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Implementing Industry 4.0 technologies: Future roles in purchasing and supply management

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ABSTRACT

Technological advancements associated with Industry 4.0 drive a paradigm shift with economic and social consequences where digitalization, robotization, and other emerging technologies reshape the interconnection between organizations. Critical areas that need to adapt to the change are inter-organizational buyer-supplier relationships managed by Purchasing and Supply Management (PSM) professionals. That is, their future responsibilities and skills are likely to change. Introducing the concept of specialized roles to summarize needed competencies, this research conducted a real-time Delphi study using an internet-based platform involving 47 procurement experts. As a result, the roles of the Data Analyst, Master Data Manager, Process Automation Manager, Supplier Onboarding Manager, System Innovation Scout, and Legislation Specialist were identified as essential Industry 4.0 PSM roles. For these roles, the probability of their occurrence, industry impact, desirability, and level of industry adoption are assessed. Based on emerging technologies in PSM and adopting a human-centered perspective, this research shows the need to focus on talent development to enable a technology-driven revolution. Thus, the contributions lay in the literature on Industry 4.0 and the PSM skills and capabilities domain, highlighting the required roles for Smart Working and effective Smart Supply Chains management as parts of the digital transformation journey.

1. Introduction

The fourth industrial revolution (Industry 4.0) introduces new technologies that fundamentally change the way businesses operate. For these technologies to be successful, they need to be used by organizations to improve their processes, which requires personnel to use them. New job roles will likely emerge within those firms successfully seizing the technologies. However, it is still not clear what these roles would look like and, more tangibly, what firms can do to profit from these technological changes. This paper addresses this gap with particular reference to the Purchasing and Supply Management (PSM) field, although the results can also be generalizable to other corporate functions.

Conventional business practices are changing significantly due to the rapidly evolving technological landscape around digitalization, connectivity, cyber-physical systems, and automation, collectively referred to as the fourth industrial revolution or Industry 4.0 (Kagermann et al., 2013; Müller et al., 2018). Research has addressed these implications by analyzing specific technologies at an individual or aggregated effect level (Culot et al., 2020), the impact on business model innovation (Frank et al., 2019b), and changes in larger business network relations (Pagani and Pardo, 2017), and how they have affected specific organizational functions, such as manufacturing (Osterrieder et al., 2020).

Frank et al. (2019a) identify that this industrial shift is driven by base technologies that change four "smart" domains: Smart Supply Chain, Smart Working, Smart Manufacturing, and Smart Products and Services. Over the last decade, scholars have mainly focused on the Smart Manufacturing and Smart Products domains, with a more limited, albeit growing, coverage of the Smart Working and Smart Supply Chain domains (Meindl et al., 2021). Research is needed to close the gap in understanding how technologies support workers in the performance of their company's activities in the supply chain and how such

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technologies change related job roles. In addition, these recent publications show that the relationship between the four smart dimensions is still unclear, particularly the connection between Smart Supply Chain and Smart Working (Meindl et al., 2021). PSM is the processes and activities by which an organization plans and acquires the direct and indirect materials, services, rights, machinery, and equipment from the supply base that it requires to generate competitive advantage (Kaufmann, 2002; Monczka et al., 2015), plays a crucial role in spanning organizational boundaries and how supply chains are managed (Schiele and Torn, 2020). As such, the question emerges of how technologies change job roles in PSM and how firms can prepare for and harness the opportunities that smart technologies offer. To contribute to this stream of literature, this research addresses the implication of the new technologies on PSM organizations and practices.

Recent research has started to address the implementation and implications of new technologies within PSM to establish a fuller picture of the field's development (Bienhaus and Haddud, 2018; van Hoek et al., 2020; Lorentz et al., 2021). In searching for justifications to invest in emerging technologies and processes, several benefits have been identified in PSM, such as operational efficiency, competitive advantage, economic advantage, and customer/market alignment (Flechsig et al., 2021; Kache and Seuring, 2017). Adopting technologies within the buyer-supplier interface, e.g., blockchain technology, reshapes inter-organizational relationships by increasing transparency and inter-organizational trust (Han and Trimi, 2022; Tapscott and Tapscott, 2017). Automation and standardization of processes can optimize risk management approaches by increasing supply chain visibility to more fully monitor sustainability goals or improve decision-making based on data analytics (Handfield et al., 2019; Schmidt and Wagner, 2019; Schiele and Torn, 2020).

To provide a PSM-focused perspective on critical implementation barriers, this research first follows the stream of PSM literature that identifies current and future skill requirements (Kolchin and Giunipero, 1993; Giunipero, 2000; Bals et al., 2019; Stek and Schiele, 2021). As new technologies can significantly impact the activities of an organization's PSM function, more research is needed to analyze how the implementation of Industry 4.0 technologies affects the human-centered aspects of PSM (Delke et al., 2023). Second, it follows the wider human resource management (HRM) literature related to the concept of Industry 4.0, identifying the implications on employment, job profiles, and qualifications (Liboni et al., 2019; Shet and Pereira, 2021). The use of technology and Smart Working creates new job roles, increasing the number of diverse and flexible career paths (Benešová and Tupa, 2017; Xu et al., 2018). Though PSM literature is limited by a lack of focus on the specifics of new technology implementation, it does not focus on addressing the link between technologies, tasks, and responsibilities.

This paper introduces a new level of analysis by addressing the link between technological developments, skills, and specific professional PSM roles. It is important to identify and describe new PSM roles that consist of specific skill sets in which practitioners fulfill tasks and responsibilities (Delke et al., 2023; Pekkanen et al., 2020; Knight et al., 2014). This task-specific specialization can be seen in highly mature organizations, as roles are defined according to business practices (Jones, 2013; Schiele, 2019). Therefore, this research answers the call of Schiele and Torn (2020), who identify that these technological developments are likely to change PSM roles and show how technology increases the number of diverse career paths (Xu et al., 2018). As such, this research addresses the following research question:

What new professional roles in PSM emerge within an Industry 4.0 context?

As discussed later in the paper, this research uses the novel research method of an internet-based real-time Delphi study to identify and define six new PSM roles that describe Smart Working PSM professionals. In addition, the research assesses the roles' expected probability of occurrence, impact on the industry, the desirability of occurrence, and current level of adoption within the industry. The results identify six new roles and show that professional roles within PSM are not stable but contingent on an organization's contextual factors. The paper contributes to the PSM skills and capabilities literature by providing a focused set of PSM roles that reflect the impact of the emerging Industry 4.0 landscape. However, the results are likely generalizable to other domains, such as marketing. The concept of a Smart Working professional who uses technology to fulfill organizational activities is eminently transferrable. From a practice perspective, the identified roles can be used by managers to organize better and develop the workforce, therefore mitigating any potential implementation barriers. In addition, the findings can guide educators in the field to structure their curricula to reflect emerging practice requirements and make them more responsive to industry-based needs.

2. Literature background

2.1. *The four smarts of Industry 4.0 and Smart Working PSM professionals*

Research has identified technologies that underpin a new industrial paradigm evolving from digitalization, connectivity, and automation. Specific examples of maturing and emerging technologies are 3D-printing (Meyer et al., 2020), digital twins (Attaran, 2020), cyber-physical systems (Bhattacharya and Chatterjee, 2021), internet-of-things (Legenvre and Gualandris, 2018), cloud computing (Manuel Maqueira et al., 2019), blockchain technology (Schmidt and Wagner, 2019), big data analytics (Chen et al., 2015; Kache and Seuring, 2017), machine learning (Bohanec et al., 2017), and artificial intelligence (Baryannis et al., 2019; Toorajipour et al., 2021). Recent research has analyzed the impact of these technologies on businesses, society, and people (Schiele et al., 2022a).

Within business-related studies, the concept of Digital Transformation is based on the four smarts of Industry 4.0, as discussed in the systematic literature study of Meindl et al. (2021). Digital Transformation is underpinned by base technologies shifting organizations' internal and external environments from an automated industry towards Industry 4.0, characterized by cyber-physical systems with autonomous machine-to-machine communication (Schiele and Torn, 2020). Over the last decade, this future industry paradigm has received significant attention, especially in its implications for manufacturing. The early focus on Smart Manufacturing (Kagermann et al., 2013), addresses the integration of current and future manufacturing assets with advanced communication, analysis, and production technologies (Kusiak, 2018). The second smart research stream receiving research attention is the Smart Products and Services domain. The product aspect addresses how artifacts, besides their physical components, utilize Industry 4.0-based technologies (Kahle et al., 2020; Porter and Heppelmann, 2014). Smart Services include offers for users based on digital technologies such as cloud services (Ardolino et al., 2018). However, the other concepts of Smart Supply Chain and Smart Working have been less well-researched (Meindl et al., 2021). The implications of advanced technology in increasing supply chain information flow and performances within Smart Supply Chain research have been identified (Frank et al., 2019a). In the Smart Working domain, the impact of Industry 4.0 technologies on an employee's operational activities in a firm has also been explored (Romero et al., 2020). In a manufacturing context, a range of operational activities were identified in the literature review of Dornelles et al. (2022), which follow a process perspective and include: "…*assembly, maintenance, training, quality control, movement, machine operation, product and process design, and production planning and control*" (Dornelles et al., 2022, p. 1) In addition, this work integrates a capabilities perspective to provide a fuller picture of how Industry 4.0 technologies are operationalized in a work context.

It is clear that these recently introduced technologies will reshape all four smart domains, where, for example, new production methods such as additive manufacturing open new possibilities for Smart Product design that are produced using Smart Manufacturing techniques and influence Smart Supply Chain layout (Haleem and Javaid, 2019; Schiele et al., 2022a).

Further, the four smarts of Industry 4.0 reflect different value-creating activities of the generic value chain of a product (Porter, 1990). The value chain starts with the Smart Supply Chain as the antecedence of Smart Manufacturing, resulting in the final Smart Product. According to their contributions, connecting the different stakeholders within the value chain shows that PSM supports organizational activities by guiding the acquisition process and managing goods from the supplier to the buyer and through to the end customer. Therefore, the proposed conceptual framework builds on the work of Frank et al. (2019a), illustrating the contribution of the supply chain partners and the Smart Working concept of PSM professionals (see Fig. 1).

