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Training Investments and Innovation Gains in Knowledge Intensive Businesses: The Role of Firm Level Human Capital and Knowledge Sharing Climate

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ABSTRACT

Training investments are important in securing innovation gains. However, research on this relationship in knowledge intensive businesses is nascent. In particular, questions remain concerning what value different types of training hold for different types of innovation, and what mechanisms underpin these relationships. Drawing on human capital resources theory and collective learning theory, we develop and test a model explicating *how* specific and general training investments, through firm level human capital, lead to incremental and radical innovation. Additionally, we propose and investigate the supposition that the predicted positive relationships between training investments, firm level human capital, and innovation will be stronger *when* knowledge sharing climate is high. We test our model with two-wave, multi-respondent panel data gathered from 816 knowledge intensive businesses in France, Finland, Sweden, and the UK. We find that specific training is positively related to incremental innovation but not radical innovation, whereas general training is positively related to both types of innovation. With respect to firm level human capital, we find that it mediates these relationships and they are stronger when knowledge sharing climate is high. Furthermore, our analysis reveals that knowledge sharing climate moderates both the relationship between the two types of training investments examined and firm level human capital, and the indirect relationship via firm level human capital to incremental and radical innovation. We discuss the implications for theory, research, and practice.

1 | Introduction

It is generally accepted that human resource management (HRM) practices are important to the achievement of innovation outcomes (Subramaniam and Youndt 2005; Shipton et al. 2006; Chowhan 2016). This has led both to significant theorizing of the links between HRM and innovation (Shipton et al. 2017), and to a corpus of empirical studies investigating these relationships (Díaz-Fernández, González-Rodríguez, and Simonetti 2015; Lakshman et al. 2022). To date scholars have taken two general approaches to the investigation of the HRM-innovation relationship. The first approach sees the adoption of a HRM system perspective involving the investigation of a distinct, but interrelated, set of HRM practices that focus on attracting and developing a firm's human resources to achieve innovation gains. These systems have been categorized according to their purposes

Summary

- What is currently known about the subject matter?
  - Investments in training can impact an organization's ability to generate innovations.
  - Both specific training and general training investments have been conceptually linked to innovation outcomes.
- What does the paper add?
  - The paper advances a theoretical explanation of the processes through which specific and general training investments influence innovation in knowledge intensive businesses.
  - The study differentiates between two types of innovation outcomes (incremental and radical) and examines the consequences of two types of training investments (specific and general).
  - The findings suggest that knowledge intensive businesses should deploy specific training for boosting incremental innovation, while general training investments are more likely to prove valuable for securing gains in both incremental and radical innovation.
  - Importantly, the prevailing knowledge sharing climate can serve to amplify the relationship between both types of training investments and firm human capital and the indirect relationship via firm human capital and both innovation outcomes.
- Implications for practitioners:
  - Knowledge intensive businesses should differentiate their training investments, depending on the types of innovation outcomes that they strive to achieve. However, investments in general training are valuable for both incremental and radical innovation.
  - In addition, knowledge intensive businesses can maximize the benefits of investments in both specific training and general training by enhancing the prevailing knowledge sharing climate within the organization.

and include, inter alia, innovation-oriented practices (Lau and Ngo 2004), learning, knowledge, and expertise development practices (Andreeva et al. 2017; Shipton et al. 2006), along with HRM systems that build human and social capital (Fu et al. 2015; Donate, Peña, and Sánchez de Pablo 2016). The second approach has centered around the investigation of individual HRM practices such as those designed to enhance creativity (Jiang et al. 2012) or to enhance employees' ability, motivation, and opportunity to innovate (Díaz-Fernández, González-Rodríguez, and Simonetti 2015).

One individual HRM practice that has received particular attention in the literature concerns the role of training, defined as formal on-and off-the-job structured practices focused on the development of employee knowledge, skills, and abilities (KSAs) (T. Garavan et al. 2020). Research on the link between training and innovation has steadily grown over the years with studies showing significant and positive relationships. For example, Børing (2017), using data from 5200 Norwegian enterprises, found that training was related to innovation activities developed inhouse, thought the study did not distinguish different types of innovation. Guisado-González, Vila-Alonso, and Guisado-Tato (2016) investigated Spanish manufacturing and service firms and found a relationship between training and radical innovation, while Chowhan (2016), employing longitudinal data from the Canadian Workplace and Employee Survey, found a positive relationship between skill enhancing practices, which included training, and innovation generally. Two other important studies employing Canadian Workplace and Employee Survey data by Dostie (2018), and Cozzarin and Percival (2021) also found support for a positive relationship. Dostie (2018) found that training led to more product and process innovation, and that on-the-job training was as effective as classroom-based training. Cozzarin and Percival (2021) found that although training was not related to new product innovation, it was related to the development of improved products. In addition, it had a positive effect on both new and improved process innovations.

On the whole, while these studies signal the value of lines of inquiry focused on untangling the relationship between training investments and innovation gains, a number of significant research opportunities remain under explored. First, studies do not, in general, explicitly differentiate the effects of specific and general training on innovation. This is an important lacuna in the body of knowledge. In a recent meta-analysis T. Garavan et al. (2020) highlighted that both general and specific training can achieve similar organizational performance outcomes, though the question of whether general and specific training are equally valuable for innovation remains unclear. Second, existing research does not allow us to draw firm conclusions about whether specific and general training are more valuable for incremental innovation or radical innovation, or indeed equally valuable for both. This raises an important issue concerning whether organizations can use different types of training investments to achieve the same innovation outcomes, the so-called principal of equifinality where there are alternative paths to the same outcome. For example, T. N. Garavan et al. (2021) found that organizations could use both general and specific training investments to achieve organizational performance. Third, there appears to be a stronger proclivity among scholars towards investigating incremental innovation rather than radical, with the result that the latter remains significantly underexplored (Barba-Aragón and Jiménez-Jiménez 2020). This is striking given that each type of innovation may be underpinned by different knowledge and skill requirements (Holahan, Sullivan, and Markham 2014; Kang, Morris, and Snell 2007). Of note, in the context of the empirical research that we report here, studies incorporating both types of innovation in a single investigation are rare. Fourth, there is a bias towards investigating the training-innovation relationship in manufacturing firms (Easa and Orra 2021) with limited research conducted in, for example, professional service (Fu et al. 2015) or knowledge intensive firms (Zavyalova and Kosheleva 2013). Finally in terms of research design, apart from a relatively small number of investigations, studies focused on the training-innovation relationship have not sufficiently accounted for temporal effects. It is generally accepted that training takes time to develop employee KSAs (T. N. Garavan et al. 2021) and there is a lag between the acquiring of these KSAs, and their translating into innovation outcomes. The result is that cross-sectional designs, which dominate the literature, are not best placed to capture the true effects of training on innovation outcomes.

Beyond these conceptual, contextual, and methodological issues, we also lack robust findings regarding "*how*" and "*when*" training impacts innovation outcomes. Scholars have conceptualized and investigated the link with innovation in different ways. For example, some point to a direct and unmediated relationship (Lau and Ngo 2004; L. H. Lin 2011), whereas others suggest that the training-innovation relationship is a mediated one (Morley et al. 2016). Mediators investigated have included learning practices (Sung and Choi 2014) and human capital (Chowhan, Pries, and Mann 2017). In addition, some scholars have sought to highlight the role of contingencies or moderators including strategic activities (Chowhan 2016), organization culture (Lau and Ngo 2004), and external cooperation (Cordón-Pozo, Vidal-Salazar, and Torre-Ruiz 2017).

In this paper we respond to some of these opportunities to advance the literature on the training-innovation relationship. Our work is underscored by three key questions as follows: *(1) What are the direct relationships between both specific and general training and both incremental and radical innovation outcomes? (2) What role does firm level human capital play as a mediator of these relationships? and (3) How does knowledge-sharing climate moderate (a) the direct relationship between both types of training and firm level human capital*, *and (b) the indirect relationship between both types of training and both incremental and radical innovation* via *firm level human capital?* Empirically, we employ novel matched panel data from 816 knowledge intensive businesses (KIBS) located in Finland, France, Sweden, and the UK. KIBS are defined as businesses where: (a) the majority of employees are highly qualified, (b) quality human capital is considered critical, and (c) the development of knowledge, skills and abilities to achieve innovation outcomes involves an ongoing effort (Miles, Belousova, and Chichkanov 2018; Laursen and Foss 2013; Chen and Huang 2009). KIBS have attracted attention from innovation, HRM and strategy scholars because they prioritize innovation (Miles 2015; Boix, De-Miguel-Molina, and Hervas-Oliver 2013). These innovation types require that KIBS invest in training to sustain innovation (Gara Bach Ouerdian et al. 2019) and are particularly reliant on employee KSAs (Bustinza, Opazo-Basaez, and Tarba 2022). Furthermore, KIBS have fewer employees relative to firms in other sectors, and they utilize training to develop a uniquely skilled and innovative talent pool to secure innovation outcomes (Andreeva et al. 2017). While these characteristics point to a central role for training, we have few insights on the criticality of such training practices to the securing of innovation gains in KIBS, and in particular, the long-term value of training and accumulated firm level human capital for innovation (Gara Bach Ouerdian et al. 2019).

