The integration of data management in the roles of purchasing professionals

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ABSTRACT,
The research in this bachelor is intended to contribute to the field of purchasing by exploring how data management can be integrated into the roles of purchasing professionals. Previous studies have identified seven potential future professional purchasing roles. Two of those roles are concerned with components of data management, being: the master data manager and the data analyst. However, little is known about how these roles can be implemented within an organization to further support data management. A multiple case study, involving eight manufacturing organizations, was conducted to explore how data management can be integrated into the roles of purchasing professionals. Based on the study, a model was developed that outlines how the eight industries desire purchasing data management to be. The model builds on existing literature as it gives more information about how the master data manager and data analyst could be stationed within an organization. Furthermore, the two roles are given more shape as objectives, activities, and desired skill and competency profiles were formulated. Through the implementation of the developed model, data management can be integrated into the roles of purchasing professionals.

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Keywords
Purchasing and Supply Management, Purchasing roles, Industry 4.0, Big Data, Data Management, Data Analytics

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1. INTRODUCTION

New challenges, e.g. more flexible and personalized demand, and intensified competition have driven companies to adopt advanced technologies within their operations to improve smart manufacturing (Lin et al., 2018, p. 1). The introduction and adoption of advanced technologies are merged into one term: Industry 4.0. The concept was first introduced by the German government at the Hannover Fair in 2011 as a high-tech strategy for 2020 and represents the fourth industrial revolution (Rojko, 2017, p. 1; Frank et al., 2019, p. 15; Birkel and Muller, 2021, p. 1). There are many different definitions of Industry 4.0. Important aspects that are almost always present in the different definitions are the vertical and horizontal integration of information and communication technologies, cyber-physical systems, advanced digitalization and automation, smart industry, and real-time interactions between people, products, and devices during the production process (Lin et al., 2018, p. 589; Zhou et al., 2015, p. 2149; Dalenogare et al., 2018, p. 383; Frank et al., 2019, p. 15). All aspects describe a merge of physical and digital worlds. For that reason, the definition of Schiele and Torn (2020, p. 507) will be used within this thesis. They define Industry 4.0 as: *"The merging of the physical and digital worlds by means of cyber-physical systems (CPSs) and autonomous machine-to-machine communication."* The definition of Schiele and Torn (2020) emphasizes a decrease in interpersonal communication and an increase in digital communication and data traffic. This is in line with Oussous et al. (2018, p. 432), who state that Industry 4.0 technologies are causing an increase in large volumes of varying data or Big Data. Oussous et al. (2018) also state that management of Big Data (*the ability to process, store, secure, and analyze data*) is expected to be an important aspect within Industry 4.0, as subtracted information from Big Data can be valuable. This suggests that mastering data management becomes an important aspect within the different organizational departments.

Throughout the years, the purchasing department has improved both in operational integration as well as in strategic influence (Mulder et al., 2005, p. 190; Kleemann et al., 2017, p. 11)[1]. Similar to the adoption of Industry 4.0 technologies, purchasing now plays a crucial role within an organizations' overall competitive performance (Castaldi et al., 2011, p. 983; Bals et al., 2019, p.1;). The increasing contribution of the purchasing department to an organization's competitive performance and effectiveness is, however, dependent on individual purchasing professionals and their skills (Stek & Schiele, 2021, p. 1). For that reason, it is important to increase the understandings on how the transformation towards Industry 4.0 will affect purchasing and, more importantly, the roles of purchasing professionals. Further, it is important to understand how the individual purchasing professionals can contribute to the transformation towards Industry 4.0 as this is currently unclear (Torn et al., 2018, p.1). This, since purchasing is expected to benefit greatly from new Industry 4.0 technologies and capabilities (Schiele & Torn, 2020, pp. 514-516). Examples are improved supplier identification and selection through artificial intelligence and improved supplier evaluation through advanced data analytics.

As described in the definition of Industry 4.0 of Schiele and Torn (2020), it is expected that the physical and digital worlds of the purchasing department will (further) merge (Bals et al., 2019). The merge of both worlds is happening through the implementation cyber-physical systems with which current purchasing activities can be automated and controlled (Glas & Kleemann, 2016, p. 62; Wu et al., 2016, p. 405; Gottge et al., 2020, p.8). Implementing cyber-physical-systems in the manufacturing- and purchasing process will cause for an increase in the amount of generated data/data traffic as new data connections between physical and digital entities are created (Deloitte, 2017, p. 6; Wu et al., 2016, p. 405; Monostori et al., 2014). An increased availability of data can, however, be beneficial to the purchasing department. This advantage can be gained through an important Industry 4.0 capability: (big) data analytics.

Data analytics is seen as an important Industry 4.0 capability as it enables purchasing professionals to improve their decision making, strategy development, operational efficiency, and/or financial performance by subtracting value from Big Data (Wang et al., 2016, p. 100; Geissbauer et al., 2016, p.8). However, Dai et al. (2020, pp. 3-4) state that implementing data analytics in manufacturing organizations is faced by challenges in data processing and storing. These two challenges are, along with data security and analytics, also components in the data management definition of Oussous et al. (2018).

The benefits of- and challenges to the implementation of data analytics in the purchasing departments of manufacturing organizations both emphasize the necessity and importance of the four components of data management of Oussous et al. (2018). As mentioned before, the purchasing department is increasingly reliant on individual purchasing professionals and their skills (Stek & Schiele, 2021, p. 1). However, no current professional purchasing roles are specialized in components of data management (Schiele, 2019). Also, little research has yet been done about the roles of professional purchasers within Industry 4.0 (Torn et al., 2018, p.2; Schiele & Torn, 2020, p. 509; Delke et al., 2021, p. 2, A). It is interesting to explore if, and how, the four components of data management can be integrated into the roles of purchasing professionals.

Based on the collected information, it can be stated that there is a need to gain insights into how data management can be integrated within the roles of purchasing professionals. When formulating the objective of the research, it is about the ultimately requested solution or answer (Van der Zwaan, 1995, p. 29) which connects the research objective to the research question. The research objective of this thesis is formulated as:

Mapping out how data management can be integrated within the roles of purchasing professionals in Industry 4.0.

The research question should be a precise indication of the insight that must be obtained to achieve the research objective (Van der Zwaan, 1995, p. 29). For that reason, the research question and sub research questions within this thesis are formulated as:

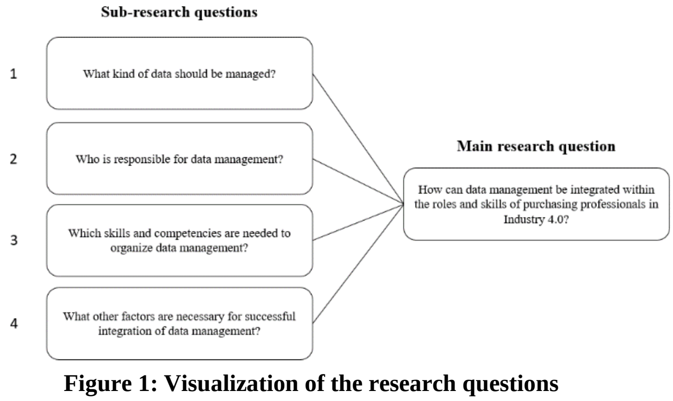

Figure 1: Visualization of the research questions

[1] The model can be seen in Appendix A

This research will contribute to the field of purchasing by exploring how data management can be integrated into roles of purchasing professionals. This is done through a qualitative explorative multiple case study. Findings from the study will be used to develop a model that outlines how manufacturing organizations desire purchasing data management to be. Further, more shape is given to the roles of purchasing professionals as new objectives, activities, and skills and competencies are identified. The model can be used by manufacturing organizations as an example or guideline for implementing the four components of data management through specialized roles of purchasing professionals.

