AI-Enabled Automation

A Framework for Identifying a Company's Automatable Core Processes

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Abstract

Driven by advances in artificial intelligence (AI), the potential for process automation is increasing. AI-enabled automation allows to substitute for human labor in a widening range of tasks and provides substantial opportunities for profit growth. The goal of this research is to develop an analytical framework for the identification of business processes that are most beneficial for AI-enabled automation. The framework's underlying automatability-competence-matrix considers two variables to categorize business processes: (1) the extent to which a process is a core process and (2) its automatability. For each category, a distinct automation strategy is recommended. The proposed analytical framework is developed through an iterative design science research approach and is comprised of a core competence analysis and an automatability assessment. The core competence analysis builds on related literature, while the automatability assessment is a novel approach. To assess a process`s potential to be automated, the automatability assessment utilizes a dataset that provides information about the automatability of skills, knowledge, and abilities. Four simulations and three expert interviews were conducted to evaluate the design. While the core competence analysis was found to be capable of correctly evaluating processes, the automatability assessment revealed certain limitations. Such limitations were, e.g., subjective process ratings during the simulations or the inability to assess high-level processes. In the end, the core competence analysis and automatability assessment require different process levels to function correctly. It is suggested that future research consecutively examines a company's core competences on a high level, and then assesses the automatability of underlying processes on a lower level. This thesis contributes to theory and practice through the development of the automatability-competence-matrix, the design of a novel approach for estimating process automatability, and proposing an approach for identifying processes that are most beneficial for AI-enabled automation.

Keywords: Artificial Intelligence, Automatability Assessment, Core Competences, Automation Strategy

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List of Abbreviations

AI	Artificial Intelligence
ACM	Automatability Competence Matrix
DAX	Deutscher Aktien Index (German Stock Index)
DSR	Design Science Research
MRO	Maintenance, Repair & Overhaul
SME	Small and Mid-sized Enterprise

1 Introduction

1.1 Situation and Research Goal

Exponential growth in computing power (also known as Moore's Law) and big data technologies have empowered the spread of "artificial intelligence" (AI) during the last years (Duan, Edwards, & Dwivedi, 2019). It has an ever-increasing impact on everyone's daily life and the business landscape (Brynjolfsson & McAfee, 2012). Driverless cars, automated online assistants, and voice recognition are only examples where AI is beginning to substitute for human labor (Bruun & Duka, 2018). For a long time, automation was only possible for manual and routine tasks, but AI enables the automation of formerly non-computerizable tasks (Autor, 2015; Bruun et al., 2018; Frey & Osborne, 2017).

In academia and politics "technological unemployment" is widely discussed (Acemoglu & Restrepo, 2017; Autor, 2015; Frey et al., 2017; Jarrahi, 2018). Also, business managers face market disruptions enabled by AI, for example, in the realm of AI-enabled decision making or by utilizing data for market predictions (Duan et al., 2019).

A McKinsey Global Institute study revealed that in 2017, 95% of all companies did not embrace AI yet, even though it promises to be a profit uplift of up to 10% of revenue (Bughin, 2018). Therefore, Jacques Bughin concludes that "wait-and-see could be a costly AI strategy" (2018). In an annual survey, which was conducted by MIT Sloan Management Review, scholars found that many companies invest in AI or start AI pilot projects to develop new sources of business value (Ransbotham, Gerbert, Reeves et al., 2018). In fact, AI-enabled automation enhances performance, outcome, and quality, it helps overcome human limits and leads to faster innovation and business transformation (Manyika, 2017).

Even though managers are compelled to automate their business processes with intelligent machines and algorithms, it is difficult to decide where to start (Bughin, Chui, & McCarthy, 2017). Many factors from technological, strategic, social, and economic perspectives influence the decision. As resources are limited, corporate strategists, consultants, and CEOs need to decide where an investment in business automation is the most promising. With AI enabling a high paced progress in all kinds of automation technologies, there is a lack of a convenient and high-level framework for analyzing business processes.

The goal of this research is to design an analytical framework for identifying business processes that are most beneficial to be automated. Such an analytical framework is required to combine insights from technical developments in the field of AI-enabled automation with the discipline of strategic management. Within the framework, business processes will be classified according to their suitability for automation, on the one hand, and their strategic relevance, on the other hand. Ultimately, an automation strategy will be defined for each process category. This results in the following research question with four sub-questions:

Q: How to design an analytical framework for identifying business processes that are most beneficial for AI-enabled automation?

- **Q1: What is AI-enabled automation?**
- **Q2: What are the current capabilities and limitations of AI-enabled automation?**
- **Q3: What theoretical framework might be used to classify business processes and recommend an AI-enabled automation strategy?**
- **Q4: Which components define an analytical framework for the identification of business processes that are most beneficial for AI-enabled automation?**

1.2 UNITY AG

The master thesis research was conducted in cooperation with UNITY AG, a management consultancy for innovation and digital transformation. With its headquarter in Büren, Germany and over 250 employees worldwide, UNITY consults both SMEs, DAX-30 and EURO-STOXX-50 companies in topics such as future business, future production, future development, and new work.

As AI and business automation receive rising interest within all industries, UNITY enlarges its range of services within this field and actively promotes research. For that reason, UNITY supported the study by providing a company supervisor as well as access to its knowledge base, experts, and partner network.