In Fig. 1, the Smart Working domain related to the PSM professional overarches the other smart domains across the three different stakeholder groups of the value chain. PSM consists of the processes and activities of an organization to plan and acquire the materials and services from the supply base to operate and generate a competitive advantage (Kaufmann, 2002; Monczka et al., 2015). However, the rationale for introducing the smart concepts into the value chain is to recognize the significant influence of new technologies on PSM activities. For example, predictive analytics of product demand within the consumer market (Handfield et al., 2019) allows PSM professionals to forecast demand more accurately, leading to improved decision-making in their ordering strategies and processes. Integrating these technologies can improve the outcome of Smart Supply Chain activities by enhancing the operational excellence of the manufacturing firm (Vos et al., 2016). As organizations are now heavily dependent on supplier relationships (Van Weele and Van Raaij, 2014), implementing new technologies and enabling Smart Working offers the potential for high levels of organizational performance. Details on the technological changes in PSM are discussed in the following.

2.2. Specific technological changes within PSM

Smart Working within PSM has been enabled by various technologies that have been introduced incrementally. Currently, e-procurement systems are maturing, supporting various PSM tasks, and significantly influencing the operational ordering of goods and services (Johnson et al., 2007). The need for human interaction is reduced by sophisticated supporting technology, where the system manages operational ordering or payments (Hawking et al., 2004). Technology is replacing operational and low-value-added activities, allowing PSM professionals to focus on value-adding activities (Meindl et al., 2021). Further, maturing technologies like sensors and actuators can directly identify demand within the warehousing function, connecting the physical and digital worlds (Schiele and Torn, 2020; Xu, 2020). These cyber-physical systems are formed using existing sensor technologies and software (Xu, 2020). Therefore, in the first step of Smart Supply Chain management, no human involvement is needed to identify demand requirements and these can be communicated directly to suppliers (Ivanov et al., 2016).

Advanced software systems within the sourcing process, also known as e-sourcing solutions, can analyze past requests for quotation (RFQs) (Kauppi et al., 2013). This data improves decision-making by Smart Working professionals (Frank et al., 2019a), improving future quotations and identifying an extensive list of suppliers (Schiele and Torn, 2020). The amount of data available, based on e-procurement systems, e-sourcing solutions, and sensor technology, facilitate big data analytics, potentially for significant benefits (Choi et al., 2018). Big data analytics is especially useful in facilitating better decision-making based on evidence rather than human intuition or judgment (Brynjolfsson et al., 2011). More data is available as more historical data becomes accessible, technology increases supply chain transparency, and advanced information technologies gather market data (Zhong et al., 2016).

Reflecting the complementary nature of Industry 4.0 technologies, artificial intelligence can also support big data analysis (Benzidia et al., 2021a; Dubey et al., 2020), which can provide additional support to smart PSM activities (Xu et al., 2021). These technologies can reduce the need for manual operational activities and improve demand forecasting based on big data analytics (Hofmann et al., 2017; Bohanec et al., 2017). Sophisticated text mining and interactive communication bots can support the key PSM processes of identifying, communicating with, and selecting suppliers (Schiele and Torn, 2020). In these activities, effectively-coded algorithms take over parts of the supplier pre-selection process, allowing Smart Working PSM professionals to focus on the more strategic role of preparing, rather than executing, the process (Lorentz et al., 2021). At a later stage of the PSM process, when negotiations take place, research has highlighted the potential for artificial intelligence to support negotiation design and execution (Schulze-Horn et al., 2020).

Autonomous systems using Robotic Process Automation (RPA) technology automate human tasks and can be applied to redesign, optimize, and automate PSM processes (Viale and Zouari, 2020). Such automation can increase operational efficiency, improve quality and generate cost savings (Flechsig et al., 2021). Blockchain technology can potentially revolutionize processes within the buyer-supplier interface by creating a truly transparent supply chain (Kouhizadeh et al., 2021; Karnik et al., 2022). It facilitates the recording of an unchangeable history of transactions, reduces information asymmetries, makes the technology useful to facilitate payment processes, addresses sustainability issues, and promotes innovation within the supply chain (Treiblmaier, 2018; Benzidia et al., 2021b). Therefore, blockchain technology enables Smart Supply Chain management by enhancing connectivity and the real-time sharing of mass data, benefiting multiple stakeholders in the supply chain (Frederico et al., 2019). Blockchain technology also enables smart contracts, which can substitute many operational activities within PSM (Chang et al., 2019; Zhang et al., 2018). Smart contracts facilitate a fully autonomous end-to-end process from the initial communication of demand to payment on delivery (Wang et al., 2019).

The significance of the scope and scale of these technological changes in a PSM context requires organizations to change their HRM practices (Delke et al., 2023; Jackson et al., 2014) to ensure that a lack of

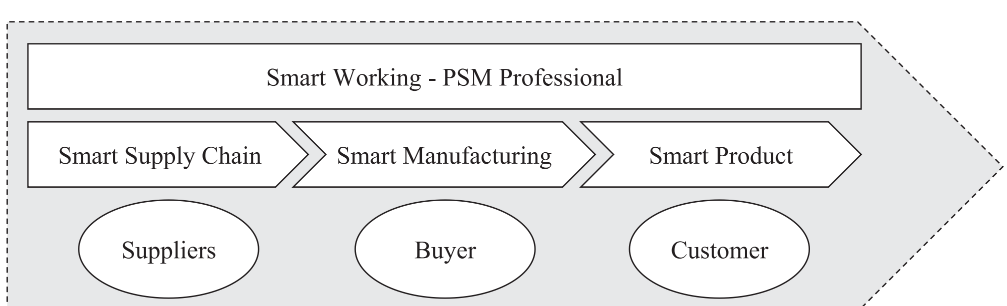

Fig. 1. Conceptional model of Smart Working PSM professionals in the value chain.

skills does not create barriers to implementation (Oke and Nair, 2021; Hawking et al., 2004; Giunipero et al., 2012).

2.3. Shaping professional roles in PSM to implement Industry 4.0 technologies

To support the implementation of new technologies within organizations, HRM activities aim to keep the workforce updated by educating and training employees to fulfill stakeholders' expectations (Jackson et al., 2014). According to Sivathanu and Pillai (2018), there needs to be alignment between an organization's HRM strategies and the practices of implementing Industry 4.0. There also needs to be a strategic focus on employment activities and developing and maintaining Industry 4.0-related skills to meet these implementation challenges (Chiarello et al., 2021; Shet and Pereira, 2021). Similar skill requirement changes have been observed with computerization which significantly altered job skill demands (Autor et al., 2003). Equipping the current workforce with future skills within the confines of their existing job roles is not wholly sufficient, as Industry 4.0 developments require new job roles (Benešová and Tupa, 2017; Shet and Pereira, 2021) or job profiles (Liboni et al., 2019; Prinz et al., 2016) in which employees manage and engage with these new technologies.

From a practice perspective, identifying new roles can lead to potentially unmanageable role inflation within a department. It is essential to see their development as dynamic, as noted in studies on other organizational functions, e.g., information and communications technology (Malandri et al., 2021), human resource management (Ulrich et al., 2013), and supply chain management (Liboni et al., 2019). This may mean that existing roles are abolished, new roles are implemented based on organizational needs, and the task or skill requirements of existing roles change.

Within PSM, various terms for the concept of professional roles exist, e.g., roles and responsibilities (Johnson et al., 1998), profiles of buyers (Faes et al., 2001), job profiles (Mulder et al., 2005), and purchasing roles (Schiele, 2019). PSM jobs are often hierarchically organized and differentiated by levels of responsibility across levels, such as purchasing manager, senior buyer, buyer, and assistant buyer (Mulder et al., 2005). In addition, various professional profiles exist that relate to PSM-specific tasks, e.g., distinguishing between information and communication, management, initial purchasing, and practical purchasing (Mulder et al., 2005). Faes et al. (2001) use cluster analysis to describe five profiles of effective buyers, including the go-getter, classic negotiator, caretaker, traditional buyer, and technical expert. More recent publications identify new specialized roles in PSM, e.g. the Innovation Promoter (Goldberg and Schiele, 2020).

As professional roles are not used consistently within PSM literature, different domains, such as HRM, have also been explored. Within the HRM profession, Ulrich et al. (2013) focus on talent and human capital in recruiting for more specialized rather than more generalist roles. Ulrich and Beatty (2001) and Ulrich et al. (2013) use the concept of roles to define six roles within HRM. Linking the concept of roles to the organization theory literature, Jones (2013) uses roles as a concept within organizational structures, defining roles based on job descriptions, the organization's function, and specific skills (Jones, 2013). However, there has been criticism that organizational roles could lead to a higher level of bureaucracy (Krantz and Maltz, 1997). Therefore, this paper uses the concept of roles as a mechanism to define and group related responsibilities within a function or organization and allocate specific skills within a structured framework (Jones, 2013). Each role requires a specific set of skills to carry out assigned tasks (see Fig. 2), although an individual employee can have multiple roles rather than a single one, and one role can be divided across different individuals.

As discussed above, the research stream in PSM-related studies has started to define roles more precisely according to the increasingly strategic role of purchasers and the professional's specialization. Schiele (2019) identifies and categorizes seven roles, which provide the basis for

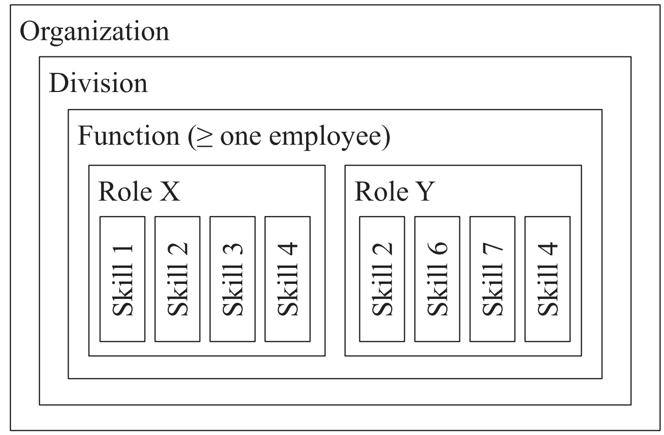

Fig. 2. Illustrating the concept of roles within an organization (based on Jones, 2013).

this paper. These seven roles include (1) Operational Procurement, (2) Purchaser of Direct Materials/Serial Purchaser, (3) Purchaser of Indirect Materials, (4) Public Procurement, (5) Purchasing Engineer, (6) Chief Purchasing Officer (CPO), and (7) other specialized roles such as Purchasing Controller, Supply Risk Manager, and Purchasing Human Resources Agent (Schiele, 2019). Recent PSM research has also begun to describe emerging roles within the field brought about by changing objectives or the introduction of technology. Goldberg and Schiele (2020) identified the promotor role in PSM to improve innovation sourcing practices, and Schulze and Bals (2020) identified the role of a sustainability officer within a wider supply chain context. Reflecting on a role change in PSM due to technology implementation, Wehrle et al. (2021) have also described the role of a data scientist. However, the extant literature has not focused on identifying and describing the specific roles needed within the PSM Industry 4.0 environment, and it is this gap that this paper addresses. Similar to other Industry 4.0-oriented studies, it is assumed that using technology and developing Smart Working increases the number of diverse and flexible career paths (Xu et al., 2018).