2. THEORETICAL FRAMEWORK

2.1 Pre-Industry 4.0 purchasing

2.1.1 Various definitions '

At first, purchasing was solely perceived as the acquirement of input material (Cousins et al., 2008, p. 11). Since then, the responsibilities of- and opinion on purchasing have changed. Within the 1990s, purchasing began to collect recognition for being a strategic function with the ability to influence the competitive performance of an organization (Cousins et al., 2008, p. 14; Castaldi et al., 2011, p. 983). Although its importance increased, one true definition of purchasing was still missing. Klasa et al. (2018, p. 458) state that purchasing is only concerned with answering the following four questions: *What to buy? From who to buy them? How to buy them? How much to pay for them?* The definition of Monczka et al. (2015) on purchasing is in line with-, but more precise than the definition of Klasa et al. (2018). Monczka et al. (2015, p. 8) define purchasing as: *Buying goods and services while doing the 'five rights': the right quality, the right quantity, at the right time, for the right price, from the right source.* Purchasing is described most comprehensively in the definition of Schiele (2019, p. 48). He defines purchasing as: *The strategic and operative process of supplying an organization with materials and services from sources external to that organization.*

2.1.2 Current objectives, activities, roles, and competencies of purchasing professionals

Based on his definition of purchasing, Schiele proposes several objectives. Originally, purchasers were set with three core objectives: [1] ensuring safe, timely, and sufficient supply at [2] appropriate quality with [3] the lowest possible costs. However, based on the premises that suppliers are increasingly influencing a firm's prosperity, Schiele includes two new objectives: [4] facilitating a well-conditioned collaborative buyer-supplier relationship that allows for a free flow of innovations from and with suppliers and [5] ensuring competitive advantage to the firm by guaranteeing privileged access to sources of supply.

Schiele translated the above-mentioned objectives into a process model of purchasing activities that is visualized in Figure 2. One could argue that objective four is not covered by either strategic sourcing or operative procurement but perhaps creates a new area of expertise. For that reason, the model could be viewed as incomplete.

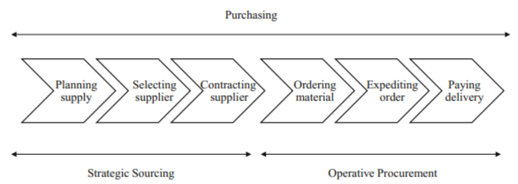

Figure 2: Purchasing activities according to Schiele (2019, pp. 48-49)

However, the core objectives (together with objective five), are included in his model. Hence, Schiele's model will be used within this paper as a visualization of the current set of purchasing activities.

Within his model, Schiele (2019) envisions seven different purchasing roles: [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, [7] other specialized roles, depending on the (size) company.

Important competencies areas, required for the in Figure 1 mentioned purchasing activities are: Technical skills, Interpersonal skills, Internal/External Enterprise Skills, and Strategic Business Skills (Tassabehji & Moorhouse, 2008; Bals et al., 2019, p. 6). Professional purchasers may have varying skill sets, depending on their tasks or specialization.

2.2 Transformation towards Industry 4.0 and its effect on the purchasing department

2.2.1 Concept of Industry 4.0

Generally accepted as the fourth industrial revolution, Industry 4.0 is making name for itself, and publications about the subject are rising quickly. Industry 4.0 entails the integration of ICT applications into an organizations' productional process to improve smart manufacturing. Important ICT applications are advanced sensor technology, improved computer science, the internet of things, communication technologies, and artificial intelligence technologies (Yan et al., 2017, p. 23484). The integration of these ICT technologies enabled a merge of the physical and digital worlds by means of cyber-physical systems, and autonomous machine-to-machine communication (Schiele & Torn, 2020, p. 507). The aim of Industry 4.0 is to create complete interconnection within all elements of an organizations' value chain that allows for the self-optimization of processes and products (Gröger, 2018, p. 2). This will, however, lead to an increase in the amount of generated data (Lee, 2015, p. 18; Yan et al., 2017, p. 23484; Oussous et al., 2018, p. 432).

2.2.2 Implementation of Industry 4.0 technologies and capabilities in the purchasing process

2.2.2.1 Cyber-physical systems

The advanced digitalization and automation of a business would also entail a change within the purchasing department. This is because purchasing professionals will be able to increasingly focus on strategic activities as simple operative activities such as ordering material and paying delivery will be automated through the implementation of new technologies (Gottge et al., 2020, p.8; Bals et al., 2019). One of the most important Industry 4.0 technologies that are used to automate activities and processes is cyber-physical-systems. Cyber-physical systems have the ability to create a connection/interaction between the physical and digital world (Monostori et al., 2014, p. 1). By deploying cyber-physical systems, an organization's physical infrastructure can be connected to a digital infrastructure which allows for improved (purchasing) process automation, control, and self-optimization (Wu et al., 2016, p. 405). This merge is in line with the previously mentioned definition of Industry 4.0 by Schiele and Torn (2020). An example of the use of cyber-physical systems in purchasing would be: triggering an automated order process of routine materials by connecting an organization's warehouse (physical world) to a purchasing system (digital world). Thus, automating (routine and simple) operative purchasing activities.

Connecting a physical world to a digital world through cyber-physical systems does, however, generate data (Wu et al., 2016,

p. 405). This, since new connections (data highways) are created between physical and digital entities through which data can traffic. Consequently, the implementation of cyber-physical systems will contribute to the amount of generated data within an organization's database. Thus, increasing the volume, variety and, velocity of data in an organization's database. The increasing volume, variety, and velocity of the generated data within an organization have also brought a new term to life; big data (Russom, 2011, p.6).

2.2.2.2 Data analytics

Data analytics is widely perceived as an important Industry 4.0 capability that enables the subtraction of valuable information from big data (Geissbauer et al., 2016, p.8). Subtracted information from big data can contribute to purchasing by improving decision making, strategy development, operational efficiency, and/or financial performance (Wang et al., 2016, p. 100; Deloitte, 2017, p. 7). For example, predictive analysis enables a more accurate forecast of demand on which purchasing strategies and processes, such as the one from Schiele (2019) from Figure 1, can be adjusted (LaValle et al., 2011, p. 26). Thus, improving the operational efficiency by increasing the supply efficiency. Other examples of the use of data analytics in purchasing are improved selection and management of suppliers (based on improved supplier evaluation; Schiele & Torn, 2020, p. 514), scenario thinking, and process optimization (LaValle et al., 2011, p. 26). Most benefits are obtained within strategic activities. For that reason, a (purchasing) data analyst will most likely be located/function before or in cooperation with strategic sourcing activities such as those mentioned in Figure 1.

Data analytics can also be integrated within cyber-physical systems. By integrating data analytics in cyber-physical systems, the self-optimization of automated purchasing activities is improved as problems and inefficiencies can be identified (Monostori et al., 2016, p. 624). Thus, again, improving the operational efficiency of (automated) purchasing activities and processes.

2.2.3 Changes in the required skills and competencies for purchasing professionals

In short, current purchasing activities are (further) digitalized and automated. In addition, (big) data analytics will be implemented. As a result, professional purchasers are required additional skills and competencies to deal with the current and upcoming changes (Bals et al., 2019, p.7; Delke et al., 2021, p. 7, B). Important new technical skills are 'Automation' and '(Big) Data Analytic skills'. Furthermore, the increasingly important strategic role and focus of purchasing have also caused 'Decision Making', 'Holistic Supply Chain Thinking', and 'Supply Network Management skills' to be added as new, important strategic business skills. Lastly, 'Strategic Management skills'. A skill needed to stay up to date with- and assess the possible contribution of current global trends (e.g. Industry 4.0 technologies and capabilities such as data analytics).

