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Knowledge management implementation in small and micro KIBS: A categorization

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Abstract

The main goal of the paper is to provide a statistical categorization of small and micro knowledge-intensive business service (KIBS) companies, based on their knowledge management (KM) attitude. Since knowledge is the main production factor and output of these companies, it is essential to achieve a better understanding of how they manage this resource. A questionnaire-based survey was conducted on a sample of Polish small and micro KIBS operating in various service sectors. A cluster analysis of the data was performed, to categorize the sample according to the KM attitude of the companies. Three main groups of companies were identified, varying in terms of their levels of "knowledge needs", "intensity of use" of KM practices and "perceived barriers to KM implementation". This classification is shown to characterize attitudes towards KM to a higher level of statistical significance than do structural characteristics. The survey was based on a single country sample. On the one hand, this provides consistency to the analysis. On the other hand, further insights can be obtained by a multi-national study. In addition, cluster analysis is exploratory in nature. The results provide useful insights for policy makers (to formulate policies for facilitating KM implementation in small KIBS) and managers (to reflect on the KM attitudes of their company). The statistical categorization of small and micro KIBS in terms of their KM attitude has been very rarely undertaken. Even the most recent investigations of KM issues used samples from large companies.

1 | INTRODUCTION

Knowledge Intensive Business Services (KIBS) are recognized as key players in modern economies (Kamp & Ruiz de Apodaca, 2017; Pina & Tether, 2016; Tuominen & Toivonen, 2011). In particular, they are deemed to exert a positive influence on the innovativeness of businesses and societies (Liu et al., 2019; Shearmur & Doloreux, 2019). As their name recalls, KIBS are companies whose function and competitiveness are substantially based on knowledge (Miles et al., 2018; Palacios-Marques et al., 2011), which is not only the key factor in their service production, but also the kind of "goods" that they sell (Strambach, 2008).

Although it is vital to understand how KIBS firms manage their knowledge assets, research on this topic is still scarce (Lara et al., 2012) and ambiguous (Miles et al., 2018). In particular, it is necessary to characterize KIBS based on their attitude and approach to knowledge management (KM) (Mangiarotti, 2012; Zieba et al., 2016). In this regard, previous studies have some limitations. First, they generally assume that this is a homogeneous sector or, at most, divided into generic classes based on their particular kind of economic production (as is done in the NACE-based classifications), or on general structural features (see, e.g., Ciriaci & Palma, 2016; Huggins, 2011). Furthermore, research has often examined large or medium companies, while small KIBS (although they represent the predominant part

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of this sector) have rarely been investigated (Bumberová & Milichovský, 2020).

This article contributes to filling this research gap by exploring and categorizing small and micro KIBS firms, based on their attitude towards KM. This can be of potential value for researchers, as it suggests a way to analyze the KM behavior of small companies in general, and small and micro KIBS in particular. In addition, insights can be provided: to policy makers regarding the different approaches to KM of small and micro KIBS and the possible policies that could favor KM implementation; and to company managers, by clarifying the characteristics of the different companies in terms of KM.

The study aims at answering the following research questions: (a) somehow far are there regularities in the KM approaches adopted by small and micro KIBS firms? (b) What are the main traits of these approaches? (c) Do companies which follow the same approach share other distinctive features? A recent study (Alexandru et al., 2020) described a cluster analysis of 216 KIBS companies whose size ranged from 5 to 250 employees (micro to medium-sized firms) in four Eastern and Southern European countries. The study presented here, in contrast, is based on data from a stratified survey of 92 micro and small KIBS (those with fewer than 50 employees), in Poland, belonging to different sectors (namely: ICT, technical services, professional services, R&D services, and marketing services). A questionnaire (partially overlapping with that of the earlier study) was submitted to company owners or directors, investigating such KM-related topics as perceived importance of knowledge as an economic resource, the perceived obstacles to the adoption of KM practices, the intensity and ways of use of such practices; and the kinds of practices adopted.

We compare and contrast our results with those of Alexandru et al. (2020) to gain further insight into the issues addressed.

2 | BACKGROUND

2.1 | Importance of KIBS and need for research in this area

Knowledge Intensive Business Services are widely considered to be key actors of modern economies (Zieba, 2021). Studies have examined their importance from different perspectives. For instance, in European regions, it has been proved that the presence of strong KIBS sectors raises the level of wealth and, additionally, is associated with regional innovativeness, measured, for example, in patenting activity (The European Cluster Observatory, 2009). The significance of KIBS is further confirmed by the growing number of employees in this sector. According to available data (see Zieba, 2021, pp. 106–108—based on Eurostat statistics retrieved in 2017), employment in KIBS in the European Union increased from less than 14 million in 2008 to nearly 16.5 million people in 2016.

KIBS companies are important knowledge sources and channels for innovations (Miles, 2005). By providing their clients with knowledge and expertise, KIBS firms affect the whole economy. This knowledge transfer occurs in different ways: for example, KIBS can perform a direct transfer of their expert knowledge to clients (Bolisani et al., 2016a), they can move experience and ideas from one context to another, act as knowledge brokers, help clients solve problems related to innovations, and more generally seras change agents by spreading innovations and new technologies for the benefit of other economic sectors (Miles, 1999).