1.3 Thesis Report Structure

After the research goal and cooperation company have already been elaborated, the following thesis report continues by laying the theoretical foundations for the analytical framework in Chapter 2. Relevant literature and scientific theories will be explored, which results in the theoretical framework as a basis for the analytical framework. Afterward, the Method Section provides details about the scientific approach. Here, the utilized design science research and the research model are elaborated. Chapter 4 summarizes the results of the study, which are the evaluation of the theoretical model and the analytical framework's design and simulation. In Chapter 5, the results will be analyzed, and future redesign options are developed. Lastly, Chapter 6 concludes the main findings and summarizes contributions to theory and practice, limitations of the research, and future research.

2 Theoretical Background

The theoretical foundations are structured as follows: at first, the literature search strategy is explained, which is followed by essential aspects of strategic management, namely resource-based view, sustained competitive advantage, and core competences. Afterward, AI, AI-enabled automation, and its limitations will be portrayed. Additionally, business processes and an approach to automation technology initiatives selection are shortly summarized. In the end, each distinct theory results in the overall theoretical framework, which constitutes the fundamental framework for the following research.

2.1 Literature Search Strategy

The literature search was primarily conducted by utilizing Scopus and Google Scholar. The two major fields of interest, strategic relevance and AI-enabled automation, have been analyzed separately. The idea of the resource-based theory and its derivatives emerged already in the early 1990s, which is why a vast amount of literature is available (a Scopus search for "resource-based view" renders 36,360 results). Therefore, it was primarily focused on foundational and often cited literature.

Table 1 Key Articles Strategic Relevance

Keywords	Article	# citations
"Competitive Advantage"	Barney (1991): Firm resources and sustained competitive advantage	16868
"Core Competence"	Prahalad and Hamel (1990): The core competence of the corporation	5158
"Resource-based theory"	Grant (1991): The resource-based theory of competitive advantage: implications for strategy formulation	2768

The literature search regarding AI-enabled automation was started by investigating the articles that refer to job automation. The numbers of publications demonstrate that after a high interest in job automation between 2002 and 2010, it took until 2013 for publications to surge again (see Appendix A). In 2013, the working paper by Frey et al. (2017), called "The future of employment: How susceptible are jobs to computerization?", was published and induced public interest. In the following years the number of publications increased, and, especially since 2017, a particular focus was set on job automation in combination with artificial intelligence (see Figure 1). Table 2 summarizes the keyword literature search results. As the number of articles is still very high, only those which have a high-ranked relevance have been analyzed and filtered according to their titles and abstracts. In the end, original and recurringly cited articles build the basis for the theory on AI-enabled automation.

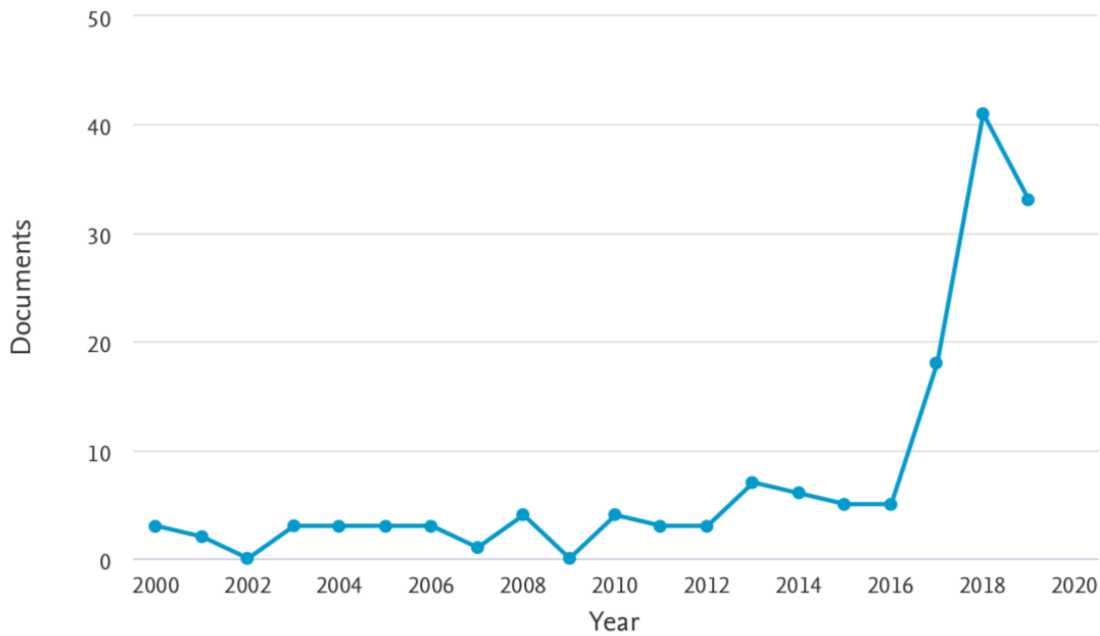

Figure 1 Publication Histogram: "Job" AND "Automation" AND "Artificial Intelligence", source: Scopus

Table 2 Key Word Literature Search Results

Keywords	# articles	2017-2019	Business or Economics
“Job” AND “Automation”	32,461	9,219	1,611
"Job" AND "Automation" AND "Artificial Intelligence"	183	92	23
“Business” AND “Automation” AND “Artificial Intelligence”	33,740	11,507	1,352
"Job" AND "Computerization"	2,864	1,109	463

For further specific aspects, the following search terms have been utilized:

- “Task” AND “Automatability”
- “Identification” AND “Core Competence”
- “Core Competence” AND “Firm Performance”
- “Automation” AND “Strategy”

2.2 Resource-based Theory, Sustained Competitive Advantage, and Core Competences

For choosing the most valuable business processes for automation, it can be drawn on research in the field of strategic management, because it provides many frameworks and approaches for analyzing a firm. Especially the research on competitive advantage can be utilized for identifying a company's value driver. According to Peteraf and Barney (2003), a company has a competitive advantage when it can create higher economic value. The decision, which business automation initiatives should be started, can be facilitated once it is understood where the value of a company originates.