2.3 Need for data management in purchasing to take advantage of Industry 4.0 capabilities

A number of challenges have to be faced before one could benefit from the opportunities, offered by data analytics. As stated in the introduction, data management entailed the following four components: processing, storing, securing, and analyzing (Oussous et al., 2018, p.432). Two components of data management are identified by Dai et al. (2020, pp. 3-4) as challenges to the implementation of data analytics within manufacturing organizations, being: data processing and storing. This, since the increasing volume, variety, and velocity of data within an enterprise makes it harder to ensure data quality and correctness (Kumar Das & Mishra, 2011, p. 129; Deloitte, 2019, p. 33; Najafabadi et al., 2015, p. 2). Thus, to ensure data quality and correctness of purchasing data, all components of data management must be integrated within purchasing and the roles of purchasing professionals. This in turn would lead to an additional objective and activity to the current purchasing model in Section 2.1; *Managing Data*.

2.4 Integrating components of data management in roles of future purchasing professionals

2.4.1 Why the different components of data management should be integrated into specialized roles

Based on the work of Jones (2013), Delke et al. (2021, A, B) have illustrated the concept of roles within an organization. This illustration can be seen in Appendix B. Within the illustration, roles are defined based on job descriptions, the organization's function, and required/specific skills. As mentioned previously, data management entails the processing, storing, securing, and analysis of data. Each component containing its own objective, activities, and required/specific skills. For that reason, a focus should be put on integrating data management in specialized purchasing roles rather than just implementing skills, technologies, or capabilities.

2.4.2 Comparing current and future roles of purchasing professionals

Within their research, Mulder et al. (2005, p. 192) identify four jobs within the purchasing profession; Assistant Buyer, Buyer, Senior Buyer, and Purchasing Manager. However, it could be argued that these job titles should only be viewed as purchasing ranks or hierarchy indicators as they do not specify tasks or specialization.

Differing from Mulder et al. (2005), Schiele (2019, p. 53) identified seven specialized purchasing roles, being: [1] *Operational procurement,* [2] *Purchaser of direct material/serial purchaser,* [3] *Purchaser of indirect materials,* [4] *Public procurement,* [5] *Purchasing Engineer*, [6] *Chief purchasing officer*, or [7] *other specialized roles* such as *Purchasing controller*, *Supply risk manager* or *Purchasing human resources agent*. However, none of these roles specialize in specific, data management-related, Industry 4.0 activities, or requirements.

The Persist IO3 (2021) paper and Delke et al. (2021, pp. 7-8, A) have analyzed existing literature about future roles of purchasing professionals. In total, seven future professional purchasing roles were identified; [1] *Process Automation Manager,* [2] *Data Analyst,* [3] *Chief Happiness Officer,* [4] *Supplier Onboarding Manager,* [5] *Master Data Manager,* [6] *System Innovation Scout,* and [7] *Legislation Specialist*. Two roles have responsibilities that are included within the data management definition of Oussous et al. (2018). These two roles are the Data Analyst and the Master Data Manager. It is interesting to identify if, and how, these roles are desired by the interviewed manufacturing organizations.

Deloitte (2019, p. 26) stresses, however, that implementing new digital technologies, such as advanced data management and data analytics, is a collaborative effort of both the purchasing department and the IT department. For that reason, the allocation of the two roles could differ between organizations. How the two roles are allocated within organizations is not mentioned within the papers of Persist IO3 (2021) and Delke et al.(2021, A).

2.4.3 The strategic role of the Data Analyst

The data analyst embodies the integration of data analytics into a role of a professional purchaser. Delke et al. (2021, A), define the role of the Data Analyst as: *"Responsible for extraction, analysis, and interpretation of purchasing data to support the* *preparation of commodity strategies and complex purchasing projects."* The extraction, analysis, and interpretation of data could be descriptive *(what happened?)*, predictive *(what could happen?)*, and/or prescriptive *(what is the best outcome given a circumstance?)*, and is most likely used for operations analysis, predictive modeling, forecasting, visualization, and optimization (Russom, 2011; Ittmann, 2015, pp. 4-5; Wang et al., 2016, 100; Deloitte, 2017, p. 4). Hypotheses can be formulated on the basis of the analyses with which decision making, strategy development, operational efficiency, and/or financial performance can be improved (Wang et al., 2016, p. 100).

Based on its job description, desired skills for the role of Data Analyst would be: 'Big Data Analytics', 'Computer Literacy', 'Critical Thinking', 'Business Acumen', 'Strategic Thinking', 'Holistic Supply Chain Thinking', and 'Supply Network Management skills' (Tassabehji and Moorhouse, 2008; Bals et al.,2019, p. 7; Delke et al., 2021, p. 7, B).

Delke et al. (2021, B) and Deloitte (2017) both emphasize how data analytics, and thus the Data Analyst, can contribute to the growing strategic influence and importance of purchasing, as visualized by Kleemann et al. (2017, Appendix A).

2.4.4 The supporting role of the Master Data Manager

Ensuring the accuracy and quality of data correctness is essential to the implementation of data analysis. Two aspects for which Delke et al. (2021, A) envision the role of the master data manager to be responsible. They define the role as: *"Responsible for the alignment between the physical and digital world and ensuring data correctness and up-to-datedness."* Implementing Master Data Management (MDM) would entail the usage of applications and technologies to process, consolidate, clean, and augment corporate data to synchronize it with all business applications, processes, and analytical tools (Kumar Das & Mishra, 2011, p. 130; White et al., 2006, p. 2). The MDM aims to create an unambiguous understanding of a company's core entities (Otto & Reichert, 2010, p. 107) that would support further data analysis.

Based on its job description, desired skills for the role of Master Data Manager would be: 'Computer Literacy', 'Structured Way of Working', 'Business Acumen' (Tassabehji and Moorhouse, 2008; Bals et al.,2019, p. 7; Delke et al., 2021, p. 7, B)

3. METHODOLOGY

3.1 Research Design

As discussed in the introduction, this thesis aims to map out how data management can be integrated within the roles of purchasing professionals in Industry 4.0.

Little is yet known about the roles of purchasing professionals in Industry 4.0 (Schiele & Torn, 2020, p. 501) and for that reason, this research is exploratory (Van der Zwaan, 1995, p. 43). According to Yin (2003, p. 7), the use of case studies is a preferred exploratory research method in answering a "how" or "why" question. Still, a choice must be made between a single- and a multiple-case study. In this thesis, a multiple case study is preferred over a single case study because the use of multiple case studies enables an exploration of differences and similarities within and between cases (Yin, 2003). Finding similarities between cases increases the uniformity of the answer to the main research question. Furthermore, according to Baxter and Jack (2008, p. 550) evidence created from a multiple case study is measured stronger and more reliable compared to a single case study.

This research relies on the in-depth response to interview questions by participants to understand their beliefs, experiences, and attitudes on how data management can be integrated within the role and skills of purchasing professionals in Industry 4.0. Therefore, this research can further be defined as a qualitative explorative multiple case study (Fossey et al., 2002, p. 723; Patton, 2005, p. 4; Jackson et al., 2007, p. 22).

