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Activity-to-skills Framework in the Intellectual Property Big Data Era

Nadja Damij, Ana Hafner, Dolores Modic

***Abstract*— With new technological advances such as the advent of big data, new opportunities are arising for companies. The dynamic nature of external environments is also causing the need to revise the necessary employees' skills. This paper focuses on exploring the data skills in the context of intellectual property (IP) processes. By combining the resource-based view with a process approach we designed our novel activity-to-skills framework to identify data skills. We posit that data skills are non-homogenous and are not singular occurrences. Subsequently, we extend the taxonomy of required data skills by defining five types of data skills, as well as deepening the understanding of how these skills are distributed within IP activities and interwoven with non-data skill types. IP data skills come to the forefront most in IP commercialization activities. We develop implications for innovation managers based on interviews with elite informants – prominent IP experts – seven of them heads of their respective IP departments.**

***Index Terms*— Data Skills, Intellectual Property Management, Innovation, Process Management, Big Data**

***Managerial relevance statement*—The paper makes several contributions to practice. Firstly, it identifies intellectual property (IP) data skills and their interdependence with other non-data IP skills, needed by employees to achieve the overall organizational innovation goals. Secondly, it develops an activity-to-skills framework to identify the data skills needed to harness and exploit IP data. Thirdly, the results are based on interviews with 10 elite informants, all executives with years of experience, with one of the interviewees appearing twice in the 50 most influential people in IP (Managing IP magazine). The elite informants were representatives of a variety of industries and affiliated with companies high in terms of patent applications and quality rankings. Fourthly, the paper addresses the information management challenges regarding (re)allocation of necessary data skills inside process activities consequently bringing insights to the innovation process. Finally, the paper presents the activity-to-skills framework, as a blueprint allowing for comparison of necessary and existing skills in a company. Based on this, IP managers can foresee and/or design appropriate additional training and if necessary, headhunt required resources to ensure the necessary skills and competences.**

I. Intellectual property Skills for the New Era

Digitalization and the advent of big data are gaining attention across industries and transforming the industrial landscape [1], [2], [3], [4], [5] and the Covid-19 pandemic has only accelerated this process [6]. The heightened emphasis on data and information is present also inside intellectual property (IP) processes as an important part of the innovation processes [7]. IP big data has a vital role in helping firms accelerate innovation processes [8], [9]. But in spite of this, there is insufficient knowledge on how to be able to exploit data within business activities in general [10], [11], [12], [13], and in relation to IP and innovation processes [9], [14]. It is essential for companies to have at their disposal, or be able to employ, human resources capable of identifying, extracting, linking and exploiting available IP data [9], [15], [16]. Only then can IP data generate worthwhile insights and benefits, thus having the 'high value' attribute [17]. The companies need to understand which skills are needed to support the goals of the organizations [18] and a purposeful selection of employees is crucial to the organizations' efficacy [19].

In this paper we explore IP skills, with a particular emphasis on IP data skills and their interdependence with other IP (non-data) skills that enable the exploration and exploitation of IP data to achieve the overall organizational innovation goals. We investigate IP data in the context of big data due to their shared 5V characteristics – volume, variety, velocity, veracity, value [20] and the ability to be analyzed with big data tools i.e. by visualizations. Despite ample traditional research on skills needed inside innovation processes (e.g., [21], [22]), the insights remain largely unconnected to the demands posed by today's large volumes of data. A possible exception is Modic and Damij [23], who indicate that big data might present challenges to innovation, and in particular intellectual property management. Although IP data as an input is required throughout the R&D and business decision-making processes [23], the knowledge gap about the relevant data skills persists.

Little is known about which data skills are needed, which come to the forefront in particular activities of the IP processes and how they are interwoven with other IP related skills. To overcome critical challenges when pursuing a coherent course of action of creating value in the long term, especially in terms of challenges related to lack of necessary skills, we develop and empirically examine an activity-to-skills framework.

This framework allows the identification of the necessary data skills to harness and exploit IP data, and related innovation data, within all IP activities. Not only does the model take into account different activities, but also the overall and specific goals, as well as available data sources and the depth of interaction with the data [8], [24]. Using the activity-to-skills framework allows us to disentangle the distinct data skill types and their aggregate dimensions, their relevance inside the activities, and how they are interwoven with other IP skills. By moving away from studying data skills as a homogenous notion – a prevailing approach especially in innovation management studies – we are able to identify five types of relevant data skills. Our five types extend our understanding of the data skill types as derived in prior research [8], [25]. The necessary skills are often studied as singular occurrences (i.e., data skills being needed or important for the processes as a whole) – but with our approach we are able to detect nuances according to activities (grouped into phases within the IP process) in terms of the specific type of IP skills, and their predominance. In contrast to much of prior literature [26], [27], we do not focus solely on the role of data experts, gaining a more holistic picture.

The paper investigates what IP skills (data and non-data related skills) employees need to successfully harness IP data. Particularly, the research into the need for data skills within innovation processes using the example of intellectual property processes is highlighted and examined by employing an activity-to-skills approach with the aim of identifying the required (data and non-data) skills in each of the identified IP activities.

We report on findings from a qualitative study involving interviews with 10 elite informants, prominent IP experts, seven of them heads of their respective IP departments, while their global companies appear in top innovation listings, such as MIT's list of the 50 Smartest Companies. The companies selected are positioned highly in terms of patent applications and quality rankings. With this research we seek to address the lack of rigorous qualitative empirical studies in this emerging area. The insights allow us to build several recommendations.

The results clearly identify that 1) the type of skills needed is dependent on the focal activity within the IP phase and that 2) the data skills permeate all phases and activities inside the IP process, however, with a higher relevance in some of the phases such as the IP commercialization phase, which is also a key phase for deriving the value from data inside the innovation process. Hence, phase-specific requirements for specific data skills may lead to the efficient allocation of experts along the IP process as well as inform recruitment.

The topic is especially relevant, since the Covid-19 pandemic has caused many different challenges to companies and organizations [28], [29], [30]. They have been forced to adopt several changes and in a very short time implement solutions based on digital technologies [31] in various fields, hence the importance of digital skills is increasing across the board. The literature also shows that IP seems to play a role as an innovation incentive at the times of global crisis, such as Covid-19 pandemic [32]. As such, it also presents a particularly salient context for (data) skills research.

II. Towards an Activity-to-Skills Framework in the Big Data Era

We define skills as a taught set of an individual's abilities that are required in order to complete designated tasks, activities and processes. We have some insight into the skills needed for handling big data [33], [34], [35], but works based on the resource-based view (RBV) theory indicate that there might be several different types of skills that are relevant [8], [34]. However, this strand of literature informs the innovation processes, and in particular IP processes, poorly. It is mostly specifically connected to data analysis, however the benefits of IP data extend to those that are derived solely from big data analysis [23]. Hence, albeit today IP is gaining importance and presents a significant part of the overall company's value [35] – with IPs being fundamental to the operation of all technology-intensive firms [36] – the knowledge gap related to needed (data and non-data) skills persists.

Our research follows the ideas of the resource-based view (RBV) which aims to explain the performance of individual firms by differences in their resources rather than market characteristics [37]. RBV suggests that beside several tangible resources (e.g., new technological advances) there are intangible ones – intellectual capital that could be used by an organization to create value [38], including managerial and technical skills that allow improvement in firm's performance. Furthermore, we take into account Bassellier et al.'s [39] skill-based approach, which is matching the user's abilities and the task at hand, going beyond the recognition that the heterogeneity would be connected only to sector-oriented skill requirements [40].