Generally, there are two approaches to understanding a firm's competitive advantage (Barney, 1991). The first one is the external analysis of opportunities and threats of a firm through environmental models of competitive advantage. During the 1980s, the strategy was mainly the result of an extensive review of the external environment of a firm, for example, through Porter's five forces and competitive positioning (Barney, 1991; Grant, 1991; Porter, 2008). The second approach follows the resource-based view and is the internal analysis of a firm's strengths and weaknesses. Since the 1990s, there was increasing interest in the link between firm resources, skills, and the firm's strategy (Grant, 1991). Until today, resource-based view is a dominant theoretical approach in management research (Nason & Wiklund, 2018).

In the background of finding the firm's most valuable business automation initiatives, the theory will be limited to the internal analysis of a firm, and the external analysis will be excluded. Therefore, the main focus will lie on foundational contributions by Grant's resource-based theory of competitive advantage (1991), Prahalad and Hamel's core competences (1990), and Barney's sustained competitive advantage (1991).

2.2.1 Grant's Resource-based Approach to Strategy Analysis

The resource-based view of the firm is the basis for the often-cited resource-based approach to strategy analysis by Robert M. Grant (1991). Resources are input factors and can be classified as financial, physical, human, technological, reputational, or organizational. Grant argues that for the establishment of a competitive advantage against industry peers, it is crucial to use the resources more efficiently than competitors. These resources can either be used to develop a cost advantage or a differentiation advantage.

Furthermore, resources are the basis for capabilities, which are the abilities to perform certain activities by making use of the resources. These capabilities again are the sources of competitive advantage. It is necessary to assess the capabilities relative to those of the competitors to exploit one's relative strength (Grant, 1991). The idea of capabilities by Grant is closely linked to the core competence model by Prahalad and Hamel (1990).

2.2.2 Barney's Firm Resources as a Source of a Sustained Competitive Advantage

As well as Grant, Jan Barney (1991) builds on the resource-based view for developing criteria for sustained competitive advantage. According to Barney (1995), "resources and capabilities include financial, physical, human and organizational assets that a company uses to develop, manufacture and deliver products and services to its customers." He argues that due to the heterogeneity of the firms and their resources within an industry, a firm can have a sustainable competitive advantage. In contrast to a competitive advantage derived from a value-creating strategy, a sustained competitive advantage is defined through the impossibility of other firms to duplicate the competitive advantage.

Assuming the heterogeneity and immobility of resources, Barney developed four attributes (VRIN) that resources need to have as a source for sustained competitive advantage. In fact, during a meta-analysis, Crook, Ketchen Jr, Combs et al. (2008) found a significant correlation (r=.29) between VRIN resources and firm performance.

Firstly, resources need to be valuable (V). Valuable resources help to conceive or implement strategies that improve the firm's efficiency and effectiveness. Secondly, to be a source for a sustained competitive advantage, a firm's bundle of resources needs to be rare (R) among the competition. Otherwise, many competitors may find it easy to implement the same strategy. The third attribute is imperfect imitability (I) and reflects the unattainability of these specific valuable and rare resources by other firms. If other firms cannot reach these resources, they cannot imitate the strategy. The last attribute is non-substitutability (N), which refers to resources that cannot be replaced by other not rare or imitable resources. When a resource can be substituted by other resources, which themselves cannot be a source for a sustained competitive advantage, then the resource cannot be a source for a sustained competitive advantage as well (Barney, 1991).

2.2.3 Prahalad and Hamel's Core Competences

Prahalad and Hamel (1990) describe core competences as the roots of a corporation and as a collection of knowledge about the coordination of diverse production skills and technologies. With core competences, a company can adapt to changing environments and develop new core products, and with these core products, it can establish a new business (Yang, 2015). Even if the market then changes and the products become obsolete, it still has the same (or also enhanced) core competences to develop into a new direction (Prahalad et al., 1990). In that way, core competences, as established by Prahalad and Hamel, can as well be seen as a source of sustained competitive advantage.

Core competences especially find application in the process of strategic outsourcing, where firms increasingly concentrate on their core competence and pass on non-core competences to other firms (Boguslauskas & Kvedaraviciene, 2009; Quinn & Hilmer, 1994). Frameworks for the identification of core competences are, for example, developed by Hafeez, Zhang, and Malak (2002) or Boguslauskas et al. (2009).