3.2 Company selection, data collection method, and data analysis

3.2.1 Company selection

The aim of this thesis is to understand how the four components of data management can be integrated within the roles of purchasing professionals in Industry 4.0. In theory, Industry 4.0 entails the integration of ICT applications into an organizations' productional process to improve smart manufacturing. Consequently, the participating companies need to be manufacturing organizations in order to fit within the idea of Industry 4.0. No other requirements were given to the participating organizations as it is interesting to analyze what other factors might be of influence, motivation, or barrier to the integration of data management into the roles of their purchasing professionals within their organization.

3.2.2 Data collection method

As mentioned earlier, this research is conducted to understand participants' beliefs, experiences, and attitudes towards integrating components of data management into the roles and skills of purchasing professionals. Jackson et al. (2007, p. 25) state that open-ended interviews are a preferable qualitative data collection method to grasp such an understanding. This, since open-ended interviews allow for more flexibility and responsiveness for both the interviewer and the respondents. Open-ended interviews are also recognized by Patton (2005, p. 4) as one of three main qualitative data collection methods. In-depth open-ended interviews can either be semi- or unstructured (Jackson et al., 2007, p. 25). This depends on whether or not the questions are based on previously acquired knowledge. Because the interview questions in this research are based on previously acquired knowledge, the interviews can be labeled as semi-structured (Kallio et al., 2016, p. 2954).

The in-depth responses to the interview questions are used for answering the sub-research questions. For that reason, the sub-research questions should be translated into interview objectives with which interview questions can be elaborated. The translation of the sub-research questions led to the formulation of the following interview objectives:

- *Identify what kind of data needs to be managed*
- *Identify how responsibilities for the different components of data management are divided*
- *Identify which skills and competencies are required for the different components of data management*
- *Identify what other factors are essential to data management*

Interview questions were constructed, based on the above-mentioned interview objectives. A trial interview was conducted to test the questions and identify deficiencies. The trial interview was intended to improve the overall quality of the interview and its questions (Rabionet, 2011, p. 564). The final version of the interview can be seen in Appendix C.

3.2.3 Data analysis

If possible, the interviews were recorded. This allowed for a post-interview transcription. Due to security reasons, one interview was not recorded. To ensure validity, the transcription of the answers was checked by the interviewee during the interview. Once transcribed, the answers were coded using research-imposed coding (Baralt , 2002, p. 209). This involves categorizing data, collected in qualitative form, to enable quantitative data analysis.

The interview questions allowed for direct responses. Direct responses can be compared with which data categorization is enabled (Holton , 2007, p. 7). However, some responses may be indirect or unrelated to questions and thus could depend on the interpretation of the researcher. To ensure their validity, interpretations were questioned and verbally confirmed or rejected by the interviewee during the interview.

Findings from the multiple case study will be visualized in a cross-comparison table in Section 4. Analyses are made, on the basis of the table. Analyses concerning roles, objectives, activities, and skills are compared with the papers of Delke et al. (2021, A, B) as their research serves as the most recent literature on the roles and competencies of the Data Analyst and the Master Data Manager. The aim of the comparison is to identify similarities, differences, or additions.

Based on the analyses and comparisons, the sub-research questions will be answered. Together, the answers to the sub-research questions will serve as an answer to the main research question with which the aim of the research is reached.

4. RESULTS

The results of the interviews are visualized within a cross-comparison table (see Table 1). Using a cross-comparison table is useful when examining relationships within data that would otherwise not be readily apparent (Aprameya, 2019). The table is organized according to the structure of the interview.

Figure 3 visualizes a developed tool with which present and available data within the company's databases could be categorized. The tool functions as a legend to Table 3 and is further explained in Section 5.1. Within Table 1 can be seen which data types and categories (as visualized in Figure 3) are currently present/available in the databases of the interviewed companies. Table 3 also shows from which data type/category the interviewed companies expect to see the largest change/increase in their database.

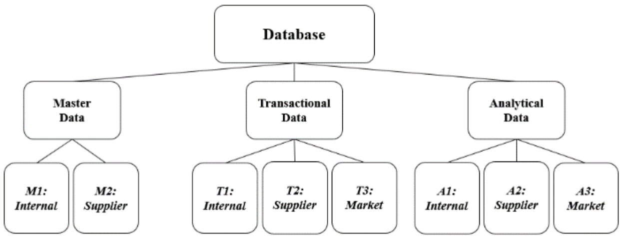

Figure 3: Enterprise data categories, based on the work of Vayghan et al. (2007

Table 1: Visualization of the answers to the interview questions by the interviewees

Subject	Question	Company 1	Company 2	Company 3	Company 4	Company 5	Company 6	Company 7	Company 8
General	***Total number of employees in company***	250<	250-500	250-500	250-500	250-500	500-1000	500-1000	>1000
	Total number of purchasing employees	4	4	8	12	15	15	25	50
Data	***Available Data***	M1, T1, A1	M1, M2, T1, T2, A1, A2	M1, T1, A1	M1, M2, T1, T2, A1, A2	M1, M2, T1, T2, T3, A1, A2, A3	M1, M2, T1, T2, A1, A2	M1, T1, A1	M1, M2, T1, T2, A1, A2
	Level of Digitization	Full	Full	Full	Full	Full	Almost full	Full	Almost full
	Change in Available Data	A1	M2, A2	M1, A1, M2, A2	M2, A2	M2, T2, A2, A3	M2, A2	M2, A2	M2, A2
Processing Storing Securing	***Responsible Department***	Purchasing	Supply Chain	IT	Purchasing	Purchasing	Purchasing and Finance	IT	Finance
	Skills and Competencies Master Data Manager	1, 2, 3, 4, 9, 10,	1, 8, 13, 16	1, 2, 5, 6, 7, 9, 11	1, 2, 4, 6, 9, 13, 19	1, 3, 5, 8, 11, 12, 16,	1, 4, 5, 6, 8, 14, 18	1, 2, 5, 7, 19	1, 2, 4, 5, 6, 12
	Essentials for successful implementation of data management	Safety and security of data Well-functioning systems Cooperation and dedication of all organizational departments	Well-functioning systems Routine checks of processes and database	Safety and security of data Well-functioning systems Creating standard input- and output processes	Well-functioning systems Cooperation and dedication of all organizational departments	Well-functioning systems Understanding a company's data management needs to avoid data overkill	Cooperation and dedication of all organizational departments Clarity about data management policies with supplier Data management must become part of business operations	Safety and security of data Well-functioning systems	Safety and security of data Cooperation and dedication of all organizational departments
	Presence of Purchasing Data Manager	No	Yes	No	Yes	Yes	No	No	Yes
Data Analysis	***Responsible Department***	Purchasing	Supply Chain	Purchasing	Purchasing	Purchasing	Purchasing and IT	Purchasing and BI Team	Purchasing
	Skills and Competencies Data Analyst	1, 2, 3, 10, 17	1, 2, 4, 6	1, 2, 3, 4, 6, 9, 15	1, 2, 3, 4	3, 4, 6, 10	1, 2, 3, 14	1, 2, 3, 4, 14	1, 2, 4, 6, 10

	Essentials for successful implementation of data analytics	Well-functioning systems Supplier information	Data integrity Complete database Utilizing the strategic purpose of Data Analytics	Well-functioning systems Complete database	Complete database Data integrity	Complete database Data integrity Having the time to do an analysis	Complete database Data integrity	Well-functioning systems Complete database Data integrity Understanding a company's data analysis needs to avoid data overkill	Data integrity Creating and using standard input- and output processes
	Presence of Purchasing Data Analyst	No	Yes	No	No	No	No	Yes	No
Usage of Data Analytics	***Internal, Supplier or Market***	Only Internal	Internal and Supplier	Only Internal	Internal and Supplier	Internal, Supplier and Market	Internal and Supplier	Internal	Internal and Supplier

*Skills and Competencies: [1] Computer technical skills [2] Broad knowledge of purchasing [3] Analytical thinking and skills [4] Strategic thinking [5] Understanding the needs of purchasers [6] Understanding the value of data [7] Translating data into information [8] Visualizing data [9] Understanding priorities between data (sets) [10] Broad knowledge of the company [11] Critical thinking [12] Creating connections between data (sets) [13] Creating a helicopter view [14] Communication skills [15] Translating data into useable reports [16] Accuracy [17] Market knowledge [18] Organizational skills [19] Automation

5. ANALYSES

5.1 Current state of databases and expectations about future changes

Categorizing business data is difficult because literature on the subject is small. Vayghan et al. (2007, p. 671) state that most enterprises contain three types of data, as visualized in Table 2. These three data types are also used by Haug and Arlbjørn (2010, p. 289). Because other options were scarcely available, the data types from Vayghan et al. (2007) were used to develop the legend in Figure 3, which acted as a tool for data categorization.