3. Methodology

3.1. The real-time Delphi method as an interactive forecasting method

This paper uses a real-time Delphi study that forecasts future professional roles in PSM based on previously developed projections, which a group of experts qualitatively and quantitatively evaluate (Rowe and Wright, 1999; Rikkonen and Tapio, 2009; Kopyto et al., 2020). The Delphi method is a structured communication technique originally developed as a systematic, interactive forecasting method (Rowe et al., 1991; Gnatzy et al., 2011). The method relies on a panel of experts and is suitable for long-term research objectives, which involve high levels of uncertainty and only limited information (Gray and Hovav, 2008; Rowe et al., 1991). This paper sources data from a specific set of experts as a structured group of individuals with expert knowledge within the field (Kopyto et al., 2020).

All types of Delphi studies are built on four general principles: (1) anonymity; (2) iteration; (3) controlled feedback; and (4) statistical group response (Dalkey and Helmer, 1963; Rowe and Wright, 2001; Kopyto et al., 2020) and are organized by systematically following several steps. The two most often used types of Delphi studies are the conventional "paper-and-pencil" type and the internet-based real-time Delphi approach (Gnatzy et al., 2011), with the latter being used in this research. Gnatzy et al. (2011) show that both approaches are comparable and lead to similar results, but the real-time approach is likely to have a positive effect on response rates and validity because of the functionalities of the software and its positive impact on the appearance, process, and reducing effort (e.g., time effort). This paper's Delphi study uses a four-step approach to meet its research objectives, 1) projection development, 2) selection of experts, 3) execution of the Delphi, and 4) the analysis of the outcome (see Fig. 3).

3.2. *Step one: developing the Delphi projections based on three World Café studies*

This real-time Delphi study aims to forecast future PSM roles based on previously developed projections (Rowe and Wright, 1999; Kopyto et al., 2020). In **step one**, these projections have been developed from a review of relevant academic and practitioner literature to give them a solid theoretical foundation and three explorative World-Cafés. The World Café method was developed for small focus group discussions on selected subjects (Brown, 2010; Wibeck et al., 2007; Prewitt, 2011) and has been used in this study as an exploratory-quantitative research approach to identify and describe a list of future PSM roles. Three consecutive World Cafés were organized with 29 PSM professionals from Estonia, Slovakia, the Netherlands, and Germany, to generate responses to the question: *What new professional roles in PSM exist within an Industry 4.0 context?* Compared to other qualitative research methods, for example, multiple-case studies or expert interviews, the World Café method provides comparable results in less time (Schiele et al., 2022b). The variation in the group configuration and the discussion among the participants enriches the results and reduces the bias in the data (Fouché and Light, 2011), and the iterative process of the World Café promotes stable and reliable data (Kidd and Parshall, 2000). Using a voting procedure, the World Café method also collects quantitative insights on which identified roles are important in future PSM.

Following the approach of Roßmann et al. (2018), an internal projection development workshop was organized to enhance their robustness further. This involved the members of the project team, representing five different Universities, that part-funded this research and was conducted to cross-validate and combine the outcome of the literature review and three explorative World-Café studies. This projection development workshop resulted in eight role projections: (1) Robotic Process Automation (RPA) Manager, (2) Data Analyst and Value, (3) Chief System Change Officer, (4) Ramp-up Manager, (5) Data Maintenance Officer, (6) Chief Disruption Manager, (7) Purchasing Innovation Scout, and (8) Digital Legislation Specialist. Eight projections were seen as beneficial, as too many projections may lead to a reduced response rate and increase the probability of a lower questionnaire response rate (Kopyto et al., 2020). To limit the complexity of the developed projections, the method of Rowe and Wright (2001) to frame the questions and projections was used, and the wording of the projections was constructed so as not to be emotional, unnecessarily complicated, or long. Projections should be long enough to define the roles adequately so that respondents do not interpret them differently, but they should not be so complicated and lengthy that they result in information overload for the experts (Rowe and Wright, 2001; Linstone and Turoff, 1975). Therefore, the suggestion of Salancik et al. (1971) was followed, and the length of each projection was limited to about 20–25 words.

As the outcome of the three World Cafés was primarily explorative and lacked depth on the specifics of each identified role, a Delphi study was used to enrich the field's understanding. In addition to the developed projections, a specific set of questions was created to assess the PSM roles in detail. This questionnaire assessed each expert's opinion of the role's name, description, expected probability of occurrence, impact on the industry, the desirability of occurrence, and assumed level of adoption. Further questions were added to the questionnaire during the Delphi process to ask the experts for clarification. The detailed questionnaire can be found in Appendix 1, which uses the Data Analyst role as an illustrative example. For the quantitative assessment, all participants were asked to rate the projections within the Delphi survey according to five measures:

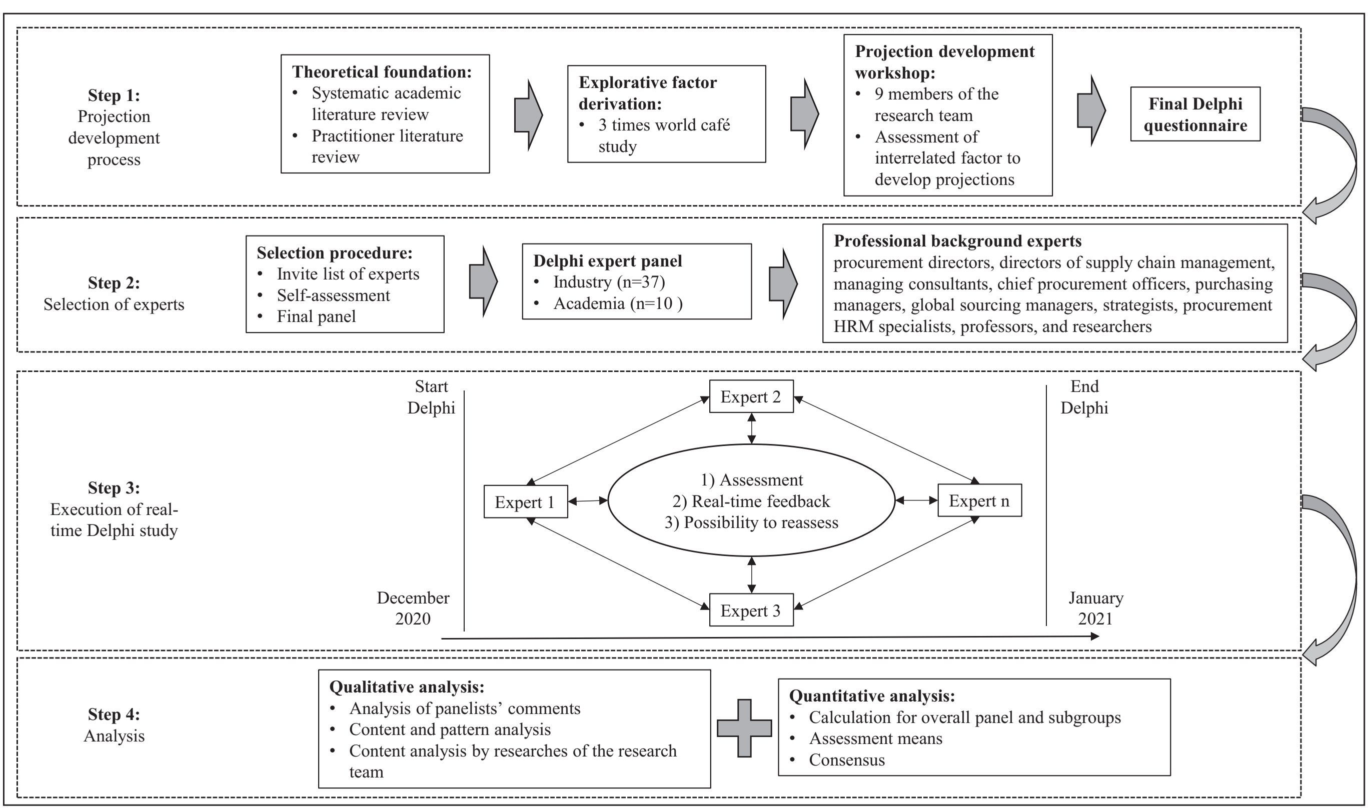

Fig. 3. Delphi study process.

1. Agreement with the name of the role and the formulation of the projection, based on a metric scale of 0–100 % (0 % = disagree, 50 % neutral, and 100 % agree)
2. Expected probability of occurrence, based on a metric scale of 0–100 % (0 % = low probability, 50 % = neutral, and 100 % = high probability)
3. Impact on PSM in the industry, based on a 5-point Likert scale (1 = very undesirable; 2 = undesirable; 3 = neutral; 4 = desirable; 5 = very desirable)
4. Desirability of occurrence, based on a 5-point Likert scale (1 = no impact; 2 = low impact; 3 = medium impact; 4 = high impact; 5 = very high Impact)
5. Level of adoption within the industry in a time frame from the current time, 5, 15, and 25 years (50 % of all firms as the threshold), based on a metric scale of 0–100 %

In addition, the experts could add qualitative justifications for their quantitative estimates within the tool's comment function, and they could also see others' comments and rate their agreement with them. The comments were used during the Delphi study to improve the projections and analyze the Delphi results.

3.3. Step two: expert selection for the participants of the Delphi study

The nature of the Delphi method means that the study's outcome heavily depends on the selection of experts (Okoli and Pawlowski, 2004; Spickermann et al., 2014). To ensure high reliability within **step two,** only experts were invited who have a solid understanding of digitalization in PSM, the concept of Industry 4.0, and PSM roles.

Heterogeneity was achieved through an open invitation, engaging experts from different industry sectors, various firm sizes, and representing academia and practice. For this reason, an open invitation was placed on the project-related website, the social network LinkedIn and also mailed by the researchers. The academic and professional networks of five research institutes within Europe were used to mail 221 potential experts with expertise related to the focal research topic, inviting them to participate in the expert panel. A careful sampling process achieved high heterogeneity and reduced various participants' cognitive biases, such as framing, anchoring, desirability biases, and the bandwagon effect (Ecken et al., 2011; Förster and von der Gracht, 2014; Winkler et al., 2015). In total, 70 experts agreed to join the study, and 47 experts completed the final Delphi survey, with 37 experts from industry and ten from academia. Table 1 shows the full demographic profile of the Delphi panelists. The high number of German participants benefits the validity of this research's results, as Germany is one of the leading countries in addressing Industry 4.0-related topics (Shet and Pereira, 2021).