Many companies, even large ones, often do not want or cannot afford having the necessary resources and professionals on board for all the varied problems or activities they need to deal with. Therefore, they seek specialist knowledge outside their boundaries and resort to the support of KIBS. Indeed, outsourcing is becoming more and more popular as regards business services (Huggins, 2011), and an increasing number of companies use KIBS for professional functions (for instance, accounting, communications, or staff recruitment). Additionally, the pace of technical development requires organizations to use some specialist knowledge, which may be expensive or simply not available in their own structures (for example, IT management, R&D projects, quality testing, and process engineering). Again, they can seek the help of specialized KIBS. In other special areas, such as, e.g., social, legal, administrative, environmental, regulatory issues, international trade, companies may lack internal professional knowledge, and this increases the demand for KIBS. In summary, the importance of the KIBS is significant and may grow in the future, underlining why KIBS is a crucial field of study.

2.2 | KM in KIBS companies

KIBS companies have been examined by researchers since the term was coined in 1995 by Miles et al. (1995). The scholars who studied this topic adopted various perspectives, both at the macrolevel of regions/economies (see, e.g., Chung, 2002; Corrocher & Cusmano, 2014; Muller & Zenker, 2001) and at the microlevel of single organizations (see, e.g., Aarikka-Stenroos & Jaakkola, 2012; Consoli & Elche-Hortelano, 2010; den Hertog, 2000).

Since KIBS sectors are based on knowledge production and delivery, the topic of KM in KIBS companies has received some examination. Some studies have focused on specific issues, such as the process of knowledge absorption (Tseng et al., 2011), the role of KIBS knowledge in the creation of innovations (Aslesen & Isaksen, 2007), the exchange of knowledge with customers (Chichkanov, 2021; Hu et al., 2018; Landry et al., 2012), and the different criteria used by executives and consultants to select knowledge sharing approaches (Powell & Ambrosini, 2017). An emerging area of research examines the KM strategies of KIBS companies. The successful implementation of such strategies has been positively related to KIBS firms' economic growth and market expansion (Bettiol et al., 2011)—especially in the case of larger companies (i.e., over 100 employees) (Lara et al., 2012)—and to their degree of innovative practices, tools and methods originate from the daily practices and learning processes of company's employees (Mangiarotti, 2012). Exploration of KM strategies has revealed that an informal and emergent approach has widely diffused among KIBS (Bolisani et al., 2016b; Zieba et al., 2016); there

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is little planning of the KM development that is taking place. Zieba et al. (2016, p. 293) describe this as one where "practices, tools and methods originate from the daily practices and learning processes of company's employees".

KM research in small and very small companies is relatively scarce (Centobelli et al., 2017) and does not provide conclusive results as to how these firms manage their knowledge, and what their attitudes to, and implementation of, are (Durst & Runar Edvardsson, 2012; Massaro et al., 2016). This is especially important to note with regard to KIBS, where knowledge and expertise are central, and where small and micro-businesses constitute a major share of all those companies (48.4% of the total in the EU28 in 2017—source: Zieba, 2021). It can be expected that small KIBS have more limited resources available to invest in KM than do large firms, and that this will lead them to take less structured approaches (Zieba, 2021; Zieba et al., 2016). But this does not preclude some smaller KIBS articulating more elaborate KM strategies—Alexandru et al. (2020) found SME KIBS to have several distinct KM approaches, differentiating between "conscious adopters" (whose adoption of KM practices is based on an explicit decision and approach), "unconscious adopters" (adopting KM practices in a less systematic way), and "marginal adopters" (with a low propensity to adopt KM practices). In general, research on small KIBS companies remains underdeveloped, especially compared to that on large KIBS (Cerchione et al., 2016; Sartori et al., 2020). Therefore, to assist in filling this research gap, the present study addresses the following research questions:

RQ1. How far are there different, distinctive, KM approaches being adopted by different small and micro KIBS firms?

RQ2. What are the main traits of these approaches?

RQ3. Do companies that follow the same approach share some distinctive structural characteristics?

The study builds on the multinational survey reported by Alexandru et al. (2020), which identifies three types of KM approach among small and medium-sized companies (up to 250 employees). In addition, no clear unequivocal relationship was found between these clusters and such structural characteristics of companies such as their KIBS sector of operation, size, or age. The failure of characteristics to be effective predictors of a company's approach to KM partially confirmed the results of other studies (Bolisani et al., 2014; Pina & Tether, 2016).

The survey described in this article differs from that used by Alexandru et al. (2020) with regard to both the sample and the questionnaire. A comparative analysis of our results with those should further improve our understanding of the issues addressed.

3 | RESEARCH METHODOLOGY

An exploratory research method was considered suitable to answer the research questions posted above, because the topic has not been sufficiently investigated yet; preliminary data, problem definitions, and basic hypotheses are needed (Shields & Rangarajan, 2013). In particular, the study aims at developing an empirical classification of the different approaches towards KM followed by micro and small KIBS companies. Constructing taxonomies to classify empirical phenomena is a widely employed method in social sciences, business, and management studies. As underlined by Bailey (1994), classification is one of the most central and generic of all our conceptual exercises; without it there could be no advanced conceptualization, reasoning, language, data analysis or, for that matter, social science research. Some authors point to limitations of focusing on classifications: for example, to be really useful, users are required to have the same view of the classified topics as the creator (Qi et al., 2010); additionally, it has been pointed out that any classification, while introducing some stability in the interpretation and use of relevant knowledge, should be truly considered as a temporary construction (Pando & De Almeida, 2016). New information and empirical data may emerge that will lead researchers to change proposed classification frameworks.

Nevertheless, the practical advantages of classifications (Bailey, 1994), make this particularly suitable for the exploratory aims of the present study. Among these advantages are the identification, comparison and analysis of similarities and differences of the categories that have been distinguished, and the formulation of hypotheses concerning their causes and underlying factors. In practical terms, although it is clear that each single case is unique, a classification can also provide a useful point of reference to business decision-makers, who may draw inspiration from how other companies with similar characteristics are performing.

