Knowledge Management Practices for Stimulating Incremental and Radical Product Innovation

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INTRODUCTION

According to Agarwal and Helfat (2009, p. 282) strategic renewal includes "*the process, content, and outcome of refreshment or replacement of attributes of an organization that have the potential to substantially affect its long-term prospects*". This is a broad definition, which can include many forms of renewal activities, both in response to external opportunities/threats and internal strengths/weaknesses. Examples of renewal activities currently receiving much attention are innovation activities, creating opportunities for both incremental and radical innovation. Crucial to innovation and the subsequent development of sustainable competitive advantage is the organization's ability to create and transfer knowledge (Nonaka, 1991, 1994). This ability depends upon the extent to which the organization succeeds in combining and exchanging existing knowledge among employees (Nahapiet and Ghoshal, 1998). Several studies have shown that the implementation of knowledge management practices that stimulate individual employees to develop their knowledge base (e.g. job rotation, training, financial incentives for new ideas), exchange their knowledge with others (e.g. teamwork, employee participation, suggestion schemes) or make their knowledge part of the organizational memory (e.g. input of knowledge in lessons learned databases) can be fruitful in this respect (e.g. Chen and Huang, 2009; Greiner, Böhmann and Krcmar, 2007; Lopez-Cabrales, Pérez-Luño and Cabrera, 2009; Wang and Noe, 2010; Zhou, Hong and Liu, 2013). These practices incite a learning process, the creation of fresh insights and the discovery of new opportunities among employees, important antecedents of new knowledge creation and innovation.

Although there is theoretical and empirical evidence for the contribution of knowledge management practices to innovation performance, several studies have shown that there might be some contingencies at play, and that the relationship between knowledge management practices and innovation might be more complex than assumed thus far. Greiner et al. (2007), for example, show that there should be an alignment between knowledge management practices and the business strategy. Lopez-Cabrales et al. (2009), in turn, conclude that knowledge features mediate the relationship between knowledge management practices and innovation, and that not all knowledge management practices equally contribute to innovation. More specifically, they show that the uniqueness of knowledge plays a mediating role in the relationship between knowledge management practices and the organization's innovative activity. They also demonstrate that especially *collaborative HRM practices* (e.g. group-oriented HRM practices such as cross-functional teams and job rotation) contribute to the uniqueness of knowledge and subsequently to innovation. *Knowledge-based HRM practices* (e.g. HRM practices focused on internal development of knowledge such as employee empowerment and training in firm-specific knowledge), in turn, do not influence the uniqueness of knowledge and therefore do not show a relationship with innovation. More recently, Zhou, Hong and Liu (2013) have shown that both a commitment oriented HRM system (emphasizing internal cohesiveness) and a collaborative oriented HRM system (building external connections) positively influence the firm's innovation. They also found a negative interaction effect between both systems. The authors rely on ambidexterity theory to explain the findings, and state that '*if the organization ambidextrously invests in both commitment and collaboration oriented HRM systems, each system may divert the resources devoted to the other system*' (Zhou et al., 2013, p. 279). Therefore, they suggest that organizations should take their innovation strategy into account (i.e. focus on incremental or radical innovation) to decide upon investments in the HRM system or try to find a balanced equilibrium if they decide to focus on both innovation strategies.

These studies show that the right choice of practices depends on whether organizations favor radical and incremental innovation and that the type of knowledge that is transferred and created might be an important mediating variable. We want to add to this discussion in two ways. First, we focus on the complexity of innovation strategies and the distinction between incremental and radical innovation in particular. Both activities demand different mindsets and approaches, which March (1991) refers to as ‘exploitation’ and ‘exploration’. Whereas *exploitative innovation* is incremental, builds further on existing knowledge and implies efficiency and refinement, *exploratory innovation* has a more radical character and requires the incorporation of diverse viewpoints, experimentation and risk taking (Lavie, Stettner, and Tushman, 2010). As mentioned by Zhou et al. (2013), ambidexterity (i.e. the ability to be equally successful in incremental and radical innovation) might very hard to realize given these opposing demands. Second, we expect that the type of innovation (incremental versus radical) asks for other types of knowledge to be created and shared. In developing the hypotheses, we therefore specifically focus on the concepts of related and unrelated knowledge. Whereas *related knowledge* refers to information, ideas, and expertise that are closely related to the existing knowledge of the individual, *unrelated knowledge* is not (closely) related to the existing knowledge of the individual.