Turning to our theoretical point of departure, we take inspiration from human capital resources theory (Ployhart et al. 2014; Ployhart and Moliterno 2011; Ray et al. 2023) to first propose that investments in specific training and general training lead to both incremental innovation and radical innovation gains. We then draw from organizational learning theory (Pereira and Bamel 2021), specifically collective learning (Jeong and Shin 2019), to theorize both the impact of firm level human capital as a mediator, and to explicate the amplifying role of knowledge sharing climate in the training-firm level human capital relationship and incremental and radical innovation via firm level human capital.

In theorizing and testing these relationships, we offer a number of contributions to the literature. First, we extend prior research and bring more nuance to the training-innovation relationship revealing, as we do, that specific training and general training contribute differently to incremental and radical innovation. We distinguish between investments in specific training and general training and uncover their distinct impact on incremental and radical innovation (Rupietta and Backes-Gellner 2019). Second, we answer calls for research highlighting the need to better understand *how* training leads to both types of innovation outcomes. In doing so we find support for a key tenet of human capital resources theory whereby, for employee KSAs to be of value for innovation, they must emerge to the firm level (Ray et al. 2023), and that the interactions of human resources and their collective learning activities are important in this context. Third, we contribute to the training and innovation performance literature by revealing *when* both specific and general training will lead to innovation outcomes. In this we introduce a key moderator to the literature, namely knowledge sharing climate, which served an important amplifying role. This, in particular, underscores the role of collective learning processes in KIBS (Jeong and Shin 2019) whereby organizational innovation is not only impacted by the KSAs of individual employees, but also by the social and collective learning processes that surround these employees.

2 | Theory and Hypotheses

2.1 | Incremental and Radical Innovation and the Role of Specific and General Training

An important distinction within the innovation literature concerns the differences between incremental and radical innovation. Incremental innovation typically involves relatively small changes to existing products or services and refinements to current knowledge and how it is used (Kang, Morris, and Snell 2007). In the context of KIBS, incremental innovations could involve enhancing the customer or client experience while not disrupting or deviating from clients or customers prior knowledge or requiring new learning by clients (Swart and Kinnie 2003). In contrast, radical innovation involves the capability to deliver new products and/or services that contain technological or knowledge breakthroughs and significantly alter how customers use and experience these products and services. For example, radical innovations may involve developing new technological processes that enhance how they work with clients/customers or may offer new technological solutions that can be leveraged by clients to achieve enhanced profitability or growth (Hayter and Link 2018). Therefore, incremental innovation refers to a quality of newness that arises for a cumulative improvement in KIBS products or services, whereas radical innovation refers to a more novel and unique breakthrough in processes, products, or services (Chan and Parhankangas 2017).

Our working assumption is that incremental and radical innovation have different KSA requirements. Incremental innovation requires task and organization-specific KSAs acquired from experience over time, whereas radical innovation requires, in addition, a broader base of knowledge and more general skills. Thus, we expect that specific training, which is aimed at developing unique firm- and task-specific KSAs (T. Garavan et al. 2020), will be important for incremental innovation, while both specific training and general training, which focuses on the development of broader and more diverse KSAs, will be important for radical innovation.

With respect to the relationship between specific training and incremental innovation (Barrett & O'Connell 2001), we propose that this type of training helps to equip employees with the KSAs to combine internal knowledge and promotes better coordination amongst employees. It is focused on unique firm specific knowledge, along with organizational processes and routines, which may have more limited relevance or value to other firms (Riley, Michael, and Mahoney 2017). These task and organizational related skills will include training interventions focused on job and organization specific processes which serve to enhance knowledge availability, and act as an aid to problem solving within an organization (T. Garavan et al. 2020). These are important for incremental innovation (Zhang et al. 2007), and for creating the conditions under which individual employee knowledge emerges to the collective level (Kim, Hahn, and Lee 2015). Incremental innovation requires KSAs in the use of internal sources of firm-specific information, modest knowledge processing requirements, and a stable human resource base (Nguyen et al. 2019). Hennessey and Amabile (2010), for example, suggested that task related job knowledge enhanced individual creativity which, when accumulated to the firm level, contributed to incremental innovation gains. We propose that specific training is less likely to lead to radical innovation gains because this type of innovation requires that employees develop KSAs to navigate external knowledge sources, to have the expertise to recognize the value of such knowledge, and to be able to integrate it into existing internal knowledge (Forés and Camisón 2016; Guisado-González, Vila-Alonso, and Guisado-Tato 2016). Specific training typically does not focus on the development of these types of individual KSAs (T. Garavan et al. 2020).

We propose that general training can lead to incremental innovation. General training involves investing in employees general KSAs and focuses on the development of knowledge around specific terms, symbols, and language among employees, thus enhancing shared models that allow them to communicate with one another (Collins and Smith 2006). General training helps employees to experiment with various ideas, and to share what they have learned with others (Colbert 2004). These KSAs are valuable for incremental innovation because they first help employees to identify and implement changes in existing product and service offerings, including adaptations (Laursen and Foss 2013; H. Zhou et al. 2011).

In addition, we propose that general training is valuable for radical innovation. Radical innovation places a premium on advanced creativity skills, learning, agility, and the ability to operate autonomously, to go beyond existing knowledge bases and to be skilled in sourcing external knowledge. Forés and Camisón (2016), for example, found that both internal and external knowledge impacted incremental innovation; however, only external knowledge accumulation impacted radical innovation. General training enables KIBS to develop diverse and broad individual KSAs which help wider and more general knowledge searches across diverse knowledge domains (K. Z. Zhou and Li 2012). KIBS can utilize these KSAs to engage in external knowledge search, cope more effectively with knowledge diversity, and generate new ideas and more "out of the box" solutions. Based on these arguments we propose the following:

H1a *Specific training will be positively related to incremental innovation.*

H1b *General training will be positively related to both (i) incremental innovation and (ii) radical innovation.*

2.2 | The Role of Firm Level Human Capital

Human capital resources theory defines firm level human capital as the combination of individual KSAs that are available to the organization and that help it to achieve strategic goals and objectives, including innovation (Ray et al. 2023). We conceptualize firm level human capital as the combination of KSAs which are available to the organization at the collective level and that have potential value for innovation. We propose that firm level human capital links both specific and general training to innovation outcomes. Consistent with human capital resources theory, we argue that individual KSAs must emerge to the collective level in the form of firm level human capital, and this human capital in turn contributes to innovation outcomes. This occurs through what are referred to in the literature as emergence processes (Ray et al. 2023) and they allow individual-level human capital to be combined into firm level human capital.

To explain these emergence processes we draw on organizational learning theory, and in particular, concepts related to collective learning. Collective learning is described as the extent to which individual employees learn interactively with one another through the process of working together (Jeong and Shin 2019). The provision of specific and general training creates conditions where collective learning processes can occur because they provide a social platform within which individual employees can collectively learn from each other (Kang, Morris, and Snell 2007), for example, when individual employees learn interactively with one another through work processes (Hirst, Van Knippenberg, and Zhou 2009). Training processes, including job instruction training, coaching, mentoring, employees' functional rotations, along with communities of practice, elicit behaviors around interaction and collaboration from employees which in turn help individual KSAs to emerge at the collective level (Buenechea-Elberdin, Sáenz, and Kianto 2017). These collective processes assist in the development of interdependencies and organizational relationships and encourage the sharing of collective tacit knowledge among employees, permitting the organization to learn (Hatch and Dyer 2004). These processes therefore enable firms to utilize the human capital that accumulates at the firm level in an effort at securing innovation gains.