The method adopted here to classify groups of KIBS in terms of their KM approach consisted of cluster analysis of survey data. It is particularly appropriate in the case of exploratory research, where an inductive approach is taken. Classifications arise from the analysis of the available empirical evidence, rather than being deduced from theoretical presuppositions (Ketchen et al., 2008; Ketchen & Shook, 1996). Statistical cluster analysis, which classifies cases in terms of quantitative analysis of empirical data, is about ninety years old (Brian et al., 2011). It is widely used in management and economic research—for example, by means of a search in the Scopus database (performed on 17th January 2022) for the term "cluster analysis" among the keywords field (limited to papers of subject area "Business, management and accounting"), more than 3500 documents were found. Cluster analysis allows for the use of different kinds of empirical variable (nominal, ordinal, interval, or ratio) as classifying factors.

To collect the data, a questionnaire was compiled, drawing inspiration from previous empirical studies on the KM approaches followed by small and medium companies (Alexandru et al., 2020; Bolisani & Scarso, 2015; Zieba et al., 2016). The questionnaire included 22 questions related to different topics: company knowledge strategies and knowledge needs; the KM practices adopted, and the promoters, enablers, and barriers to their introduction; extent to which these practices can be used voluntarily and flexibly, their diffusion throughout the company, and integration with other management tools and methods; and finally, the company's level of familiarity with KM concepts and applications. Most of the questions were answered on a 1–5 point Likert scale.

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TABLE 1 Topics investigated and variables employed

Aspect investigated	Variables (items)	Measure
1. Knowledge strategies	1.1. Knowledge (technical, managerial, and market-related) is the most important source of our company's competitiveness. 1.2. In our company, we have identified and analyzed the types and sources of knowledge that are used to conduct business. 1.3. In our company, we have clearly defined and disseminated the way in which employees should manage knowledge. 1.4. In our company, we have identified and are aware of problems related to knowledge management. 1.5. In our company, we have adopted technical and/or organizational solutions to solve problems related to knowledge management. 1.6. In our company, we employ one or more employees who (full- or part-time) deal with finding and implementing solutions to knowledge management problems	Likert scale 1-definitely no 5-definitely yes
2. KM practices used	2.1. Acquiring and storing technical or market knowledge in an electronic repository or in the form of documents (e.g., manuals, descriptions) 2.2. Using e-mail to share and transfer technical and market knowledge 2.3. Use of social media (e.g., wiki, blogs, Facebook applications) to publish and obtain information 2.4. Building and maintaining employee knowledge and skills (through seminars, specialist training, mentoring, knowledge refresher courses). 2.5. Identification and dissemination of internal or external best practices regarding technological, market, or operational solutions 2.6. Creating conditions conducive to the exchange of knowledge (e.g., availability of conference rooms, organization of rest places for employees). 2.7. Rewarding (financial or nonfinancial) employees who share their knowledge. 2.8. Organizing regular meetings (formal/informal) to exchange information on projects, products, market, etc. 2.9. Using CRM or ERP software not only to manage operational data about customers, but also to obtain information about markets, ways of managing customer relationships, etc. 2.10. Using the community of practitioners to share knowledge	Yes/No
3. Preliminary strategic analysis	3.1. These practices were introduced after a strategic analysis of knowledge-related problems, carried out by the owner or manager of the company	Likert scale, 1-definitely no -5-definitely yes
4. Promoters of KM practices	4.1. Almost only regular employees 4.2. Almost only employees, with some participation of managers/owners of the company. 4.3. Regular employees and managers/owners to the same extent 4.4. Almost only managers/owners, with some involvement of regular employees. 4.5. Almost only managers/owners of the company	Likert scale, 1-only regular employees -5 only managers
5. Barriers to the implementation of KM practices	5.1. Limited financial resources 5.2. Limited human resources 5.3. Lack of specialists 5.3. Insufficient number of KM people 5.4. Lack of time for KM 5.5. Employee resistance to use KM practices	Likert scale, 1-definitely no -5-definitely yes
6. Characteristics of use of practice	6.1. Voluntary practices (employees may decide whether or not to use them). 6.2. Practices closely connected (integrated) with other practices/systems used in the company 6.3. Practices used throughout the company 6.4. Flexible practices, easy-to-adapt to needs of company and/or employees	Likert scale, 1-definitely no -5-definitely yes

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TABLE 1 (Continued)

Aspect investigated	Variables (items)	Measure
7. Factors enabling the introduction of the practices	7.1. Board leadership 7.2. Communication at all levels 7.3. Motivating employees 7.4. Available resources 7.5. Training 7.6. Profitability and business case justification	Likert scale, 1-definitely no -5-definitely yes
8. Knowledge needs	8.1. Knowledge must be properly codified (in available/written form). 8.2. Knowledge must be evenly distributed. 8.3. Knowledge must be properly stored. 8.4. Knowledge must be protected because it is at risk of theft, loss, etc.	Likert scale, 1-definitely no -5-definitely yes
9. Familiarity with KM concepts and applications	9.1. Acquaintance with KM concepts and applications	Likert scale, 1-definitely no -5-definitely yes
10. Provision of a KM definition	Are you able to provide your definition of knowledge management? Provide your own definition of KM. (NOTE: open written answer)	Yes/no

Source: Own elaboration.