2.3 Artificial Intelligence

Kaplan and Haenlein define AI as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (2019, p. 1). AI is a term that is considered to be found during the Dartmouth Summer Research Project on Artificial Intelligence in 1956 (Kline, 2010). Since then, scholars have been researching machines that demonstrate human-like intelligence (McCarthy, 1989), but initially, computers did not possess enough computing power to calculate complex tasks. After an initial hype for AI and the following "AI-winter" (McCorduck, 2004), it took until the '80s for the development of the first expert systems, which were the first truly successful form of AI (Russell & Norvig, 2016). The expert systems solved complex problems through a variety of if-then rules. Since the hardware then had enough storage capacity and was able to cope with complex calculations, data-supply became the limiting factor. A second AI-winter emerged, and the interest and funding for AI were low (McCorduck, 2004).

It took until the late 1990s and early 21st century until AI found application in a variety of domains (Russell et al., 2016), and since then, the success story of AI has not ended. Important milestones are, for example, the Jeopardy! match in 2011 (Markoff, 2011) or the win against the Go champion Lee Sedol in 2016 (Koch, 2016). By utilizing deep learning methods and neural networks, today, AI finds application in many parts of everyone's daily life and is the engine of further progress (Bruun et al., 2018; Brynjolfsson et al., 2012). Experts predict an immense transformational power of AI whose significant impact is yet to come. As a new type of general-purpose technology, it will drastically change core processes and business models across industries (Brynjolfsson & Mcafee, 2017).

2.4 AI-Enabled Automation

Frey and Osborne (2017) use the term "computerization" to describe the effect of "job automation by means of computer-controlled equipment" (p. 254). A more detailed definition is given by Wright and Schultz (2018), who define business automation as "a technique, method, or system of operating or controlling business processes by mechanical or electronic means that replaces human labor" (p. 824). This definition does not limit the means of automation to a specific technology. Additionally, the labor-saving objective is essential. Arguably, most technologies developed for the workplace had the goal to save human labor, e.g., through stronger machines (tractors), more consistent machines (assembly lines), or less error-prone tools (digital spreadsheets) (Autor, 2015).

Acemoglu and Restrepo (2018) observed that "robotics and current practice in AI are continuing what other automation technologies have done in the past: using machines and computers to substitute for human labor in a widening range of tasks and industrial processes" (p. 3). Here, Acemoglu and Restrepo differentiate between an "old" automation, and a "new" automation through AI and robotics, which allows for replacing humans in ever more activities. This new wave of AI-enabled automation is the origin of modern unrest about technological unemployment and the cause of a wide range of research related to job automation (Bruun et al., 2018; Duckworth, Graham, & Osborne, 2019; Manyika, 2017; Pfeiffer, 2018; Wright et al., 2018).

Therefore, within the context of this thesis report, the term automation refers to the new wave of AI-enabled automation and the widening possibilities of replacing human labor engaged with complex tasks. In that sense, AI-enabled automation is not limited to solely physical robot automation or the automation of solely cognitive tasks. It instead contains all aspects of human labor substitution empowered by artificially intelligent systems. This means they can interpret and learn from external data and have the capability to flexibly adapt to achieving a specific goal (see above: AI definition by Kaplan and Haenlein, 2019).

Looking at the business perspective of automation, companies achieve a positive impact of AI-enabled automation technology through efficiency increases, but automation also contributes to GDP growth per capita because it boosts productivity (Manyika, 2017). Manyika (2017) argues that automation provides benefits through better performance, outcome, and quality, it helps overcome human limits and leads to faster innovation and business transformation.

2.5 Limitations of AI-Enabled Automation

For being able to identify the processes most beneficial for automation, it is crucial to develop an understanding of what is automatable and what is not. Until now, AI-enabled automation is majorly looked at from macroeconomic perspectives to predict the influence of AI on employment (e.g.: Acemoglu et al., 2017; Arntz, Gregory, & Zierahn, 2017; Autor, 2015; Bruun et al., 2018; Frey et al., 2017; Pfeiffer, 2018). As these were focused on predicting what kind of activities and occupational groups are more susceptible to automation, the results will be transferred to the microeconomic level and used as a predictor for process automatability. Hence, this chapter serves to elaborate on what job automation researchers have identified as limitations of AI-enabled automation.

2.5.1 Classification of Routine / non-Routine and Abstract / Manual Tasks

Acemoglu and Autor (2011) were the first to separate tasks that were either routine or non-routine and between tasks that were either abstract (cognitive) or manual. They argue that computer-controlled equipment is highly efficient at performing structured tasks, which can be explicitly scripted by a programmer. According to Acemoglu and Autor, those tasks, which cannot be scripted, are not possible to be computerized.

Abstract or cognitive tasks are those, which require problem-solving, intuition, persuasion, and creativity. Hence, abstract tasks characterize managerial, technical, and creative jobs such as lawyers, doctors, scientists, engineers, designers, or managers. In contrast, manual tasks lie at the other end of the professional skill level and require less formal education. Nevertheless, Acemoglu and Autor argue that non-routine manual tasks are challenging to automate because they need adaption and response to unscripted interaction with the environment or with humans (Acemoglu et al., 2011).

2.5.2 Bottlenecks of Computerization

Frey and Osborne (2017) agree that routine manual tasks and routine cognitive tasks can well be automated, but they argue that with technological progress, especially in the fields of AI and robotics, many non-routine tasks can be automated as well. Activities such as driving a car, legal writing, and medical diagnosis are increasingly being automated with the help of AI. Therefore, they developed new criteria for explaining the automatability of a job. They define the bottlenecks of computerization as ‘perception and manipulation tasks,’ ‘creative intelligence tasks,’ and ‘social intelligence tasks’ (Frey et al., 2017).