Table 2: Enterprise Data categories according to Vayghan et al. (2017)

Type of data	Definition	Example
Master	Data that defines primary business entities	Data about employees, products, customers, inventory, suppliers, and site
Transactional	Data that defines key business events, included in areas such as manufacturing, sales, purchasing, order management	Data, used at the moment of transaction concerning price, time, place, or payment method
Historical/analytical	Numerical values, metrics and measurements that provide intelligence and support decision making	Data concerning performance such as productivity, (re)liability, efficiency

Within a manufacturing supply chain, three (basic) primary roles can be identified: supplier, manufacturer, and customer. For that reason, a database could contain master data from three areas: internal, supplier(s), and customer(s). However, as defined in Section 2.1, purchasing is concerned with the strategic and operative process of supplying an organization with materials and services from sources external to that organization. For that reason, only internal [M1]- and supplier [M2] master data will be displayed in the legend in Figure 2. From Schiele's (2019) purchasing activities in Figure, M1 and M2 data is most likely generated by, and used for contracting supplier (supplier information) and ordering material (product information).

According to Vayghan et al. (2007), transactional data is produced through key business events within or between enterprises. Transactional data is mostly generated by the following purchasing activities from Figure 1: ordering material and paying delivery. Two enterprises, and their accessory transactional data, are of main interest to purchasing; their own and that of their supplier. However, transactions (can) also take place on the market. Market transactions could, for example, add value to purchasing by providing insight into trends that are related to commodity prices. Consequently, within this thesis, transactional data is further divided into three categories: internal [T]), supplier [T2], and market [T3].

Lastly, based on transactional data, an enterprise could develop analytical data with which purchasing professionals can improve their decision making, strategy development, operational efficiency, and/or financial performance. From the purchasing activities in Figure 1, analytical data is most likely used for planning supply and selecting suppliers. Because it is based on transactional data, analytical data is also related to trends or performances in one of three categories: internal [A1], supplier [A2], and market [A3].

The above-mentioned data categories are most often structured or semi-structured (Negash, 2004, p. 180). Structured data can be defined as data that is assigned to dedicated fields and that can thereby be directly processed without further computing (Baars & Kemper, 2008, p. 132). Semi-structured data can thus be defined as data that is partially assigned to dedicated fields and needs some computing before it can be processed. The structure of data is important as it can increase the difficulty level of (components of) data management.

Figure 4 has been developed on the basis of Table 1. Figure 4 visualizes to what extent the aforementioned data types and categories are currently present in the databases of the interviewed companies. Further, it visualizes how the interviewees expect the content of their database to change.

All databases contain M1-, T1-, and A1 data. The collective of those data types is therefore viewed as database-level one. However, from Figure 4 can be deduced that most of the interviewed companies are in a transition phase to a new, more advanced and diverse, database level. This transition phase encompasses the acquisition or further extension of M2-, T2-, and A2 data into their database. Several interviewees stated that the transition towards database-level 2 is based on their: *"desire to gain more insights into the (live) state of affairs of their suppliers"*. One interviewee indicated that the reason behind this desire is to decrease supply uncertainty. This could, in its turn, improve the operational efficiency of a purchasing department. The interviewees indicated that an important aspect within acquiring external data is the development and implementation of automated electronic data interchange (EDI) systems with suppliers.

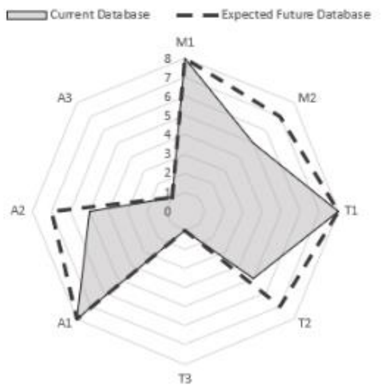

Figure 4: Visualization of the current state of the enterprise databases, and the expected state of the enterprise databases, based on the results from Table 3

Building on the above-mentioned desire, one could argue that a future transition could encompass the acquisition of T3- and A3 data. This would entail the creation of a third database level. Acquiring T3 and A3 data would allow companies to quickly adapt their overall strategy to sudden changes in the market that could improve their competitive performance (Koçoğlu et al., 2011, p. 1632). More specifically, T3 and A3 data could enable purchasing professionals to quickly adapt their strategy by providing information about changed commodity prices through scarcity or sudden changes in demand. Currently, only company 5 has included T3- and A3 data in its database.

The information gathered in this section, together with the analysis of the results of the interviews, can be used to answer sub-research question 1.

As the majority of the companies are in a transition towards a more advanced and diverse database, it is difficult to identify what kind of data currently needs to be managed. In contrast, it is possible to identify what kind of data needs to be managed in the future, as this scenario has been outlined by the interviewees themselves. As a result, it can be stated that, in general, the following data types will need to be managed: Master, Transactional, and Historical/Analytical. Further, based on the expectancies of the interviewees, it can be stated that not all companies will attain the same database level. However, the majority of the companies are expected to be in database-level 2. For that reason, it can be stated that the aforementioned data types, on average, will mostly concern internal and supplier-related data.

5.2 Division of responsibility of the different components of data management

This section is intended to identify how responsibilities for the processing, storing, securing, and analysis of the previously mentioned purchasing data are divided amongst the participating companies so as to identify potential differences. Also, to determine whether, or how, the roles of Master Data Manager and Data Analyst are currently present in the companies. In addition, it tries to establish an overview of expectancies for future, or desired, scenarios with regard to both the division of responsibilities as well as the presence of the specialized roles.

5.2.1 Data processing, storage. and security

From Table 1 can be stated that the division of responsibility for the processing, storing, and securing of purchasing data currently differs between the interviewed companies. In total, four different departments were identified as responsible; Purchasing, Supply Chain, IT, and Finance. The latter was somewhat unexpected. It did, however, become clear that the responsibility was most of the time in the hand of the department who initiated the implementation or development of the database systems. Nevertheless, a number of interviewees indicated that they would like to have a different division of responsibility with regard to the processing, storing, and securing of purchasing data. This, since the current division of responsibility can be vague or inefficient.

When asked, five interviewees stated that their company desired a general data management team. Such a team would be responsible for the development, control, and security of a company's database and digital infrastructure. It would function independently so that all wishes and requirements of the various departments in an organization are met.

Within the desired scenario of the five interviewees, a specialized role, being: the master data manager (MDM), would be placed in between the general database and an individual department. There, the MDM would function as an intermediary that is responsible for the processing and storing of data, generated by strategic and operational processes and activities, into a company's database to create a high-quality database. To do so, it was indicated that each specialized MDM should possess department-specific knowledge. Such knowledge was ought to be needed to be able to understand, compute, and categorize semi-structured data.

