saturated model)*		*HI 95*
SRMR	0.057		0.058
d_{ULS}	2.961		3.090
d_G	2.867		6.530
	T-statistics	Outer loading	Outer weight
Org1 → Organizational factors	1.613	*0.796*	0.296
Org2 → Organizational factors	2.354	*0.756*	0.294
Org3 → Organizational factors	1.157	*0.814*	0.224
Org4 → Organizational factors	2.182	*0.866*	0.415
Tech1 → Technological factors	2.479	*0.890*	0.467
Tech2 → Technological factors	1.914	*0.906*	0.403
Tech3 → Technological factors	1.167	*0.748*	0.292

This three stage approach relies on three steps:

1. estimating the model without the high order construct;
2. estimating the model by replacing the low order construct with high order constructs; and
3. adjusting estimated parameters for attenuation.

The result of the analysis confirms the usefulness of the high-order construct for hard factors of KM because it shows a satisfactory level of quality for the measurement and structural models. However, the assumed composition of the high construct for KM outcomes is not tenable in the model due to the negative outer weighting of financial outcome. Thus, financial performance should not be considered a dimension of KM outcomes. The calculated weights, reliability parameters and criteria for measurement and structural model quality are presented in Table VII.

Because our measurement model is confirmed to be of acceptable quality, we can continue with structural model assessment.

Table VII Hierarchical construct analysis			
Model	*Path coefficient*	*Constructs*	*R square*
KA→ KM outcomes	0.235	KA	0.153
KMO→KM outcomes	−0.028	KU	0.638
KR→ KM outcomes	0.473	KIT	0.390
KU→ KM outcomes	−0.340	KI	0.224
KIT→ KM outcomes	0.100	KM outcomes	0.559
KT→ KM outcomes	−0.043	KUP	0.295
KS→ KM outcomes	−0.109	KMO	0.428
KM factors → KIT	0.222	KR	0.366
KM factors → KU	0.173	KS	0.561
KM factors → KMO	0.440	KT	0.375
KM factors → KR	0.776	KA	0.153
KM factors → KS	0.463		
Model	Weights	Constructs	ρA
Competency Outcome → KM outcomes	0.85	KM outcomes	0.898
Customer Outcome → KM outcomes	0.316		
Innovation Outcome → KM outcomes	0.218		
Financial Outcome → KM outcomes	−0.05		

Notes: KA: Knowledge acquisition; KIT: Knowledge internalization; KI: Knowledge identification; KMO: Knowledge modeling; KR: Knowledge retrieval; KS: Knowledge store; KT: Knowledge transfer; KU: Knowledge utilization; KUP: Knowledge update

5.4 Structural model assessment

The point of departure for the assessment of the structural model is the coefficient of determination *R*2. It quantifies, for an endogenous variable, the amount of variance explained by its predictors. *R*2 values of 0.75, 0.50 and 0.25 are described as substantial, moderate and weak, respectively. However, the limit values are reduced for exploratory research.

Next, the path coefficient is assessed in term of size, effect and significance. Hence, a bootstrap procedure with 5000 resamples is performed to obtain the confidence interval for each path.

For the significant paths, the substantial contributions of the predictors to the endogenous variables are checked with the criterion effect size (f2).

Table VIII displays the results of this analysis, as applied to our model. It shows that the *R*2 values are healthy values for all endogenous constructs, taking into consideration the exploratory nature of our research.

Looking at the path coefficient, we can identify the key constructs relevant (relative importance) to the endogenous KM outcomes; f2 and the total effect show how strongly each factor influences key target variable.

Research hypotheses are either accepted or rejected based on the significance of associated paths.

For hypotheses *H1a* to *H1i*, which assessed the sequential relationships among KM activities, *H1b*, *H1c*, *H1e*, *H1f*, *H1h* and *H1i* are supported, while *H1a*, *H1d* and *H1g* are not.

H2 and *H3*, which state that soft and hard factors affect KM activities, are supported.