In explaining the link between firm level human capital and innovation, collective learning theory emphasizes processes of discovery, more variation in the number of ideas generated, different combinations and permutations of those ideas, more robust evaluations of the ideas advanced, along with the subsequent implementation of those ideas selected (Maitlis and Sonenshein 2010). Therefore, firm level human capital thorough collective learning processes builds a capacity for experimentation, dialog, risk taking, and the generation of new and novel ideas leading to incremental and radical innovation. However, these collective learning processes take time to develop, and consequently, firm level human capital also takes time to generate innovation outcomes. We, therefore, propose the following hypotheses:

H2a *Firm level human capital will mediate the positive relationship between specific training and incremental innovation.*

H2b *Firm level human capital will mediate the positive relationship between general training and both (i) incremental innovation and (ii) radical innovation.*

2.3 | The Role of Knowledge Sharing Climate

We now turn to the moderating role of knowledge sharing climate. We define knowledge sharing climate as beliefs and cognitions concerning "the exchange of employee knowledge, experiences, and skills through the whole department or organization" (H. Lin 2007: 315). We first propose that knowledge sharing climate will moderate the "a" path in our model between both types of training, and firm level human capital. This proposed moderation is consistent with a key premise of human capital resources theory outlined earlier, namely the concept of human capital resources emergence, whereby individual-level human capital is combined into a single higher level heterogenous human capital with employee KSAs being transformed to a collective resource (Eckardt, Crocker, and Tsai 2021). Importantly, emergence can and does result in modifications to the stock of KSAs, with individual level human capital being augmented and made more valuable as it emerges to the unit or collective level. Consistent with Eckardt and Jiang (2019), we view knowledge sharing climate as an ambient cognitive emergence enabling state, because it emphasizes shared cognitive structures and orientations around knowledge sharing. Collective learning helps to explain the role of knowledge sharing climate in facilitating human capital emergence. It underscores the criticality of this climate to the development of knowledge sharing norms, to deepening memory related to shared task knowledge, and to raising awareness of organizational members' skill sets (Eckardt, Crocker, and Tsai 2021). In addition, it provides the conditions for social interaction. Such interaction is central to collective learning whereby employees feel safe in interacting with each other, in engaging in questioning others to seek their knowledge, and in utilizing their own knowledge. It has been suggested that it has a trickle-down effect on employee attitudes and on their fundamental willingness to share their knowledge, something which cannot be taken for granted (Castellani et al. 2021). As has been suggested, employees may choose to withhold their knowledge and not share it for reasons of personal gain (Adler and Kwon 2002), and their collaboration and cooperation among each other is required for individual human capital to emerge to the firm level (Gerhart and Feng 2021). Overall, therefore, we propose that when the knowledge sharing climate is higher, it will amplify the extent to which KSAs, developed through both specific and general training, will lead to higher levels of firm level human capital. We therefore propose the following hypotheses:

H3a *The positive relationship between specific training and firm level human capital will be moderated by the prevailing knowledge sharing climate such that the relationship will be stronger when the climate is higher.*

H3b *The positive relationship between general training and firm level human capital will be moderated by the prevailing knowledge sharing climate such that the relationship will be stronger when the climate is higher.*

In addition, we propose that the prevailing knowledge sharing climate will moderate the "b" path in our model between firm level human capital and both incremental and radical innovation. Our reasoning lies in the idea that having a knowledge sharing climate helps KIBS get the most out of their firm level human capital when it comes to securing innovation outcomes. It facilitates incremental innovation because this collective human capital is more open to adaptation and change and the climate is supportive of employees collectively making improvements to processes, services and products (Yoo 2017). In addition, it helps internal knowledge integration which is important for incremental innovation. In the case of radical innovation, a positive knowledge sharing climate helps employees to collectively be more receptive to new knowledge acquired from the external environment, along with its integration into existing knowledge. A key feature of knowledge sharing climate is that it enables employees to collectively take the risks required to achieve radical innovation and yields conditions where failure is not viewed in a negative way (Beraies 2020). We therefore propose the following hypotheses (Figure 1):

H3c *The positive relationship between firm level human capital and incremental innovation will be moderated by the prevailing knowledge sharing climate such that the relationship will be stronger when the climate is higher.*

H3d *The positive relationship between firm level human capital and radical innovation will be moderated by the prevailing knowledge sharing climate such that the relationship will be stronger when the climate is higher.*

Finally, putting together the moderation hypotheses presented in this section with the mediation hypotheses advanced previously, we suggest that the indirect relationships proposed between training, firm level human capital, and innovation will be

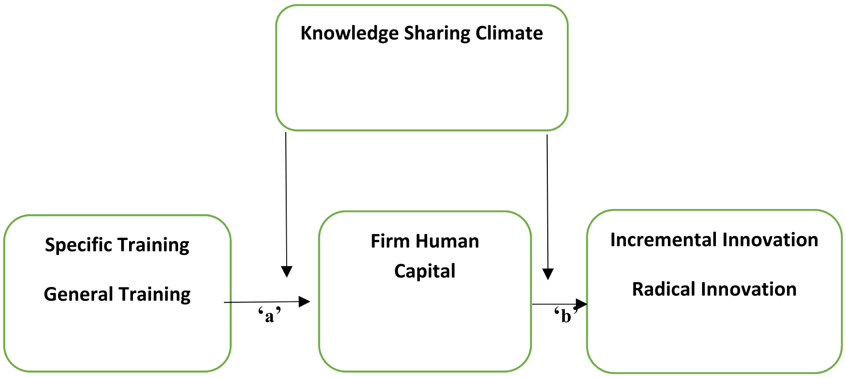

FIGURE 1 | Conceptual model: Training, knowledge-sharing climate, firm human capital, and innovation.

moderated by knowledge sharing climate. To capture this, the following moderated mediation hypotheses are offered:

H3e *The positive indirect relationship between specific training, firm human capital, and incremental innovation will be stronger when the knowledge sharing climate is higher*

H3f *The positive indirect relationship between general training, firm level human capital, and both (i) incremental innovation and (ii) radical innovation will be stronger when the knowledge sharing climate is higher.*

3 | Data and Methods

3.1 | Research Setting, Study Participants, and Procedures

We collected our data from KIBS in Finland, France, Sweden, and the UK. We identified sample businesses using the Dun and Bradstreet (D&B) Global Reference Solution (GRS) Database and used four criteria as follows to derive a stratified random sample: (1) all firms had to be within the European Commission NACE economic activity classification of KIBS codes, 72–74.9; (2) the firms had to employ at least 10 employees; (3) the firms could not be foreign owned; and (4) the firms had to be in operation for at least 18 months. The study population was broken into these sub-groups, then randomly sampled from these stratified groups.

We collected our data in two waves (2013 and 2016). We collected data over this time interval because research highlights that innovation takes time to accrue as a result of investments in training (Dostie 2018). We utilized R&D managers to gather our data on innovation because they are considered a reliable source of data of this kind in organizations (Armbruster et al. 2008), while HR managers provided data on firm characteristics, firm level human capital, specific and general training, and perceptions of knowledge sharing climate. HR Managers were also asked to provide data on previous and current incremental and radical innovation, but the innovation data provided by the R&D managers were ultimately used in our estimations, a point we return to below. We first sent emails to R&D and HR managers and a professional survey company (ISO9000 certified) then administered the survey which took approximately 40 min to complete. Our final sample for this analysis comprised 816 KIBS with a matched response rate over both periods and for both respondents as follows: Finland (n = 205) (=25%); France (n = 181) (=22%); Sweden (n = 212) (=26%); and UK (n = 218) (=27%). We conducted several statistical tests including The Kolmogorov-Smirnov test (Kleinbaum, Kupper, and Muller 1988) to test for normality (at the $p < 0.05$ level) and the two-stage Heckman Test to investigate response bias ($p < 0.05$ level). We ensured that our two-wave data collection was not impacted by significant changes within each firm, and we confirmed that attrition between the two time periods was random using attrition probits Stata coding test (Fitzgerald, Gottschalk, and Moffitt 1998; Baluch and Quisumbing 2010). We found no statistically significant evidence of non-randomness for firms with attrition and without attrition (at the $p < 0.05$ level). (Results of these tests are available from the first author upon request).

3.2 | Sample Characteristics

The average number of employees in each of our samples was 121 (SD = 312.22), and the average firm age was 16.2 years (SD = 20.40); median R&D expenditure was approximately 32,000 Euro per annum (SD = 2.54). Across the sample, the median days of training was 9.3 (5.2 firm-specific; and 4.1 general). This is higher than the European Union (EU) average of 6.32 days, likely reflecting the influence of their KIBS status. The firms were distributed as follows across the represented NACEs sub-samples: 242 NACE 72 (Scientific Research and Development); 265 NACE 73(Advertising and Market Research); and 309 NACE 74 (other Professional, Scientific and Technical Activities). Sixty-three percent of firms innovated in the past 3 years; and this was distributed across the countries as follows: Finland 64.2%; France 54.5%; Sweden 67.2%; and UK 56.2%. This compares to an overall enterprise-level EU-wide innovation rate in 2018 of 50.3%.

3.3 | Measures

All measures were derived using a double-blind translation-back-translation procedure, first translating original English measures into Finnish, French and Swedish, then translating each language version into English, to ensure measurement equivalence (Cascio 2012).

3.3.1 | Firm Human Capital (FHC)

We measured firm level human capital at T1. HR managers provided data on firm level human capital utilizing all five of Subramaniam and Youndt's measures (2005: 463) on a seven-point Likert scale indicating the extent to which respondents strongly disagreed (1) or strongly agreed (7) with each measure. Sample items included: "our employees are highly skilled" and "our employees are experts in their particular jobs and functions." Confirmatory factor analysis results were as follows: (CFA) fit (T1: $\chi^2 = 129.68$, $df = 18$; $p < 0.001$; RMSEA = 0.050, CFI = 0.991; TLI = 0.972) and (α) = 0.901.

3.3.2 | Specific Training (ST)

We measured specific training at T1. HR managers were provided with the following definition of specific training: "In this study, we define specific training as training that is directly related to the operation of the firm and the roles that employees perform. Examples that are likely to be relevant to your firm would be your quality control procedures; firm-specific software; training related to improving the satisfaction of your firm's supply chain stakeholders". Respondents provided data on the average number of days per annum allocated to specific training per employee.