A self-assessment questionnaire was launched before the Delphi study to increase the validity of the results and confirm that the experts have a good understanding of the research focus. This approach of self-rating has been confirmed as a legitimate instrument for selecting panels (Rowe and Wright, 1996; Culot et al., 2020; Kopyto et al., 2020). Within the self-assessment, each expert assessed their knowledge based on a 5-point Likert scale resulting in an average group score for knowledge addressing digital transformation in PSM of 3.03 (advanced competence), knowledge addressing the impact of Industry 4.0 on PSM of 2.85 (advanced competence), knowledge addressing skills and competences in PSM of 3.58 (outstanding competence), and knowledge addressing professional roles (job descriptions) in PSM of 3.49 (advanced competence).

A common understanding of the concepts of professional roles and Industry 4.0 was tested at the beginning of the Delphi study (see Table 2). These definitions were added at the start of the Delphi survey, where participants rated their level of agreement based on a metric scale of 0–100 % (0 % disagree, 50 % neutral, and 100 % agree).

Table 1
Demographic profile of the Delphi panelists ($n = 47$).

Dimension	Number	% of total
Gender		
Male	33	70 %
Female	14	30 %
Country of origin		
Germany	23	49 %
Slovakia	7	15 %
Finland	4	9 %
Netherlands	3	6 %
Italy	2	4 %
Switzerland	2	4 %
Austria; Brazil; Czech Republic; France	4	9 %
Academic background (subtotal)	10	21 %
Professor	5	11 %
Researcher	4	9 %
Research assistant	1	2 %
Industry background (subtotal)	37	79 %
Head of procurement	8	17 %
Procurement director	6	13 %
Procurement manager	5	11 %
Commodity lead procurement	3	6 %
Procurement director and supply chain management	3	6 %
Procurement strategist	3	6 %
Chief procurement officer	2	4 %
Procurement senior director	2	4 %
Procurement specialist	2	4 %
Procurement advisor	2	4 %
Head of Supplier Management	1	2 %
Total	**47**	**100 %**

Table 2
Definitions within the Delphi study.

Definition	Consensus in %	Stability in %	Std. deviation
"A role can be understood as an organizing concept. Each role is bound to responsibilities and tasks within the organization. Each role requires a specific set of skills to carry out these tasks. One employee can have multiple roles or can be allocated to one specific role. One role can be divided among different individuals. Larger organizations will allocate one role to specialized employees. Smaller organizations will have employees with multiple roles."	88.86	82.97	15.13
"Roles are concepts that allow for organizational development towards a higher maturity level. To allow maturity to increase, new roles will be implemented, and existing roles change, e.g., *the skill requirements or tasks. Each role's set of skills and tasks changes according to the available technology."*	78.84	75.39	19.40
"Industry 4.0 is characterized by cyber-physical systems with autonomous machine-to-machine communication."	70.44	59.04	28.85

3.4. Step three: execution of the internet-based real-time Delphi study

The internet-based real-time Delphi approach using the Calibrum Surveylet software was conducted in **step three** of this study. The software facilitated an immediate quantitative analysis of the experts' assessment (Aengenheyster et al., 2017) and conformed to all four general Delphi principles. Participants were treated anonymously, real-time iteration was possible, controlled feedback could be provided via mail, and statistical group responses were presented within the projection assessment phase. This variant of the Delphi allowed a fast return and iteration of feedback to the experts (Aengenheyster et al., 2017; Gnatzy et al., 2011). For the quantitative assessment, all participants were asked to rate the projections within the Delphi survey according to five measures. Also, as discussed previously, experts could add qualitative justifications for their quantitative estimates within the tool's comment function.

The Delphi study started at the beginning of December 2020 and concluded at the end of January 2021. After two weeks, 44 responses were gathered, and the Delphi facilitator analyzed the first outcomes. Based on the results and comments provided by the participants, changes were made to the initial projections of the Delphi study, as role names and descriptions were adjusted according to the experts' suggestions. The changes were mailed to the participating experts to ensure transparency, and they were asked to reassess the projections. On the 7th of January 2021, a second analysis of the intermediate results was performed, resulting in some minor changes to those projections that achieved a low consensus value. A question on where specific roles could be implemented within the organization was also added, and any changes to the questionnaire were communicated to the participants. Two weeks before closing the Delphi study, all participants received a reminder to complete the study, which closed at the end of January. In February 2021, the results of the Delphi were shared with the participants via mail.

3.5. Step four: analysis of the real-time Delphi study results

The Delphi study provides qualitative and quantitative results, and these were both analyzed systematically in **step four**. First, the quantitative results were analyzed based on numerical values, and second, the qualitative results by analyzing the comments and text input provided by the Delphi experts. To visualize the group's long-term judgments for the expected probability of occurrence, impact on the industry, desirability of occurrence, and level of adoption within the industry, their respective arithmetic mean values were determined (Kopyto et al., 2020; Roßmann et al., 2018). Further, the consensus and stability values were analyzed to evaluate the feasibility of the projections, and this consensus measurement is a central part of a Delphi survey. To measure group agreement, Surveylet calculates four consensus-related measures: consensus score, choice of consensus, group stability, stability threshold, and consensus status. Within this study, the arithmetic mean value was used as a consensus measure, and for these items, the Coefficient of Variation was used to calculate the group stability to indicate the strength or level of consensus. This measurement shows the strength of agreement on the consensus choice between all respondents, and for this study, a threshold of 50 % was selected. The arithmetic mean was calculated and used as a consensus score for those items, measured based on a metric scale of 0–100. The arithmetic mean was calculated for those items measured on a 5-point Likert scale, and the closest rank was selected as the outcome.

In addition to the quantitative assessment, the experts provided 247 written comments, which were analyzed to improve role descriptions, and two researchers analyzed these comments to provide qualitative justifications for the quantitative outcome of this study.

4. Results and analysis

4.1. Defining six new PSM roles in the era of Industry 4.0

During the Delphi study process, multiple projections were changed, with some receiving minor changes, for example, the name of the role, and others undergoing significant changes, where the full descriptions of the projection were changed or, in the case of one projection, deleted. At the end of the Delphi study, seven future Industry 4.0 PSM roles were identified, and the final names and descriptions are shown in Table 3, along with the role's desirability and impact. In addition, for the consensus value addressing the role description, the differences between the experts from industry backgrounds ('I') and academic ('A') backgrounds are indicated, and these are discussed further in Section 4.2.

In the following, the identified roles are discussed in detail according to their rational, scope, and implementation factors. These results are summarized in Table 4. The role of the **Data Analyst** was identified as being key, receiving a consensus value of 86.40 % and stability of 84.55 %, indicating that the experts have a high agreement level with this role. It is also highly desired and has a high impact on PSM. Within the Delphi study, it was noted that the *"scope can vary depending on if internal data only or both internal and external data are considered"* (Expert 8). For some organizations, the role of a Data Analyst may already exist. However, as the technologies of Industry 4.0 starts fully impact PSM, the amount of data available increases, including internal historical data of past contracts, requests for quotation or offers, as well as newly available data, such as market screening and supply risk analysis (Zhong et al., 2016). Therefore, the decision-making process within strategic PSM is

Table 3
Projection results addressing future professional roles in PSM.

Description	Consensus in %[a]	Stability in %	Std. Dev.	Desirability	Impact
"The **Data Analyst** in purchasing is responsible for extraction and analysis of purchasing data to support the preparation of commodity strategies and complex purchasing projects."	**86.40** (I: 88.52) (A: 79.11)	84.55	13.35	Very desirable	High
"The **Legislation Specialist** in purchasing is responsible for ensuring that digital purchasing processes and sourcing projects comply with any relevant laws and regulations, including their implementation into the purchasing systems."	**69.91** (I: 74.08) (A: 54.90)	57.52	29.70	Desirable	Medium
"The **Master Data Manager** in purchasing is responsible for the alignment between the physical and digital world and ensuring data correctness and up-to-dateness."	**67.79** (I: 67.46) (A: 60.00)	53.63	31.43	Desirable	High
"The **Supplier Onboarding Manager** in purchasing is responsible for setting up the digital interface between the buying firm and suppliers, involving the harmonization of data and effective stakeholder communication."	**64.98** (I: 69.38) (A: 48.70)	55.39	28.99	Desirable	High
"The **Process Automation Manager** works at the interface between purchasing and IT, responsible for implementing and operative running of RPA tasks within purchasing."	**62.62** (I: 62.35) (A: 63.60)	59.81	25.16	Desirable	High
"The **System Innovation Scout** is responsible for identifying and implementing new Industry 4.0 technologies or systems within purchasing."	**59.55** (I: 60.24) (A: 57.00)	48.85	30.46	Desirable	High
"The **Chief Happiness Officer** in purchasing is responsible for change management during system automatization and ongoing caretaking of human needs within a digitized working environment."	**39.22** (I: 44.47) (A: 20.56)	24.32	29.68	Neutral	Low

[a] Consensus value for all participants in bold, I = experts from industry, and A = experts from academia.

Table 4
Projection results addressing future professional roles in PSM.