To assess the hypothesis *H4*, HC analysis is applied to the KM outcomes constructs, which reveals that financial performance is not a dimension of KM outcomes. However, the effect of KM activities on global KM outcomes is confirmed. Separate analysis of each dimension of KM outcomes reveals that KUP and KT are positively related to the innovation outcome, and KA and KR are positively related to the competency outcome, but the effects of the KM activities on the customer satisfaction outcome are nonsignificant. Accordingly, *H4a* and *H4c* are supported, but *H4b* and *H4d* are not.

Regarding the factors of KM and their effects on KM outcomes, *H5* is supported while *H6* is not.

5.5 Reciprocal causation

Testing *H1j* involves establishing the effects of KI on KT, where an indirect effect is already verified between KT and KI. When direct and indirect effects are verified, KI and KT are assumed to have a reciprocal effect.

Models that contain reciprocal causation are called non-recursive. The use of conventional PLS for the estimation of such a model is not possible due to the violation of an assumption (the error term of KI is correlated with KT). Instead, a procedure called two-stage least square (2SLS), an extension of the ordinary least square, is used.

Applying the 2SLS to this case requires two steps: the first step considers an instrumental variable (KIT) that is not correlated to the residual error of the problematic variable (KI) to compute predicted values. The second step proceeds to the estimation of the regression model, composing the dependent variable KI, the independent variable KT and the instrumental variable KIT, using computed values in the first step.

Table VIII Structural model analysis			
Model	*Path coefficient (t-value)*	*Biased corrected 95% CI*	*f2*
Innovation outcome			
Soft factors → Innovation outcome	0.371** (2.077)	(−0.025, 0.472)	0.105
KUP → Innovation outcome	0.415** (2.288)	(0.002, 0.487)	0.132
KT → Innovation outcome	−0.340*** (1.920)	(−0.425, 0.007)	0.065
Customer outcome			
Soft factors → Customer outcome	0.336* (3.041)	(0.088, 0.468)	0.119
KUP → Customer outcome	−0.225*** (1.633)	(−0.370, 0.035)	0.011
Competency outcome			
KA → Competency outcome	0.348** (2.052)	(0.008, 0.436)	0.093
KR → Competency outcome	0.417** (2.023)	(−0.005, 0.400)	0.099
Soft Factors → Competency outcome	0.382* (3.611)	(0.155, 0.527)	0.110
KM activities			
KI → KR	0.344* (2.964)	(0.069, 0.388)	0.137
KI → KA	0.000(0.187)	(−0.154, 0.188)	
KA → KMO	0.467* (3.959)	(0.216, 0.619)	0.320
KA → KS	0.512* (3.448)	(0.172, 0.600)	0.379
KMO→ KS	−0.090(0.286)	(−0.264, 0.353)	
KS → KR	0.209** (2.382)	(0.044, 0.426)	0.042
KR → KU	0.696* (4.677)	(0.297, 0.819)	1.024
KR→ KIT	0.142(0.928)	(−0.340, 0.649)	0.013
KU → KIT	0.431* (1.643)	(−0.201, 0.827)	
KIT → KT	0.513* (2.713)	(0.089, 0.699)	0.340
KUP→KMO	0.205** (1.961)	(−0.029, 0.454)	0.048
KUP→KA	0.326** (2.390)	(0.020, 0.431)	0.086
KUP → KS	0.208*** (1.841)	(−0.011, 0.408)	0.061
KUP → KA	0.326** (2.390)	(0.020, 0.431)	0.086
KM factors			
Hard factors → KIT	0.216*** (1.837)	(−0.002, 0.294)	0.022
Hard factors → KUP	0.581* (2.767)	(0.078, 0.489)	0.166
Hard factors → KMO	0.435** (2.288)	(0.037, 0.406)	0.098
Hard factors → KR	0.761* (2.635)	(0.072, 0.545)	0.238
Hard factors → KS	0.456*** (1.722)	(−0.010, 0.378)	0 0.128
Soft factors → KU	−0.221** (2.237)	(−0.286, −0.025)	0.082
Soft factors → KIT	0.222** (2.519)	(0.048, 0.330)	0.046
Soft factors → KS	−0.441* (3.178)	(−0.460, −0.125)	0.275