In this study, we hypothesize that certain knowledge management practices improve incremental product innovation performance, while others are more appropriate for radical product innovation. Using a sample of 822 Flemish manufacturing and service companies, we find that incentives oriented at the transfer and creation of related knowledge stimulate incremental innovation performance, whereas incentives oriented at the transfer and creation of unrelated knowledge stimulate radical innovation performance.

This study enriches the theoretical understanding of the relationship between knowledge management practices and innovation performance, by pointing to the potential roles of related and unrelated knowledge. It also warns against a ‘one-size-fits-all’ approach to stimulating knowledge transfer and creation, and shows that companies should carefully select practices that fit with their innovation strategy.

LITERATURE REVIEW AND HYPOTHESES

The role of related and unrelated knowledge for incremental and radical innovation

In line with Greiner et al. (2007), we argue that practices focusing on stimulating employees to develop, transfer, communicate and exchange their knowledge (rather than practices focusing on codifying knowledge) are the most optimal choice for innovation. The central objective of these practices is leveraging the value of tacit knowledge, i.e. highly personal knowledge of individuals which is rooted in action, firm-specific and difficult to formalize and communicate (Nonaka, 1991). Tacit knowledge is considered to be the crucial ingredient of innovation and a source of sustained competitive advantage because it is unique, valuable, scarce, and inimitable (Oliver, 1997), and can only be acquired and exchanged through experience and interaction with others (e.g. via observation, imitation, practice) (Nonaka, 1991).

Although tacit knowledge is beneficial for innovation, it is also generally accepted that the improvement of existing products and technologies requires different types of tacit knowledge than the creation of radically new products and competencies. On the one hand, exploratory innovation requires the integration of divergent opinions and viewpoints into a new synthesis or artifact (Schön, 1963; Pelz and Andrews, 1966). Whereas some have argued that exploration requires the integration of knowledge from outside the firm (see overview by Lavie Stettner, and Tushman, 2010), others have shown that the integration of divergent knowledge and viewpoints from different individuals and different parts of the firm can also foster explorative innovation (de Visser et al., 2010). Truly novel solutions and insights hence build on the transfer between individuals of unrelated knowledge, which can be defined as information, ideas, and expertise that are not (closely) related to the existing knowledge of the individual.

On the other hand, this knowledge diversity appears less beneficial for exploitative, incremental innovation. Instead, exploitative innovation results from the refinement and more efficient use of the existing knowledge base (Lavie, Stettner, and Tushman, 2010; March, 1991; O'Reilly and Tushman, 2004). This refinement is best achieved through the transfer and creation of related knowledge, which can be defined as information, ideas, and expertise that are closely related to the existing knowledge of the individual. Bringing together diverse knowledge and viewpoints is not beneficial for incremental innovation, since it triggers conflicting expectations and an overload of opinions from diverse individuals (Song et al., 1998; de Visser et al., 2010). This can disrupt existing work routines and decision making, which in turn hampers the ability for continuous optimization and refinement of existing products and technologies (Song and Xie, 2000; de Visser et al., 2010). Overall, it can therefore be expected that knowledge management practices aimed at the transfer and creation of related knowledge will contribute to incremental product innovation performance, while knowledge management techniques aimed at the transfer and creation of unrelated knowledge will contribute particularly to radical product innovation performance.

In what follows, we elaborate on the above reasoning for specific knowledge management practices that were questioned in the sixth edition of the Community Innovation Survey (CIS, 2011) and that can be related to the personalization strategy as mentioned by Greiner et al. (2007). More specifically, these are all knowledge management practices focusing on stimulating employees to develop, transfer, communicate and exchange their knowledge.