We combine this skill-based approach with a process approach, taking into account that processes are generally divided into phases, activities and tasks [23], [41], [42], which allows us to tease out the nuances in necessary skills along the IP process, as the necessary skills are diverse not only in terms of the tasks that need to be performed, but also in terms of the needed inputs and predicted outputs. The IP skills depend on three key aspects: (1) the available data sources; (2) the necessary data handling, i.e., tasks related to the exploration and exploitation of data; and (3) the specific goals that are pursued with a particular activity (in our case a particular IP activity).

Furthermore, within this work we conceptualize IP data as also exhibiting big data characteristics, and take note of some insights generated by the related literature. Big data is often described as large, complex and/or variable, and requiring technologies to enable the capture, storage, distribution, management, and analysis of the information [3], [43]. Big data exhibits so-called 5Vs; derived from 'classical' 3Vs – both in general [3] and in connection to IP [44] and 'additional' 2Vs [20]. Volume, variety and velocity, i.e. 3V, refer to large amounts of data, data being available in several sources and formats, and being generated at a rapid rate, respectively. The 'additional' two Vs, i.e. veracity and value, refer to the need to diligently extract valuable information from given data and the potential for extracting worthwhile insights and benefits [17]. We know that IP (big) data is incremental for accelerated innovation processes [8], [9], we however focus in particular on IP processes, and posit that the derived value from the IP data is highly dependent on the available skills.

A. The resource based view and types of IP skills

Literature based on the RBV posits that there are several different types of skills that might be of relevance in this new era of data abundance [8], [17], [34]. Typically, literature recognizes two broad types of data skills needed to derive value from data: technical and managerial-oriented [17]. The later are also referred to as business skills [24]. While more emphasis has been placed traditionally on technical skills, managerial-oriented skills are gaining prominence as well [45]. Mikalef et al. [8] further divide the big data skills into technical (e.g. related to database management, programming knowledge or data retrieval), business (e.g. related to deriving strategic insights), relational (enabling information flow) and business analytics (e.g. simulation or scenario development or data visualization). Mikalef et al. [8] indicate that at least some of them (in particular data analytics) can contribute to innovation performance. But this stream of literature tells us little about which of these types of skills appear in which part of the processes and how they are interwoven inside innovation processes both with each other, and also with other non-data skills. We also know less about the data skills necessary when the focus is not on data scientists [46], but rather on employees included in diverse parts of IP processes.

In terms of innovation and IP literature, skills and competences are usually addressed in academic papers investigating the innovation process and team dynamics [21], [22]. Works on IP strategy or IP management are also plentiful (e.g. [47], [48], [49]) as there is a prevailing notion that the management of IP has moved from a legal matter to a strategic issue [50]. But their insights remain unconnected to the demands posed by big data and its potential for IP management. However, Modic and Damij [23] have already pointed out the importance of understanding the newly needed IP-related skills contingent on new advances and potential related to IP (big) data.

Lastly, the research themes focusing on big data generally range from general information and knowledge management approaches [16], [51], [52], to investigating big data analytics approaches [41], [53], [54] and concrete IP tools and data sources [15], [55], [56]. We have relatively little insight into the skills needed for handling big data [33], [34], [57]. Despite the hype surrounding big data, most studies to date have primarily focused on issues such as infrastructure or analytics tools, whilst other related resources, such as human skills and knowledge, remain largely outside the current debates [8]. Some authors dealing with big data or related IT skills make the division into hard (technical) and soft (non-technical, 'personal') skills (see e.g., [58], [59], [60]). Furthermore, Gupta and George [34] emphasize the organizations' lack of knowledge to build big data analytics capabilities and/or the lack of understanding of how to build a supporting activity flow that creates an environment for human resources to be able to fully exploit the potential of IPR big data, i.e. the skills needed.

B. The contribution of the skill-based approach and the process approach to the activity-to-skills framework

Our activity-oriented approach is particularly useful for practice since multiple skills are required in a single job role [25], thus the understanding of which skills are required within particular activities is of utmost importance. Bassellier et al. [39] further identified a skill-based approach by looking for the match between the user's abilities and the task at hand. We take this into account and combine it with our process view. Processes are generally divided into phases, activities and tasks [23], [41], [42]. This is true also for IP processes with their IP specific phases, activities and tasks, such as valuation techniques, enforcement or the usability of patents (e.g., [61], [62], [63]). To analyze and operationalize the activity-to-skills framework, we first combined the activities overview by Modic and Damij [23] with the overview of patent retrieval, analysis and monitoring tasks by Bonino et al. [41]. We adapt the results of both studies in order to construct the table combining activities and their goals with required data sources and skills in each of the IP phases.

Inside individual activities the exploration and exploitation of data from diverse structured and unstructured data sources [64] takes place. There is a variety of more or less structured data sources available [15], with data differing in terms of availability (their openness) and connectivity (linking to other data) [65]. Data are also in various formats and require different tools for managing. Consequently, different types of experts are needed to retrieve and analyze them.

There are four key consequences when handling IP data: firstly, knowing how to deal with different types of stakeholders; secondly, organizing diverse experts' entry points and their IP analytic skills; thirdly, defining various IP activities being carried out by the experts; and fourthly, extracting the information from various IP databases and data sources. Furthermore, strategic and operational layers need to be taken into account as they influence the process differently. The former requires individuals interested in exploiting IP assets to achieve business goals (keeping competitive advantage, building strategic alliances, maximizing IP portfolios etc.), whereas the latter focuses on the individual level (e.g. the contribution of specific IP data to further development). Some tasks inside individual IP activities will involve individuals interested in exploiting IP assets to achieve business goals (keeping competitive advantage, building strategic alliances, maximizing IP portfolios etc.), others will depend upon the

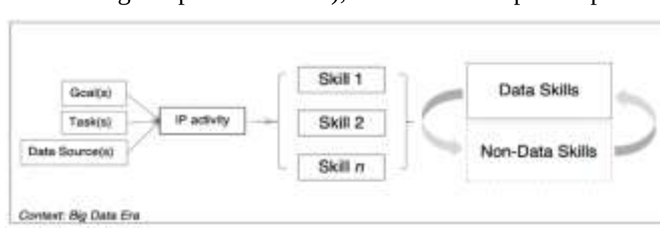


Fig. 1. Activity-to-skills framework design

focus on the individual level (e.g., the contribution of specific IP data to further development).

In our activity-to-skills framework (Fig. 1) we, for each of the activities, establish the connection between overall and specific goals of the activity and skills, as well as identifying relevant database sources and tasks. Following the indications from previous literature on innovation and IP processes, while focusing in particular on data skills, we acknowledge these can be interwoven also with other non-data skills. This allows us to answer the question of which specific (data and other non-data) skills are needed inside each activity of the innovation process. The developed activity-to-skills framework is structured in a way that allows highlighting of those skills. Such acknowledgement of skill bundling is also aligned with Mikalef et al.'s [66] identification of skills as it enables us to emulate Bassellier et al. [39] who identified a skill-based approach by looking for the match between the user's abilities and the task at hand, which we take into account when adopting our process view approach.

Our idea of skills as being ubiquitous extends beyond only understanding their connection to individual activities and is also mirrored in the fact we do not focus solely on the role of data experts. Thereby, we are deviating from the glorification of the data scientists' role in the organization, and rather focus on the importance of all employees within an organization possessing data skills [46], [67]. This broadens the scope of individuals, for whom we need to understand which are the adequate data skills for the activities they are taking part in, thereby providing relevant implications for IP practitioners.

III. Methodology

A. Research method

Research interview is one of the most widely used and important qualitative data collection methods [68]. We interviewed so-called elite informants which are typically highly skilled professionals [69] or top-ranking executives [70]. Elite informants have been a staple of the methodological toolkit in management for more than half a century [71].