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; CI: confidence interval, KA: Knowledge acquisition; KIT: Knowledge internalization; KI: Knowledge identification; KMO: Knowledge modeling; KR: Knowledge retrieval; KS: Knowledge store; KT: Knowledge transfer; KU: Knowledge utilization; KUP: Knowledge update

The results of the estimation of the F-test show that there is a linear relationship between variables with F = 11,747 and 117 degrees of freedom. The regression function gives KI = 0.357KIT + 0.250KT, and the *t*-test shows that the path coefficients are highly significant.

5.6 Knowledge management project index development

By mobilizing our theoretical framework, we show that a KM project does the following:

- implements *n* KM activities (KMA), where KMA ϵ {KI, KA, KMO, KS, KR, KIT, KU, KT, KUP};
- is conditioned by KM factors (soft and hard); and
- contributes to the achievement of "m" KM outcomes (KMO), where KMO ϵ {FinOut, InovOut, CompeOut, CustoOut}.

Consequently, we can derive an index for performance measurement of KM projects based on the performance of the model constructs. This index assesses the KM flow implemented, the level of achievement of target KM outcomes and the adherence of contextual factors.

We call the indexes for KM activities, intended KM outcomes and KM factors, KMAI, KMOI and KMFI, respectively.

Hence, the KM project performance index (KMPI) is made of KMAI, KMFI and KMOI, as follows:

$$KMPI = KMAI + KMFI + KMOI$$

Each index indicates the degree to which the KM driver/outcome reaches the most desirable level. This is obtained based on the factor score estimation for each construct, via the application of PLS regression to the research model.

In the following, we proceed to the factor score calculation for each of the model constructs.

The factor score ξ_{KMA} for KMA is calculated using equation (1):

$$\xi_{KMA} = \sum_{i=1}^{k} X_i x_i \tag{1}$$

Where the following holds:

KMA = is a KM activity ϵ {KI, KA, KMO, KS, KR, KIT, KU, KT, KUP}, measured using "k" manifest variables.

X_i = is the factor score coefficient.

x_i = is the value of the ith measurement item for the activity KMA.

The best estimate for the factor score coefficient X_i is $\hat{X}_i$ which is the mean value of each estimated X_i obtained through the application of the bootstrap procedure across 5000 bootstrap samples (Chen and Fong, 2015; Henseler *et al.*, 2016).

Similarly, factor scores ξ_{KMF}, ξ_{KMO} are estimated by applying regression respectively to KM factors and KM outcomes constructs.

Using the approach of Eskildsen *et al.* (2001), we set the maximum value for the KMAI to 1000 units. KMAI is calculated based on the relative impact of the best factor score estimation on the maximum factor score, all multiplied by 1,000, as represented in equation (2):

$$KMAI = \left(\hat{\xi}_{KMA} / \hat{\xi}_{KMA(\max)}\right) * 1000 \tag{2}$$

Where $\hat{\xi}_{KMA(\max)} = \sum_{i=1}^{k} \hat{X}_i * \max(x_i)$.