The sample was obtained from a database of Polish KIBS firms, purchased from the company “Infobrokering”. Companies from the following divisions were identified and selected according to NACE Rev.1.1. classification: Divisions 62, 63, 69, 70, 71, 72, 73, 74, and 78. In total, the database included 18,034 KIBS companies, with the following sectoral composition: ICT services 17.41%, R&D services 2.81%, technical services 31.54%, professional services 37.81% and marketing services 10.35%; this distribution, according to the data provider, reflects the real picture in Poland. Stratified sampling was then applied to select representative companies with respect to region, size and KIBS subsector (based on the NACE Rev.1.1 categories). The survey was distributed in two forms: an online survey and a paper version sent via traditional post, together with an invitation letter. In total, the survey was sent to 1000 companies by email and 2000 companies by traditional mail. The survey was structured in exactly the same way in both online and paper forms, and both surveys were sent to companies from the same sample, in order to eliminate the response bias (Mutepfa & Tapera, 2019). The invitation letter to companies also included a link to the online form, so some respondents simply chose to use this instead of sending back the filled-in forms. The response rate from the email survey was very low, so it was necessary to use traditional mail, which is also in line with the literature that considers it a more powerful way of collecting responses (Triga & Manavopoulos, 2019). In total, 102 companies responded to the survey, which gives a response rate of 3.5%. Of these, 92 questionnaires were considered usable: those with incomplete or inconsistent responses were discarded. Data was collected in two waves, in 2018 and 2019, reflecting extension of the data collection period due to an initial poor response rate, leading to the decision to change the method of reaching the companies.

Compared to the previous study by Alexandru et al. (2020), the sample only focused on small and micro KIBS companies (less than 50 employees), while the cited study included companies up to 250 employees. A totally different group of companies was contacted, and all these firms were located in Poland. The sample of Alexandru et al. (2020) included Poland, Italy, Spain, and Romania (and sampling methods varied across countries); thus, possible “country-specific” effects (as also emerged in that study) were eliminated here. With less “noisy” data, we can hope to have a clearer view of any distinctive clusters that may emerge,

Furthermore, although the questionnaire used in the study was based on the one adopted by Alexandru et al. (2019), some significant changes were made to better operationalize the variables. Some questions that, as a result of an ANOVA analysis, had proved to be little significant in the previous version were omitted, and some that had been in single/multiple choice response format were transformed into a Likert scale response, to give more consistency to the statistical analysis. Table 1 presents the list of the aspects investigated, the variables (i.e., items) included in the questionnaire in the form of questions, and the measures used to assess each variable. The questions were based on antecedent studies, with some adaptations. The Alexandru et al. (2020) study was a primary source of inspiration; the list of KM practices was derived from Wong and Aspinwall (2005),

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TABLE 2 Sample composition by company size and sector

Sector	Size class 0–4	5–10	>10	Total	%	Avg. size
ICT	7	1	5	13	14.13	10.60
R&D	1	3	6	10	10.87	24.50
Technical	8	6	7	21	22.83	7.90
Professional	12	15	9	36	39.81	10.61
Marketing	8	1	3	12	13.04	5.92
Total	36	26	30	92	100.00	10.87

Source: Own elaboration.

TABLE 3 Sample composition by company age

Age	# companies
0–5	9
6–10	12
11–20	28
> 20	42
n. a.	1

Source: Own elaboration.

and that of potential constraints in KM implementation was drawn from past studies of KM barriers (Ajmal et al., 2010; Zieba & Zieba, 2014). The possible features of the different KM approaches were drawn from the qualitative literature on this topic (Bolisani et al., 2016b; Zieba et al., 2016).

A cluster analysis was applied to the collected data in order to classify companies according to their approach to KM implementation.

3.1 | Sample composition

The composition of the sample of 92 small and micro KIBS companies whose questionnaire was analyzed is shown in Table 2. The sample is rather balanced in terms of sectoral and size distribution, and it reflects the composition of the original dataset (see Section 3) with slight over-representation of R&D and marketing services, and under-representation of ICT and technical companies.

The companies surveyed have a long business history: their average age is about 19, and only 9 have been working for just 5 years or less (Table 3). Therefore, it may be assumed that they have gained a notable experience, which makes their responses particularly interesting: they should have accumulated substantial knowledge.

TABLE 4 Average values of the variables used for cluster analysis[a]

	Whole sample	Cluster 1	Cluster 2	Cluster 3
Knowledge strategies				
Knowledge is our most important competitive resource	4.03	4.48	3.56	3.93
Knowledge sources have been identified and analyzed	3.80	4.17	2.50	4.09
Ways in which employees must manage knowledge are clearly defined	3.68	4.21	2.33	3.89
Problems related to management of knowledge are known	3.86	4.21	2.50	4.18
Solutions to knowledge management problems have been adopted	3.52	3.83	2.28	3.82
There are people dedicated to managing the company's knowledge	1.84	1.86	1.06	2.13
Knowledge needs				
Knowledge must be properly codified	3.36	4.24	3.61	2.69
Knowledge must evenly distribute	3.22	4.03	3.28	2.67
Knowledge must be properly stored	3.15	4.17	3.17	2.49
Knowledge must be protected	2.88	3.62	2.67	2.49
Number of used practices	5.62	6.14	3.56	6.11
Preliminary strategic analysis	3.26	3.97	1.94	3.33
Implementation barriers				
Limited financial resources	3.28	3.79	3.72	2.78
Limited human resources	3.46	3.66	4.17	3.04
Lack of specialists	3.11	3.72	3.44	2.58
Insufficient number of KM people	3.02	3.48	3.72	2.44
Lack of time to devote to the management of knowledge	3.51	3.76	4.39	3.00
Resistance of employees	2.41	2.34	3.28	2.11

Source: Own elaboration.
[a]average Likert score for all variables with the exception of the variable "number of practices used" (the average total number is reported).