There is, however, no direct flow of data/information between the specialized purchasing MDM and the purchasing activities from Schiele's (2019) model. This is because all interviewed companies use ERP systems or systems that are equivalent to an ERP system. Generated data is sent to, or flows directly through those systems. For that reason, it could be argued that a specialized purchasing MDM is responsible for extracting, processing, and storing of purchasing data that flows through (equivalents of) ERP systems, into a general database. The desired scenario concerning the purchasing MDM is visualized in Figure 5. Currently, four companies have implemented a purchasing MDM role in a way that is similar to the developed model in Figure 5.

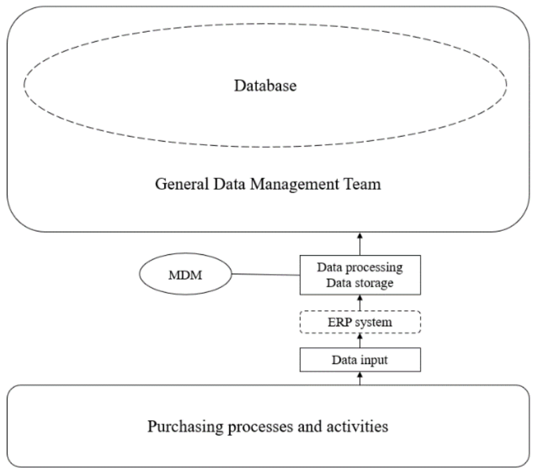

Figure 5: Desired future scenario concerning the division of responsibilities with regard to the processing, storing and securing of purchasing data

5.2.2 Data analysis

Contrary to the previous section, the division of responsibility with regard to data analysis is similar between the interviewed companies. It can be seen from Table 1 that the responsibilities are centered around the purchasing department. Nevertheless, three explainable differences were found. Firstly, within company 3, where the supply chain department is the overarching department of the purchasing department. Secondly, within company 6, where the responsible employee is located in between the purchasing- and IT departments. Lastly, within company 7, where the analysis of data, which is used for purchasing activities, is a combined effort of two employees, stationed in the purchasing department and the business intelligence team.

Similar to the previous section, six companies would desire an independently functioning general business intelligence team (BI). Such a team would be responsible for combining operational data with analytical tools to present complex and competitive information to planners and decision-makers. The objective of the BI team would be to support strategic and operational decision-making. However, several interviewees indicated that specific business knowledge is required to properly understand the information needs from the different departments. Without such knowledge, a BI team would be unable to understand which data needs to be translated into competitive information or what kind of output is desired. The interviewees suggested including specialized roles, such as a purchasing data analyst (DA), in the BI team. Each specialized DA would possess the required department-specific knowledge to better understand and support the operational and strategic decision-making of the individual departments.

Within Schiele's (2019) model from Figure 1, a specialized purchasing DA would most likely function before- and in cooperation with the strategic sourcing activities. In particular, planning of supply and selecting of suppliers. This, since those activities, would benefit most from complex and competitive information. The desired scenario concerning the BI team and the specialized purchasing DA have been included in the model from Figure 5. The new model is visualized in Figure 6. Currently, only two companies have implemented a purchasing DA role in a way that is similar to the developed model in Figure 6.

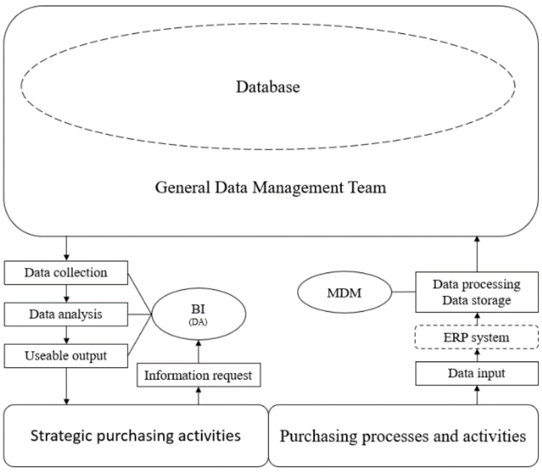

Figure 6: Desired future scenario concerning the division of responsibilities with regard to the processing, storing, securing, and analyzing of purchasing data

From the analysis in Section 5.2.1 and 5.2.2 can be stated that the majority of the interviewed companies would desire the developed model from Figure 6. Within this model, the responsibility for processing, storing, securing, and analyzing purchasing data is divided between the master data manager, the general data management team, and the general business intelligence team, respectively.

5.3 Needed skills and competencies to organize the different components of data management

This section is intended to map out which skills and competencies were deemed important, or necessary, by the interviewees to organize data management, as visualized in Figure 6. Within the model in Figure 6, three actors can be distinguished that are involved in carrying out the four components of data management, namely; the master data manager (*processing and storing*), the general data management team (*securing*), and the business intelligence team (*analyzing*). However, because the scope of this thesis is on the roles of purchasing professionals, only the skill and competency profiles of the master data manager and the data analyst will be formed. As stated in Section 2.3, the MDM and DA are viewed as roles. Each role requiring its own individual set of skills. Thus, the skills and competencies from Table 3 and 4 should be viewed as a combined set, rather than as individuals. It is interesting to identify whether or not the mentioned or desired sets of skills and competencies are in line with the tasks and objectives of the specialized roles, as visualized in Figure 6.

5.3.1 Skill and competency profile of the master data manager

A total of seventeen skills and competencies were considered important by the interviewees for the master data manager (MDM). The mentioned skills and competencies will be classified into the competency areas of Tassabehji and Moorhouse (2008) in Table 3. These areas were previously mentioned in Section 2.1. Percentages are visualized to emphasize that

Table 3. Skills and competencies deemed necessary by the interviewees for the master data manager together with the percentage of cases in which they were mentioned

Technical		Interpersonal		Internal/External Enterprise		Strategic Business	
Computer technical skills *	100%	Understanding the needs of purchasers	62,5%	Communication skills	12,5%	Strategic thinking *	50%
Knowledge of purchasing *	62,5%	Visualizing data	37,5%			Understanding the value of data	37,5%
Creating connections between data (sets)	25%	Translating data into information	25%			Understanding priorities between data (sets)	37,5%
Creating a helicopter view	25%	Analytical thinking *	25%			Critical thinking *	25%
Accuracy	25%					Broad knowledge of the company	12,5%
Automation	25%						
Organizational skills	12,5%						

**Also identified by Tassabehji and Moorhouse (2008) and Bals et al. (2019)*

From Figure 6 can be stated that a purchasing MDM is responsible for the creation of a high-quality database that a general BI team (and the specialized data analyst) can use to support strategic and operational decision making. To create such a database, it could be argued that a purchasing MDM should be able to do three things: [1] understand where the collected data comes from, [2] understand what the data means, and [3] store the data in a way that is useable and efficient for strategic purposes.

Based on Table 3, a distinction can be made between two types of skills and competencies. The first type accounts for all MDM's whereas the second type is department-specific. Further, percentages are shown to visualize which skills and competencies are highly desired, but also to emphasize the importance of including fewer-mentioned skills and competencies in the formulated skill and competency profile. This, since these skills and competencies are sometimes forgotten but can be truly valuable. Also, because other skills and competencies might be dependent on or improved by them.