Role	Rational	Scope	Implementation factors
Data Analyst	• amount of data in PSM increases due to the implementation of (Industry 4.0) technologies • possibility of utilizing artificial intelligence	• analyses of internal and external data • internal data from past contracts and activities • external market data • predictive analyses to estimate disruption impact • end-to-end supply chain	• implementation at a corporate level, e.g., in centralized PSM • team of Data Analysts in larger organizations • in smaller organizations implemented as a shared resource
Legislation Specialist	• privacy and security of data is a major concern in Smart Supply Chains with high data exchange stakeholders • increasing data privacy and security requirements	• ensuring that digital PSM processes comply with laws and regulations • implementation of advanced technology, e.g. processes automation and smart contracts	• implemented as a supportive role in PSM or the legal department by assigning people to procurement topics
Master Data Manager	• advanced systems require experts to manage the alignment between multiple systems and the flow of data • in Industry 4.0, the role enables cyber-physical systems and digital twins	• preparing the database by extracting, processing, and storing data generated by PSM processes • aligning the physical and digital worlds by ensuring the availability and accuracy of data	• operates at the interface between departments • establishing and maintaining the digital links to suppliers and customers within the Smart Supply Chain
Supplier Onboarding Manager	• important to build a Smart Supply Chain and utilize more technologies in the buyer-supplier interface • Smart Supply Chains require flawless connections • particularly needed during supplier integration	• onboard suppliers to the organization's digital environments and practices • collecting information and data needed to set up an approved supplier • goal to achieve higher data accuracy and transparency	• for supply chain data in high volumes production • setting up the digital interface is done by the IT department, but alignment is a PSM responsibility • involving stakeholders, making contacts, and explaining processes
Process Automation Manager	• process automation will allow PSM professionals to work smarter and focus on value-adding activities • autonomous systems perform activities without human intervention	• implementing and operational running of Robotic Process Automation (RPA) tasks • automated process perform operational tasks, e. g., ordering and payment	• at the interface between PSM and IT • one person responsible for end-to-end processes • in agreement with the PSM department to reduce administrative routines
System Innovation Scout	• e-procurement systems are complemented and replaced by advanced information, communication, and connectivity technologies • technology reduces human involvement and enables Smart Supply Chains	• identify the needs and implement new technologies in PSM • discovering new technologies and evaluating their impact on the organization	• an expert in PSM to ensure system up-to-dateness since the IT department is not specialized in PSM requirements • by implementing the role in PSM, a organizationally mature approach is taken
Chief Happiness Officer	• a person responsible for human needs during the change process is required in Industry 4.0	• change management during system automation and the caretaking of human needs in a digitized working environment	• was not evaluated as important in future PSM and therefore excluded from further analysis

supported, and the Data Analyst can be seen as a smart working professional who utilizes technology to improve business performance (Segura et al., 2020; Frank et al., 2019a). In addition, the qualitative comments of the experts support Choi et al. (2018) by showing that the supply management field is orientating itself towards "*big data*" (Expert 29). In the future, Data Analysts will use artificial intelligence (Romero et al., 2020). However, an Artificial Intelligence specialist role was not addressed separately, as the experts included this task within the Data Analyst role. Larger organizations will have *"not only one person but a team of Data Analysts"* (Expert 4). Also, organizations could choose to implement a "*business intelligence department*" (Expert 28), which is responsible for analyzing data and providing reports to PSM practitioners, showing how big data can have a business impact (Chen et al., 2012). Within PSM, big data can be a valuable source for predictive analyses in estimating the impact of supply chain risk and disruption based on market insight statistics or information (Ivanov et al., 2016; Javaid et al., 2021). The Data Analyst role can also be implemented at a corporate level, e.g., in centralized PSM, to provide data analysis services for the whole organization or within category management teams. For smaller organizations, the Data Analyst will most likely "*be implemented as a shared resource with other areas, e.g., finance*" (Expert 22).

The second-highest consensus was achieved for the role of the **Legislation Specialist**, which ensures that digital PSM processes and sourcing projects comply with relevant laws and regulations. According to Expert 29: *"the word digital shifts the focus of the role more towards the digitalization aspect of purchasing, where more processes are automated, and there is a need to comply with the law."* However, the role in PSM would need to focus on both aspects, as a specialist is needed beyond the digital sphere. This role's rising importance reflects increasing data privacy and security requirements and reflects a societal shift to more state internationalism and regulated markets. Within Smart Supply Chains, characterized by high data exchange, the privacy and security of data are a major concern (Ogbuke et al., 2022; Frederico et al., 2019). Moving forward towards increased automation within the buyer-supplier interface, the competencies of PSM professionals will shift from drafting paper-based contracts to the implementation of smart contracts (Wang et al., 2019), and so the legal implications of advanced technology used within the supply chain need to be addressed by PSM (Frederico et al., 2019). However, the experts debated whether this role would be implemented within the PSM or legal department, as: *"compliance in purchasing is more important today"* (Expert 9), but: *"this could be a role in the legal team, assigning people to procurement"* (Expert 9).

The **Master Data Manager** received the third-highest consensus value with 67.79 % and stability of 53.63 %. This PSM role is responsible for aligning the physical and digital worlds and ensuring the availability and accuracy of up-to-date data, which is becoming increasingly important. As noticed by Kauppi et al. (2013), more procurement-oriented systems, known as Supplier Relationship Management (SRM), Purchase to Pay systems (P2P), e-procurement, e-sourcing systems, and further systems, are being introduced, which require experts to manage the alignment between multiple systems and the consistency and flow of data. Within an Industry 4.0 context, the Master Data Manager allows cyber-physical systems and digital twins to interact effectively (Schiele and Torn, 2020). To enable Smart Working within PSM using large amounts of data, the Master Data Manager is responsible for preparing the database by extracting, processing, and storing data generated by strategic and operational processes (Oussous et al., 2018). This interface role becomes crucial in establishing and maintaining the created digital links to suppliers and customers within the Smart Supply Chain (Barreto et al., 2017; Frank et al., 2019a).

To illustrate the core of these findings and provide an example case on how the future roles may operate in an organization, the collaborative tasks of Master Data Manager and Data Analyst are presented in Fig. 4. The Master Data Manager is needed to extract, process, and store

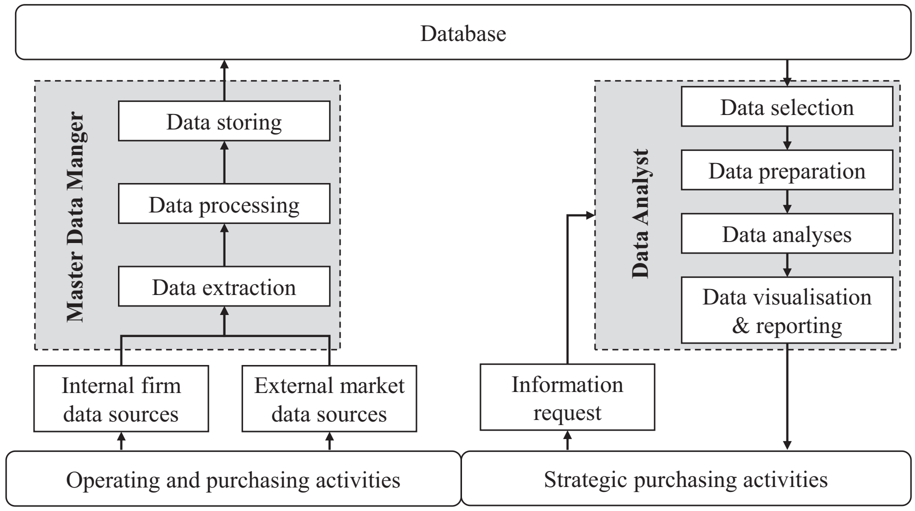

Fig. 4. The relation between the Master Data Manager and Data Analyst in PSM.

the data generated by strategic and operational processes and activities in a company's database, creating a high-quality resource. Next, the Data Analyst in PSM is responsible for analyzing the available data and preparing reports for advising strategic purchasing activities.

The fourth PSM role, the **Supplier Onboarding Manager**, will become increasingly important in building a Smart Supply Chain (Frederico et al., 2019; Kauppi et al., 2013). The key responsibility of this role is to onboard suppliers (i.e., collecting the information and data needed to set up an organization as an approved supplier) to the organization's digital environments and practices. According to Expert 10, onboarding includes: *"involving stakeholders, making contacts, and explaining processes to make sure that everything works."* The Supplier Onboarding Manager is particularly needed during the first phase of supplier integration. Implementing this role results in higher data accuracy (Viale and Zouari, 2020; Lamba and Singh, 2017) and data transparency (Lorentz et al., 2021; Karnik et al., 2022). In a Smart Supply Chain, advanced systems can run autonomously, which requires a flawless connection between stakeholders (Ivanov et al., 2016). These connections are most likely established for: *"supply chain data in high volumes production,"* where: *"setting up digital interface is an IT job and ensuring all interfaces fit well, is purchasing responsibility"* (Expert 8).

The **Process Automation Manager** works at the interface between PSM and IT and is responsible for implementing and operational running Robotic Process Automation (RPA) tasks. In PSM processes, an automated process can perform many operational tasks, including the ordering and payment of deliveries (Flechsig et al., 2021). Therefore, process automation will allow PSM professionals to work smarter and focus on value-adding activities (Fantini et al., 2020), such as innovation sourcing (Johnsen et al., 2022). According to Expert 10, the role's importance becomes clear since: *"having one person responsible for end-to-end processes is a clear benefit in automation projects."* When looking at the tasks of this PSM role, Expert 21 explained that the: *"Process Automation Manager, in agreement with the purchasing and PSM departments, has to set up many big changes in the well-established process of administrative routines."* Later technological developments in Industry 4.0 towards autonomous systems mean that a wider range of activities can be automated and run without human intervention. A best practice example within PSM activities is smart contracts, which use blockchain technology to manage the process from identifying demand to the final payment (Wang et al., 2019).

A **System Innovation Scout** is needed to identify and implement new technologies in PSM. The functionalities of past e-procurement systems that focused on the operational ordering of goods and services (Johnson et al., 2007) are complemented and replaced by new functionalities based on improvements in information, communication, and connectivity technologies (Bharadwaj et al., 2013; Kauppi et al., 2013). This sophisticated technology reduces human involvement and enables Smart Supply Chain management (Son et al., 2021; Frederico et al., 2019). The System Innovation Scout's responsibilities are split between discovering new technologies and evaluating the impact of innovation on the organization, which could significantly shape the future of PSM. Studies such as Kopyto et al. (2020) present the benefits and implementation of technology within the supply chain, but professionals lack insights on how to move forward with their implementation activities. PSM development towards Industry 4.0 and the various smart domains, can be seen as a step-by-step approach, where incremental changes, e.g., the implementation of new technologies, are realized. Expert 43 points out that: *"to ensure system up-to-dateness from a purchasing point of view,"* this PSM role is needed because: *"the IT department is often focused on sales-software"*. Taking a more strategic and organizationally mature approach includes the implementation of the role in the PSM department.

The last role addressed within the Delphi study is that of the **Chief Happiness Officer**, who is responsible for change management during system automatization and the ongoing caretaking of human needs within a digitized working environment. Based on the research objective, to explore future roles in PSM in an Industry 4.0 era, a person responsible for these human needs during the change process may be required. However, based on the low consensus value of 39.22 % and low stability of 24.32 %, this role is seemingly less warranted in PSM. The experts did not agree with the name and definition of the role and selecting different names, e.g., Chief Happiness Officer, the Employee Wellbeing Officer, or Chief Wealth Officer, did not improve the group consensus. Due to these factors, this role was excluded from further analysis.