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4 | MAIN FINDINGS

A common characteristic of companies (see Table 4 for details) is that they generally consider knowledge as their most important competitive resource (average score of 4.03 in a 1–5 Likert scale). For this reason, it can be expected that KM is also deemed vital. Indeed, on average, they are aware of the KM implications of their activity (3.86 on a 1–5 Likert scale) and have adopted KM solutions (3.52 on a 1–5 Likert scale). However, they generally declare that they have no employees explicitly assigned to KM roles (1.84 on a 1–5 Likert scale). Lack of time for KM (3.51 on a 1–5 Likert scale) and limited financial resources (3.28 on a 1–5 Likert scale) are cited as major barriers to the introduction of KM practices. These general characteristics of the sample are not surprising considering the small/very small size of companies.

Nevertheless, at a deeper level, the data show that companies differ considerably with respect to these and other variables (see Table 4). A cluster analysis, to detect specific subgroups of firms that share common traits, is thus appropriate. Cluster analysis across the whole set of variables measured in the questionnaire failed to provide meaningful results in terms of statistical significance and the interpretation of the cluster traits; thus, analysis of a subset of variables was pursued. Specifically, since the goal of the study was to investigate the attitudes of firms towards KM, items that most denoted the companies' approach to KM implementation were examined. These were: the knowledge strategies and needs; number of KM practices used by the company; implementation of a strategic analysis before introduction of KM; and the barriers to implementation. We experimented with different methods, but a k-means clustering approach was selected—see Appendix A.

TABLE 5 *p*-Values, global comparison

Cluster	1	2	3
1		0.0005	0.0005
2			0.0005
3			

Note: See Appendix A for the derivation of these significance tests.
Source: Own elaboration.

TABLE 6 Average values of additional variables

	Whole sample	Cluster 1 KM eagers	Cluster 2 KM indifferents	Cluster 3 KM pragmatists
Characteristics of the used practices				
Practices are voluntarily used	3.48	3.45	3.61	3.44
Practices are integrated with the others	3.46	3.93	2.78	3.42
Practices are diffusely used	3.90	4.34	3.61	3.73
Practices are flexible	3.86	3.83	3.61	3.98
Factors enabling the introduction of the practices				
Leadership	4.03	4.07	4.17	3.95
Communication at all levels	4.26	4.72	3.94	4.09
Motivating employees	4.05	4.28	3.72	4.04
Available resource	4.18	4.59	4.00	4.00
Training	3.97	4.48	3.44	3.84
Profitability/Business case	3.70	4.31	3.28	3.67
Main promoters of the introduction (owners/top managers)	3.99	4.11	4.06	3.89

Source: Own elaboration.

TABLE 7 Values of descriptors variables

	Whole sample	Cluster 1 KM eagers	Cluster 2 KM indifferents	Cluster 3 KM pragmatists
Familiarity with KM concepts and applications (average value)	3.57	3.86	2.33	3.89
Provision of a KM definition (% of companies)	44.57	51.72	22.22	48.89
Average age of companies	18.78	20.62	17.24	18.18
Average size of companies	10.87	10.00	6.94	13.00

Source: Own elaboration.

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This resulted in the detection of three clusters—Table 4 contrasts these in terms of the variables used in the cluster analysis. These differ substantially in terms of statistical significance (see Table 5), and with differing characteristics that could be fairly easily understood. Having grouped the companies in the three resulting clusters, the remaining variables (called "additional variables" below) were used to complete the description of the groups: some of these also displayed statistically significant differences. Table 6 shows the average values of these additional variables—ones included in the questionnaire but not used for the cluster analysis—for each cluster and for the whole sample.

Size, age, sector, familiarity with KM concepts and applications, ability to provide a definition of KM were used as descriptor variables. Table 7 shows the average values of the descriptor variables (excluding "sector") for each cluster and for the entire sample. For the variable "Acquaintance with KM concepts and applications", the average Likert score is reported; the other variables show the percentage of companies that provided a definition of KM, and the average age and size of the companies belonging to the different Clusters.

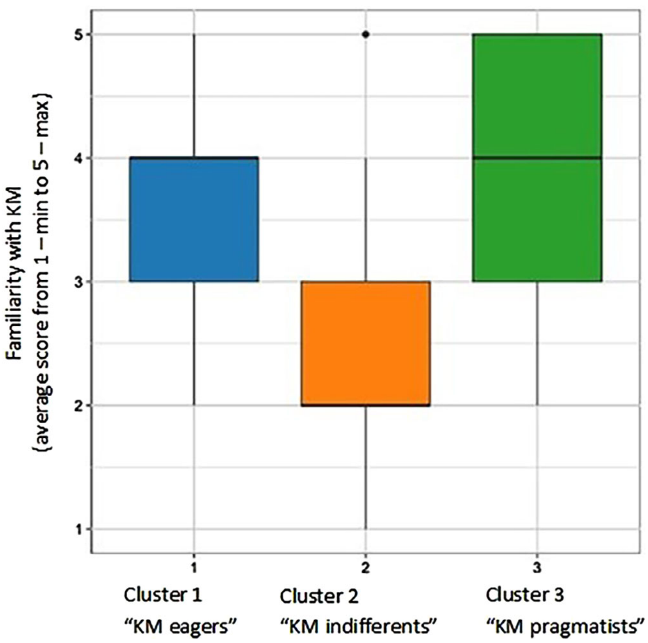

FIGURE 1 Level of familiarity with KM concepts and applications in the three clusters [Colour figure can be viewed at wileyonlinelibrary.com]

Directional permutation tests were applied to compare clusters in terms of structural variables such as age and size of companies, with reference to their acquaintance with the concept of KM and ability to provide a definition of KM. Companies from cluster 2 tend (see Figure 1) to display significantly lower knowledge of the concept than the other two clusters. The median value of this variable (called KMCONC) is substantially lower in this cluster, as is evident from the position of the thick horizontal line inside each box (i.e., each colored rectangle delimited by the first and third quartiles).