Knowledge management practices for the transfer and creation of related knowledge

Brainstorm sessions. Organizing brainstorm sessions is a management technique to generate ideas and stimulate creative thoughts (Nunamaker, Applegate and Konsynski, 1987). This can be done both individually and in a group setting. According to Nunamaker et al. (1987)

individual brainstorm sessions are highly effective in terms of the number and quality of ideas that are generated. Yet, because they are individually organized, there is no exchange of knowledge between employees. We therefore argue that the new ideas will be based upon existing knowledge of the individuals and thus especially concern related knowledge.

Brainstorm sessions in group, in turn, rely on a number of people to generate ideas. Although the basic premise is that a group of people working together will be more creative in problem solving as compared to individuals, previous research has shown that this is not always the case. Brainstorming in group seems to be very difficult to organize because a lot of ideas have to be generated by different people in a relatively small amount of time. We argue that brainstorm sessions in group primarily lead to the transfer and creation of related knowledge. First, previous research has shown that groups are inclined "*to focus on information they have in common rather than on sharing unique expertise*" (Stasser, 1999; cited by Paulus and Yang, 2000, p. 77). Next, although diversity of participants in brainstorm sessions might be important for the number and newness of ideas, group comfort and cohesion are as – or even more – important (Wilson, 2006). People might be unwilling to state some of their ideas because they are afraid of being negatively evaluated by others (Paulus and Yang, 2000). This process is called evaluation apprehension and will be more likely when people do not know each other. Group comfort and cohesion might prevent evaluation apprehension and are higher when employees know each other. Finally, Wilson (2006) argues that ideas should be expressed very quickly, one by one, and without undue elaboration or stories to prevent production blocking (Diehl and Stroebe, 1991). Listening to others' ideas my distract people and hinder them in developing own new ideas. Therefore, too much interaction might be pernicious. These mechanisms imply that especially related knowledge will be transferred and created in brainstorm sessions in group, and that the transfer and creation of unrelated knowledge might be hindered.

In sum, we argue that the nature of brainstorm sessions – whether they are individual or collective – makes them especially suitable for the transfer and creation of related knowledge, which in turn leads to incremental innovation. We thus hypothesize that:

> *H1: The use of brainstorm sessions stimulates the transfer and creation of related knowledge and therefore has a positive effect on incremental product innovation performance.*

Financial and non-financial incentives for new ideas. Financial (e.g. bonus) and non-financial incentives (e.g. extra holidays) for new ideas are extrinsic rewards. According to the expectancy theory (Vroom, 1964), financial and non-financial incentives can steer employees to act or behave in a certain way because they know that their efforts will be valued and rewarded by the organization. More specifically, financial and non-financial incentives for new ideas can motivate employees to generate new ideas (in the case of individual incentives) or to share their knowledge with other employees (in the case of group incentives) because the incentives send a signal of recognition towards the employee and show that the organization values knowledge sharing behavior (Cabrera and Cabrera, 2005). Yet, although financial and non-financial incentives may stimulate employees to generate new ideas or to share their knowledge, they may especially instigate them to look for related knowledge which inherently incorporates lower uncertainty and hence higher changes of reaping these financial and non-financial benefits (see for example Holmström, 1989 on the tendency of risk-averse managers to reallocate resources from R&D investments to less risky projects). This in turn can be expected to improve especially incremental innovation performance. This leads to the following hypothesis:

H2: The use of financial and non-financial incentives for new ideas stimulates the transfer and creation of related knowledge and therefore has a positive effect on incremental product innovation performance.

Knowledge management practices for the transfer and creation of unrelated knowledge

Job rotation. Job rotation implies *"a lateral transfer of employees among a number of different positions and tasks within jobs where each requires different skills and responsibilities"* (Huang, 1999, p. 75). It helps members of an organization to understand – through experience – the business from a multiplicity of perspectives (Nonaka, 1994, p. 29) and allows building redundancy of information into an organization. According to Nonaka (1994), redundancy of information facilitates interaction among organizational members and consequently makes it easier to transfer tacit knowledge among them, a necessary condition for new knowledge creation and innovation. Cabrera and Cabrera (2005), in turn, argue from a social capital perspective that the opportunity to share and subsequently create knowledge is determined by the extent to which employees share the same language and narratives. The likelihood that employees share the same language and narratives enhances when people frequently change positions and jobs throughout the organization.