In terms of the interview design process, there are many decisions that must be carefully considered, such as who to interview, how many interviewees will be required, what type of interview to conduct, and how the interview data will be analyzed [72]. Semi-structured interviews, which we employed, are the most common of all qualitative research methods [73] and consist of open-ended question preparation, usually structured in relevant thematic areas. Thus, the focus is on the interviewer incorporating a series of broad themes to be covered during the interview to help direct the conversation toward the topics and issues about which the interviewers want to learn [74].

B. Data collection

Interviews were conducted with 10 elite informants who are prominent IP experts; seven of them were also head IP managers within their respective companies. We proceeded with an iterative process of simultaneously collecting data, analyzing data and seeking new elite informants [75]. For a concept-gathering exercise or a mapping exercise such as ours, i.e., when discovering the salient or critical themes, patterns, and categories, a relatively small number of respondents/cases can be advantageous [76], [77].

All the interviewed elite informants are executives with years of experience and one of the interviewees appeared twice in the 50 most influential people in IP, as listed by the Managing Intellectual Property magazine. Views expressed inside the interviews were their own and did not necessarily reflect the views of the companies with which they are affiliated (see Table 1). The respondents are representatives of a variety of industries and were affiliated with companies high in terms of patent applications and quality rankings. Furthermore, many appear on top innovation listings, such as MIT's list of the 50 Smartest Companies.

TABLE I
LIST OF RESPONDENTS

ELITE INFORMANT			*SOURCES*		
Role type	Affiliation industry	No. of patent applications	Interview	Int. materials	Internet search
Head of IP Management	Pharmaceutical	50,000+	X		X
Chief IP Officer	Automotive	50,000+	X	X	X
Chief IP Officer	Manufacturing & Electronics	50,000+	X		X
Chief IP Officer	Chemicals Manufacturing	50,000+	X		X
Chief IP Officer	Automotive	500 - 10,000	X		X
Patent Manager	Chemical	500 - 10,000	X		X
Head of IP Management	Engineering & Steel	500 - 10,000	X	X	X
Head of Licensing	Pharmaceutical	500 - 10,000	X		X
Counsel for IP	Automotive	< 500	X		
Chief IP Officer	Telecommunication	< 500	X		X

Interviews were conducted either in person or via online meeting platforms in 2017 and 2018; 90 pages of accumulated transcripts were analyzed using MAXQDA Analytics Pro 12 software. Interview questions were divided into three sections (IP management, formalization and optimization of processes and gap reduction). Questions related to the issues of and around IP data were harnessed and linked with other key IP related topics.

Additionally, secondary data were purposefully sampled from two other types of sources with the specific objective to triangulate, assess or better understand the statements by our interviewees. We collected the material, firstly, from publicly available materials, such as companies' websites, as well as from relevant conferences and events, if they included materials such as presentations on the relevant topic by our respondents, or by others that have focused on the companies with which our respondents were affiliated. Secondly, we include the few documents given to us by the respondents directly, which are otherwise not in the public domain.

IV. Findings

A. Setting the scene

The elite informants were quick to recognize and understand the benefits of IP data on a strategic level. There is limited knowledge and practical experience however permeating the IP professional world related to it. The respondents do acknowledge the need for integration of databases, and the role of analytics (e.g., predictive analytics or new advances for optical data recognition). In terms of the application of big data in IP processes, our respondents believe there is still a lack of information on its application, but a strong hype surrounding it. They see three potential issues, which point to the complexity of using IP big data: data type, data quality and the computer power limitations.

Our respondents saw more potential in harnessing macro level data, but warned about the potential of this data breaking down in smaller samples. What the elite informants emphasized is that in the end all IP decisions are reserved for humans. In the words of one of our respondents “The real good results are in my opinion only achieved if you put human resources to it”. Another identified it as a “two faced model”, where general information is generated automatically, but it is the staff's responsibility to make sense of it. Understanding and utilizing new techniques and tools to make optimal predictions will become even more important in the future, as IP saturation levels rise and the volume and complexity of IP data increase. Our interviews have confirmed that the time is ripe for the (re)examination of the interplay between IP data and the necessary skills to harness it.

B. Data analysis and results: Understanding data skills for IP

We first engaged in open coding or so-called first order codes or terms (i.e., language used by the elite informants). After searching for similarities and ensuring language consistency, the result was a myriad of so-called first order terms or concepts. We have thus adapted the Gioia approach to analyzing data ([75], [78]). We proceeded with axial coding, where we searched for relationships, similarities and differences between these terms, and reduced the germane concepts into more manageable second order themes [75], [78]. For example, we subsumed the ‘skills to use tool X for measuring the quality of the patent portfolio’ or ‘ability of good quality external data entry and linkages together with internal’ or ‘how I can create extra value with new tools’ features’ under ‘IPR (intellectual property rights) data tool skills’ second order theme. Or we subsumed ‘taking into account the legislation in many countries, needing a lot of human resources/skills’ under ‘skills for navigating IPR systems’ and ‘ability to add to the patent and claims’ under ‘patent drafting and legal expertize’.

The two groups of data and non-data skills started to emerge, and we had 11 second order themes related to data skills, and 11 second order themes related to non-data skills (see Fig. 2). Lastly, we distilled our data into so-called third level codes, or as Gioia et al. [78] call them, (2nd order) aggregate dimensions. This allowed us to build a data structure, to both provide a visual representation of how we progressed to higher level codes as well as to allow us to think about the data not only methodologically, but also theoretically [78]. Fig. 2 shows in blue the data structure including second order themes and aggregate dimensions, as well as the relationships between them, in terms of data skills for IP. Furthermore, Appendix A provides a matrix of respondents and aggregate dimensions.

Five aggregate dimensions of data skill types emerge: 1) Data management skills; 2) Data discovery and extraction skills; 3) Data analysis skills; 4) Data visualization skills; and 5) IP data tools skills (in blue boxes in Fig. 2). Inside the blue arrows the related second order themes as mentioned by the elite informants are presented. They also encompass what would typically be categorized as technical skills in works related to big data (e.g., [8], [17]); or more recently also works related to artificial intelligence related skills (e.g., [24]).

Colored in orange (with dotted line) in Fig. 2 there is a group of skills beyond those data related ones, i.e., non-data skills. We identify the following non-data skills: 1) Innovation harvesting skills; 2) IP process management skills; 3) Legal skills; 4) Patent valuation and commercialization skills; and 5) IP awareness raising skills.

These non-data skills were often mentioned by our elite respondents, and need to be exposed to understand the context in which the data related skills appear and their co-dependencies. For example, skills in data visualization and the IP data tools skills are related to skills of raising IP awareness, as being able to visualize data and use IP tools can also increase the levels of IP awareness. Visualization of data can also increase the IP management, as it can be an efficient way to convey information between inventors, the IP department, and the management. Therefore, such identification of dimensions allows us to explore how data skills are interwoven with non-data skills within and across IP activities.

C. Testing the activity-to-skills framework throughout IP phases

Process modelling is an essential activity in business process management [79]. By using our activity-to-skills framework and the inputs from the interviews, Tables 2 and 3 present IP phases and their activities, attributes, and the connected skills (i.e. notice the use of 2nd order themes from Fig. 2). The tables additionally highlight the connection between (both overall and specific) goals and skills as well as providing relevant database types, i.e. IP data sources, for each of the activities.

The radar charts focus on the interplay between the required data (in blue) and non-data (in orange) related skills for each of the IP phases and were a chosen approach to highlight the managers in their decision making process [80]. They not only provide information on whether activities in a particular phase require more data/non-data skills, but also which skills are needed and their importance, i.e. frequency of focal skills within each phase based on axial coding of the language used by the elite informants and organized into second order themes. For example, in the IP Creation Phase, the Data discovery and search skills are recognized as more important than IPR process skills.