As indicated by the interviewees, the most essential skill for the MDM is computer literacy. A skill needed to understand and control organizational systems. Further, without it, a MDM would be unable to get access to or extract data from (equivalents of) ERP systems. Although labeled differently, the interviewees also desire a MDM to have numerous basic (technical) organizational skills. For instance, they expect a MDM to be able to create connections between data sets, create a helicopter view, and be accurate. However, as indicated by the interviewees, these skills and competencies alone won't bring true value to the data management process from Figure 6. To create and ensure a high-quality database, a MDM is expected to be able to understand where the data comes from and what the data means. This is where the first department-specific skill/competency comes to light. To understand where the data comes from and what it means, a MDM should have a broad knowledge of the entire organization and, more importantly, knowledge about the specific department, its activities, and processes. For example, understanding which activity from Schiele's (2019) model has generated the data. Such knowledge improves other skills and competencies. For instance: understanding the value of data and/or understanding/identifying priorities between data sets. Both are about looking critically at data. Furthermore, department-specific knowledge enables a MDM to compute and categorize semi-structured data. The combination of these skills and competencies further improve a MDM's ability to create and ensure a high-quality database.

The last step in the process of a MDM is to store data in a way that is useable and efficient for strategic purposes (e.g. BI team or purchasers). Thus, adjusting a database on the desires of strategic users. One interviewee indicated that communication skills are highly important in this step. This, since tailoring a database to the desires of a specific department can only be achieved through (extensive) communication. Finally, interviewees emphasized the importance of strategic thinking. A competency deemed necessary to understand how to adjust a database for strategic use.

5.3.2 Skill and competency profile of the data analyst

Nine skills and competencies were considered important by the interviewees for the DA. Similar to the previous section, the mentioned skills and competencies are classified into the competency areas of Tassabehji and Moorhouse (2008) in Table 4.

Table 4. Skills and competencies deemed necessary by the interviewees for the data analyst together with the percentage of cases in which they were mentioned

Technical		Interpersonal		Internal/External Enterprise		Strategic Business	
Computer technical skills *	87,5%	Analytical thinking *	62,5%	Communication skills *	12,5%	Strategic thinking *	62,5%
Knowledge of purchasing *	87,5%	Translating data into useable reports	12,5%			Understanding the value of data	50%
						Broad knowledge of the company	37,5%
						Broad knowledge of the market	12,5%

Also identified by Tassabehji and Moorhouse (2008) and Bals et al. (2019)

From Table 4 can be stated that there is an overlap between the desired skills and competencies for the MDM and the DA. However, a distinction between the roles is also made through the way the skills and competencies are used. On the one hand, the skills and competencies are used to translate data into information with which a high-quality database is developed and ensured (MDM). On the other hand, the skills and competencies are used to analyze the high-quality database in order to support strategic and operational decision-making (DA). For example, to support the strategic activities from Schiele's (2019) model in Figure 1. To do so, it could be argued that a DA must be able to do two things: [1] understand which data can support strategic and operational decision making, and [2] understand how to combine the valuable data with analytical tools. Similar to Table 3, percentages are shown to visualize which skills are highly desired, but also to emphasize the importance of including fewer-mentioned skills and competencies in the formulated set of desired skills and competencies. Also, to be able to compare the roles and perhaps identify how certain skills or competencies are more/less desired for one role compared to the other.

Several interviewees indicated that they expect a specialized purchasing DA to have strong knowledge of a purchasing process and its individual activities. Such knowledge would be needed to understand the information needs of purchasers. Thus, emphasizing the importance of analytical thinking. Also, it would be necessary to understand the strategic purpose/use, and thus, the value of data. Therefore combining strategic and analytical thinking with knowledge of purchasing. From Table 4 can be seen that all three aspects are highly desired by the interviewees. Even more so than for the MDM. This is because they see the added value of collaborating with or including, a DA in strategic purchasing processes and activities. Further, it is expected that a DA is able to combine operational data with analytical tools. This can be seen in the highly desired computer technical skills. Finally, one interviewee indicated that they also expect a DA to be able to communicate the data, or analysis, in a way that is understandable and useable by purchasers. Thus expecting a DA to understand specific output needs. This combines the ability to translate information into useable reports with communication skills.

The different use of skills and competencies by the MDM and DA are in line with the objectives and activities, formulated for both roles in Section 5.2. For this reason, it can be stated that the formulated skill and competency profiles are complementary to the model in Figure 6.

5.4 Necessary factors, needed for the implementation of data management

This section intends to map out which other essentials are deemed necessary by the interviewees for the successful implementation of the data management model from Figure 6.

5.4.1 Essentials for data processing, storage, and security

During the interviews, eight different essentials were mentioned for the processing, storing, and securing of purchasing data. These essentials are visualized in Table 7. Based on Table 7, it can be stated that the processing storing, and securing of purchasing data is dependent on three main areas of essentials. A secure and well-functioning system was thought to be the most important essential. According to the interviewees, the security of an organization's digital systems and data(bases) has become increasingly important as cyber-attacks occur more often than before. However, two interviewees made an important side note. They argue that data security can also form a barrier to data sharing and thus, indirectly, to potential advancements in a company's database level. It could also even affect the quality of their data analysis. Choices in the field of data security must therefore be carefully considered. Further, based on the developed model in Figure 5, it can be argued that the development of a high-quality database is a collaborative effort between all specialized master data managers and the general data management team. This idea is supported by the interviewees since cooperation between- and efforts of all departments is also considered essential. Finally, the development, use, and routine checks of standard input- and output processes and databases. As indicated by the interviewees, such processes are needed to ensure the quality of data(bases).

Table 5. Essentials for the processing, storing, and securing of purchasing data together with the percentage of cases in which they were mentioned

Essential	
Well-functioning systems	75%
Safety and security of data	50%
Creating and using standard input- and output processes	50%
Dedication of all departments	25%
Cooperation between departments	25%
Routine checks of processes and database	13%
Data management must become part of business operations	13%
Clarity about data management policies with suppliers	13%

5.4.2 Essentials for data analysis

As in Section 5.3, a distinction is made between the essentials in Table 7 and 8 in their purpose. The essentials from Table 7 are considered important for the development of a high-quality database. The interviewees indicated that a data analyst relies on a complete, high-quality database and well-functioning systems to support strategic and operational decision-making. This dependency was previously identified by Najafabadi et al. (2015), as mentioned in Section 2.3. Since data analysis relies on a complete, high-quality database and well-functioning systems, those three aspects were deemed most essential by the interviewees for the analysis of purchasing data. As a result, it can be stated that the essentials from Table 7 are considered important for the development of a high-quality database whereas the essentials from Table 8 are considered important for the support of strategic and operational decision making.

Table 6. Essentials for the analysis of purchasing data together with the percentage of cases in which they were mentioned

Essential	
Complete database	75%
Data integrity	50%
Well-functioning systems	25%
Supplier information	13%
Having the time to do an analysis	13%

6. DISCUSSION

6.1 Theoretical implications

Previous research on purchasing in Industry 4.0 has been focused on the implementation and possible benefits of new technologies in purchasing processes and activities (Torn et al., 2018), the identification of new Industry 4.0 purchasing roles (Delke et al., 2021, A), and in what way the transformation towards Industry 4.0 will affect the required skills and competencies of purchasing professionals (Bals et al., 2019; Delke et al., 2021, B). All combined provided the basis for this research.

The main objective of this research was to map out how data management can be integrated within the roles of purchasing professionals in Industry 4.0. This led to the formulation of the following research question:

How can data management be integrated within the roles and skills of purchasing professionals in Industry 4.0?