4.2. Assessing the adoption level of Industry 4.0 roles in PSM

Within the Delphi study, the assumed level of adoption of these roles was also analyzed. Experts assessed the timeframe in which organizations will adopt the described roles, starting from the date of the study and looking over the next 5, 15, and 25 years based on a metric scale of 0–100 % (see Fig. 5). As there are 37 participants with an industrial background and ten with an academic one, the data has also been plotted and analyzed for the whole sample of participants and the two groups. This Delphi study's research objective was to identify the *future* PSM roles that are needed in an Industry 4.0 environment, but the experts identified that multiple roles already have a high adoption level

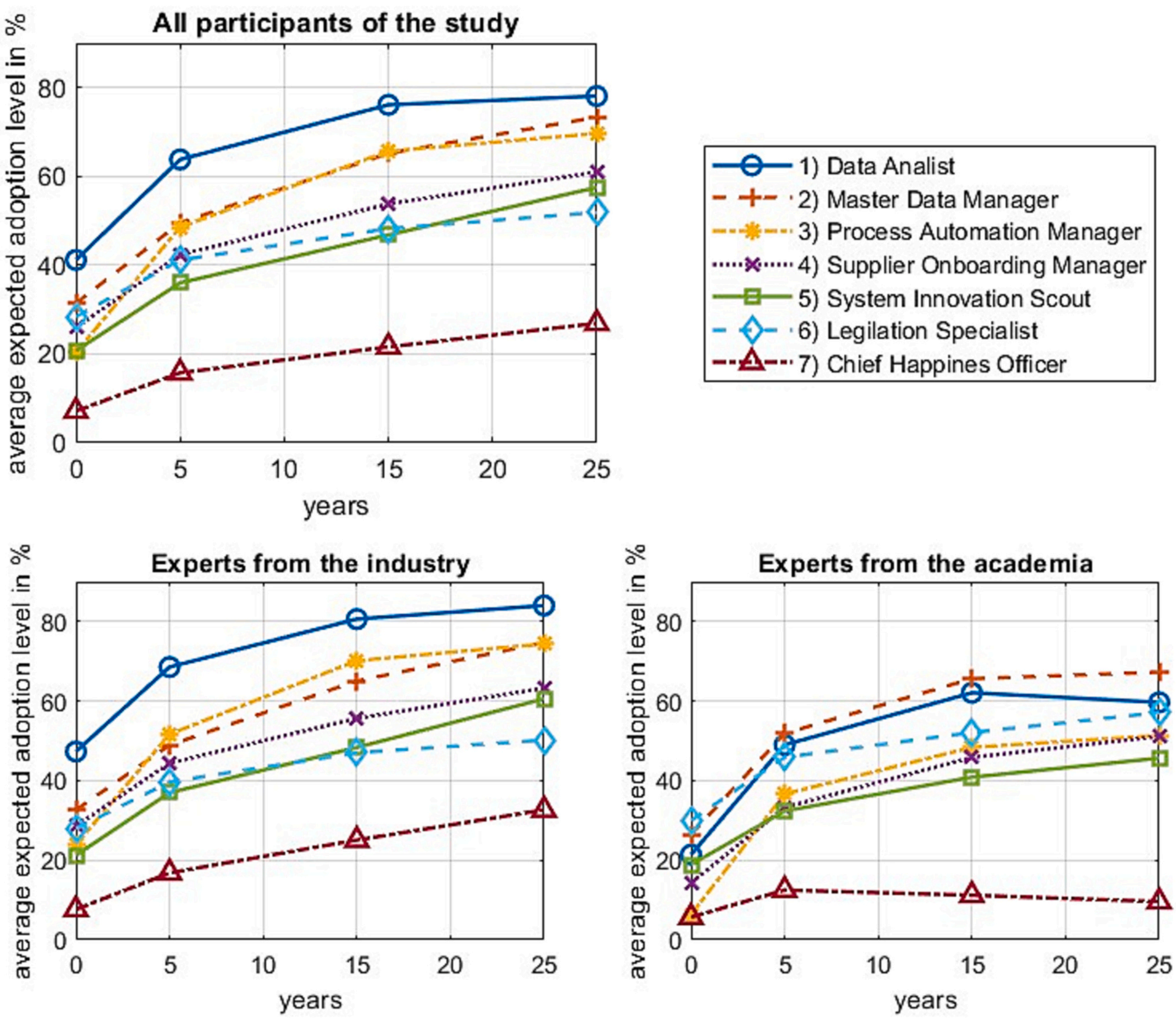

Fig. 5. Graphical illustration of the adoption of future professional roles in PSM.

within the industry (i.e., between 20 %–40 % have already adopted these roles as of today). This outcome was not expected and could be explained by the sample selection criteria, resulting in the constitution of the Delphi study's expert panel, who had HRM knowledge in a PSM context and understood the skills and competencies required by PSM practitioners, and knowledge of digitalization or Industry 4.0. In addition, multiple experts were from larger organizations with correspondingly advanced PSM practices.

The expert panel's assessment clearly shows that the roles of Data Analyst, Master Data Manager, and Process Automation Manager will dominate the future of PSM and will be widely implemented in the coming years. When it comes to implementation, the roles of Data Analyst and Master Data Manager are difficult to separate, as they directly complement each other. Both roles are fundamental in supporting Smart Working within the PSM domain as they enable improved decision-making using technology (Segura et al., 2020; Meindl et al., 2021). A rapid increase in the relevance of the role of the Process Automation Manager is expected in the next five years, as related technologies become more readily available in the market and offer the possibility of greater added value. The work of Flechsig et al. (2021) has shown how process automation technology, such as RPA, can automate a large amount of the ordering and payment process, which will soon change the tasks of PSM professionals. The introduction of the System Innovation Scout reflects the heightened organizational significance of PSM and its strategic impact. The implementation of technology within PSM is a continuous process, beginning with e-Procurement systems (Hawking et al., 2004), continuing with advanced system support within the supply chain (Kauppi et al., 2013), to the benefits of innovative technology such as blockchain and artificial intelligence (Frederico et al., 2019; Schulze-Horn et al., 2020). A similar timescale is also expected for the Supplier Onboarding Manager, as not every organization can fully and actively shape its supplier interface due to its resource availability. To achieve a Smart Supply Chain, the active role of the Supplier Onboarding Manager is needed to shape upstream supply relationships (Meindl et al., 2021). The role of the Legislation Specialist, although having specific PSM aspects, may be implemented as a shared resource across an organization and is needed over the next decade to address ethical, privacy, and security issues within the Smart Supply Chain context (Ogbuke et al., 2022). As discussed previously, according to the experts, the Chief Happiness Officer is not seen as a necessary or viable future role in PSM.

The debate over the 'gaps' between academia and practice in business and management studies is wide-ranging and long-standing. Although the primary aim of the research was not to focus on these distinctions, it nonetheless provided an opportunity, due to the mix of participants, to compare their responses. Many consensus levels between academics and practitioners are broadly similar, so the discussion will focus on those that reflect the main differences.

Research has shown that, in general, compared to academics, practitioners tend to emphasize operating issues (Gopinath and Hoffman, 1995). Closer to this studies area of research, a higher percentage of academics reported that demand for and interest in big data will continue to increase, but practitioners have higher levels of agreement with statements about how big data could help with operational tasks and activities (Rezaee and Wang, 2019). This is reflected in the study, showing higher levels of practitioner agreement concerning the roles of the Legislation Specialist and Data Analyst. This may demonstrate their heightened perception of the complexities of how Industry 4.0 technologies can be embedded into operational practices. Also, in a study of blockchain technology and sustainable supply chains, practitioners appear more technology-oriented, e.g., more concerned about the technology itself than the other general issues (Kouhizadeh et al., 2021). The findings would seem to contradict this, as academics exhibit lower levels of agreement over the role of the Chief Happiness Office, which is the ongoing caretaking of human needs within a digitized working environment. Still, academics have a (slightly) higher level of consensus on the Process Automation Manager role. Although data was not captured on the reasons for these differences, it is suggested that this may be a practitioner's exposure to the impact of employee wellbeing on work activities.

Several similarities emerge when time is factored in, such as the adoption level of the Process Automation Manager increasing rapidly in the next five years. However, there are also differences, such as a decline in the adoption level of the Data Analyst being observed in the academic expert group, as noted by (academic) Expert 42 that the "*role will become obsolete*" due to the introduction of more advanced systems and the introduction of artificial intelligence in PSM. This is perhaps reflective of a traditional practitioner's focus on operational activities, as discussed above.

4.3. *The expected impact of future roles on PSM*

Following the approach of Kopyto et al. (2020), the mean impact and mean probability of existence for each role were assessed to evaluate the relevance for the PSM field (see Fig. 6). The experts were asked to assess the impact of each role on PSM, based on a 5-point Likert scale, and the expected probability of occurrence, based on a metric scale of 0–100 %. Again, the results have been plotted and analyzed according to the whole sample and the two expert groups.

Within the probable roles that will more significantly shape the future of PSM, the opportunities for harnessing big data technologies and processes mean that the role of the Data Analyst has the highest impact and probability. Data Analytics is used within the PSM field to evaluate suppliers or their supply offers (Schiele and Torn, 2020). The second most probable role is the Master Data Manager, who provides the overarching support and impetus for these data analysis activities. Due to advanced sensor technology, the increasing amount and availability of historical data and systems that screen current market data mean that processing, storing, and securing data have become increasingly important (Oussous et al., 2018). The role of the Process Automation Manager is very likely to be needed, having a significant impact on PSM activities, as many tasks can already be automated. Implementing RPA