3.3.3 | General Training (GT)

We measured general training at T1. We provided HR managers with the following definition of general training: "In this study, we define general training as training that has application to multiple organizations and is therefore transferable to other organizations. Examples that are likely to be relevant to your firm would be the coverage of fees for employees' post graduate studies (e.g., MBAs, MScs; PhDs/DBAs); language training; coaching; training in general software languages (e.g., Java, Python)." Respondents provided data on the average number of days per annum allocated to general training per employee.

3.3.4 | Knowledge Sharing Climate (KSC)

We measured knowledge sharing climate at T1. HR managers were asked to indicate (on a seven-point Likert scale) the extent to which they strongly disagreed (1) or strongly agreed (7) with four statements. Following Foss et al., (2015: 966) (adapted from ideas developed by Husted and Michailova 2002) all four statements were formulated negatively as "discouraging knowledge sharing". They were subsequently reverse coded in the statistical analysis. The four statements were: "It is important to keep your own ideas secret until one is acknowledged as the source of the idea; " "Knowledge sharing reduces the incentive for others to create new knowledge; " "Time spent on knowledge sharing could be spent on more important activities; " and "Sharing knowledge is risky because others may misinterpret the shared knowledge". Confirmatory factor analysis (CFA) results were as follows ($T = 1$: $\chi 2 = 136.22$, $df = 18$; $p < 0.001$; RMSEA = 0.051, CFI = 0.990; TLI = 0.974) and (α) = 0.919. The variable was calculated as the average of the four items.

3.4 | Innovation Respondents and Measures

As indicated earlier, R&D and HR managers provided data on both incremental and radical innovation at T1 and T2. The correlation between the respondents was $\rho = 0.89$ (Incremental innovation) and $\rho = 0.86$ (Radical innovation) (both $p < 0.001$) in T1; and $\rho = 0.91$(Incremental Innovation) and $\rho = 0.88$ (Radical Innovation) (both $p < 0.001$) in T2. The data provided by the R&D managers are used in the estimations related to innovation. Analyses were re-run using the data from HR managers and no significant differences emerged. These results are available from the first author upon request.

After a comprehensive review of the innovation literature, four scholars and two senior executives, all of whom were experts in innovation in the NACE context were consulted about the most appropriate scales to reflect incremental and radical innovation, within the study's broader context of training and knowledge sharing. After extensive consultation, a consensus emerged that the scales used previously by López-Cabrales, Pérez-Luño, and Cabrera (2009) and Govindarajan and Kopalle (2006) were the most appropriate. Given that we were adapting the innovation scales, and they were being utilized in a new context, and based on the recommendations by Churchill (1979), the 8-item scale for incremental innovation (López-Cabrales, Pérez-Luño, and Cabrera 2009) and 5-item scale for radical innovation (Govindarajan and Kopalle 2006), these six individuals were again consulted on the adaption of the scales to better reflect the NACE context. Based on their feedback minor adjustments to the wording of scale items were made. Guided by Govindarajan and Kopalle (2006), the scales were piloted in two stages. In the first stage, the translated scales were tested with five Executive MBA candidates in the four study countries (a total of 20 pilots) for clarity and relevance, and for the definitions and descriptions of the innovations. Scale items were then reworded based on their feedback. Following this, we pilot tested the scales in two NACE based companies in the four study countries with a respondent from R&D and HR (a total of 16 pilots). In both pilot tests, the respondents read the description of the two types of innovation, which were illustrated with an example of each, and then responded to the corresponding scale item. The Cronbach alphas were all above 0.75 and, at this stage, only very minor refinements were made (all linked to minor translation adjustments). None of the responses to these pilots were included in the analysis. The final measures of innovation were as follows:

3.4.1 | Incremental Innovation (II)

We collected data for incremental innovation at T1 focusing on the 3 years prior to the survey. The T2 re-measure was taken following a 3-year interval. This timeline is consistent with surveys on innovation (e.g., Community Innovation Survey 2013).

We provided respondents with the definition of incremental innovation as follows: "Incremental innovation involves making small and continuous improvements to existing products, services, processes, or business models, based on customer feedback, market trends, or operational efficiency." We measured incremental innovation using an adapted scale developed by López-Cabrales, Pérez-Luño, and Cabrera (2009). Respondents were asked to indicate (on a seven-point Likert scale) to six items the extent to which they strongly disagreed (1) or strongly agreed (7) (in the context of "over the past 3 years"). Sample items include: 1. This firm market introduces technologically new products (good or service) developed by the company (totally or in part); 2. This firm market introduces technologically improved products (good or service) developed by the company (totally or in part); 3. This firm market introduces extensions of existing product lines (good or service) (that do not only entail changes to esthetic aspects); 4. This firm market introduces changes to existing products, entailing significant improvements; 5. This firm frequently markets new lines/ranges of products (good or service). Following confirmatory factor analysis, we eliminated two items (3 and 4) from both T1 and T2 measurement because the standardized loadings were too low at 0.34 and 0.30 respectively with insignificant t-coefficients. These eliminations did not impact scale reliability (T1 with all items α = 0.853; and T1 with final scale items α = 0.842; and T2 with all items α = 0.880; and T2 with final scale items α = 0.856). Confirmatory factor analyses (CFA) revealed the following results: (T1: $X^2 = 126.14$, $df = 18$; $p < 0.001$; RMSEA = 0.032, CF1 = 0.980; TLI = 0.973; and T2: $X^2 = 119.44$, $df = 18$; $p < 0.001$; RMSEA = 0.030, CFI = 0.989; TLI = 0.970).

3.4.2 | Radical Innovation (RI)

We provided respondents with the definition of radical innovation as follows: "Radical innovation is conceptualized as substantial changes in technology and assumes important changes in a firm's knowledge, offering new benefits to existent or new markets and customers." We measured radical innovation using a 5-item scale adapted from Govindarajan and Kopalle (2006). Respondents were asked to indicate (on a seven-point Likert scale) the extent to which they strongly disagreed (1) or strongly agreed (7) with 5 statements (in the context of "over the past 3 years"). Sample items include: 1. This firm introduces radical innovations; 2. This firm rarely introduces radical innovations; 3, This firm lags behind in introducing radical innovations; 4. The new products that were introduced by this firm were very attractive to a different customer segment at the time of the product introduction; and 5. The new products that were introduced were those where the mainstream customers found the innovation attractive over time. Confirmatory factor analyses (CFA) revealed the following results (T1: X^2 = 189.76, df = 18; p < 0.001; RMSEA = 0.029, CF1 = 0.970; TLI = 0.966; and T2: $X^2 = 117.45$, $df = 18$; $p < 0.001$; RMSEA = 0.030, CFI = 0.971; TLI = 0.965); and (α) at T1 = 0.818 and 0.820 T2.

3.4.3 | Control Variables (T = 1)

Following Bernerth and Aguinis (2016), we selected several control variables consistent with previous research. Internal resources including: number of employees ("ln (firm size)"), age ("ln (firm age)"); "Industry" refers to which NACE the firm operates (NACE 72, 73, 74) (Brenner et al. 2018); previous financial performance ("ln profit per employee"); previous R&D expenditure ("ln prior R&D expenditure"), whether the firm is a single site; prior incremental innovation ("II (t = 1)"); prior radical innovation ("RI (t = 1)"); and trade union density ("UD (%)") were controlled for in our estimations (Sheehan, Garavan, and Morley 2023; Walsworth 2010); and the national context (Finland, France, Sweden, and the UK). These country control variables reflect important institutional contexts which are likely to impact innovation performance (Adam 2014). Lasso regression ("least absolute shrinkage and selection operator" (see Y. Jiang et al. (2016) for further detail) found that all the estimated control variable coefficients were non-zero and were therefore retained in the analysis.

3.5 | Measure Reliability and Validity Checks

To test for convergent validity Average Variance Extracted (AVE) and Composite Reliability (CR) values for the scales were calculated. The results are as follows: 1. FHC = 0.81 (AVE); 0.78 (CR); 2. KSC = 0.85 (AVE); 0.80 (CR); 3. II(T1) = 0.76 (AVE); 0.79 (CR); 4. RI(T1) = 0.74 (AVE); 0.77 (CR); 5. II(T2) = 0.77 (AVE); 0.79 (CR); and 6. RI(T2) = 0.74 (AVE); 0.78 (CR). Values above 0.7 for AVE are considered to be very good whereas, the level of 0.5 is acceptable; and for CR, values above 0.7 are acceptable (Alarcón and Sánchez 2015). Therefore, convergent validity is established for all scales. We tested for discriminant validity using the Heterotrait-Monotrait (HTMT) ratio criterion using the formula suggested by Henseler, Ringle, and Sarstedt (2015). From the HTMT results, the values in Table 1 indicate there are no discriminant validity problems according to the HTMT = 0.85 criterion.