Non-routine manual tasks are especially demanding to automate in unstructured environments because a computer would be required to analyze and handle a variety of irregular objects under potentially severe perception conditions. This is why perception and manipulation tasks, e.g., on a construction site, are more difficult to automate than in a logistics warehouse, which represents a thoroughly structured and controlled environment (Frey et al., 2017).

Creative intelligence tasks require to come up with ideas that are perceived to be novel and valuable. Even though there are some approaches to artificial creativity (DiPaola, Gabora, & McCaig, 2018), it appears to be unlikely that real creative intelligence will be automated soon.

Social intelligence tasks are those that require negotiation, persuasion, and care. Even though research takes place in this field (Skewes, Amodio, & Seibt, 2019), social interaction, real-time processing of human emotions, and adequate reactions to humans remain very difficult. Therefore, jobs that require much social intelligence are less prune to automation (Frey et al., 2017).

2.5.3 Inferring Work Task Automatability from AI Expert Evidence

Duckworth et al. (2019) recently surveyed 150 AI experts for estimations of which activities are automatable with today's technology. It is a follow-up research at the same institute as the Frey and Osbourne (2017) article. They made use of the O*NET database, which provides highly granular job data and breaks down occupations into numerical variables. By nowcasting the survey results onto the O*NET database, Duckworth et al. estimated the automatability of all work activities, tasks, and occupations in the database. Within the model, each occupation is represented by a feature vector comprising numerical ratings of skills, knowledge, and abilities. The O*NET database provides data about the feature ratings of each occupation from one to five. As part of their sensitivity analysis, Duckworth et al. generated gradients that demonstrate the automatability increasing or decreasing influence of the features. For example, an increase of an activity's rating in the feature called "Fine Arts" by one point leads on average to a decrease of automatability by 0.11 (Duckworth et al., 2019). The 25 most automatability-increasing and decreasing features across the activity space can be seen in Appendix C.

Such specific gradients leave the impression of absolute exactness, but in fact, they remain survey results extrapolated on a database, which naturally induces a certain degree of fuzziness. Different approaches often lead to diverging results: for example, the prediction of overall labor automation varies from 47% (Frey et al., 2017) to 14% (Nedelkoska & Quintini, 2018). Nevertheless, Duckworth et al.'s (2019) dataset is the most recent research in this field, and the quantified results allow novel research approaches. Therefore, this is a reminder that the numbers are estimations and might not perfectly represent reality.

2.6 Business Processes

Through the course of this thesis report, often, it will be referred to different process categories, -maps, -levels, and -decompositions. If required, an explanation of these terms can be found in Appendix E.

2.7 Automation Technology Initiatives Selection

Thomassen, Sjøbakk, and Alfnes (2014) developed a strategic approach for automation technology initiatives selection because existing models are time-consuming, require large computations and are challenging to use. After choosing a technology strategy and process/technology pairs, they propose a matrix that uses the variables "Ease of Implementation" and "Strategic Importance" to assess the pairs (see Figure 2). In that way it allows the decision for an automation initiative.

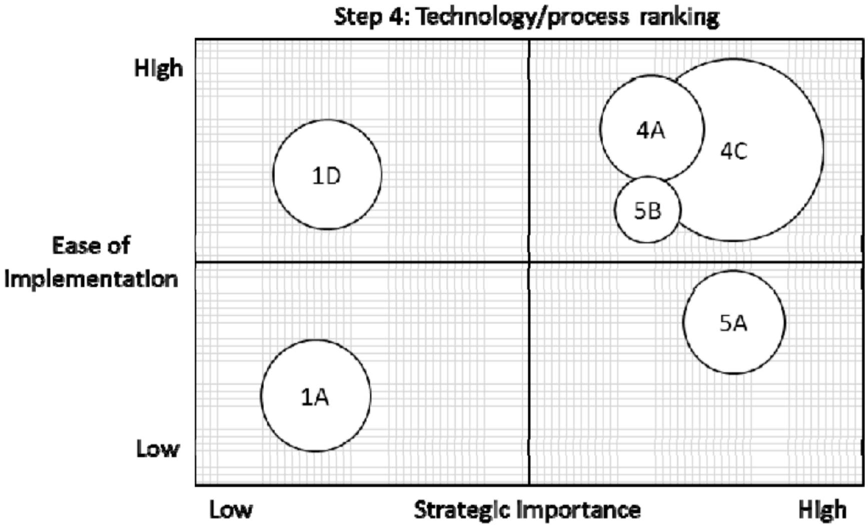

Figure 2 Technology/Process Ranking (Thomassen et al., 2014)

Thomassen et al.'s approach is very generic, and the variables' assessments are not specified, yet it can be adapted to fit the context of AI-enabled automation better. The variable "Ease of Implementation" strongly relates to the limitations of AI-enabled automation, and "Strategic Importance" can be further framed through resource-based theory.

2.8 Theoretical Framework

The theoretical framework for the analytical framework combines all theories that have so far been elaborated. The central concept is the alignment of the automation of business processes with strategic management through core competences. First, the theoretical framework itself will be explained, and afterward, it will be applied to an example from the insurance industry.

The focus on the resource-based view, especially the core competences, originates from the fact that it is internal-oriented and well applicable to the business process level. The framework offers precise requirements and characteristics, which can be well combined with the automatability analysis.