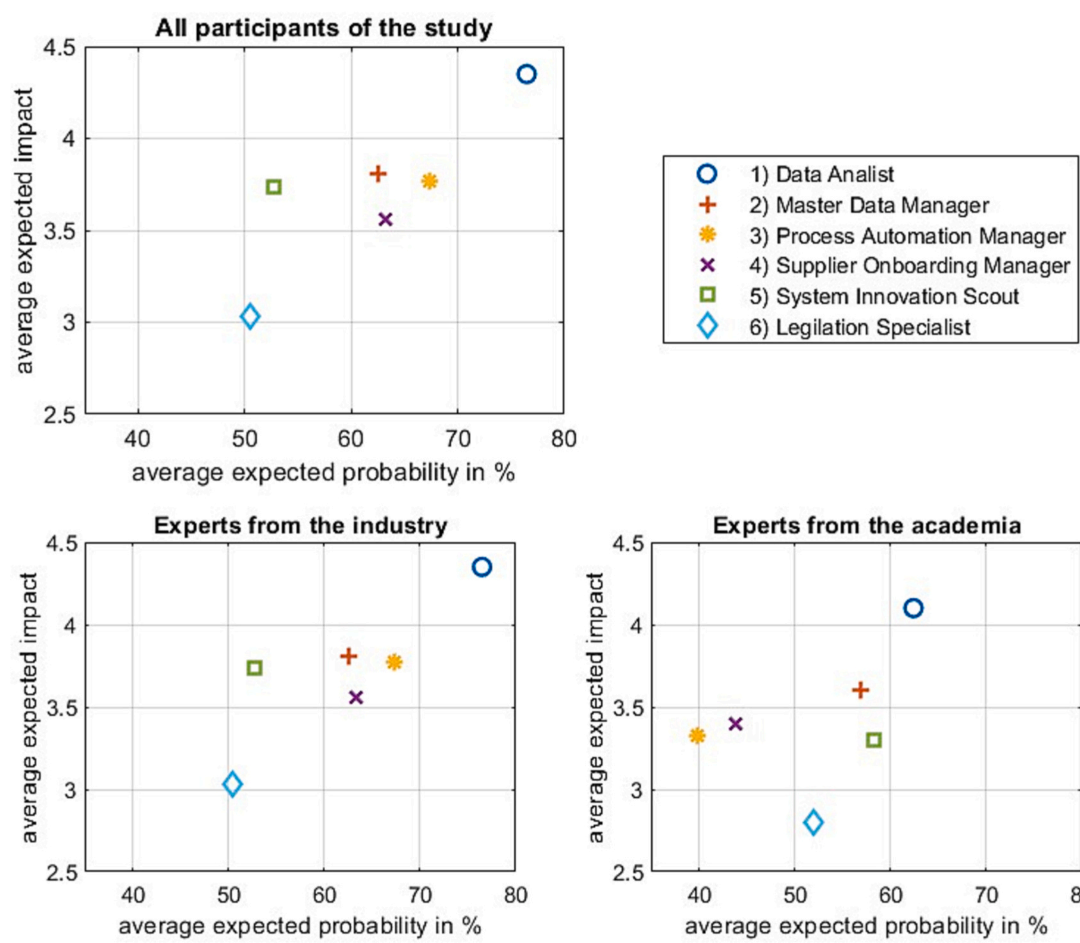

Fig. 6. The expected impact of roles on the PSM by expected probability of occurrence.

for repetitive tasks can enhance operational efficiency, quality improvement, and cost savings (Flechsig et al., 2021).

The less likely, but still possible roles within future PSM include the Supplier Onboarding Manager, System Innovation Scout, and Legislation Specialist. To shape the future buyer-supplier interface, utilizing technology to facilitate communication, the Supplier Onboarding Manager is likely to exist and impact the field. In the future, a faultless and seamless connection between the buyer and supplier is required to facilitate a Smart Supply Chain (Frederico et al., 2019). The role of the System Innovation Scout is required in the short term since this role shapes and therefore impacts the future of PSM by identifying and implementing new systems within PSM that later process changes are dependent on. Finally, the Legislation Specialist will ensure that future processes comply with relevant regulations. The use of such systems heightens this need based on blockchain technology, in which many operational activities could be substituted by, for example, smart contracts (Wang et al., 2019).

When the responses across both academic and practitioner participants is considered, we see a broadly similar pattern, with the exception of two roles, the Process Automation Manager and Supplier Onboarding Manager, with the former seen as both more likely and impactful by practitioners and the latter being seen as less likely by academics. The suggested reasons for this could be the traditional focus of practitioners on operations aspects of the Process Automation Manager and also their awareness of the contextual challenges in integrating suppliers, particularly new ones, into their processes and ways of working.

5. Discussion

5.1. Theoretical implications: benefiting from Industry 4.0 through implementing new job roles

The starting point of this research was to support the implementation of Industry 4.0 technologies by identifying future PSM professional roles. However, many of these technological developments are not field- or function-specific, allowing for a generalization of the results beyond the PSM context. For example, from a broader perspective, the Smart Working dimension considers the activities of operators, managers, and engineers in a manufacturing-focused Industry 4.0 context (Dornelles et al., 2022). Therefore, in addition to its Smart Working in PSM contribution, this paper also contributes to human capital theory and the domain of HRM within the paradigm of Industry 4.0.

Recent literature highlights the significant implications of technological developments for businesses, society, and people (Schiele et al., 2022a; Culot et al., 2020). Over the last decade, research has assessed the implications of new technologies on the manufacturing and product domain, and the impact of technologies, such as additive manufacturing, on the layout of production processes and the finished product. Therefore, within the wider smart context, the two concepts of Smart Manufacturing and Smart Products and Services have received significant attention (Meindl et al., 2021; Haleem and Javaid, 2019). In addition, work has assessed the impact of new technologies, such as cloud services and blockchain technology, on the network of stakeholders within the value chain of the product, resulting in advanced practices in supply chain management, coining the term Smart Supply Chain Management, in which organizations use technology to facilitate closer business network collaborations (Frederico et al., 2019; Pagani and Pardo, 2017). Therefore, a reshaping of a firm's external and internal environment can be seen, in which workers take on new tasks and responsibilities in a changing working environment (Romero et al., 2020). In the manufacturing environment and supporting activities, professionals become technology-enhanced workers who utilize technology to support company activities, resulting in Smart Working within various firm functions (Segura et al., 2020; Frank et al., 2019a). The study of Dornelles et al. (2022) identifies fifteen technologies that directly and indirectly impact specific manufacturing workers' activities, resulting in enhanced capabilities based on technology. Besides various limitation factors or negative impacts, the technology-enhanced workers, e.g., Operators 4.0, benefit from improved performance based on technology (Dornelles et al., 2022). However, the literature on Smart Working, especially in a nonproduction-related context such as PSM, is a less explored dimension that warrants further attention. This study identified a number of different activities that highlight the impact of Smart Working technologies in the operation of PSM. This helps the field understand the impact of Smart Working practices in organizations, and different functions need to be understood as this can significantly contribute to organizational performance (Palumbo et al., 2022). In particular, different parts of the PSM process could be enhanced by Industry 4.0 technologies, such as using artificial intelligence and big data for a faster and more accurate collation of organizational spend data to inform more effective supplier selection decision-making or using blockchain technology to substitute the operational activities in identifying and monitoring supply chain sources and enhance traceability and transparency.

Nevertheless, the presented study shows technologies' impact on future PSM professionals' jobs. On the one hand, technology compliments the work of professionals by increasing task performance, e.g., data analytics will support the decision-making process for strategic purchasing. On the other hand, implementing technology, e.g., process automation, will substitute work in operational PSM activities such as ordering and managing payment processes. Similar shifts have been observed by Autor et al. (2003), where computerization substitutes work for cognitive and manual tasks and complement work for nonroutine problem-solving and communications tasks. Thus, the trend of labor inputs into routine manual and routine cognitive tasks towards increased engagement in nonroutine cognitive tasks will continue (Autor et al., 2003). Technologies related to Industry 4.0 will also impact more complex tasks, such as negotiations, resulting in less work and improved negotiation outcomes (Schulze-Horn et al., 2020). Thus, technology will substitute jobs in operational and routine activities, confirming the expectations of Frey and Osborne (2017), where some operational buying or negotiation activities have a high probability of computerization. However, various jobs in the management and business context have a low likelihood of computerization and will even emerge due to technological advancement, e.g., new jobs such as the Process Automation Manager or System Innovation Scout are shaped. Therefore, within Industry 4.0, the alteration of worker profiles is expected, requiring new job roles or job profiles in which employees manage and engage with these new technologies (Shet and Pereira, 2021; Liboni et al., 2019). Ultimately, the impact of Industry 4.0 and Smart Working requires different skill profiles and education approaches (Benešová and Tupa, 2017; Prinz et al., 2016).

This study supports Industry 4.0 technology implementation by identifying and defining future PSM Smart Working roles as technology-enhanced workers. The results show that technological advancement will shape the future industry paradigm and, based on the breadth of identified roles and implications, it confirms that Industry 4.0 is not defined by one single technology (Frank et al., 2019b; Chiarello et al., 2021). Therefore, the paper's contribution is to offer a new level of analysis within the future-oriented PSM skills, capabilities, and competencies literature, extending the work of Bals et al. (2019) with PSM roles that are impacted by Industry 4.0 technology implementation. It complements research such as the five profiles of effective buyers identified by Faes et al. (2001), the job profile research of Mulder et al. (2005), and the roles in PSM developed by Schiele (2019). As a further contribution, the study uses Smart Working and Smart Supply Chains concepts to position these roles within a more technologically focused context.

The identified roles link directly to key technologies and operational activities within future PSM. The Data Analyst and Master Data Management roles relate to the increasing amount and value of data within PSM, resulting in big data analytics (Chen et al., 2015; Kache and

Seuring, 2017). Within Industry 4.0, the Data Analyst will use artificial intelligence to improve decision-making and sourcing strategies (Baryannis et al., 2019; Toorajipour et al., 2021) and support the design and execution of negotiation activities (Schulze-Horn et al., 2020). In collaboration with the Supplier Onboarding Manager, the Automation Manager is responsible for automating processes within the buyer-supplier interface through which short-term benefits to operational efficiency, quality improvement, and cost savings are expected based on RPA (Flechsig et al., 2021). Within Industry 4.0, blockchain technology can potentially revolutionize processes, creating a fully transparent supply chain by recording the transactions' unchangeable history and reducing information asymmetries (Kouhizadeh et al., 2021; Karnik et al., 2022; Frederico et al., 2019). Within PSM, blockchain technology is expected to facilitate payment processes and address sustainability issues and innovation (Treiblmaier, 2018; Benzidia et al., 2021b). In these activities, the role of the Legislation Specialist is needed to ensure that future PSM processes and sourcing projects comply with any relevant laws and regulations (Ogbuke et al., 2022). Also, in relation to contractual management, by using blockchain technology, many operational activities could be substituted by smart contracts (Chang et al., 2019; Zhang et al., 2018). The System Innovation Scout is responsible for identifying and implementing technologies to support technology implementation with PSM. Who takes responsibility for how future technologies shape the PSM environment remains to be seen. Ulrich et al. (2013) show that an increased focus on talent and human capital is needed for future education, training, and recruitment according to the requirements of different roles.