To test for model fit we first estimated the hypothesized models with four factors: ST, GT, FHC and KSC for II (T2) and RI (T2). For II (T2) (Model A, Table 2), the four-factor model showed a good fit to the data ($X^2/df = 2.49$; robust RMSEA = 0.018 (0.000, 0.043); robust CFI = 0.959; and robust TLI = 0.930). Next, we estimated three alterative models: Model B, the three factor model (ST & GT are combined), FHC and KSC combined into one factor): (X^2/df = 5.77; RMSEA = 0.053 (0.044, 0.093); CFI = 0.782; and TLI = 0.658); Model C, the two factor model (ST, GT, FHC are combined) and KSC combined into one factor): ($X^2/df = 10.77$; RMSEA = 0.181 (0.124, 0.241); CFI = 0.546; and TLI = 0.482); and finally Model D, the one factor model (all factor combined into a single factor: (X^2/df = 13.22; RMSEA = 0.199 (0.119, 0.330); CFI = 0.397; and TLI = 0.299).

For RI (T2) (Model A, Table 3) the four-factor model showed a good fit to the data ($X^2/df = 2.65$; robust RMSEA = 0.023 (0.000, 0.047); robust CFI = 0.768; and robust TLI = 0.920). Next, we estimated three alterative models: Model B, the three factor model (ST&GT are combined), FHC and KSC combined into one factor): (X^2/df = 6.01; RMSEA = 0.061 (0.049, 0.099); CFI = 0.768; and TLI = 0.645); Model C, the two factor model (ST, GT, FHC are combined) and KSC combined into one factor): ($X^2/df = 11.34$; RMSEA = 0.195 (0.130, 0.265); CFI = 0.529;

TABLE 1 | Heterotrait-monotrait (HTMT) ratio results.

Variable	FHC	KSC	Incremental innovation (II) T1	Radical innovation (RI) T1	Incremental innovation (II) T2
Firm level human capital (FHC)	—				
Knowledge-sharing climate (KSC)	0.72	—			
Incremental innovation (II) T1	0.64	0.77	—		
Radical innovation (RI) T1	0.68	0.65	0.52		—
Incremental innovation (II) T2	0.64	0.76	0.54	0.55	
Radical innovation (RI) T2	0.68	0.65	0.60	0.48	0.51

TABLE 2 | Model fit indices and model comparisons for estimated CFA models: Incremental innovation.

Number of factors	X^2/df	Robust root mean squared error of approximation (RMSEA)	Robust comparative fit index (CFI)	Robust Tucker Lewis index (TLI)	Model comparison
Four factor model A[a]	2.49	0.018 (0.000, 0.043)	0.959	0.930	
Three factor model B[b]	5.77	0.053 (0.044, 0.093)	0.782	0.658	Vs 4-factor model
Two factor model C[c]	10.77	0.181 (0.124, 0.241)	0.546	0.482	Vs 4-factor model
One factor model D[d]	13.22	0.199 (0.119, 0.330)	0.397	0.299	Vs 4-factor model

[a]In Model A (the four factor model), ST, GT, FHC and KSC were combined into one factor.
[b]In Model B (the three factor model), ST& GT (are combined), FHC and KSC were combined into one factor.
[c]In Model C (the two factor model), ST, GT & FHC (are combined) and KSC were combined into one factor.
[d]In Model D (the one factor model) all factors are combined into a single factor.

TABLE 3 | Model fit indices and model comparisons for estimated CFA models: Radical innovation.

Number of factors	X^2/df	Robust root mean squared error of approximation (RMSEA)	Robust comparative fit index (CFI)	Robust Tucker Lewis index (TLI)	Model comparison
Four factor model A[a]	2.65	0.023 (0.000, 0.047)	0.940	0.920	
Three factor model B[b]	6.01	0.061 (0.049, 0.099)	0.768	0.645	Vs 4-factor model
Two factor model C[c]	11.34	0.195 (0.130, 0.265)	0.529	0.467	Vs 4-factor model
One factor model D[d]	14.02	0.208 (0.128, 0.342)	0.369	0.279	Vs 4-factor model

[a]In Model A (the four factor model), ST, GT, FHC and KSC were combined into one factor.
[b]In Model B (the three factor model), ST& GT (are combined), FHC and KSC were combined into one factor.
[c]In Model C (the two factor model), ST, GT & FHC (are combined) and KSC were combined into one factor.
[d]In Model D (the one factor model) all factors are combined into a single factor.

and TLI = 0.467); and finally Model D, the one factor model (all factor combined into a single factor: (X^2/df = 14.02; RMSEA = 0.208 (0.128, 0.342); CFI = 0.369; and TLI = 0.279). In conclusion, the CFA results provide support for the four-factor model used in the estimations of both incremental innovation (T2) and radical innovation (T2).

We computed a Wald test based on the null hypothesis of the independence of residual terms. The p value for this test was 0.363. We, therefore, fail to reject the hypothesis that the residuals are independent, indicating that autocorrelation is not an issue in our estimations. We conducted a Breusch-Pagan test for heteroscedasticity in the control model and the results reveal that this was an issue for these estimates [X^2 (18) = 22.46, $p < 0.001$] and we therefore corrected for this using heteroscedasticity-consistent robust standard errors (reported for the estimations). We investigated longitudinal invariance for both innovation measures using the four-step method proposed by Van de Schoot, Lugtig, and Hox (2012) and concluded that both measures of innovation used in the estimations are time invariant.[1]

3.6 | Data Analysis

Table 3 reports the correlation matrix. As correlations do not exceed 0.66 (Kline 2005) and the variance inflation factors (VIF) in each regression equation were low, ranging from 1.11 to 1.96 (Rogerson 2001), the data do not indicate the presence of multicollinearity (Table 4).

Hypotheses H1a, H1b (i) and (ii) were tested using hierarchical regression. All of these estimates were done in PROCESS (Version, 4.31). Hypotheses H2a,H2b (i) and (ii) were estimated using the simple mediation model (PROCESS Model 4) with 5000 bootstraps. Hypotheses H3a, H3b, H3c and H3d were estimated by the simple moderation model (PROCESS Model 1). Hypotheses H3e and H3f (i) and (ii) were estimated using moderation-mediation techniques (PROCESS Model 58). In advance of testing for moderation, we mean-centered our variables before creating the interaction (Aiken, West, and Reno 1991).

4 | Results

We found that specific training was positively associated with incremental innovation ($B = 0.202$, $p < 0.01$) therefore supporting Hypothesis 1a. (Models 1 and 2; Table 5). We additionally found that general training was positively associated with both incremental ($B = 0.220$, $p < 0.01$) and radical ($B = 0.257$, $p < 0.001$) innovation. We therefore found support for Hypothesis 1b (i) and (ii) (Models 3 and 4). In turn, we found that both types of training were significantly and positively related to firm level human capital ($B = 0.623$, $p < 0.01$) (specific training) and ($B = 0.482$, $p < 0.001$) (general training) (Models 10 and 11). We also found that firm level human capital was significantly related to incremental ($B = 0.267$, $p < 0.001$) and radical ($B = 0.432$, $p < 0.001$) innovation (Models 5 and 6). Finally, when specific training and general training and firm level human capital are entered into the model simultaneously, the coefficient for specific training and incremental innovation decreases to ($B = 0.172$, $p < 0.05$) (Model 7), and in the case of general training, the coefficient for incremental innovation decreases to ($B = 0.196$, $p < 0.05$) and for radical innovation it decreases to ($B = 0.219$, $p < 0.01$) (Models 8 and 9).

The indirect effects tests indicated significant indirect effects through firm level human capital between specific training and incremental innovation (0.107, 95% CI = 0.032–0.184). Hypothesis 2a is supported. There were significant indirect effects through firm level human capital between general training and incremental innovation (indirect effect = 0.095, 95% CI = 0.008–0.217) and radical innovation (0.152, 95% CI = 0.026–0.315). Hypotheses 2b (i) and (ii) are supported.

To test the moderation and moderated-mediation hypotheses, we first tested if the "a" path relationships between specific training and firm level human capital and general training and firm level human capital were moderated by knowledge sharing climate. The results in Model 10 show that knowledge sharing climate interacted significantly with specific training ($B = 0.215$, $p < 0.01$) and general training ($B = 0.357$, $p < 0.001$) (Model 11), and positively impact firm level human capital. We then plotted the significant interactions for scores above and below one standard deviation of the mean of the moderator (Figures 2 and 3). Overall, the positive association between both specific training and general training and firm level human capital was significant only when knowledge sharing climate was high ($B = 0.18$, $t = 2.05$, $p < 0.01$) in the case of specific training) and ($B = 0.39$, $t = 3.32$, $p < 0.001$) in the case of general training, compared to when knowledge sharing climate is low, when the relationships are positive but not significant.

We then tested if the "b" path relationship between firm level human capital and incremental and radical innovation is moderated by knowledge sharing climate. The results show that knowledge sharing climate interacted significantly with incremental innovation ($B = 0.223$, $p < 0.01$) (Model 12) and radical innovation ($B = 0.361$, $p < 0.01$) (Model 13) to positively impact firm level human capital. We then plotted the significant interactions for scores above and below one standard deviation of the mean of the moderator (Figures 4 and 5). Overall, the positive association between both incremental innovation and radical innovation and firm level human capital was significant only when knowledge sharing climate was high ($B = 0.15$, $t = 2.00$, $p < 0.05$ (incremental innovation) and $B = 0.23$, $t = 2.2$, $p < 0.01$ (radical innovation), compared to when knowledge sharing climate is low, when the relationships were positive but not significant. Hypotheses 3c and 3d are supported.