Moreover, when this rotation concerns the transfer between different departments and business units (as we measured it), the employee is continuously provided with new information from new and different perspectives, i.e. unrelated knowledge. When combined with the employee's existing knowledge, this new unrelated knowledge will lead to a process of new and unique knowledge creation (Lopez-Cabrales et al., 2009), and subsequently to radical product innovation. We therefore hypothesize that:

H3: The use of job rotation stimulates the transfer and creation of unrelated knowledge and therefore has a positive effect on radical product innovation performance.

Cross-functional or multidisciplinary teams. Cross-functional or multidisciplinary structures bring together specialists of different departments within a single team structure for a particular innovation project (Griffin, 1997). Cabrera and Cabrera (2005) argue that teamwork gives employees the opportunity to work closely and frequently with others and therefore encourages tacit knowledge sharing. According to Noe et al. (2003), when team members have a shared responsibility and are accountable for the results, action learning occurs. To achieve a positive result the team members seek out information and share what they find with others. Teamwork thus stimulates tacit knowledge sharing and subsequently knowledge creation and innovation.

The integration of several domain specialists in a cross-functional or multidisciplinary team is especially effective for transferring unrelated knowledge because social ties are created between employees from different groups (Allen, 2001; Cabrera and Cabrera, 2005; Hargadon, 2003). The connection of previously unrelated tacit knowledge sets will contribute to new knowledge creation, and subsequently to radical product innovation. In line with previous empirical findings by de Visser et al. (2010), we therefore hypothesize that:

H4: The use of cross-functional teams stimulates the transfer and creation of unrelated knowledge and therefore has a positive effect on radical product innovation performance.

METHOD

In 2011, the sixth edition of the Community Innovation Survey (CIS) was conducted in several Member States of the European Union. The survey sought to develop insights into the innovative behavior of companies and included a one-off module on knowledge management practices. For the Flemish part of the CIS2011 survey, a representative sample of 4951 – mostly private – Belgian manufacturing and service firms was selected. Top management of the organizations received a 20-page questionnaire, inquiring about different innovation-related issues in the period 2008-2010. The response rate was 49 % (2418 firms). A comparison between respondents and non-respondents showed no bias in terms of innovation. Due to missing values for the variables used in our models, the analyses were restricted to a final sample of 822 firms. Descriptive statistics are given in Table 1.

Insert Table 1 here

Variables and descriptive statistics

Dependent variables: radical and incremental innovation performance

We follow the work by a.o. Mohnen and Mairesse (2002), Faems, Van Looy and Debackere (2005) and Laursen and Salter (2006), who measured product innovation success as product innovations' share in total sales. We use two different dependent variables, representing radical product innovation performance, and incremental product innovation performance. We measure the successful development of radically new products or services as the share of turnover in 2010 from goods and services that were new to the market and that were introduced during the period 2008 to 2010. We label this variable *Rad_Inno*. The average firm in the sample obtained about 7.9% of its turnover from goods and services that were new to the market. Similarly, *Incr_Inno* represents the successful development of incremental product or service innovations and is measured as the share of turnover in 2010 from goods and services that were new to the firm but that were already available on the market and that were introduced during the period 2008 to 2010. The average firm in the sample obtained about 7.2% of its turnover from incremental goods and services innovations. The two dependent variables have the advantage of directly measuring the commercial success of innovative output.

Independent variables: knowledge management practices

The CIS2011 asked companies about their use of various knowledge management practices in line with a personalization strategy during the period 2008-2010 (see also Nonaka, 1994; Cabrera and Cabrera, 2005). *Brainstorm* is a binary variable that indicates whether or not a company used brainstorming sessions. *Crossfunc* measures whether or not a company used multidisciplinary or cross-functional teams. *Jobrot* is a binary variable that indicates whether or not a company used job rotation between different departments or different companies within the group. *Finin* indicates whether or not a company used financial incentives for the development of new ideas. Finally, the dummy variable *Nfinin* indicates whether or not a company used non-financial incentives for the development of new ideas, such as extra holidays, public recognition, and more interesting work.