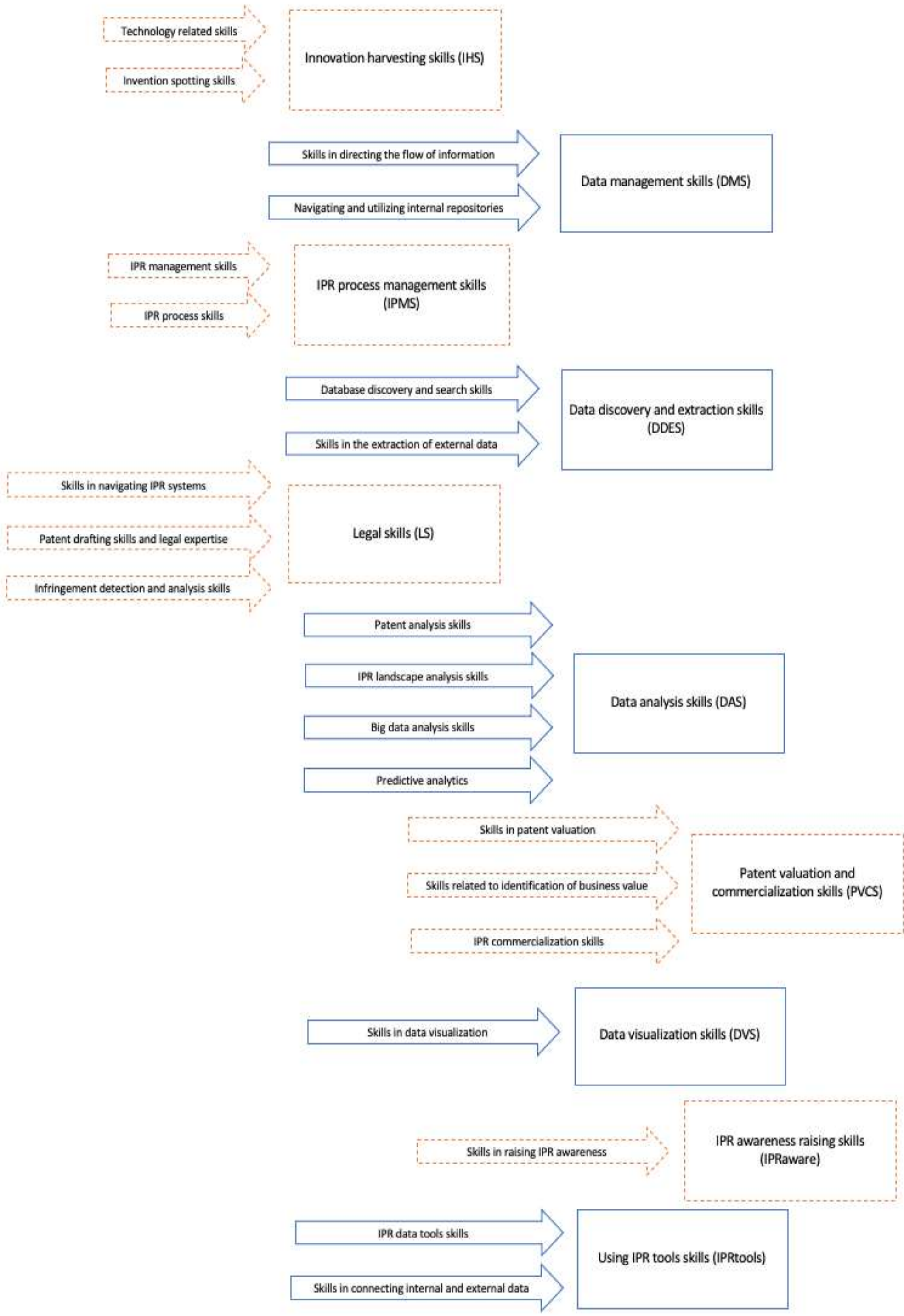


Fig. 2. Structure of data and non-data IP skills

Note. Arrows represent second order themes, boxes represent aggregate dimensions. In blue are data related skills, in orange (dotted line) are other non-data IP skills.

The importance of skills shown in these charts is furthermore comparable not only with the individual chart but also between the phases; i.e. the necessity for Skills related to identification of business value (IP Pre-evaluation phase) is higher than the need for Patent analysis skills (IP Commercialization phase).

Our activity-to-skills approach is based on linking the necessary skills to activities within the following six IP process phases: IP Creation phase, IP Pre-evaluation phase, IPR Registration phase, IP Commercialization phase, IPR Infringement phase and IP Post-evaluation phase. In each of these phases, three to eight specific activities are performed (for example, IP Creation phase consists of Technology search, Internal invention spotting, External opportunity spotting, and Preliminary state-of-the-art check) and for each of these activities necessary skills were defined.

The IP Creation phase addresses the begin activities of the IP process, namely a technology search by identifying inputs from previous solutions, acquiring internal invention reports and external potential opportunities, and finally conducting a preliminary state-of-the-art check to identify the key market comparables. To deploy these activities successfully, internal and external databases are used to carry out the analysis. For this reason, a mixed set of skills related to the technology itself as well as IP related skills is required, with the database discovery and search skills at the forefront, followed by IP tools skills (both IP skills), as well as skills in navigating the flow of information, skills in raising IP awareness and other technology related skills. The overall goal of the phase is for a company to decide what to invent in order to achieve their R&D goal.

The second phase focuses on pre-evaluating the IP, and is the most comprehensible out of all the phases. Contrary to the previous phase, which is more technology (R&D) oriented, this phase prioritizes the company's business goals and for this reason collects data via internal and external databases. The eight activities focus on justification of any further investments and appropriateness of intellectual property rights (IPR) protection, whether the application will result in an awarded patent, evaluating correctness and alignment with the company's R&D goals, how to obtain permits, cost estimation and finally, defining the IP scope. Given the broad spectrum of utilized databases and required analyses, the necessary skills are also extensive. Skills related to identification of business value are significantly at the forefront, with IP landscape analyses, predictive analytics, database discovery and search, connecting internal and external data, extraction of external data and navigating and utilizing internal repositories skills (all technology related skills) following.

The IPR Registration phase is, on the other hand, one of the shortest phases of the process consisting of only four activities that address challenges such as where to apply for IPR protection, preparing the application itself and its subsequent submission, and finally, amending the application if needed based on the feedback from the IP office. The activities mainly use external databases that require a mixed set of skills, with the IP related ones such as patent drafting and legal expertise skills, and skills in navigating IP systems being the most important.

The IP Commercialization phase addresses key activities dealing with the potential of IP on the market, evaluates its competitive edge and the expected income if IP is licensed or sold by executing the activities such as freedom to operate and seeking other value-creating strategies, like engaging in patent pools.

Among all phases, this is a phase where mastering data skills and combining internal and external data sources (together with unstructured sources, such as blogs or news) is particularly important, especially in the context of identifying other IP blocking marketing opportunities as well as IP value gathering opportunities. Since the overall goals are business goals, this phase requires skills such as big data analysis, predictive analytics, database discovery and search skills, skills in the extraction of external data, skills in data visualization, IP landscape analysis skills, etc. Other sets of skills required are especially skills related to the identification of business value, IP commercialization skills and patent valuation.

Once the IP is acquired, all focus shifts to its retention and effectiveness. Goal is to detect and/or to prevent IPR infringement through the execution of activities that deal with protecting the IPR, preparing to litigate a competitor's patent, identifying proactive approaches against third parties, defining the scope of the infringement, and analyzing legal prospects. All activities require searches between internal and external databases, their continuous review and analysis of new patent applications as well as searching the internet for products which could contain protected solutions. IPR Enforcement phase requires a mixed set of legal and data related skills with infringement detection and analytic skills being the most important, followed by IP landscape analysis skills. This is the phase where legal skills are the most important (including knowledge about legal procedures in case of infringement and good negotiation skills).