Because the moderation hypotheses, H3a-d were supported, we proceeded to test the moderation mediation models predicted in H3e-f using PROOCESS MODEL 58. In testing H3e we found significant interaction terms between specific training and knowledge sharing climate in predicting firm level human capital ($B = 0.23^{**}$, $p < 0.01$), and between firm level human capital and knowledge sharing climate in predicting incremental innovation ($B = 0.24^{***}$, $p < 0.001$). The findings indicate that the indirect effect of specific training on incremental innovation via firm level human capital is conditional on the level of knowledge sharing climate. When the knowledge sharing climate is high, the indirect effect is significant (0.151, 95% CI [0.006–0.258], while when the knowledge sharing climate is low it is not (0.098, 95% CI [-0.06–0.23]. Thus, H3e is supported.

In testing H3f (i), we found significant interaction terms between general training and knowledge sharing climate in predicting firm level human capital ($B = 0.37^{***}$, $p < 0.001$), and between firm level human capital and knowledge sharing climate in predicting incremental innovation ($B = 0.24^{***}$, $p < 0.001$). This finding also indicated that the indirect effect of general training on *incremental* innovation via firm level human capital is conditional on the level of knowledge sharing climate. When the knowledge sharing climate is high, the indirect effect is significant (0.179, 95% CI [0.009–0.312], whereas when the knowledge sharing climate is low it is not (0.087, 95% CI [−0.132–0.291]. Hypothesis Hf (i) is supported.

TABLE 4 | Correlation coefficients for study variables.

Construct	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
V1 ln (firm size) ($t = 1$)	4.79	312.22																		
V2 ln (firm age) ($t = 1$)	2.79	20.40	0.10																	
V3 industry ($t = 1$)	0.67	0.46	0.06	0.11																
V4 ln (prior firm financial performance (profit per employee) ($t = 1$)	3.44	2.25	0.25***	0.15	0.04															
V5 ln (prior R&D expenditure) ($t = 1$)	1.5	2.54	0.29***	0.19*	0.07	0.28***														
V6 single site ($t = 1$)	0.60	0.44	0.11	0.04	0.02	0.10	0.07													
V7 prior II ($t = 1$)	3.90	2.46	0.21**	0.19*	0.06	0.21**	0.36***	0.07												
V8 prior RI ($t = 1$)	3.03	2.56	0.25***	0.15	0.03	0.29***	0.45***	0.03	0.38***											
V9 UD (%) ($t = 1$)	40.31	33.31	0.20*	0.23**	0.02	−0.03	0.11	0.07	0.11	0.06										
V10 Finland	0.48	0.19	0.06	0.05	0.07	0.08	0.08	0.02	0.13	0.12	0.14									
V11 France	0.49	0.10	0.11	0.1	0.05	0.02	0.09	0.06	0.11	0.07	0.03	0.20*								
V12 Sweden (control)	0.50	0.16	0.09	0.05	0.03	0.08	0.09	0.04	0.12	0.14	0.10	−0.09	0.02	0.03						
V13 UK	0.49	0.12	0.12	0.09	0.01	0.05	0.07	0.03	−0.07	−0.07	−0.09	−0.06	−0.03	−0.02	—					
V14 ST: days ($t = 1$)	0.93	1.94	0.25**	0.15	0.03	0.24**	0.23**	−0.08	0.19*	0.26***	0.19*	0.18*	0.23**	0.20*	0.19*					
V15 GT: days ($t = 1$)	0.79	0.71	0.31***	0.29***	0.08	0.30***	0.24***	−0.05	0.25***	0.41***	0.11	0.21*	0.16	0.19*	0.25**	0.58***				
V16 FHC ($t = 1$)	5.91	0.67	0.26***	0.24**	0.09	0.26***	0.41***	0.06	0.26***	0.56***	0.08	0.18*	0.15	0.20*	0.14	0.57***	0.66***			
V17 KSC ($t = 1$)	4.02	0.77	0.07	−0.04	0.10	0.09	0.27***	0.09	0.19*	0.33***	0.20*	0.19*	0.09	0.20*	0.10	0.30***	0.51***	0.38***		
V18 II ($t = 2$)	4.04	2.18	0.25***	0.19*	0.08	0.26***	0.20*	0.10	0.32***	0.41***	0.14	0.17	0.13	0.18*	0.12	0.23**	0.35***	0.22**	0.29***	
V19 RI ($t = 2$)	3.66	2.29	0.20*	0.14	0.09	0.28***	0.33***	0.09	0.39***	0.60***	0.10	0.11	0.09	0.16	0.11	0.19*	0.56***	0.31***	0.48***	0.45***

Note: $n = 816$ businesses. robust standard errors.
Abbreviations: FHC, firm level human capital; GT, general training; II, incremental innovation; KSC, knowledge sharing climate; RI, radical innovation; ST, specific training.
*$p < 0.05$; **$p < 0.01$ and ***$p < 0.001$ (two-tailed t-tests).

TABLE 5 | Results of hierarchical regression analysis.

Variables	Firm-level II T2 Model 1	Firm-level RI T2 Model 2	Firm-level II T2 Model 3	Firm-level RI T2 Model 4	Firm-level II T2 Model 5	Firm-level RI T2 Model 6	Firm-level II T2 Model 7	Firm-level II T2 Model 8	Firm level RI T2 Model 9	FHC T1 Model 10	FHC T1 Model 11	Firm-level II T2 Model 12	Firm-level R1 T2 Model 13
ln (firm size) ($t = 1$)	0.008	0.014	0.008	0.014	0.008	0.014	0.007	0.007	0.013	0.107	0.107	0.007	0.0132
	(0.087)	(0.012)	(0.087)	(0.012)	(0.087)	(0.012)	(0.087)	(0.087)	(0.011)	(0.067)	(0.067)	(0.087)	(0.011)
ln (firm age) ($t = 1$)	0.003	0.005	0.003	0.005	0.003	0.005	0.003	0.003	0.004	0.182	0.182	0.003	0.004
	(0.030)	(0.032)	(0.030)	(0.032)	(0.030)	(0.032)	(0.029)	(0.029)	(0.031)	(0.107)	(0.107)	(0.029)	(0.031)
Industry ($t = 1$)	0.036	0.096	0.036	0.096	0.036	0.096	0.035	0.035	0.096	0.095	0.095	0.035	0.096
	(0.075)	(0.078)	(0.075)	(0.078)	(0.075)	(0.078)	(0.074)	(0.074)	(0.077)	(0.081)	(0.081)	(0.074)	(0.077)
ln (prior firm financial performance (profit per employee)) ($t = 1$)	0.143**	0.124*	0.143**	0.124*	0.143**	0.124*	0.143**	0.143**	0.124*	0.155**	0.155**	0.143**	0.124*
	(0.060)	(0.065)	(0.060)	(0.065)	(0.060)	(0.065)	(0.059)	(0.059)	(0.063)	(0.070)	(0.070)	(0.059)	(0.063)
ln (prior R&D expenditure) ($t = 1$)	0.160*	0.222***	0.160*	0.222***	0.160*	0.222***	0.160*	0.160*	0.221***	0.145*	0.145*	0.159*	0.221***
	(0.087)	(0.071)	(0.087)	(0.071)	(0.087)	(0.071)	(0.086)	(0.086)	(0.070)	(0.079)	(0.079)	(0.086)	(0.070)
Single site ($t = 1$)	−0.004	0.004	−0.004	0.004	−0.004	0.004	−0.004	−0.004	0.003	−0.09	−0.09	−0.004	0.003
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.075)	(0.075)	(0.004)	(0.004)
Prior II ($t = 1$)	0.205**	0.181*	0.205**	0.181*	0.205**	0.181*	0.204**	0.204**	0.180*	0.214**	0.214**	0.204**	0.181*
	(0.088)	(0.100)	(0.088)	(0.100)	(0.088)	(0.100)	(0.087)	(0.087)	(0.099)	(0.097)	(0.097)	(0.087)	(0.099)
Prior RI ($t = 1$)	0.207**	0.232***	0.207**	0.232***	0.207**	0.232***	0.207**	0.207**	0.231***	0.246***	0.246***	0.208**	0.231***
	(0.091)	(0.078)	(0.091)	(0.078)	(0.091)	(0.078)	(0.090)	(0.090)	(0.077)	(0.077)	(0.077)	(0.090)	(0.077)
UD (%) ($t = 1$)	−0.096	−0.107	−0.096	−0.107	−0.096	−0.107	−0.095	−0.095	−0.106	0.132	0.132	−0.095	−0.106
	(0.075)	(0.067)	(0.075)	(0.067)	(0.075)	(0.067)	(0.074)	(0.074)	(0.066)	(0.082)	(0.082)	(0.074)	(0.066)
Finland	0.013	0.053	0.013	0.053	0.013	0.053	0.012	0.012	0.052	0.052	0.052	0.012	0.052
	(0.046)	(0.040)	(0.046)	(0.040)	(0.046)	(0.040)	(0.045)	(0.045)	(0.040)	(0.041)	(0.041)	(0.045)	(0.040)
France	−0.071	−0.081	−0.071	−0.081	−0.071	−0.081	−0.070	−0.070	−0.080	0.102	0.102	−0.070	−0.080
	(0.058)	(0.057)	(0.058)	(0.057)	(0.058)	(0.057)	(0.057)	(0.057)	(0.056)	(0.063)	(0.063)	(0.057)	(0.056)
UK	−0.172	−0.168	−0.172	−0.168	−0.171	−0.167	−0.170	−0.170	−0.166	−0.153	−0.153	−0.170	−0.166
	(0.086)	(0.085)	(0.086)	(0.085)	(0.086)	(0.085)	(0.085)	(0.085)	(0.085)	(0.081)	(0.081)	(0.085)	(0.085)
Independent variables													
ST ($t = 1$)	0.202**	0.152	—	—	—	—	0.172*	—	—	0.623***		—	—
	(0.092)	(0.099)					(0.091)			(0.188)			
GT ($t = 1$)	—	—	0.220**	0.257***	—	—	—	0.196*	0.219**		0.482***	0.196*	0.219**
			(0.10)	(0.085)				(0.103)	(0.089)		(0.166)	(0.103)	(0.089)