Using the concept of Smart Working, the roles identified are not only PSM-specific and relate to Xu et al. (2018), who show that Industry 4.0 increases the number of diverse career paths, justifying emerging roles within other disciplines. This relationship between technology and new job roles is also illustrated by Malandri et al. (2021) within information and communications technology, describing emerging field-specific occupations. For example, the Data Analyst or Process Automation role may also exist within the customer interface of a firm, where sales and market data will be analyzed, HRM (Ulrich et al., 2013), or supply chain management (Liboni et al., 2019). Thus, the findings discussed above on PSM roles will shape the work organizations at the micro-level, e.g., the job description of PSM professionals in terms of skill requirements and responsibilities and also at a macro-level, e.g., organizational structures and allocation of people (Cagliano et al., 2019). Most procurement organizations are organized decentralized according to customer segments or category management (Monczka et al., 2015; Schiele, 2019). As discussed by the Delphi experts, these future roles in PSM must be implemented according to the functional objectives and organizational characteristics. The findings indicate that some flexibility will be required, for example, in a larger organization, a Data Analyst will work within one commodity area to improve strategic decision-making. However, smaller organizations will implement the role as a shared resource across categories or departments. These micro and macro-level changes will be significant challenges for managers in the future.

5.2. Managerial implications: managers benefit from identified roles to develop towards Smart Working

In a rapidly evolving technological landscape driven by digitalization, connectivity, cyber-physical systems, and automation, Industry 4.0 has implications for businesses, society, and people. Organizations are expected to benefit from recently introduced technologies by improving business processes and practices to increase operational efficiency and competitive advantage. However, organizations need to understand the implications and require guidelines on future developments to keep up with the rapid pace of technology developments and automation. The results presented in this research provide opportunities for standardizing managerial behavior by assigning specific professional roles that support technology implementation. These roles help managers implement technologies by focusing employees on specific tasks and responsibilities and the skills required to perform them. As developments in Industry 4.0 are incremental, a similar approach can be adopted when implementing the different roles identified in this research. In combination with the findings of Jones (2013) and Schiele and Torn (2020), these PSM roles can be implemented systematically to increase PSM maturity. Starting with PSM roles via a 'bottom-up' approach can create the foundations for the effective implementation of maturing and emerging technologies within PSM. This is critical, as such implementation depends on organizational characteristics such as the degree of process digitalization.

For larger organizations, higher levels of employee specialization are possible, as a single employee can take responsibility for one specific PSM role. In smaller organizations, it is more likely that one employee will need to take on multiple roles. Therefore, for educators and HRM within PSM, this role perspective is more valuable than analyzing specific skills, as each role requires a specific set of skills to allow employees to fulfill their tasks. As past research has focused on identifying roles according to PSM objectives or specialization (Delke et al., 2023; Schiele, 2019; Faes et al., 2001), new roles need to be added, and existing roles may change due to technology implementation. Some existing roles could become redundant, and others see changes in their responsibilities and required skill sets. For educators, the challenge lies in equipping the current workforce and future PSM students with the necessary skills within Industry 4.0, and suitable methods need to be found to keep up with these rapidly changing requirements (Liboni et al., 2019). HRM within organizations will need to identify the roles required by their organizations, allocate employees accordingly and provide tailored training plans to meet the skill requirements of such roles.

6. Conclusion, limitations, and future research

In making its two main contributions of further exploring the four smarts of Industry 4.0 and how PSM roles can enable Industry 4.0 technology implementation, this paper addressed the research question: *What new professional roles in PSM emerge within an Industry 4.0 context?* The research results show that six specific roles of the Data Analyst, Master Data Manager, Process Automation Manager, Supplier Onboarding Manager, System Innovation Scout, and Legislation Specialist will be needed. The field of PSM has received increasing strategic attention due to its significant contribution to an organization's performance. However, the emergence of new technologies may mean that there will be more specialist and fewer generalist roles emerging as they become less relevant. Even today, PSM professionals are highly skilled and specialized in their tasks, and Industry 4.0 will accelerate this specialization as new roles emerge and old ones change due to technology implementation. To meet these requirements, specific responsibilities and skills for each role need to be compiled. This can be illustrated by the example of a soccer match broadcast, in which there is often one reporter in the role of live commentator and another acting as an analysis expert, with both having some common competencies in terms of soccer expertise. However, the competence profile of the live commentator needs to be complemented by rhetorical skills, while the analysis expert benefits from other analytical, statistical, and database skills. The same principle applies to PSM, which has evolved in recent years and in which there is not just a single type of practitioner, as, depending on the size of the organization and other factors, they fulfill more than one role. This is also clear in the soccer analogy: in a less important match, the commentator covers both the role of live commentator and analysis expert. In Industry 4.0 Smart Working, we can expect a combination of specialization and technical support for practitioners. The Data Analyst role described in this study is performed by an expert who has the required data analysis skills and familiarity with the corresponding system infrastructure. Their responsibility is to analyze PSM data to support PSM projects and strategy development. As discussed in 5.2, the added value of this role perspective for PSM managers and HRM is seen in the practical feasibility and smooth implementation of Industry 4.0 technologies.

As with any research, this study has limitations due to the research method applied. The Delphi method is limited to the experts' knowledge and their judgment on how technologies impact the field of PSM, and, as this is a future-oriented study, the identified role projections cannot be assumed to represent reality. However, to compensate for potential bias and improve the research outcomes, the expert group included practitioners and academics with experience in skills and competencies for PSM and knowledge of digitalization or Industry 4.0 in the field. As this Delphi study engaged 47 participants, some generalizability can be assumed, but future research should be on a larger scale, e.g., a significant survey study, to improve generalizability. Also, the Delphi study is influenced by the facilitator's involvement, as they interpret the expert's qualitative justifications to improve studies and facilitate a group to reach a consensus, which could influence the study results. The software tool did not include all desired functionalities. For example, experts could provide written comments to other experts, so the researchers provided improvement suggestions to the software developer. As the suggested role of a Chief Happiness Officer in this research did not receive a sufficient consensus value, future research could investigate if a role that is responsible for human needs during the change process towards Industry 4.0 is actually required.

Besides the methodology-based suggestions for future research, there are also opportunities to research how the suggested roles could be implemented within organizations. Following the approach described by Cagliano et al. (2019), future work needs to understand how the above-described future roles will affect work organizations on a micro and macro level. On a micro level, future job descriptions will change based on the detailed set of skills needed to perform specific tasks in PSM and to complement research in other fields such as Dornelles et al. (2022). Therefore, future research needs to identify these skill sets for each role to organize HRM in PSM and education (Jones, 2013; Faes et al., 2001). Bals et al. (2019) provide a foundation of PSM skills that could be allocated to the identified PSM roles. This will then guide how future and current PSM professionals can be educated and trained in specific roles, allowing for a higher level of specialization (Delke et al., 2021; Pekkanen et al., 2020; Ulrich et al., 2013). As this research focuses on the influence of new technologies on PSM roles, future research needs to address the implication of content changes within the field. For example, specific roles will be needed to identify product innovation and sustainability within PSM (Schiele, 2010; Schulze and Bals, 2020). Further, on a micro level, future research is needed to understand which technologies will impact specific tasks in PSM and how these affect the capabilities of professionals. Dornelles et al. (2022) identified how fifteen technologies impact manufacturing workers' tasks and activities, as well as their capabilities, showing technology's positive and negative impacts. Detailed studies on performance increase and the specific nature of their changing tasks across the PSM process due to technology are needed to fully understand the potential of technology-enhanced work or Smart Working in the PSM domain.

On an organization's macro level, the suggested future roles will reshape the organizational structure and allocation of people in the procurement function. Future research needs to understand how people and talent in the procurement department are distributed. Where roles may be shared as support staff to improve operative processes or strategic decision-making. In addition, the suggested roles could be explored in conjunction with a maturity assessment, as not all roles will be implemented within different PSM maturity stages. As identified by the Delphi experts, the importance or combination of roles in an organization will depend on context-specific organizational characteristics and objectives. The capabilities and responsibilities of roles will depend on the availability of technology within a given organization. For example, the Data Analyst role is based on internal data availability, which is likely to be more limited in lower-maturity organizations, but more data may be available from external sources (e.g., suppliers). Although this research addresses the implications of Industry 4.0, scholars have started to address the wider impact of the emergence of the next generation of Industry 4.0 (Sigov et al., 2022). A detailed perspective on which future technologies will impact Smart Working beyond Industry 4.0 is a different area of research that could fruitfully be explored.

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CRediT authorship contribution statement

Vincent Delke: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Holger Schiele:** Conceptualization, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition. **Wolfgang Buchholz:** Conceptualization, Writing – original draft, Supervision, Funding acquisition, Writing – review & editing. **Stephen Kelly:** Methodology, Investigation, Writing – original draft, Writing – review & editing, Funding acquisition.

Data availability

Data will be made available on request.

Appendix 1. Detailed questionnaire, example Data Analyst

ROLE: "The Data Analyst in purchasing is responsible for extraction and analysis of purchasing data to support the preparation of commodity strategies and complex purchasing projects."

1. Agreement with name and description of the "Data Analyst" role
   - Quantitative assessment based on a metric scale of 0–100 %
     - 0 % - disagree ← neutral → 100 % - agree
   - Qualitative assessment based on a written comment
     - Experts can rate their agreement with other experts comments
2. Expected probability of occurrence of the role "Data Analyst"
   - Quantitative assessment based on a metric scale of 0–100 % based on a metric scale of 0–100 %
     - 0 % - Not probable ←→ 100 % very probable
   - Qualitative assessment based on a written comment
     - Experts can rate their agreement with other experts comments
3. **Desirability of occurrence of the role "Data Analyst"**,
   - Quantitative assessment based on a 5-point Likert scale
     - 1 – Very undesirable; 2 – Undesirable; 3 – neutral; 4 – Desirable; 5 – Very desirable
   - Qualitative assessment based on a written comment
     - Experts can rate their agreement with other experts comments
4. **Impact of the role "Data Analyst" on purchasing and supply management (PSM)**,
   - Quantitative assessment based on a 5-point Likert scale
     - 1 – Not impact; 2 – Low impact; 3 – Medium impact; 4 – High impact; 5 – Very high Impact
   - Qualitative assessment based on a written comment
     - Experts can rate their agreement with other experts comments
5. Which percentage of firms will have adopted the "Data Analyst" role today, in 5 years, 15 years and 25 years?
   - Quantitative assessment based on a metric scale of 0–100 %

- 0 % - not adopted ←→ 100 % - adopted
- Qualitative assessment based on a written comment
  - Experts can rate their agreement with other experts comments

6. **Additional question for clarification**:
   - For the description above, which name for this role fits the best?
   - We noticed that various participants assume a high adoption rate of the role Data Analyst. If you did implement this role within your organization, please let us know how you implemented this role.

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