As shown in Table 1, the use of practices varies widely. While 80% of the firms used brainstorming sessions (*Brainstorm*) and 63% used cross-functional teams (*Crossfunc*), only 27% used financial incentives (*Finin*) and 23% used non-financial incentives (*Nfinin*). Job rotation (*Jobrot*) was used by 36% of the firms in our sample.

Control variables

A limitation of many existing studies is that they focus solely on the impact of knowledge management practices without controlling for other factors that affect innovation performance (or firm performance in general) (see critique by Shadur and Snell, 2002). In order to avoid possible omitted variable bias that could lead to an over- or underestimation of the effects of employee stimuli, we include a number of control variables in our models.

R&D intensity. We expect a positive effect of internal innovation efforts on a company's innovation performance. In line with previous work, we therefore control for the firm's internal innovation efforts by including the variable *RD_Intensity*, measured as the firm's internal R&D expenditures in 2010 divided by its turnover in 2010. The average firm in our sample spends about 14% of its turnover on internal R&D. Due to the skewed distribution of this variable, we transformed it by taking the natural logarithm of 1 + RD_*Intensity* (see for example Czarnitzki and Kraft, 2010 for previous use of this measure). We labeled this variable *Ln_RD_Intensity*.

Group. A company that is part of a larger group may have easier access to resources in terms of capital and knowledge and hence have a better chance to introduce innovations than stand-alone companies (Mention, 2011). For product innovations, group members may also benefit from better access to markets through their affiliates' distribution system. Therefore we included the dummy variable *Group*, which takes the value 1 if the company belongs to a larger group, and the value 0 if it is an independent company. Approximately 68% of the observations in our sample belong to a group.

Collaboration. Innovation is best achieved through a combination of internal and external communication (Van de Ven, 1986; Damanpour, 1991; Teece, 2007). Collaboration with outsiders is positively connected to innovative outcomes (Kessler and Chakrabarti, 1996; Phelps, 2010) because it increases knowledge diversity and heterogeneity which many authors consider indispensable for innovation (see for example Kane and Alavi, 2007). We control for this by including the dummy variable *Collab* in our analyses. It takes the value 1 if the company engaged in collaborations for the development of new products or processes during the period 2008-2010, and the value 0 if it did not. Approximately 38% of the observations in our sample collaborate with external parties to develop innovations.

Size. Since the seminal writings of Schumpeter (1939), the relation between size and firm performance has been much debated (Ahuja et al., 2008; Cohen, 1995). Several theoretical arguments have been brought forward to substantiate potential innovative advantages of both small and large firms (see for example Acs and Audretsch, 1990). While many empirical studies report a positive link between size and innovation (e.g. Skuras, Tsegenidi and Tsekouras, 2008; Un, Cuervo-Cazurra and Asakawa, 2010), others report a negative (Knudsen, 2007; Spithoven, Frantzen and Clarysse, 2010) or quadratic relation (Arvanitis, 2008). To control for the size of the company we use the number of employees in 2010 (*Size*). The average firm in our sample has 161 employees, while the biggest firm in the sample has more than 4800 employees. For the regression analysis we used the natural logarithm of 1 + *Size*. We label this variable *Ln_Size* and also include its square to analyze possible curvilinear effects.

Age. The firms' age is also used as control variable, as younger firms may be more innovative than older ones (e.g. de Jong and Vermeulen, 2006; Schneider and Veugelers, 2010). In particular, younger firms may achieve a higher share of sales with new products simply because they have less established products than older firms. Based on the firm's founding date, we obtained the firm's age (*Age*). The average age of the respondent firms is 26. The oldest firm in the sample is 110 years old. For the regression analysis we used the natural logarithm of 1 + *Age*. We label this variable *Ln_Age*.