(Continues)

TABLE 5 | (Continued)

Variables	Firm-level II T2 Model 1	Firm-level RI T2 Model 2	Firm-level II T2 Model 3	Firm-level RI T2 Model 4	Firm-level II T2 Model 5	Firm-level RI T2 Model 6	Firm-level II T2 Model 7	Firm-level II T2 Model 8	Firm level RI T2 Model 9	FHC T1 Model 10	FHC T1 Model 11	Firm-level II T2 Model 12	Firm-level R1 T2 Model 13
Mediator, moderator & interactions													
FHC ($t = 1$)	—	—	—	—	0.267*** (0.091)	0.432*** (0.102)	0.239*** (0.100)	0.239*** (0.100)	0.413*** (0.103)			0.239*** (0.100)	0.413*** (0.103)
KSC ($t = 1$)										0.539*** (0.123)	0.541*** (0.121)		
ST × KSC										0.215* (0.101)	—		
GT × KSC											0.357*** (0.110)		
FHC × KSC												0.223** (0.10)	0.361*** (0.103)
F-statistic	122.65***	115.98***	135.79***	123.46***	103.63***	100.23***	133.46***	125.24***	142.67***	35.81***	45.64***	129.04***	144.92***
Adj. R^2	0.757	0.666	0.710	0.684	0.788	0.754	0.813	0.803	0.783	0.322	0.316	0.811	0.821

Note: $n = 816$ businesses. robust standard errors.
Abbreviations: FHC, firm level human capital; GT, general training; II, incremental innovation; KSC, knowledge sharing climate; RI, radical innovation; ST, specific training.
*$p < 0.05$; **$p < 0.01$ and ***$p < 0.001$ (two-tailed t-tests).

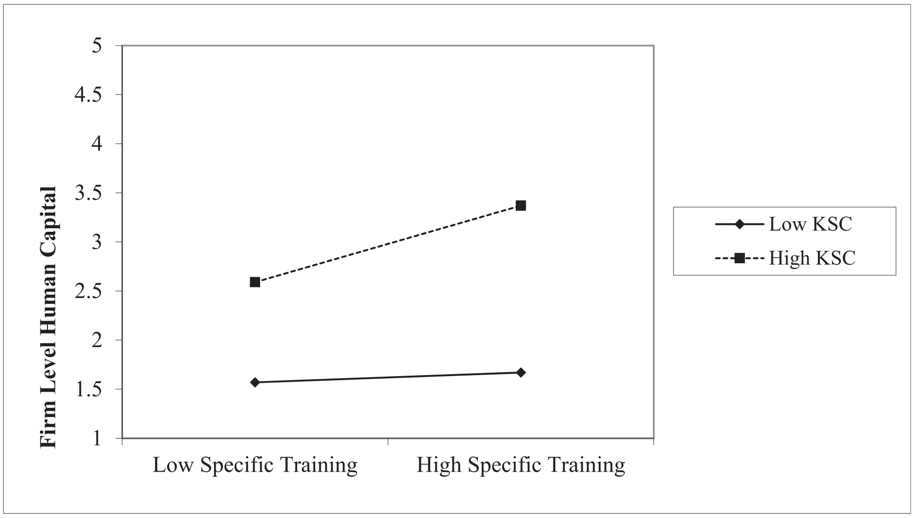

FIGURE 2 | Moderation of knowledge sharing climate on relationship between specific training and firm level human capital. KSC, Knowledge Sharing Climate.

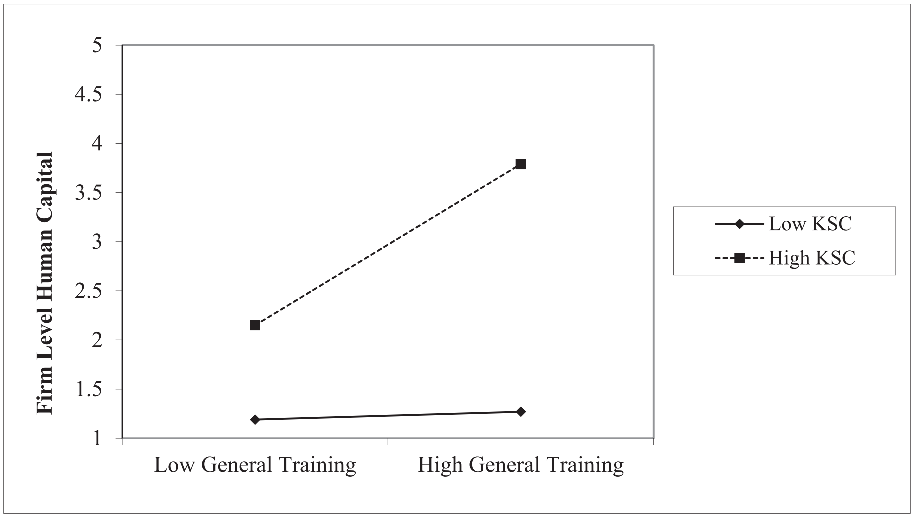

FIGURE 3 | Moderation of knowledge sharing climate on the relationship between general training and firm level human capital.

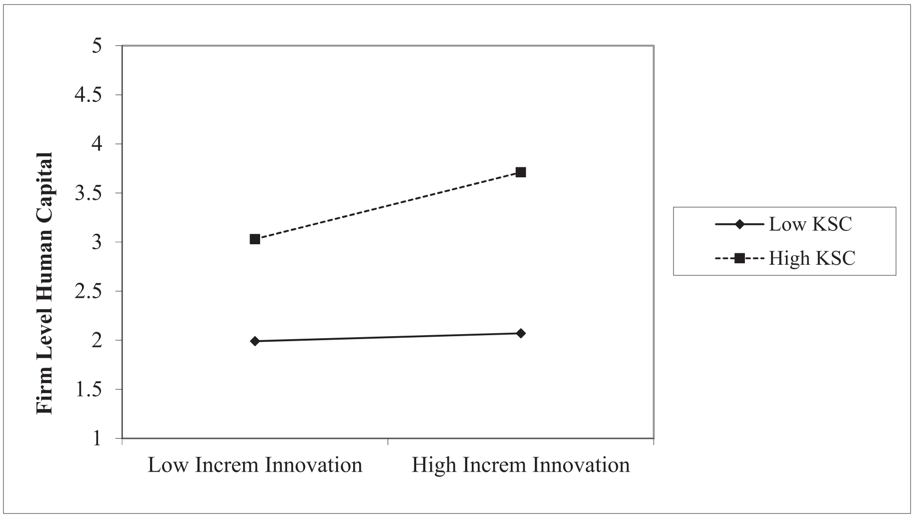

FIGURE 4 | Moderation of knowledge sharing climate on the relationship between incremental innovation and firm level human capital. KSC, Knowledge Sharing Climate.