Evaluation phase focuses on the development, utilization and lifespan of individual IPRs. The goals are predominantly business related, however there are also R&D implications with legal expertise playing a supporting role (i.e. what Modic & Damij [23] designate as back-office). The phase consists of three activities and focuses on IP technical evaluation, evaluating ROI and deciding on IPR termination.

While identifying IPR related problems and approaches requires only internal data searches, the other two key activities require a combination of internal and external database searches, leading to an interplay of broad and specific focus. In order to decide whether IPR should be terminated or abandoned a good mix of skills, both data related skills and others, is required. The two key skills identified are identification of business value and navigating and utilizing internal repositories.

D. The data and non-data skills interplay in IP processes

We turn now to the interplay between data skills and non-data skills. Fig. 3 shows the aggregate dimensions for each of the six phases, emphasizing the link between necessary data skills and other non-data skills such as business and legal skills. It details the aggregate dimensions (see also Fig.2) of all phases in the IP process, highlighting the influence of data versus non-data skill requirements in each phase. In addition, the radar charts within Fig. 3 use the same unit level, thus enabling comparison between the aggregate dimensions of the phases, showing that the most skills intensive phase is the IP Pre-evaluation phase, followed by the IPR Enforcement phase.

The number of circles in each chart is defined by the frequency of how many times skills aggregated into third level codes were highlighted by the elite informants. All other phases are equally reliant on data as well as other skills. With the exception of the IP Commercialization phase, the ratio between IP data skills and other non-data skills is more or less equal. The IP Commercialization phase, however, is the only phase that relies significantly more on the use of data skills. Data discovery and extraction skills together with data management skills emerge as very important (other) skills in the IP Creation

TABLE II
IDENTIFICATION OF DATA AND NON-DATA SKILLS ACCORDING TO THE ACTIVITY-TO-SKILLS FRAMEWORK (IP CREATION, IP PRE-EVALUATION AND IP REGISTRATION PHASES).

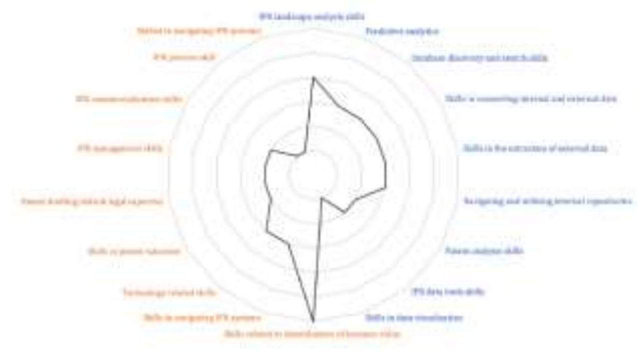
Phase	Activity / Scope	Database: Internal: INTERNET SEARCH	Database: Internal: BUSINESS	Database: Internal: R&D	Database: Internal: IPR	Database: External: PATENT & IPR	Database: External: BUSINESS	Database: External: SCIENTIFIC	Required Skills	
IP CREATION PHASE	*Technology search* Identifying inputs (from previous solutions)	√		√		√		√	Technology related skills; Database discovery and search skills; Navigating and utilizing internal repositories; Skills in raising IPR awareness	
	Internal invention spotting Acquire invention reports			√					Invention spotting skills; Navigating and utilizing internal repositories; Skills in navigating the flow of information; IPR process; Skills in raising IPR awareness	
	External opportunity spotting Acquire external opportunities.	√				√		√	Technology related skills; Database discovery and search skills; Skills in the extraction of external data; Skills in navigating the flow of information; IPR tools skills; Skills in connecting internal and external data	
	Preliminary state-of-the-art check Browsing IPR databases and key market comparables	√				√			Database discovery and search skills; Patent analysis skills; IPR landscape analysis skills; IPR tools skills; Skills related to identification of business value	
IP PRE-EVALUATION PHASE	*Patent or IPR triage* Viability of invention disclosure to justify further investment					√			IPR landscape analysis skills; Skills in navigating IPR systems; Skills related to identification of business value; Skills in patent valuation; Predictive analytics	
	Checking technology detectability Understanding the appropriateness for IPR protection	√		√					Technology related skills; Database discovery and search skills; Patent drafting skills & legal expertise; Skills in connecting internal and external data	
	Patentability assessment Analysing whether patent application has the potential to result in a patent	√				√			Database discovery and search skills; Skills in the extraction of external data; Skills in connecting internal and external data; Patent analysis skills; IPR landscape analysis skills; Patent drafting skills & legal expertise; Skills in navigating IPR systems; IPR tools skills	
	Evaluating coreness & alignment with product strategy Assessing the importance in terms of the company's R&D goals		√	√					Navigating and utilizing internal repositories; IPR management skills; IPR process skills; Skills related to identification of business value; Skills in data visualization; Predictive analytics	
	Addressing standardization and registration issues Whether and how do permits need to be obtained	√		√					Technology related skills; Database discovery and search skills; IPR management skills; Skills related to identification of business value; Skills in connecting internal and external data	
	Bundling considerations The need to bundle different IPRs to protect a product	√	√	√					Skills related to identification of business value; IPR commercialization skills; IPR management skills; IPR process skills	
	Defining IPR costs Estimating costs of IPR protection	√	√	√	√				Skills related to identification of business value; Navigating and utilizing internal repositories; Skills in the extraction of external data	
	Defining IPR scope Defining the broadness and specifics of the claim			√	√	√			Skilled in navigating IPR systems; IPR landscape analysis skills; Technology related skills; Navigating and utilizing internal repositories; Skills in the extraction of external data; Patent analysis skills; IPR tools skills	
IP REGISTRATION PHASE	*Determining geographic scope of application* Determining where to apply for IPR protection	√			√				Skills related to identification of business value; Skills in navigating IPR systems; Patent drafting skills & Legal expertise; Skills in directing the flow of information; Skills in connecting internal and external data	
	IPR application writing and submission Writing the application, understanding the needs of different application processes			√	√	√	√	√	Patent drafting skills; Skills in navigating IPR systems; Technology related skills; Skills in directing the flow of information; Database discovery and search skills; Skills in the extraction of external data	
	Amending application Communication with the IPR office in order to successfully complete the application					√		√	Patent drafting skills; Skills in navigating IPR systems ; Skills in connecting internal and external data; IPR tools skills	
	Determining geographic scope of application Determining where to apply for IPR protection	√			√				Skills related to identification of business value; Skills in navigating IPR systems; Patent drafting skills & Legal expertise; Skills in directing the flow of information; Skills in connecting internal and external data	

TABLE III
IDENTIFICATION OF DATA AND NON-DATA SKILLS ACCORDING TO THE ACTIVITY-TO-SKILLS FRAMEWORK (IP COMMERCIALIZATION, IP ENFORCEMENT AND IP POST-EVALUATION PHASES)