Other frameworks, such as the Business Model Canvas (Osterwalder & Pigneur, 2010), PESTEL (Yüksel, 2012), or Porter's Five Forces (Porter, 2008), are not applicable. For instance, in Business Model Canvas, specific processes only play a minor role, and the focus is very high-level. PESTEL and Porter's Five Forces, on the other hand, are external-oriented frameworks and only analyze a company's environment. Hence, those frameworks cannot be utilized. Another possible approach is the value chain analysis, which is as well an internal analysis and explains a firm's competitive advantage through differentiation or cost advantages (Porter, 2001). In the end, the resource-based view was still preferred over the value chain analysis as it allows an investigation on a lower level and provides more clear-cut analysis criteria.

2.8.1 Theoretical Framework Description

Business automation has the target of operating or controlling business processes without human labor (Wright et al., 2018), but some jobs are more straightforward to automate than others. The bottlenecks of computerization ('perception and manipulation tasks,' 'creative intelligence tasks' and 'social intelligence tasks') serve as an indicator for the automatability of jobs and processes (Frey et al., 2017). The more a process involves activities related to the bottlenecks of computerization, the more complicated its automation will be, and the lower is the "Ease of Implementation."

The resources of a firm can be seen as a source for core competences and sustainable competitive advantage if the resources fulfill the related criteria (Barney, 1991; Grant, 1991; Prahalad et al., 1990). Core competences are not limited to main processes; instead, managerial, main, and support processes can all be core competences.

To choose the best automation initiatives, companies should identify processes that have high ease of automation (high automatability) while delivering the best benefit for the business (strategic importance). Two arguments speak for the focus on core processes. Firstly, these processes hold the most significant incentive to be automated, because core competences are the source for sustainable competitive advantage, new products, and new services (Prahalad et al., 1990). Secondly, the distinct set of resources used for sustainable competitive advantages can, per definition, only be accessed by the firm itself (Barney, 1991). Hence, no other firm or subcontractor has either the incentive or the ability to automate that particular process. As a consequence, many non-core competences will be available as a commodity and as-a-service in the future, but the core competence of a firm needs to be automated in-house.

In the end, Figure 2 can be customized to AI-enabled automation by replacing "Ease of Implementation" with "Automatability," and "Strategic Importance" with "Core Competence." Both criteria for the analytical framework are visualized in the automatability-competence-matrix (ACM). It divides all processes under investigation into four quadrants with distinct strategic recommendations.

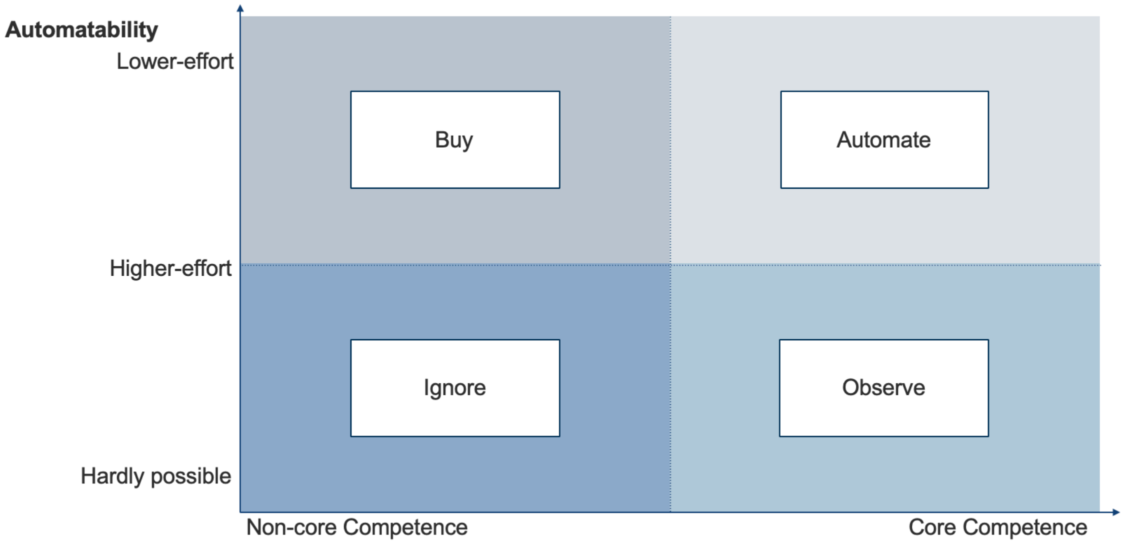

Figure 3 Automatability Competence Matrix (ACM), own figure based on Thomassen et al. (2014)

Automate: This category relates to all processes that the analytical framework recommends to automate in-house. For these processes, only the firm itself has the ability and incentive for automation, while the automation is relatively achievable.

Observe: These are the core processes that are not automatable, yet. Hence, technological progress needs to be observed as these processes might move from Observe to Automate over time.

Buy: Automatable non-core competences contain commodity processes that will probably be taken over by third-party firms, which are specialized in that particular process. Their services can be bought, which is comparable to conventional outsourcing.

Ignore: Not-automatable non-core competences might be ignored and stay as they are. After a certain time, they possibly will move to the Buy quadrant.