Additionally, most of the companies belonging to this cluster are not capable of defining KM (see Table 7). On the other hand, the clusters are essentially similar in terms of age, with the *p*-values of the permutation test that are all greater than 0.05. Finally, companies in cluster 2 appear to be, to some extent, smaller than those in cluster 3 (see Table 7).

Table 8 shows the clusters' composition by sector. The possible mutual dependence between clusters and sectors of operation of companies was verified by means of a chi-square test, and no evidence (*p*-value equal to 0.52) was found supporting such a dependence.

5 | DISCUSSION

First, we consider the distinctive characteristics of the three clusters that have been differentiated. Cluster 1 (see Tables 4 and 6), which will be called here "KM eagers", represents 31.5% of the whole sample. It consists of companies that actively manage their knowledge assets. These companies show the highest scores in perception of knowledge as a competitive resource (4.88 on a 1–5 Likert scale); they have identified and analyzed their sources of knowledge (4.17), and they are aware of their KM problems (4.21) and of the possible management solutions (4.21). This KM-proactive behavior is confirmed by the fact that they show the highest levels of awareness that knowledge must be codified (4.24), evenly distributed (4.03), stored (4.17), and protected (3.62). Not surprisingly, they report using the highest number of KM practices (on average 6.14 compared to 3.56 and 6.11 of the other clusters); these are liable to have been introduced after a preliminary strategic analysis (3.97). This cluster also displays the

TABLE 8 Clusters' composition by sector

% per cluster	Total	Cluster 1 KM eagers	Cluster 2 KM indifferents	Cluster 3 KM pragmatists
ICT	14.13%	17.24%	27.78%	6.67%
R&D	10.87%	6.90%	11.11%	13.33%
Tech	22.83%	20.69%	22.22%	24.44%
Prof	39.13%	44.83%	22.22%	42.22%
MKG	13.04%	10.34%	16.67%	13.33%
Total	100.00%	100.00%	100.00%	100.00%

Source: Own elaboration.

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highest scores for the wide diffusion of practices within companies (4.34), and for close connection/integration with other working practices (3.93). These companies also show that the proactive introduction of KM is linked to their effort to motivate employees (4.28), make resources available (4.59), implement training activities (4.28), and communicate about KM at all levels (4.72). Lack of financial resources (3.79) and specialists (3.72) are seen as the strongest barriers to KM. Finally, "KM eagers" (see Table 7) have high scores on the acquaintance with the concept of KM (3.86); accordingly, this was the cluster in which the highest share of members (about 52%) was able to provide a definition of KM.

To sum up, this cluster was called "KM eagers" because companies show the greatest propensity to KM adoption: they are aware of the importance of knowledge and KM, and they have considered a possible KM strategy which has led them to adopt many KM practices and to make efforts for their effective implementation and use across all organizations. On the other hand, these companies are "eager" because they would probably like to do more, but see insufficient resources and lack of specialists as representing barriers to further adopting of KM to fit their strategic goals.

Cluster 2, named "KM indifferent", is the smallest (about 20% of the sample). Compared to KM eagers, this group comprises companies that are characterized by the lowest attention to knowledge, knowledge sources and problems, and KM solutions (see Table 4). They affirm that they have insufficient knowledge of KM concepts (2.33)—only 22.22% of this cluster were able to provide a definition of KM. They use, on average, the lowest number of KM practices (3.56), with these being little diffused (3.61—lowest score of the sample) or integrated (2.78—lowest score) in the organization. Compared to the other clusters, less promotion was attempted: these companies report the least effort to motivate (3,72) or train (3.44) employees. This may help explain the substantial resistance to adoption by employees (3.28, highest score): and possibly the finding that KM practices, when adopted, are employed substantially on a voluntary basis (3.61, highest score) follows from this too. The highest barriers to KM are also signaled, especially with regard to lack of human resources (4.17) and lack of time (4.39).

The "KM indifferent" cluster, then, includes companies who are unwilling to invest resources in KM, have limited knowledge of KM practices and methods, and probably do not believe much in their potential. In other words, it is not that these companies do not see that there are needs for codifying, storing, protecting and sharing knowledge, though their score here are below those of Cluster 1. Possibly they do not believe that existing KM methods can efficiently ensure that such needs are met for a company of their type. Therefore, this may explain why KM practices are left substantially to the voluntary application of employees, without particular effort in their planning or promotion.

Cluster 3 is called "KM pragmatists". This is the largest cluster (almost one-half of the sample). It consists of companies that declare themselves to have a rather active management of their knowledge assets, although not at the same level of "KM eagers". They adopted a large number of practices (on average 6.11, almost the same as "KM eagers"); they report relatively high acquaintance with the concept of knowledge management (scoring 3.89, which is even higher than "KM eagers") and about 49% are able to provide a definition of KM (close to "KM eagers"). They also affirm that KM practices were often implemented after a strategic analysis (scoring 3.33) but less actively than "KM eagers".

On the other hand, the implementation of KM in these companies is apparently the result of a pragmatic attitude. Indeed, compared to "KM eagers", these companies do not report strong needs for codification, distribution, storage and protection of knowledge (scores for these questions were lower than for the other two clusters—see Table 6). It may be that, in these companies, KM practices are being introduced to face specific practical problems but, possibly, with no particular expectations as to their transformative potential. This cluster gives the lowest scores to possible barriers to KM implementation, suggesting that these companies prefer to invest in those KM practices that can immediately show potential uses and low application problems. This is why they are named "KM pragmatists".