Phase	*Activity* / *Scope*	Database: Internal: INTERNET SEARCH	Internal: BUSINESS	Internal: R&D	Internal: IPR	External: PATENT & IPR	External: BUSINESS	External: SCIENTIFIC	**Required Skills**
IPR COMMERCIALIZATION PHASE	*FTO search* Investigating whether other patents are blocking marketing opportunities of the new technology					√	√	√	Big data analysis skills; Patent analysis skills; Predictive analytics IPR process skills; Database discovery and search skills; Skills in the extraction of external data; Skills in connecting internal and external data
	Ensuring potential in/cross-licensing or MTA needs Potential need for complementary IPR is assessed	√		√		√			Technology related skills; IPR landscape analysis skills Skills related to identification of business value; IPR commercialization skills; Skills in connecting internal and external data
	Classification of IPR IPR classification by business value potential				√				Skills related to identification of business value; Skills in patent valuation; Skills in connecting internal and external data; Navigating and utilizing internal repositories; Skills in data visualization; Predictive analytics
	Decision to extend scope of use Identifying other IPR value generating opportunities	√				√	√	√	Big data analysis skills; Predictive analytics; Skills in data visualization
IPR ENFORCEMENT PHASE	*Clearance and invalidity search* Protecting the IPR or preparing to litigate a competitor's patent	√				√		√	IPR management skills; IPR landscape analysis skills; Skills in the extraction of external data; Database discovery and search skills
	Single patent monitoring IPR specific proactive management against specific third party IPR	√				√	√		Skills in navigating IPR systems; Skills in the extraction of external data; Patent analysis skills; IPR landscape analysis skills; Infringement detection skills
	Infringement analysis Defining the scope of the infringement	√							Infringement detection skills; Skills in connecting internal and external data; Skills in infringement analysis; Legal expertise
	IPR infringement related negotiations or lawsuits Analysing the legal prospects				√	√			Infringement detection skills; Skills in infringement analysis; IPR landscape analysis skills; IPR management skills; IPR process skills; Legal expertise
IPR POST-EVALUATION PHASE	*IPR technical evaluation* Identifying solved problems and approaches			√	√				Technology related skills; Skills related to identification of business value; Big data analysis skills; Predictive analytics; Navigating and utilizing internal repositories
	Evaluating ROI Evaluating of the total return on investment of IPR		√			√			Skills related to identification of business value; Skills in patent valuation; Big data analysis skills; Predictive analytics; Navigating and utilizing internal repositories; Skills in directing the flow of information
	Decision to abandon IPR Deciding on IPR termination	√	√	√	√	√	√	√	Skills related to identification of business value; Skills in patent valuation; Navigating and utilizing internal repositories; Skills in directing the flow of information; Skills in connecting internal and external data; IPR tools skills Skills in raising IPR awareness

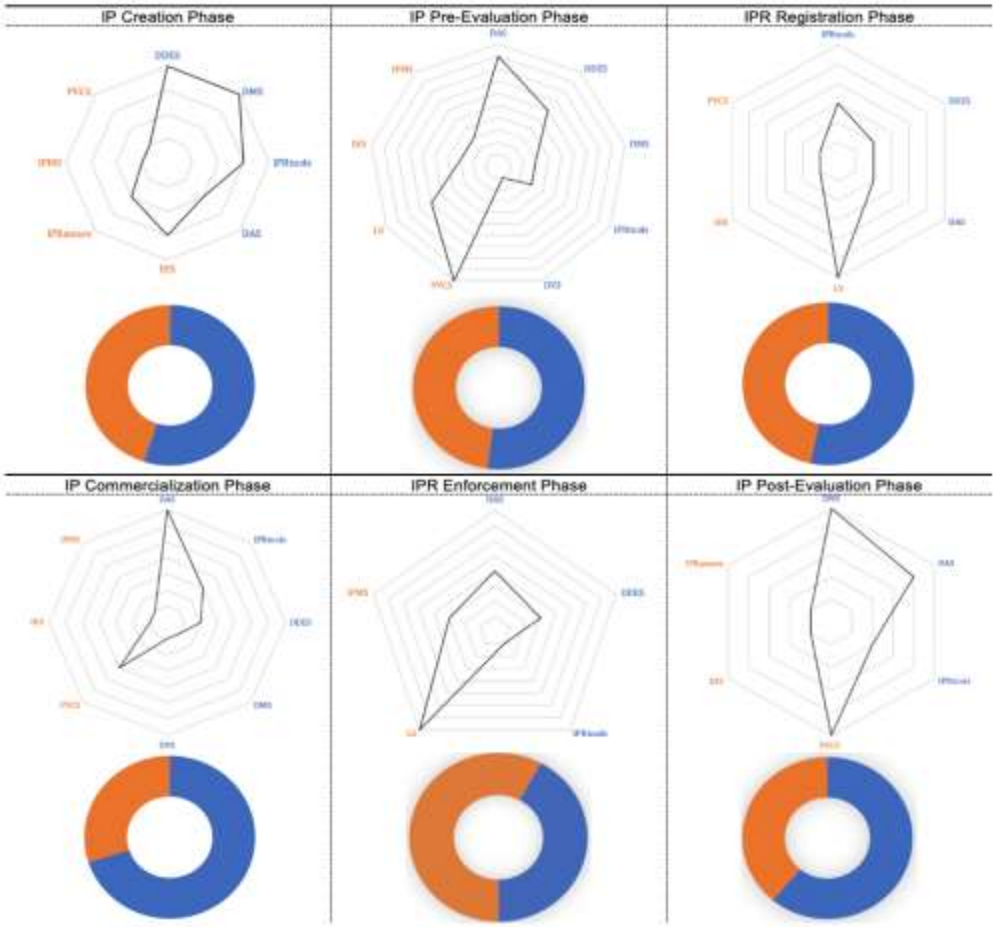


Fig. 3. Aggregate dimensions and phases

Note. IP data related skills shown in blue, non-data skills in orange. Legend: DAS = Data Analysis Skills; DDES = Data Discovery and Extraction Skills, IPRTools = Using IPR Tools Skills, DMS = Data Management Skills, DVS = Data Visualization Skills, IPaware = IPR Awareness Raising Skills, IPRS = IPR Process Management Skills, HIS = Innovation Harvesting Skills, LH = Legal Skills, PVCS = Patent Visualization and Commercialization Skills.

phase. Yet, in the IP Pre-evaluation phase, their importance is already overshadowed by the data analysis skills. The same is true for the IPR Enforcement phase. Legal skills overshadow all other skills in the IP Registration phase, but from the data-skills perspective the IP tools skills come to the forefront. Finally, in the IP Post-evaluation phase, the data management skills accompanied by the data analysis skills emerge as the most important data skills. Legal skills, for example, emerge as the most important in the IP Registration phase and in IPR Enforcement phase. Another non-data skill that is highly relevant across all the phases is Patent valuation and commercialization, particularly in IP Pre-evaluation and IP Post-evaluation phases.

V. Discussion

This paper offers insights into the requirements and expectations of some of the top IP experts from 10 IP-savvy multinational companies, allowing us to identify some relevant IP skills in the context of the new era of big data. New technology-enablers, users' attitudes and expectations, shift the importance from IP data availability to other facets. We emphasize the skills necessary for harnessing IP data.

A. Nuanced understanding of the IP data and non-data skills

In the previous section we engaged in the identification of the skills needed to realize the potential of IP in today's world of emerging IP-related big data. Most of the literature relates to skills required by (big) data professionals, whereas our focus is the IP data skills that a myriad of employees—tasked with diverse IP activities—need to possess, which is in line with Prescott's [45] notion of the importance of data skills for all employees.

We identified the skills based on the analysis of the interviews and grouped them into two overarching skills types: data skills, with five aggregate dimensions (i.e. subtypes): data management skills, data discovery and extraction skills, data analysis skills, data visualization skills, using IP tools skills); and non-data skills, with five subtypes: innovation harvesting skills, IP process management skills, legal skills, patent valuation and commercialization skills and IP awareness raising skills. The proposed distinction between data and non-data skills does not fit the division into hard (technical) and soft (non-technical, 'personal') skills perfectly (see e.g., [58], [59], [60], although some of the non-data skills are more or less soft skills (e.g., IP awareness raising). The non-data skills do encompass what Wamba et al. [17] refer to as managerial-oriented, and Mikalef and Gupta [24] as business skills.