Based on the same logic, KMFI and KMOI are provided by equations (3) and (4):

$$KMFI = \left(\hat{\xi}_{KMF} / \hat{\xi}_{KMF(\max)}\right) * 1000 \tag{3}$$

$$KMOI = \left(\hat{\xi}_{KMO} / \hat{\xi}_{KMO(\max)}\right) * 1000 \tag{4}$$

Using the factor score summation procedure of Distefano *et al.* (2009), KMPI is calculated based on the means of the sums of relative impact of implemented KM activities, intended KM outcomes and KM factors. All of these are multiplied by 1,000, as indicated in equation (5):

$$KMPI = \left(\left(\sum_{i=1}^{n} \frac{\hat{\xi}_{KMAi}}{\hat{\xi}_{KMAi(\max)}} \right) \Big/ n + \left(\sum \frac{\hat{\xi}_{KMF}}{\hat{\xi}_{KMF(\max)}} \right) \Big/ 2 + \left(\sum_{j=1}^{m} \frac{\hat{\xi}_{KMOj}}{\hat{\xi}_{KMOj(\max)}} \right) \Big/ m \right) * 1000 \tag{5}$$

Hence, a KM project performance index is derived from the KM performance constructs that have been designed. This index is indicative of the ability of the KM project to fulfill the intended KM outcomes, attain KM flow effectiveness and adhere to contextual factors.

5.7 Importance performance map analysis

Importance performance map analysis (IPMA) extends the PLS-SEM capacity of analyzing the relative importance of predictors on target constructs by including the performance dimension (through the average values of the latent variable scores). Hence, conclusions are drawn on both importance and performance dimension. Indeed, actions for target performance improvement are oriented toward constructs that exhibit a large importance but have low performance, which is knowledge that is particularly important for prioritizing managerial actions.

IPMA provides a graphical map of importance–performance that presents the predictor construct's importance in shaping the target construct (the total effect), with its performance indicated by the average latent variable score. Two levels of abstraction are proposed: the construct level and the indicator level.

Figure 3 displays the IPMA map for the innovation outcome on both constructs and indicators levels. It shows that the KR followed by KIT has a relatively high importance, according to target construct innovation: a one-unit improvement on KR performance from 54 to 55 per cent increases the performance of innovation outcome by 0.52.

Similarly, KIT followed by KS plays an important role in fostering the financial performance.

The same analysis is performed for all target constructs.

6. Discussion and conclusions

6.1 Discussion

Drawing on anterior KM performance-measurement studies and theories, this study proposes a performance-measurement model for KM projects. The activities, factors and outcomes of KM are the key constructs of this model; they represent the drivers and outcomes of KM project performance. Hence, this work verifies, in an empirical study, the measurement scales for each construct, its consistency and tests the relationships between drivers and outcomes.

For the first construct introduced by this study, KM activities, the model assessment results confirm the validity of all measurement scales for KM activities. The sequential effects among KM activities are globally confirmed, while three assumptions related to KM flow cycle are rejected; these concern the effects of KI on KA, of KMO on KS and of KR on KIT.

In fact, theoretically, KI is the preliminary KM activity in the KM flow cycle. It operates on crucial knowledge and identifies it so that it can be acquired, structured, stored and processed in subsequent activities (Al-hawary and Alwan, 2016). However, our empirical findings reject any positive effect between KI and KA. Furthermore, an important positive effect is observed between KI and KR. This result is unexpected because previous work (Chen and Fong, 2015) confirms a positive effect here.

Our empirical results support the positive effect of KA on KMO and reject a hypothesis for an effect of KMO on KS. This finding suggests that storing knowledge may depend on additional KM activities such as knowledge generation, as stated by Zaim *et al.* (2013).

Our empirical results also deny the positive impact of KR on KIT, but the results found by Chatzoudes *et al.* (2015) indicate that socialization is the only practice leading to KIT, as these activities together constitute knowledge learning. Socialization is viewed by Chatzoudes *et al.* (2015) as a multi-stage process. To draw meaningful conclusions, socialization should be decomposed, and further studies should be undertaken to study the impact of each sub-process.

Globally, it is noted that the three assumptions that are rejected are all related to KM activities relying on some cognitive activities and not being supported by technological tools. Moreover, they are the least studied by scholars and practitioners, and their practice is also limited in firms (Bimba *et al.*, 2016). This issue may suggest in-depth study of those constructs to ensure better clarity of concepts and an improved measurement scale.