2.8.2 Example: Insurance Company

An example of tagging processes according to the ACM will be given for a fictitious insurance company. Along the value chain of an insurance company, exemplary processes are the recruitment of personnel, the calculation of new insurances and risks, customer administration, and sales.

Sales and actuary (risk calculations) might be found to be the core competences of the insurance company. Risk calculation, on the one hand, is necessary for ensuring the firm's profitability in the long-run, and usually, insurers have human resources, which are highly specialized for that task. Furthermore, the sales process of insurance firms heavily relies on their broad network of insurance agents and brokers, who promote and relationship sell the firm's products regionally (Hain, Rutherford, & Hair Jr, 2019). They are the centerpiece of the sales process. Even though customer administration and recruitment are critical processes, they are not a source for the sustained competitive advantage of the example company. Therefore, they are considered as non-core competence.

When looking at the processes' automatabilities, customer administration, and risk calculation show little relatedness to the bottlenecks of computerization. Customer administration is a process that is already well automated with customer relationship management software (Triznova, Maťova, Dvoracek et al., 2015), and risk calculation is a highly analytical and number-driven task (cf. Appendix I.2). Sales, on the other hand, especially personal selling through insurance agents, require high social intelligence. Therefore, its automation is many degrees more complicated than the risk calculation or customer administration.

The recruitment process is an excellent example of where process decomposition is required. Even though performing job interviews requires extremely high social intelligence, many recruitment processes (e.g., candidate sourcing) are already automated (Bischke, 2018). For analyzing the automatability of the recruitment, the process needs to be broken down into a lower abstractness. In this case, only job interviews will be placed in the Ignore quadrant of the ACM. The ACM with the exemplary processes can be seen in the following Figure:

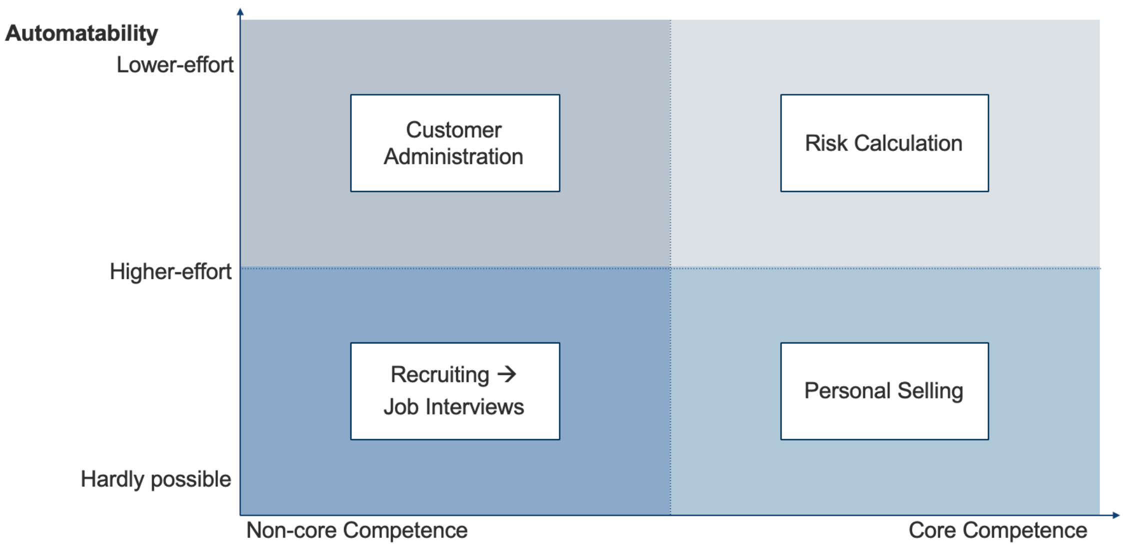

Figure 4 ACM Example: Insurance Company

3 Method

3.1 Design Science Research

Design science research (DSR) has its roots in the discipline of information systems and is increasingly used in many fields whenever the development of an artifact or model is the goal of the research (Thuan, Drechsler, & Antunes, 2019). Generally, when designing an artifact, DSR takes the related environment and knowledge base into account. The environment represents the business world and application domain, which provide their business needs to the design process. From the knowledge base, knowledge is extracted from all research fields that are relevant for the artifact. In that way, it is possible to develop artifacts that are designed to solve a particular problem. DSR is an iterative process, which requires constant evaluation of the designed artifact and the next redesign (Hevner, 2007).

Hevner (2007) describes DSR in three iterative cycles: a relevance cycle, a design cycle, and a rigor cycle. The framework can be seen in Figure 5, which is customized to the research.