TABLE IV
2-BY-2 CORRESPONDENCE MATRIX FOR IP DATA SKILLS

		Mikalef et al. (2018) dimensions			
		Technical	*Business*	*Relational*	*Business analytics*
Activity-to-skills dimensions	*Data discovery and extraction*	X			
	Data management skills	X		X	
	Data analysis		X		X
	Data visualization				X
	Using IP tools skills	X			

Our focus on all employees within an organization that need to possess relevant IP data and non-data skills, together with the specifics of the innovation IP processes as well as our adoption of the process and skill-based approaches [23], [39], [41], [42], might influence the fact that there are no one-to-one correspondences between the Mikalef et al. [8] model of data skills dimensions—based on literature review—and the activity-to-skills data skills dimensions as identified in this paper (Table 4).

Consequently, we offer several extensions and adaptations to the Mikalef et al. [8] model of data skills dimensions. Data visualization is, according to the Skills Framework for the Information Age [81], typically defined as the process of interpreting concepts, ideas, and facts by using graphical representations, and is thus a separate dimension from data analytics. However, Mikalef et al. [8] subsume it under the business analytics knowledge. Similarly, according to them the technical skills encompass both data discovery and using the necessary tools. However, especially in innovation processes, data discovery combined with its extraction are a prerequisite for a successful innovation process and go far beyond only “technical” skills (e.g., acknowledged by Mikalef et al. [8] as “managerial skills” when trying to understand the relationship between big data analytics capabilities and innovation capabilities). We keep the skills related to IP tools separate, with our respondents emphasizing that they “use a lot of tools for searching patent information, for analyzing patent information and so on” (Respondent 2, R2) or that are also “monitoring tools” because “you do not miss due dates” (R4), with others pointing out that some “are not great for senior managers, they are not good for attorneys” (R3) – also reinforcing our approach that does not focus solely on a particular profile within a company.

Next, our identified data analysis dimension encompasses both what is typically seen as the business dimension and the business analytics dimension: first, by including, for example, IP landscape analysis and predictive analytics, as strategic foresight related; second, by encompassing, for example, patent analysis skills. Data analysis skills were recognized as one of the key skills by all our respondents (see Appendix A).

Our activity-to-skills approach was based on the matching of necessary skills and the tasks (i.e. activities) at hand. The results plainly show two important facets: 1) the type of skills needed is dependent on the focal activity within the IP phase where the activities are framed by the type of data and the level of interaction with data, and 2) albeit the importance of non-data skills is crucial, there is no denying that the data skills permeate all phases and activities inside the IP process. However, the data skills are more relevant in some phases than in others, with their importance accentuated in the IP Commercialization phase and least relevant in the IPR Enforcement phase (Fig. 3). The IP commercialization phase is also a key phase for deriving the value from data inside the innovation process. This is relevant, since if managers are able to recognize the skills requirements, they can motivate and manage the human resources more efficiently [82] and this is particularly important for exploration and exploitation of IP data throughout the IP process.

B. Towards more efficient HR management: IP skills-intensity in various phases

Organizations can suffer from a lack of the required skilled individuals in appropriate job positions to be able to derive meaningful insights from (big) data [83] whilst knowing that a particular individual will need to have a combination of both data and non-data skills [25]. In this line we compared the various data and other non-data skills on the aggregate level per each of the six phases, i.e., within specific activities. Understanding where those activities that need more data skills are within the innovation process, can be important to either clear bottlenecks or to allocate the staff more effectively, which is in turn a key driver of the organizations’ efficacy [19]. In other words, the role of human resource departments is not only to focus on the individuals with easily identified skills to fill the job offerings but also to understand and anticipate the less well-defined skills [84].

Fig. 4 illustrates the analyzed results of the aggregate dimensions of skills in a single figure. The aim is to compare the various data and other non-data skills on the aggregate level per each of the six phases. The aggregate dimensions (for abbreviations refer back to Fig. 2) in blue are the data related skills whereas those in orange represent the other (business, legal, etc.) non-data skills. The figure also shows the need for each type of skill, thus showing how skill-intensive each of the phases is.

Since the needs for certain (data and non-data) skills differ throughout the phases, the model employee profile is phase specific. For the IP Creation phase, a model employee would be a person with a natural sciences/engineering degree skilled in patent database searching. In the IP Pre-evaluation phase, an economist with excellent knowledge in technology the company is manufacturing, as well as being well-versed in IP knowledge and database search, would be optimal. For the IPR Registration phase the model employee is an engineer/scientist with excellent IP knowledge – including patent databases search – similar to a patent attorney. For the IP Commercialization phase, an economist with good knowledge of IP and the company's technology, skilled in data management would be optimal. For the IPR Enforcement phase, an IP lawyer who also has a good understanding of the technical solution and is skilled in IP landscape analyses would be best. And finally, in the IP Post-evaluation phase a model employee would be an economist skilled in predictive analytics and other strategically important data analyses.

Understanding phase-specific needs for data skills can help optimize not only the allocation of the most appropriate experts along the IP process, but also inform recruitment. However, finding employees with appropriate skills can be a daunting task for either the human resource manager or the Head of IP. Opportunities to acquire the necessary data skills for non-data professionals are limited today [85]. In big companies there needs to be reliance on internal training and on-the-job training [23], however, some research surprisingly shows that innovation training rarely happens even within Fortune 1000 companies [22]. There are limited offerings of external data training that are specific to the IP, for example at the European Patent Office (EPO) and the World Intellectual Property Organization (WIPO). Still, such specific courses do not really cover the multiple skills necessary within the process as a whole. As Michaelis and Markham [22] concluded, insufficient training in the innovation field can lock a company in incrementalism, leading to missed opportunities and lost growth. Our recommendation for companies would be to pay more attention to this area, and at the same time this is also an opportunity for organizations such as EPO, WIPO and others to offer or further design training which could be adapted to a specific company’s needs.

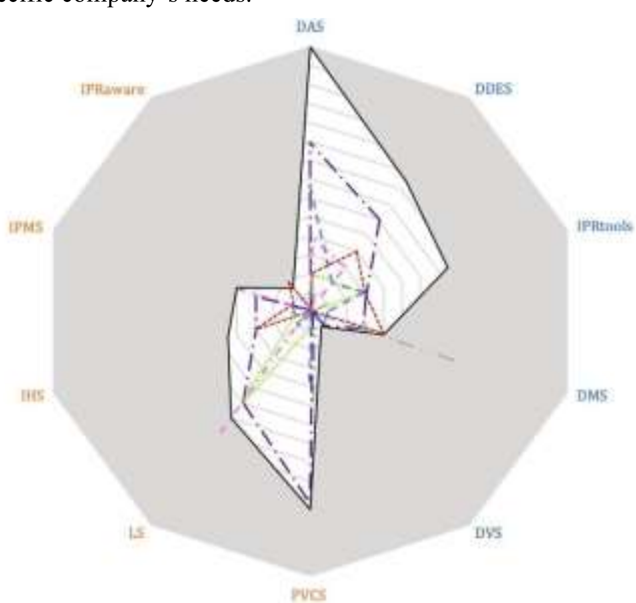


Fig. 4. Activity-to-skills framework for data management in innovation process.

Note. The black line shows the overall amount of data (in blue) and other non-data skills (in orange) needed in all of the phases, followed by the violet line representing the required skills in the IP Pre-evaluation phase. The red line presents the skills needed in the IP Creation phase, the green line skills needed in the IPR Registration phase, the blue in the IP Commercialization phase, the pink in the IPR Enforcement phase, and finally the grey line illustrates the skills needed in the IP Post-evaluation phase. What we can see is that the overall picture of the need for data skills corresponds with the IP Commercialization phase, but other phases differ from this pattern. Legend: DAS = Data Analysis Skills; DDES = Data Discovery and Extraction Skills, IPRTools = Using IPR Tools Skills, DMS = Data Management Skills, DVS = Data Visualization Skills, IPaware = IPR Awareness Raising Skills, IPRS = IPR Process Management Skills, HIS = Innovation Harvesting Skills, LH = Legal Skills, PVCS = Patent Visualization and Commercialization Skills.