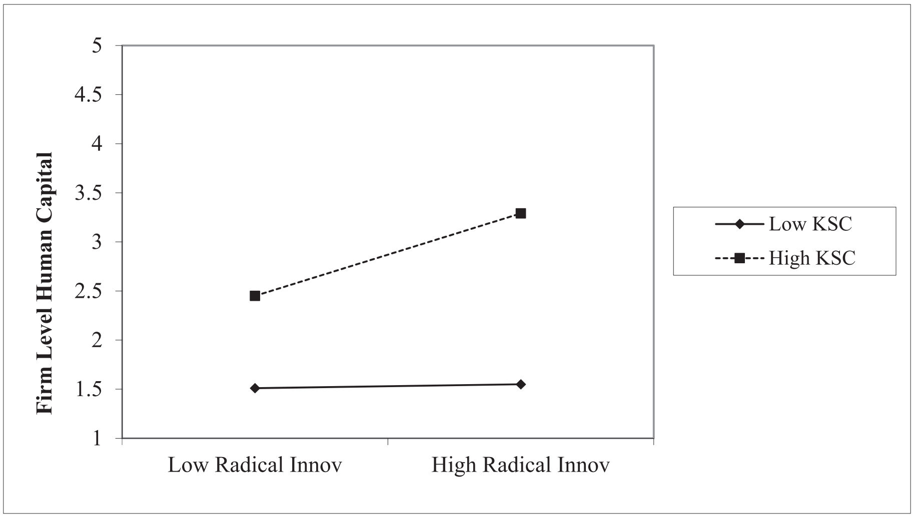

FIGURE 5 | Moderation of knowledge sharing climate on the relationship between radical innovation and firm level human capital. KSC, Knowledge Sharing Climate.

For the final hypothesis, H3f (ii), we found significant interaction terms between general training and knowledge sharing climate in predicting firm level human capital (B = 0.37***, p < 0.001), and between firm human capital and knowledge sharing climate in predicting *radical innovation* (B = 0.38***, p < 0.001). The findings also indicate that the indirect effect of general training on radical innovation via firm level human capital is conditional on the level of knowledge sharing climate. When the knowledge sharing climate is high, the indirect effect is (0.312, 95% CI [0.096–0.435], whereas when the knowledge sharing climate is low, it is (0.063, 95% CI [-0.003 – 0.137]. Hypothesis Hf (ii) is supported.

5 | Discussion

Drawing on the intellectual utility of ideas from human capital resources theory and organizational learning theory, we proposed a model to understand *how* and *when* investments by KIBS in both specific and general training directly influence incremental and radical innovation, and indirectly influence it through firm level human capital. We additionally investigated the moderating role of knowledge sharing climate on the relationship between both types of training and firm level human capital, and on the indirect relationship via firm level human capital on both incremental and radical innovation. We tested our ideas using multi respondent, two-wave data from 816 KIBS in France, Finland, Sweden, and the UK. We found that specific training contributes to incremental innovation, whereas general training contributes to both incremental and radical innovation. Our hypothesis concerning the mediating role of firm level human capital also found support, as did the moderating and moderated-mediation role of knowledge sharing climate.

5.1 | Theoretical Contributions

Our findings have several important theoretical implications. First, we extend the literature on training and innovation in a number of significant ways. We show that general training is valuable for both incremental and radical innovation and that specific training is valuable for incremental innovation. In formulating our hypotheses, based on extant literature we envisaged the possibility of equifinality. To this end, our finding on the link between both types of training and incremental innovation supports this equifinality principle whereby organizations can achieve the same outcome via different paths (T. Garavan et al. 2020). We did not however find support for equifinality in the case of radical innovation. We additionally included both measures of innovation in the same study thus allowing comparisons of the training requirements for each type of innovation. Such a comparison has been highlighted in the HRM literature (Shipton et al. 2017) but is rarely investigated in the same study. We also extend the literature through our particular study design involving two-wave, multi-respondent panel data in order to examine the impacts of training on innovation. In this context, we build on the work of Dostie (2018) and Chatterjee (2017). In the case of Dostie (2018), his focus was on incremental product and process innovation whereas we also investigated the impacts of training on radical innovation. Chatterjee (2017) longitudinally investigated the effects of specific and general training and found support for their different impacts on organizational performance. Overall, our study offers a nuanced understanding of the relationship between different types of training and their utility for innovation in KIBS.

While it is generally accepted in the HRM literature that training impacts organizational outcomes through its effects on human capital development, only a small number of studies have investigated the mediating role of firm level human capital opting instead for individual-level human capital conceptualizations (Jiang et al. 2012). Consistent with human capital resources theory, human capital must emerge to the firm level to be available for innovation outcomes. When it emerges at the firm level it affords KIBS agility and flexibility (Donate, Peña, and Sánchez de Pablo 2016; Jemielniak and Kociatkiewicz 2009). We extend understanding of the mediating role of firm level capital by first highlighting that both specific training and general training each enhance this human capital, and it leads to both innovation outcomes (Ployhart et al. 2014; Camps et al. 2016). This latter dimension occurs because the emergence of human capital to the firm level facilitates collective learning processes of discovery and the permeation of novel solutions. Emergence to the firm level safeguards interactions amongst employees and the development and flow of ideas (Marion 2012).

Our work surfaces an important contextual factor that helps explain the "*when*" of the relationships under investigation. First, we found that knowledge sharing climate moderated the direct relationship between both types training and firm level human capital. Second, we found that knowledge sharing climate moderated the relationship between firm level human capital and both types of innovation. Third, we found that knowledge sharing climate moderated the indirect relationship between training and both innovation outcomes via firm level human capital. Overall, we found that all the moderated relationships were stronger when knowledge sharing climate was high. Taken together, we highlight knowledge sharing climate as a cognitive emergence enabling state (Eckardt, Crocker, and Tsai 2021) with an important trickle-down role in impacting the cognitions of employees around the sharing of knowledge, collaboration, and interaction. In the case of its moderated-mediation effect, knowledge sharing climate has an amplifying effect on the innovation outcomes. This climate is ambient in nature, and it helps to facilitate collective learning processes and the creation of conditions for novel knowledge integration to secure radical innovation (C. H. Lin and Sanders 2017).

5.2 | Strengths, Limitations and Future Research

In terms of strengths, unlike many multi-time-point, multi-country studies, where there is a tendency to employ secondary data collected or compiled for other purposes (Parry et al. 2021), we engaged in a significant data gathering exercise across four countries. In addition, we collected our data from both R&D and HR managers in each firm, and we conducted our study in KIBS where innovation is especially important (Swart and Kinnie 2003). In addition, we used a matched sample, thus permitting us to address the long-term value of training for innovation. However, future research should investigate whether our findings generalize to sectors beyond KIBS. Additionally, building on the methodological approach adopted here, we would encourage scholars to use panel research designs to capture the long-term effects of training investments, to control for prior innovation, and to gather multiple rounds of data.

We conducted our research using perceptual measures of innovation, which are highly correlated with objective measures (Singh, Darwish, and Potočnik 2016). Nevertheless, we recognize potential common method bias. Future research should also, through gathering examples of each, explore in more detail how respondents differentiate between incremental and radical innovations, along with exploring other potential definitions of innovations (Subramaniam and Youndt 2005). The use of "average number of days of training per annum" as a proxy to capture investment in general and specific training is also a limitation and future research should aim to obtain measures such as training expenditure. We do however point out that most organizations have good records of the number of days training, and it is the most commonly used metric by many HR and training departments. Future research should also establish how employees perceive firm-specific and general training. Other institutional contexts beyond those covered by our research should also be considered. We completed our study in four countries that are all above the EU median for innovation, therefore how the relationships apply in average and lower innovation countries is, as yet, unknown. Future research should investigate countries with lower levels of national human capital. We also recognize that additional amplifiers, including affective and behavioral emergence enabling states such as organizational learning, coordination, leadership, communication processes and teamwork, may also prove relevant (Ployhart and Moliterno 2011).

5.3 | Practical Implications

KIBS operate in a highly competitive arena and therefore firm level human capital is an imperative to achieve and sustain innovation outcomes. Our findings suggest a number of important practice implications. Given our findings concerning equifinality, it makes sense for KIBS to focus on general training investments as these are useful for both types of innovation. This general training might usefully include areas such as critical thinking, creative problem solving, idea evaluation skills, along with project management for idea implementation. However, such an approach is not without risks as competitor KIBS will value employees who have general KSA and there is the possibility of poaching.

Second, knowledge sharing climate has a major amplifying role and it is therefore important that KIBS take time to develop and buttress a knowledge sharing climate in order to accrue the benefits arising from training investments. KIBS can take steps to develop such a climate. Thus, for example, workshops to brainstorm important value around knowledge sharing, the use of rewards and performance management to reinforce the importance of knowledge sharing, strong leadership at the top, and the development of manager skills to facilitate teamwork and collaboration could prove value-adding.

6 | Conclusions

In this study we utilized both human capital resources theory and organizational learning theory to develop and test a research model explicating the relationship between specific and general training and two types of innovation—incremental and radical. Utilizing a matched sample of data derived from a two-wave investigation among a large sample of KIBS located in France, Finland, Sweden, and the UK, we found that specific training can both directly and indirectly promote incremental innovation, whereas general training can directly and indirectly promote both incremental and radical innovation. We found support for an important mediator, firm level human capital, and for the amplifying role of knowledge sharing climate. Overall, our findings underscore the value of training investments as a strategy that KIBS can employ to attain and sustain incremental and radical innovation gains.

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Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Endnotes

[1] Longitudinal measurement invariance assesses whether the same constructs are measured equally in different time points within a same group to ensure that growth and/or development in observed scores over time can be attributed to actual development and/or changes in the construct under investigation—in this case the measures of innovation (Millsap and Cham 2012).

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