Industry. The literature indicates an industry effect on both innovation and innovation success (Spithoven, Frantzen and Clarysse, 2010; Ettlie and Rosenthal, 2011) and especially points to differences between the manufacturing sector and the service sector (Evangelista and Vezzani, 2010). Based on the main NACE[1] code of each firm, we construct the dummy variable *Serv*, which gets the value zero for manufacturing firms and one for service firms. About 54% of the companies in our sample are manufacturing companies, while 46% are service firms. Using the same NACE code, we construct another dummy variable *Hitech*, which gets the value zero for firms active in low-tech and medium-low-tech sectors and one for firms active in medium-high-tech and high-tech sectors[2]. About 44% of the companies in our sample are

[1] NACE, which is short for "Nomenclature générale des Activités économiques dans les Communautés Européennes", refers to the industrial classification used by Eurostat and is the subject of legislation at the European Union level, which imposes the use of the classification uniformly within all the Member States.
[2] Based on the sector's average R&D intensity (R&D expenditures/value added) Eurostat classifies the NACE codes into high-tech, medium-high-tech, medium-low-tech, and low-tech sectors. See http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/Annexes/htec_esms_an2.pdf.

classified as high-tech, while 66% are classified as low-tech firms. Table 2 contains the correlations between the variables.

Insert Table 2 here

RESULTS

Table 3 provides an overview of our OLS regression results[3]. *Brainstorming* has positive effects for both radical and incremental innovation. Hypothesis 1 is thus confirmed. Yet, contrary to our expectations, it seems that brainstorm sessions might be fruitful for the transfer and creation of unrelated knowledge, and subsequently radical innovation, as well. *Financial incentives* have a positive and significant effect on incremental innovation. *Non-financial incentives* do not influence incremental innovation. Hypothesis 2 is thus partially – only for financial incentives – confirmed. *Cross-functional teams* have, in line with hypothesis 3, a positive significant effect on radical innovation. Finally, we do not find evidence for a relationship between *job rotation* and radical innovation. Hypothesis 4 is thus not confirmed.

As for the control variables, we find a significant positive effect of *R&D intensity* and *high-technology activities* on radical innovation but not on incremental innovation. *Age* and size have a significant negative effect on radical innovation but not on incremental innovation. No curvilinear effect is found for the square of *size*. *Collaboration* has a positive significant effect on both incremental and radical innovation. Finally, contrary to our expectations, *membership*

[3] Despite the fact that our dependent variables are left censored, we did not apply Tobit regressions but used OLS as a valid alternative (see also Angrist and Pischke, 2008).

of a group and *industry (service versus manufacturing)* do not have an impact on incremental nor on radical innovation.

Insert Table 3 here

DISCUSSION

In this study, we focused on innovation as one potential outcome of strategic renewal. Firms' innovation strategies are known to be complex, encompassing not only the improvement of existing products and technologies, but also the creation of new products and competencies (Chang, 2015). Chang (2015) articulates the need for ambidexterity if both types of innovation are focused upon and shows how high performance work systems (HPWS) can positively influence organizational units' human capital and subsequently the units' ambidexterity. Moreover, this positive influence is stronger if the organization also has a positive social climate, i.e. *a climate of trust, cooperation, shared codes and languages* (Chang, 2015, p. 81). Prieto-Pastor and Martin-Perez (2015), in turn, show how high involvement HR systems positively influence employees' ambidextrous learning and subsequently the firm's ambidextrous learning. Moreover, they provide evidence of a positive moderating effect of management support in the relationship between high involvement HR systems and employees' ambidextrous learning. Although both studies show the importance of human and social capital as well as management support for ambidexterity, they do not go into the different types of knowledge that are required for incremental and radical innovation, nor do they go into how these different types of knowledge can be stimulated by individual practices. On the other hand, whereas many studies show how overall innovation performance benefits from stimulating knowledge transfer and creation, most do not take into account the complexity of innovations strategies and the distinction between incremental and radical innovation (Zhou et al., 2013). In addition, they focus solely on the impact of knowledge management practices without controlling for other factors that are known to affect innovation performance. By overcoming these limitations, this study contributes to the knowledge management, innovation and HRM literature. In particular, it enriches the theoretical understanding of the relationship between knowledge management practices and innovation performance, by distinguishing between the crucial roles of related and unrelated knowledge (see Figure 1). Our study suggests that knowledge management practices can stimulate the transfer and creation of related or unrelated knowledge, which in turn affect incremental and radical innovation performance respectively.