On the other hand, the cyclic nature of KM flow suggests that each activity in the KM flow cycle is effective for increasing and enhancing subsequent KM activity. Conversely, non-implemented KM activity negatively affects subsequent KM activity in the KM flow cycle. As a result, firms should practice all KM activities to achieve effective knowledge flow. Their KMS should implement the whole KM cycle from KI to the KT because there is a risk of project failure if some KM activities are neglected.

For the second construct of the model, KM factors, the empirical results emphasize the significant effects of both soft and hard factors on KM activities: technology, culture and structure have a positive influence on the handling of KM activities. The results also endorse KM technological and organizational factors as a HC. This finding is in line with prior studies suggesting that KM activities occurring in a group require an efficient IT-based system, combined with a dedicated organizational KM structure (Chong *et al.*, 2007; Lee and Wong, 2015; Migdadi, 2008; Zaied, 2012), and a conducive KM culture enables some individual KM activities, such as KIT(Lee and Choi, 2003; Lee *et al.*, 2012).

Another important contribution of this study regards the third construct of the model: KM outcomes, particularly the verification of the multidimensional aspect of KM outcomes, using testing of the hierarchical nature of the constructs, in addition to the testing of their relationships with drivers.

Hence, it is confirmed that competency development, innovation and customer satisfaction measure the same concept, which is the KM outcome. This finding is consistent with the literature (Anantatmula, 2007; Chen and Fong, 2015; Lyu *et al.*, 2016). However, financial performance is not a KM outcome.

This study also contributes to the identification of antecedents to KM outcomes among KM activities. In fact, the results confirm the existence of significant effects of KM activities (KU and KR) on the HC KM outcomes. This result is consistent with the existing literature, which associates the KU with global organizational performance (Chen and Fong, 2015; Lyu *et al.*, 2016; Yeşil *et al.*, 2013).

The findings also indicate the existence of some significant effects between KM activities and each of the dimensions of KM performance. Indeed, significant but opposed relationships exist between KUP and KT and innovation outcomes. This result contradicts previous studies that assert a positive effect (Al-Sa'di *et al.*, 2017; Kamhawi, 2012) but could be justified by the existence of a mediating variable, namely, knowledge creation, as identified by Andreeva and Kianto (2011).

Important and significant effects of KA and KR on the competency development outcome are also observed. This aspect is not dealt with by the existing literature, but it seems quite logical because employees that acquire and retrieve organizational knowledge also naturally develop their competencies.

The results also indicate a significant direct effect between soft factors and KM outcomes. Indeed, firms that aim to improve KM outcomes are recommended to increase awareness of KM among their knowledge workers by promoting KM culture. This finding is in line with some prior research (Gold *et al.*, 2001; Theriou *et al.*, 2011). Surprisingly, hard factors seemed not to affect KM outcomes. This finding, which contradicts much previous work (Andreeva and Kianto, 2012; Chong *et al.*, 2007; Lee and Choi, 2003; Theriou *et al.*, 2011) but is consistent with one previous study (Chen and Fong, 2015), may be interpreted by the firm sector. In fact, it is observed elsewhere (Andreeva and Kianto, 2011; Yu *et al.*, 2007) that, depending on the knowledge-intensive conditions of the firm, success factors contribute differently to KM outcomes.

Another interesting finding of this study, established by the IPMA, is the identification of actionable variables that are candidates for the improvement of KM outcomes. For instance, the competency development outcome is best predicted by KA, which has a moderate importance (0.18) and a performance score of 57 per cent. Because KA has moderate performance, there is a room for improvement on acting on this construct's predictor. The competency development outcome performs better. This analysis, applied to all endogenous variables allows the identification of the most important area for specific actions and enables performance enhancement.

6.2 Implications for theory

This study proposes a theoretical model for performance measurement in KM projects, undertaken with empirical validation. The designed model is based on three constructs: the activities, outcomes and factors of KM. This study provides five main contributions:

First, a KM cyclic flow model is designed, and sequential interactions inside this model are assumed and verified. The empirical results reveal that sequential effects among KM activities are significant. Indeed, any non-implemented KM activity in the organization could negatively affect the remaining KM activities.