5.1 | Categorization based on structural criteria

The significance of the findings of the cluster analysis was tested using another method. The literature about KIBS has often emphasized that this sector is actually made of different subsectors, which can therefore have different knowledge bases and KM attitudes, due to the specific products, services, and processes related to their own business. In the field's foundational study (Miles et al., 1995) and later work (e.g., Pina & Tether, 2016), various subsectors are proposed. The literature distinguishes, for example, between T-KIBS (services based on technologies, especially computer services), P-KIBS (professional services, like, e.g., accounting or employment support), or C-KIBS (creative services, including marketing, design, and advertising). This classification resembles the typical division into economic sectors that are used in official statistics (such as NACE or NAICS), although there are some industries that do not readily fit only one subsector (e.g., architecture).

It might be expected that the clustering of our sample in terms of KM is linked to the sector of operations of companies— namely: do companies of the same sector tend to manage their knowledge assets in the same distinctive manner? However, the picture that emerges is unclear and controversial.

The statistical analysis did not find a clear association between a KIBS (sub)sector and the attitude of KM (i.e., a dominant cluster) of its companies. For most sectors, indeed, companies are almost evenly distributed in the 3 clusters (see Table 8), with two exceptions: ICT and professional services. Among the former, there is a prevalence of "KM indifferents", and this is surprising, since ICT service companies could expect to be more oriented towards KM methods and tools (many of which are ICT-based, and where there has been much discussion of formalizing approaches such as software engineering). Similarly, it is worth underlining that there are relatively few "KM indifferents" among professional services firms, which are less ICT-based. This result deserves further attention.

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The same can be said as regards the age of companies: no remarkable difference emerges here. For "KM eagers", the average age is 20.62 years, for "KM indifferents" 17.24 years, and for "KM pragmatists" 18.18 years.

Regarding the size of companies, it can be expected that micro-KIBS companies (for example, those with just one or two employees) show little interest in KM, since the key knowledge inevitably restricted to few people. The results indicate that the average size of "KM indifferents" is significantly smaller than that of "KM pragmatists" (Table 7). This signal that the behavior of companies that are not oriented to KM is partially affected by their size is also worth further attention: with a larger sample we might investigate whether there is a straightforward relationship between size and KM practice, or whether there is some kind of threshold encountered where the perceived costs and benefits change substantially.

5.2 | Comparison with previous results

This study has confirmed the conclusion of Alexandru et al. (2020) that it is possible to categorize KIBS companies based on their attitude or propensity to use KM, which, as mentioned, implies different intensity of KM use, different pathways to adoption, and different participation of top management. Although some differences were introduced with respect to the sample and the questionnaire, it is possible to compare and contrast some of the findings obtained. One similarity between the studies is that while the clusters identified are not identical, neither study suggests that KIBS' KM attitudes can be readily predicted by their sector of operation. This also confirms what was argued in some previous studies on the cognitive traits of KIBS (Bolisani et al., 2014; Pina & Tether, 2016). Another common point of the two studies is that they both identified three clusters which, with the exception of some details that may reflect differences in sample and survey instrument, are roughly similar. It suggests that a clustering of this sort can help in the identification of KM practices across micro and small KIBS, and quite possibly a wider range of businesses.

Regarding size, the present study shows, as expected, that the smaller companies (i.e., few people) report implementing fewer KM practices than larger ones (with 40 or 50 employees) and not having their own KM specialists. But, in general, as in Alexandru et al. (2020), only a partial connection between the organizational size and type of cluster.

A striking difference from the results of the earlier study concerns our finding that ICT companies participating in our survey showed a slightly lower propensity towards KM than the other clusters (see Table 8). In Alexandru et al. (2020), ICT KIBS appeared to be somewhat more active in KM than the other sectors. As mentioned, this result is particularly interesting because one may expect that ICT companies, which presumably are more familiar with the use of technologies and methods for sharing, codifying, and storing information (and knowledge), should be the ones that are more active in KM. Size may be an important factor behind the different results: our sample features smaller companies (on average, 10.6 employees for ICT companies) than that of Alexandru et al. (2020) (51 employees on average). This possible explanation needs, however, further investigation.

6 | CONCLUSION

The main contribution of this study is that it sheds light on the different attitudes towards KM of small and micro KIBS, which represents an important but still understudied component of modern economies. Regarding the implications for research, the study helps to achieve a better understanding of how small and micro KIBS firms work with regard to KM (past research has mainly focused on large KIBS). While there are recurring traits—for example, recognition of a general lack of resources for KM—the study shows that smaller businesses in this economic sector are far from being homogeneous. Cluster analysis has shown that, despite the fact that knowledge is the most important ingredient in business for all these companies, their approaches to KM vary. As argued in previous studies, these findings confirm that there may be no universal approach to KM, even considering KIBS companies of the same size class. This can inspire new lines of research that can help explain the specificities of these companies.

Indeed, based on the collected data, there is a positive response to the research question RQ1 ("How far are there different, distinctive, KM approaches being adopted by different small and micro KIBS firms?"). While these KIBS did share some traits in common, it was possible to group companies into statistically significant distinct categories, within which features were shared. The investigation made it possible to answer RQ2 ("What are the main characteristics of these approaches?") by identifying characteristics shared within clusters, such as the level of promptness, intensity of use, and perceived barriers to KM.

Regarding RQ3 ("Do companies that follow the same approach share some distinctive structural characteristics?"), the results are less definitive. We have found no clear statistical evidence that the subdivision in clusters (based on approach or propensity to KM) overlaps with the typical structural characteristics such as sector of operation and age of the company (and, partially, firm size although with some caveats). In short, these structural features cannot be used to predict the approach or attitude of a small/micro KIBS company towards KM. The counterintuitive results showing the ICT sector to have lower interest in KM indicates the need for further research into features of knowledge and its application in these and other businesses.