VI. Conclusion

In this paper we have tackled the issue of the need for data skills within innovation processes using the example of intellectual property processes. All relevant IP activities have been examined, alongside the skills required in order to harvest the full potential of IP data. We do so by employing an ingenious activity-to-skills approach allowing us to identify the necessary skills in each of the relevant IP activities.

Our context was one of the era of big data, thus we also relied on insights from big data and big data management research. Both areas are still relatively new, and many times rather than being theory-driven, this research remains phenomenon driven. Such an approach has been lamented in other fields, due to e.g. legitimacy problems. Nonetheless, this approach often also brings with it an inherent genuine interest to understand the phenomenon under study, and to research relevant issues. Big data research is also not firmly rooted in any particular discipline but draws on a kaleidoscope of theories and perspectives [20]. This allows us to explore a wide range of issues both when doing research on big data, or when using the big data as a context. Both allow easier use of derived insights from research related to big data to inform other fields (such as e.g. the innovation field).

We disentangle the distinct data skill types—understanding ‘data’ skills as a heterogeneous notion—in contrast to the prevailing approach in innovation management studies, where data skills related to innovation and IP are often seen as a homogenous concept. Our analysis then leads us to build up the aggregate dimensions of these data skills, where we add not only to the typology of these inside the innovation processes in particular, but also more widely to the typologies of skills related to data exploration and exploitation, i.e., bringing insights to information management. Our process-oriented approach also allowed us to detect nuances according to phases and activities in terms of the specific type of IP skills, the predominance of particular aggregate dimensions, as well as how they are intertwined with other IP skills.

It is worth acknowledging some limitations of our study. In statistical terms, external validity is often a limitation of qualitative research, and the focus is on so-called analytical generalization, i.e. referring to the generalization on the axis from empirical observations to theory [86], [87] points out that one of the directions for extracting theory using process-oriented approaches is via collecting fine grained qualitative data, i.e. “plunging itself deeply into the processes themselves”, which we had adhered to. We provided a deep understanding of the topic at hand, aided by additional secondary material. Nonetheless, we believe that a quantitative confirmatory analysis can bring more clarity in terms of statistical generalization, i.e., testing our model. At the same time, even though we explore the focal phenomena using not only literal, but also theoretical replication [86] – i.e. including not only the selection of cases that (re-)confirm our identified patterns, but also cases that may disprove them – the quantitative analysis could also capture some potential sector-dependent nuances, which could enrich the findings of this paper, or vice-versa confirm also by using variance based methods, the validity of our findings. Other approaches that could also enrich this work would be to use some configurational approaches, and explore which configurations would be e.g. leading to high performance in terms of IP, emulating perhaps the procedure to do so by Mikalef et al. [26].

Our approach is also in line with Cook and Campbell's [88] and Coviello and Jones' [89] recommendations that useful empirical results can be obtained from a study sample with well-developed selection criteria. Due to the high relevance of our elite respondents, we have reached the point of saturation with 10 respondents. But although they come from a variety of sectors, they are geographically bound to Europe. Nonetheless, there might be opportunities arising from additional work, which would focus on other well-developed countries in terms of IP, such as the US or China, or on some less developed countries, to understand whether the framework needs to be adapted to some localities.

Furthermore, a valid concern remains that by focusing on large (IP savvy) companies, we fail to account for potential heterogeneity permeating different organizations. Similar questions may find different answers depending on the context under scrutiny [90], because certain aspects of a phenomenon and/or theorizing of the phenomenon do not transfer across contexts. Smaller companies might struggle with other problems related to skills and competences, with an especially relevant issue being that of potential external resources they might employ to complete the necessary skill set and knowledge for harnessing the IP data. Further research should be dedicated to unveiling potential heterogeneity in these, most likely less IP savvy contexts, since IPs are fundamental to the operation of all, bigger and smaller technology-intensive firms [36].

The last limitation stems from the fact that our research was completed before the Covid-19 pandemic. The pandemic has changed the operational conditions of firms, which have been forced to operate in a highly unstable and unpredictable environment [91], and several IP challenges may emerge as well [32] especially for firms dealing with crisis critical products. Our findings relate to stable economic conditions, and a longitudinal study could be helpful to identify whether changes caused by Covid-19, its immediate uncertainties and the subsequent recovery needs have affected also the IP skillset required. However, the Covid-19 pandemic has also caused a noticeable acceleration toward digitalization and immediate adoption of new technologies identified [6], [92]. Therefore, we anticipate that data skills will be even more important in the future. One of the definite and inevitable future trends will be the widespread support of artificial intelligence (AI) in almost all IP phases, from creation and registration to enforcement and litigation (Chikkamath et al. [93], Setchi et al. [94] and other researchers are already exploring possibilities of AI for patent novelty detecting). This will further enrich the necessary, and ever evolving, data skill set; and also shows that due to the dynamic of the field, our results should be retested periodically.

Despite these limitations, we were able to convincingly attribute concrete necessary skills to individual IP activities in order to allow more informed human resource management decisions and consequently, more successful harnessing and exploitation of IP data. This is important as new skills are coming to the forefront with the rise of big data inside business processes. IP managers need to be able to identify these skills in order to efficiently identify staff with relevant data skills and allocate the staff with the necessary combinations of data and non-data skills to particular activities. Furthermore, this framework is a blueprint which allows comparison of necessary and existing skills in a company. Based on this, the IP managers can foresee and/or design appropriate additional training and if necessary, headhunt required resources to ensure the necessary skills and competences. Lastly, the article also allows insights for organizers of training on digital skills for non-technical experts.

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Nadja Damij (PhD) is an Associate Professor in Business Information Management and Head of Subject Group for Entrepreneurship and Innovation at Newcastle Business School, Northumbria University, UK. She is also a Chair of Digital Business Innovation and a co-chair of Business, Environment and Social Cause Research Interest Groups. She is a co-author of the top 25% most downloaded Springer's Process Management eBook collection in 2018 and was awarded the 2017 Excellence in Leadership Award from the International Institute for Applied Knowledge Management, USA. As a principal investigator, she has led and participated in international research consortiums financed by the EC, national governments, and private industry.

Ana Hafner (PhD) is a lecturer at Faculty of Information Studies, DOBA Business School, and School of Advanced Social Studies, Slovenia. Her research interests are inventions and intellectual property, especially in connection to digitalization. She cooperated in several research projects, including "Innovation Potential of Slovenian Automotive Industry" supported by European Regional Development Fund.

Dolores Modic (PhD) is an Associate Professor in Innovation and Management at Nord University Business School, Norway. Her research interests span from innovation to technology transfer, patent informatics, innovation for circular economy and IPR management. She has been involved in several informatics projects, including in the area of supercomputing. Dolores has also been both a Fulbright Scholar in US and a JSPS scholar in Japan.

APPENDIX-A: Matrix of respondents' and skills' aggregate dimensions

Third order aggregate dimensions	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
Innovation harvesting skills	√	√	√	√	√	√	√		√	
Data management skills	√	√	√	√	√		√		√	√
Data discovery and extraction skills	√	√		√			√	√	√	
Data analysis skills	√	√	√	√	√	√	√	√	√	√
Data visualization skills			√	√						√
IPR data tools skills		√	√	√	√	√	√			√
IPR awareness raising skills				√	√		√	√	√	
Legal skills	√	√	√	√	√	√	√	√	√	√
IPR process and management skills		√	√	√	√	√	√		√	√
Patent valuation, commercialization and infringement skills	√	√	√	√	√	√	√	√	√	√