A model has been developed that outlines how data management can be integrated into the roles of purchasing professionals and thus answers the main research question. The model concerns the division of responsibility, objectives, activities, required skills and competencies, and other influencing/essential factors for the four components of data management. The model contributes to previous research in a number of ways. First, the different components of data management, as given in the definition of Oussous et al. (2018), have also been found in the results. Thus, confirming that the definition of data management of Oussous et al. (2018) also accounts for the purchasing department. Further, the research of Delke et al. (2021, A) is extended as more shape is given to two of their identified roles, being: the master data manager and the data analyst. This, since more clarity is created about their specific objectives, activities, and location within the organizational structure. The purchasing master data manager is located in between the purchasing department and the general database and is responsible for the processing and storing of data that flows through purchasing systems to create a high-quality database. The purchasing data analyst is part of a general BI team that is located in between the general database and the purchasing department and is responsible for combining data with analytical tools to answer the specific information needs of strategic or operational purchasers. Thus, supporting of, and contributing to strategic and operational decision making in the purchasing department. Finally, the research of Bals et al. (2019) and Delke et al. (2021, B) is confirmed and extended. Their research has identified several future/Industry 4.0 skills and competencies. Within this research, those skills and competencies were confirmed as they were also mentioned and deemed important by the interviewees. This research extends previous research as role-specific skill and competency profiles have been formulated.

6.2 Managerial implications

Numerous benefits of data analytics have been mentioned throughout this research. However, as stated before, data analytics is highly reliant on the quality and completeness of data. Thus, emphasizing the important role of data processing, storing, and securing.

The developed model in this research visualizes how these components of data management could be ensured so that the benefits of data analytics can be obtained. A model, to which the specialized master data manager and data analyst contribute significantly. The model can be used by organizations as motivation, example, or guideline for changing or improving data management in their purchasing department. Furthermore, this research can be used as a motivation or guideline for implementing the specialized purchasing roles of the master data manager and the data analyst. This can be done with the formulated objectives, activities, and skill and competency profiles of both roles.

7. LIMITATIONS AND FUTURE RESEARCH

First, this qualitative explorative research tried to gain a deeper understanding of how the different components of data management could be ensured within a purchasing department and in which way the specialized roles could contribute to it. However, due to the small sample size (eight participants), it can be stated that generalization of the developed model is currently impossible. For that reason, future research should focus on testing the qualitative outcome (developed model) by doing quantitative research (Queirós et al., 2017, p. 370). This will increase the generalizability of the developed model.

Further, all participating companies are based in and around the same region in the Netherlands (Twente region). This problem is partially related to the previously mentioned sample size. The outcome of this research could, unintentionally, have been influenced by the region. For that reason, further research should be conducted at a national, or even international, level to again, increase the generalizability of the developed model.

Finally, three interviewees had objections to the developed model. They stated that the implementation of a general data management or BI team would only be feasible when their company would grow. In their opinion, the amount of generated data in their companies is not large enough that a general data management or BI team is needed. Thus, the costs of implementing (one of) both teams, and their systems, would not outweigh the benefits. This challenge is also mentioned in the paper of Negash (2004, pp. 184-185). However, the model has been developed on the premise that the amount of (generated) data will grow as a result of the digitalization and automation of organizations and processes. For that reason, it could be argued that the model accounts for manufacturing organizations that are (about to be) dealing with big data. This is in line with Vargas-Solar et al. (2017, p. 336), who also state that the next generation of data management is needed to deal with increasingly large sets of data or big data.

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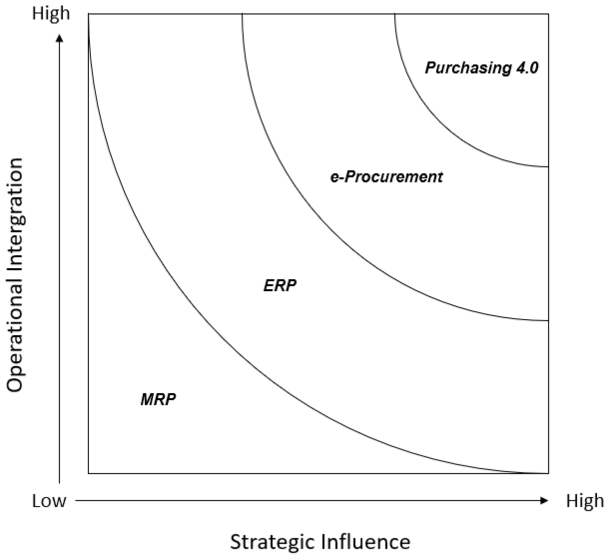
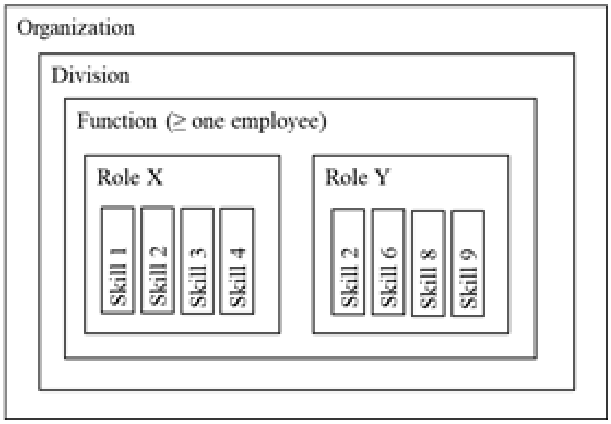
APPENDICES

Appendix A: Evolution of Purchasing according to Kleemann et al. (2017)



Appendix B: Illustration of the concept of roles within an organization according to Delke et al. (2021)



Appendix C: Interview

This interview serves as data collection for Ilco van Buuren's bachelor thesis at the University of Twente. The research is conducted within the Faculty of Behavioral, Management and Social Sciences and the Purchasing and Supply Management department. The purpose of this interview is to investigate how data management is currently applied/integrated within your organization. Also, it is tries to identify in what way your purchasing department would desire data management to be and what effect this has on the role and required skills of buyers. If permitted, the interview may be recorded. Recordings will be destroyed after completion of the research. Questions can be emailed to: i.vanbuuren@student.utwente.nl.

General

1. What is your function within the organization?
2. How many employees are there in your organization?
3. How many employees are assigned to the purchasing department?

Data

1. What kind of data is available/present within the purchasing department of your organization?
2. What are the different sources for the data? Are they internal or external?
3. To what extent are the sources digitalized?
4. Do you expect an increase, or change, in the amount of available data? And why?

A. Will the change (mostly) be within the amount of internal or external data?

Data processing/storage/security

1. Who are/is responsible for the collection, storage and accuracy of ‘purchasing’ data?
2. Are the responsible people assigned to a specific department? (e.g. IT or Purchasing or in-between)
3. In what way is purchasing data collected and stored?
    A. Which systems are used?
    B. Is each department interconnected within this system?
4. According to you, what are needed skills for a data manager of purchasing data?
5. According to you, what are essential aspects, needed for successful data management?
6. Do you expect a change in the way data will be collected and stored in the future?
    A. To what extent would this change the needed skillset for a data manager of purchasing data?
7. Would you desire a general data management team?

Data Analysis

1. Who are/is responsible for the analysis of purchasing data?
2. Are the responsible people assigned to a specific department? (e.g. IT or Purchasing)
3. According to you, what are needed skills to successfully analyze big data?
4. According to you, what are essential aspects, needed for successful implementation of data analytics?
5. Do you expect a change in the way data analytics is used within your organization?
    A. Will this affect the division of responsibilities or the needed skillset for the analysis of purchasing data?
6. Would you desire a general Business Intelligence team?

Implementation of data analysis in the purchasing department

1. In what way is data analytics used within the purchasing department?
2. In what way does data analytics contribute to the functionality and performance of the purchasing department?
3. In your opinion, to what extent has/will data analytics change(d) the role of purchasing professionals within your organization?
    A. Is there or will there be a change in the needed skillset?