The study also provides insights concerning the potential of KM for small and micro KIBS that can interest business managers and policy makers. KIBS managers (and possibly those in other sectors) may consider the specific characteristics of the KM approach followed in their own company and, therefore, reflect on the way in which their KM needs can be better met. Suppliers of KM solutions may be informed as to the characteristics of users and markets. For policy makers, a deeper understanding about the heterogeneity of this important sector can help to set tailored supporting measures that can facilitate fruitful implementation of KM by different clusters of companies. For example, the division into groups may suggest that a

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systematic investment in resources for the training and promotion of KM may have better effects for some companies (such as "KM eagers" and "KM pragmatists") than for others.

The paper has some limitations that must also be mentioned, but they provide inspiration for future research. First of all, the results refer to a single country. This was useful because it demonstrates that there are many differences in KIBS even in the same cultural or economic context. Replicating the analysis in other countries can help to analyze the influence of this specific factor and may also shed light on different institutional and organizational characteristics of KIBS in different countries. Second, cluster analysis techniques themselves all have their own limitations (for example, the reliance of k-means on a random initialization, introducing a dependence of the results on the adopted random seed) although these were mitigated by using the particular algorithm implemented in R, and the statistical tests showed the goodness of the results and a significant "distance" between the identified clusters. In any case, future clustering approaches might well be explored to check the validity of the obtained results. Finally, data on economic or organizational performance of companies were not collected in this study. Analysis of such features of the firms could deepen understanding of the causes and consequences of different KM practices, as would the sort of historical analysis of the evolution of practices in specific companies that is more often accomplished through case studies than via survey research. There are thus many opportunities for future research on this topic, which is liable to become of increasing interest as new technology is applied increasing to professional activities and the work of KIBS, and/or as KM systems themselves become more accessible.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the authors upon reasonable requests. In any case, the Authors and the Funding Institutions reserve the right to apply specific restrictions to data sharing.

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APPENDIX A: Clustering method

Two clustering algorithms were initially considered: k-means (Lloyd, 1982; MacQueen, 1967; Wong & Hartigan, 1979) and hierarchical clustering (Johnson, 1967; Murtagh & Legendre, 2014).

The k-means approach partitions the data set into K groups by assigning each data point to a specific group, given the desired number of clusters, K. Starting from a random partition, at each iteration, the algorithm assigns each data point to the cluster for which the sum of the squared distance between the data point and the cluster mean is minimum, and the cluster means is updated. The algorithm aims to minimize the variability within each cluster and maximize the difference between clusters and stops when no further improvement can be achieved.

On the other hand, hierarchical clustering starts by assigning each observation to a different cluster and then iteratively aggregates the couple of clusters that are the most similar. The process ends when a single cluster is achieved. In this analysis, Ward's criterion (Murtagh & Legendre, 2014) is adopted for agglomeration and the Euclidean distance is used as a distance metric.

After performing a standardization process of the available data, for each algorithm, the optimal number of clusters (K*) was estimated, and the partitions thus achieved were compared by means of appropriate clustering validity indices, to identify the best algorithm.

We employed multiple indices commonly adopted to this end, and provided in Charrad et al.'s (2014) R package. For each algorithm, the basic idea was to choose the number of clusters that optimizes the highest number of clustering validity indices, such as the Calinski and Harabasz index (Caliński & Harabasz, 1974), the Davies and Bouldin index (Davies & Bouldin, 1979), and the Silhouette index (Rousseeuw, 1987). The complete list of indices considered can be found in Charrad et al. (2014).

Once the best partitions were identified, the solutions provided by the k-means and hierarchical clustering methods were compared. K-means turned out to be the better algorithm for the current problem, according to both the Calinski and Harabasz and the Davies and Bouldin index.

To further evaluate the goodness of the partition obtained from the k-means approach, the K* clusters were assessed by using the NonParametric Combination technique (Pesarin & Salmaso, 2010), to check if they were significantly different from each other in terms of the variables adopted in the cluster analysis. This technique made it possible to achieve a global p-value and to assess the significance of the difference between clusters by combining the results of several partial permutation tests evaluating the differences related to each single variable.

Finally, permutation tests (Pesarin & Salmaso, 2010) and a chi-square test of independence (McHugh, 2013) were also used to compare the clusters with respect to a set of additional variables, in order to identify relevant characteristics of each group of companies.

Both k-means clustering and hierarchical clustering were applied to the chosen variables to search for the optimal number of clusters (the range of three to ten clusters was examined). According to the NbClust procedure (Charrad et al., 2014), three clusters were the optimal choice for the k-means method, and four for the hierarchical clustering method.

Based on the resulting partitions, the Calinski and Harabasz index (which should be maximized) was equal to 13.6 for the k-means method and a lower value (10.2) for hierarchical clustering. The Davies and Bouldin indices were equal to 2.3 and 2.5, respectively, and provided further indications in favor of the use of k-means (this method showed the lowest value).

Consequently, the k-means method was preferred, and the partition into three clusters was therefore retained. The NonParametric Combination technique was then applied, performing all three possible pairwise comparisons between clusters. The mean difference was used as a statistical test, and 2000 permutations along with the Fisher combining function (Pesarin & Salmaso, 2010) were used to achieve the global *p*-values. Table 5 (see main text above) shows the *p*-values related to each comparison: all are lower than the 0.05 significance level; telling us that all clusters are significantly different from each other in terms of these key variables.

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