In particular, we found that brainstorm sessions affect both incremental and radical innovation performance. This suggests that this knowledge management practice can stimulate the transfer and creation of both related and unrelated knowledge. We did not expect brainstorm sessions to enhance both incremental and radical innovation. However, this finding can probably be explained by differences in the professionalism with which the brainstorm sessions are implemented in the organizations and in the composition of participants in the session. We expected related knowledge to be transferred and created by means of brainstorm sessions. Yet, Paulus and Yang (2000) argue that they can also be an effective means to enhance radical innovation under the right conditions. They, for example, conclude that using a group-writing procedure can effectively overcome the potential problems of production blocking or evaluation apprehension which hinder the creation of unrelated knowledge. Next, the composition of the group might play a role as well. If the group only includes employees with a similar function, related knowledge will be transferred and created. However, if the group consists in different domain specialists and is professionally organized, the likelihood that unrelated knowledge is transferred and created increases. Cross-functional teams appear to induce mostly unrelated knowledge transfer and creation, which in turn increase radical innovation performance. When offered financial rewards, employees apparently tend to put forward related ideas for incremental innovation, which has a higher chance of success – and hence financial rewards – as compared to unrelated ideas for radical innovation. Contrary to our expectations, non-financial incentives have no influence. According to the expectancy theory (Vroom, 1964), incentives are motivating only if they are considered valuable by the employee. Because the generation of new ideas will lead to innovation and added value for the organization in monetary terms, it is possible that employees want their share of this added value and therefore prefer money above non-financial incentives. Finally, we do not find evidence for a relationship between job rotation and radical innovation. It is possible that job rotation will only have an influence if it is flanked by collaborative practices such as team work or collective brainstorm sessions. That way the accumulated knowledge through job rotation will also be exchanged with other employees, which might be a crucial condition for radical innovation.

Our findings are relevant for practitioners since they warn against a 'one-size-fits-all' approach to knowledge management. It shows that companies should carefully select incentives for knowledge creation that fit with their innovation strategy and goals, whether this encompasses incremental innovation, radical innovation, or a combination of both.

Insert Figure 1 here

Limitations and suggestions for further research

In this study, we examined the impact of knowledge management practices in the period 2008-2010 on innovation performance in 2010. Whereas this design allows generating insights into the short-term performance implications of these stimuli, we acknowledge that this time-frame is too short to fully grasp the long-term performance effects. We therefore stress the importance of future research that systematically assesses the performance implications of stimuli for knowledge creation and transfer across different time-frames.

Whereas we focused on the presence/absence of various knowledge management practices, we did not consider the extent to which they are dispersed throughout the company, nor the way in which they are implemented. Future research might focus on implementation issues such as the level at which these initiatives are introduced, i.e. the individual or group level. More detailed information on this topic might be especially valuable for the brainstorm sessions and financial incentives. Previous research has discussed the differential effects of both practices depending on the level of implementation (Diehl and Stroebe, 1991; Bartol and Srivastava, 2002). It might be worthwhile to study the impact of these issues on the contribution of knowledge management practices to incremental versus radical innovation.

In this study we focused upon four knowledge management practices and studied their independent effects on innovation. Future studies might focus upon the interaction between these practices. It is likely that the positive impact of cross-functional teams on radical innovation will be higher when these teams get financial incentives for innovative results or when professional brainstorm sessions are organized within these teams. On the other hand, the combination of cross-functional teams and individual financial incentives might be destructive for radical innovation. Insights in the interdependencies of practices might help practitioners to develop a strong knowledge management system, existing in “powerful connections” and avoiding “deadly combinations” of practices (Delaney and Huselid, 1996; Delery, 1998).

Further research might also focus upon other knowledge management practices, and their impact upon incremental versus radical innovation. We focused on financial practices and practices related to job design. Other practices could be considered as well, such as the use of collective situational tests in selection procedures, training in problem solving, formal suggestion schemes, or mentoring and coaching practices. Each of these practices has been related to innovation before. Yet, their impact on incremental versus radical innovation has not yet been studied. Literature on the relationship between HRM and innovation might be inspiring here (e.g. Seeck and Diehl, 2016).