Second, technology, culture and structure are assumed to be factors that influence KM activities. The results show that the corresponding effects are significant.

Third, identified organizational objectives are tested, and three of them are confirmed as effective KM outcomes, and their relationships with KM drivers are also confirmed.

Fourth, a measurement system and a score for the performance of a KM project are provided.

Last, through IPMA, a prospective aspect of performance measurement is developed; it is thus now possible to contribute to KM project performance enhancement by identifying actionable variables that have a room for improvement. Meanwhile, further theoretical exploration should be performed to resolve certain empirical findings.

6.3 Implications for practice

The present study tends to improve the management of KM projects by measuring their performance. It aims to meet companies' need for organizing KM on the project level by providing measurement indicators, whereas existing models deal with KM assessment on the firm level. In fact, the findings of this study carry important practical implications; the proposal of an empirically tested model can result in the creation of indicators that constitute a basic structure against which a scorecard can be built for the KM performance analysis. This scorecard may eventually be integrated to the global company performance scorecard.

Additionally, the findings highlight that knowledge activities play an important role in boosting organizational performance; managing knowledge enhances competency development, promotes innovation and improves customer satisfaction. Accordingly, managers should place greater emphasis on support for KM to obtain better firm performance.

Obtaining a clear grasp of the expected contribution of each KM activity in the organizational performance dimensions will assist firms to prioritize their investment and to select the correct KM initiative to serve the needed KM activity and contribute to the intended performance dimension.

The results also show that socio-technical factors are important drivers for the effectiveness of KM, letting knowledge activities depending on the full implementation of technological, cultural and structural factors. Managers should reinforce these factors to achieve better knowledge flow.

The conclusions drawn from the knowledge flow model and its cyclic aspect include the interdependency between KM activities. In fact, KM projects cannot be considered as standalone projects; they are a component of a global KM system that implements the entire model of KM activities. Managers should consider this aspect and build a KM strategy that is compliant with the cyclic aspect of knowledge flow.

6.4 Limitations

Although this study provides some important results, some limitations should be considered to evaluate the findings. The measurement instrument used in this study is a survey that relies on self-administered questions, and the survey respondents are exclusively from Morocco. Thus, the results cannot be generalized to other societies that have different cultural contexts. Another limitation is the difficulty in recruiting respondents, which leads to a reduced sample size and prevents us from performing advanced analysis, such as heterogeneity analysis.

6.5 Avenues for further research

The results of this study and the existing literature on KM performance measurement research together provide promising avenues for future research.

First, there remains a need for additional theoretic exploration to explain the individual effects between drivers, activities and outcomes of KM. Following this direction, more studies should be undertaken to explore how each KM factor and each KM activity affect the dimensions of KM outcomes.

Second, certain findings of this study may be regarded as in conflict with the existing literature; this includes the effect of socio-technical factors on KM outcomes. It should be noted in this connection that the approaches to performance measurement proposed in the literature are rooted in Western-based management theories and the special Western socio-cultural setting, which is characterized by individualism, instrumentalism and competitiveness. Approaches with this origin may fail to capture North African contexts, which are more collectivistic and paternalistic and where cultural values have much larger impact (Kamoche *et al.*, 2012). Our research sheds light on certain elements characterizing KM in the North African context. Further research should be directed toward consideration of the specificities of the African setting and elaborating more suitable KM frameworks.

Third, this is a cross-sectional study that takes a snapshot of the KM project at a specific time. The performance assessment of KM and the identification of areas of possible improvement areas can be more accurately verified using a longitudinal study that tracks performance changes in KM through changes in predictors. Future research may wish to use a longitudinal study.

Fourth, the results can be validated in broader empirical contexts that would contain a large sample of firms belonging to multiple activity sectors.

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