We studied knowledge management practices resulting from a personalization strategy because Greiner et al. (2007) showed them to be more fruitful for innovation as compared to practices resulting from a codification strategy. Although we follow their reasoning for radical innovation in which tacit knowledge plays a prominent role, it might be possible that some knowledge codification practices focusing on the storage of explicit knowledge might be interesting for incremental innovation as well. Future research could dig into this relationship.

We argue that the type of knowledge that is transferred and created plays a determining role in stimulating incremental versus radical innovation. We thereby focus on related versus unrelated knowledge. Yet, we did not measure these constructs. Future research might try to develop a measurement instrument to capture the related versus unrelated nature of knowledge and to actually test the mediating role of these constructs in the relationship between knowledge management practices, and incremental versus radical innovation as visualized in Figure 1.

This study involves knowledge management practices of Flemish firms. Replication of our findings in other regions and countries is necessary to test their generalizability.

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TABLE 1: Descriptive statistics (822 observations)

	Mean	Std. Dev.	Min	Max.
Rad_Inno	7.906566	19.69737	0	100
Incr_Inno	7.18176	16.9883	0	100
Brainstorm	.7907543	.4070178	0	1
Crossfunc	.6277372	.4837022	0	1
Jobrot	.3613139	.4806737	0	1
Finin	.2664234	.4423573	0	1
Nfinin	.2262774	.4186755	0	1
RD_Intensity	.1407204	2.094078	0	58.6
Group	.6751825	.4685917	0	1
Collab	.3807786	.4858739	0	1
Size	161.4064	394.601	1	4825
Age	26.33333	18.59939	1	110
Serv	.4586375	.4985896	0	1
Hitech	.4355231	.4961272	0	1

TABLE 2: Correlations (822 observations)

	Rad_In	*Incr_In*	*Brainsto*	*Crossfu*	*Jobr*	*Finin*	*Nfini*	*Ln_RD_Inten*	*Grou*	*Coll*	*Ln_Si*	*Ln_A*	*Serv*	*Hite*
Rad_Inno	1													
Incr_Inno	0.0920	1												
Brainstorm	0.1347	0.1093	1											
Crossfunc	0.1875	0.0519	0.2164	1										
Jobrot	0.0745	0.0825	0.0196	0.1811	1									
Finin	0.0296	0.0915	0.0259	0.0884	0.23	1								
Nfinin	0.0997	0.0729	0.0923	0.1217	0.27	0.41	1							
Ln_RD_Inten	0.3211	0.0653	0.0267	0.1086	0.03	0.05	0.03	1						
Group	-0.0118	0.0247	0.0455	0.2236	0.07	0.05	0.03	0.0134	1					
Collab	0.2781	0.2127	0.1324	0.2463	0.04	-	0.05	0.2134	0.11	1				
Ln_Size	-0.0313	0.0503	0.0462	0.3040	0.18	0.12	0.01	-0.0581	0.42	0.21	1			
Ln_Age	-0.1576	0.0058	-0.0625	-0.0052	0.01	-	-	-0.1420	0.01	-	0.329	1		
Serv	0.0045	-0.0183	0.0233	0.0371	-	-	0.06	0.0826	-	0.13	-	-	1	
Hitech	0.1861	0.0628	0.0477	0.0927	0.05	0.02	0.00	0.2019	-	0.17	-	-	0.11	1

TABLE 3: Regression results (822 observations)

	Rad_Inno	*Incr_Inno*
Brainstorm	3.30**	3.65**
Crossfunc	4.64***	-1.33
Jobrot	1.30	2.08
Finin	-.90	2.90**
Nfinin	2.44	.51
Ln_RD_Intensity	22.33*	1.14
Group	-1.29	-.04
Collab	6.99***	7.28***
Ln_Size	-6.61*	.99
$(Ln\_Size)^2$	.67	-.13
Ln_Age	-2.31**	.83
Serv	-1.60	.48
Hitech	2.55*	.88
R^2	0.2005	0.0661

* Significant at $p < 0.10$

** Significant at $p < 0.05$

*** Significant at $p < 0.01$

FIGURE 1: Conceptual model