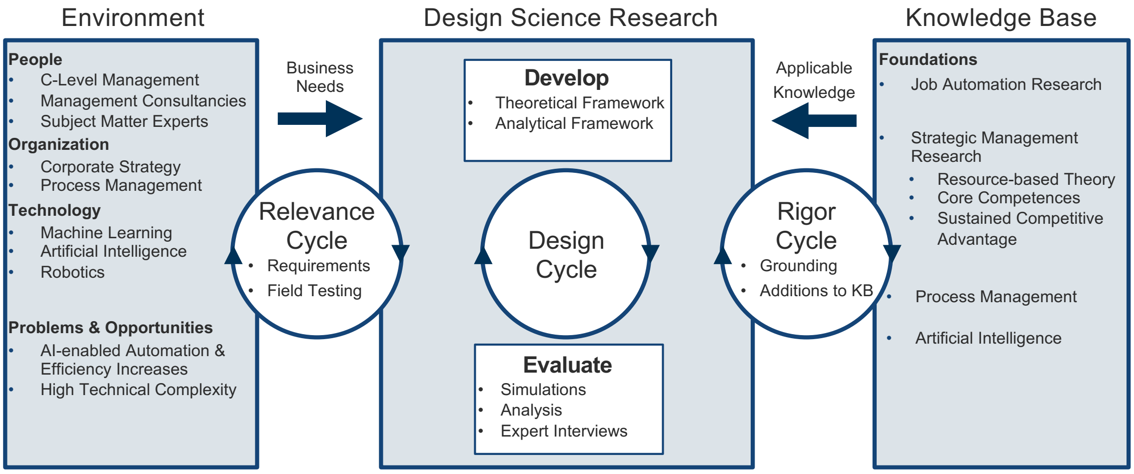

Figure 5 Design Science Research Cycles, adapted from Hevner (2007)

Peffers, Tuunanen, Rothenberger, & Chatterjee (2007) proposed a DSR methodology, which helps to structure DSR cycles. Depending on the research entry points, it defines the steps and iterations necessary to conduct DSR (see Appendix A).

Since this research was conducted in cooperation with UNITY AG, the demand for practical relevance is high. Additionally, Van Aken (2005) argues that there is a relevance gap in academic management research. Arguably, conventional deductive (testing a theory) or inductive (building a theory) business management research approaches can hardly be applied to answer design-related research questions. DSR has proven to be successful for explorative and solution-oriented studies (Peffers et al., 2007) and hence is well eligible for developing an analytical framework. Therefore, this research is structured according to the DSR cycles and methodology.

3.2 Research Model

Figure 6 provides a graphical overview of the research model derived from the iterative approach by Peffers et al. (2007) to ensure a rigorous framework design. The research started with a problem-centered initiation, which is elaborated in Chapter 1.1. The resulting research goal and research questions outline the objectives of the research.

The objectives of the analytical framework have been developed during a semi-structured interview with Strategy Expert 1 (see Appendix H). In that way, it was possible to integrate practical requirements directly from the start and to increase the artifact's applicability.

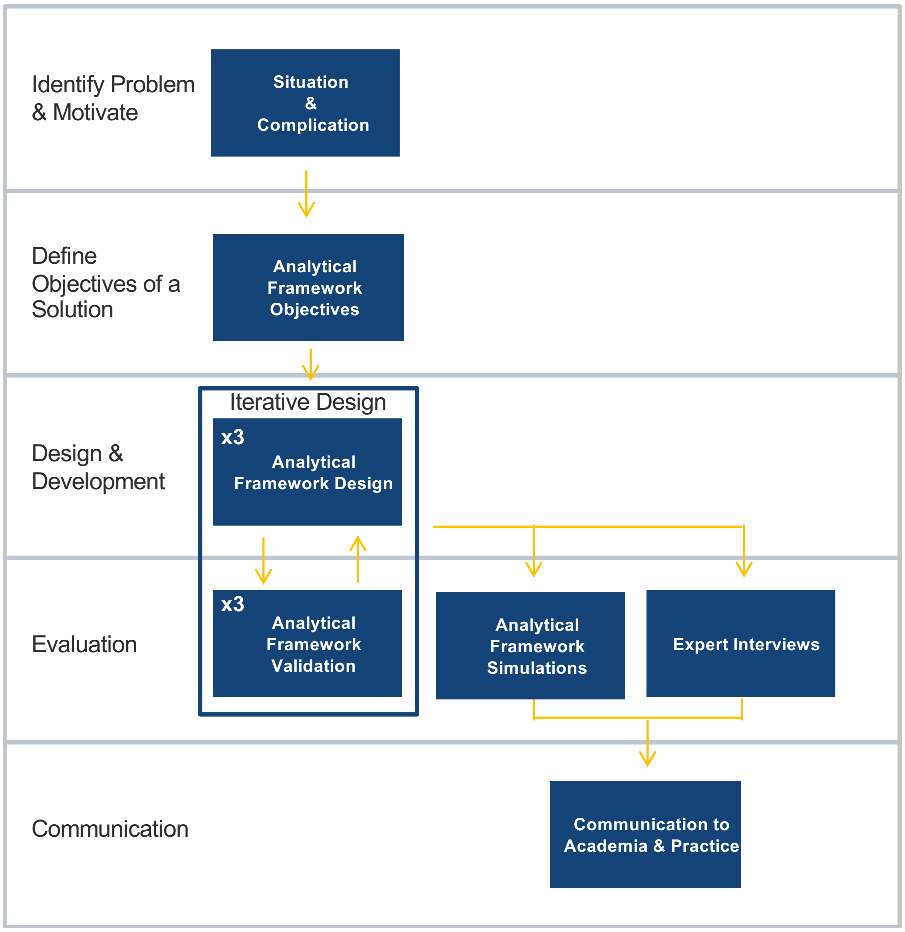

Figure 6 Research Model Overview

The next step was to design the analytical framework iteratively with three rounds of validation and refinement. For that purpose, the different versions of the analytical framework have been evaluated in cooperation with the Medical Technology Expert (see Appendix H), who took over the role of a business manager for a medical technology company. After each round of validation, the Medical Technology Expert gave feedback on the usability, and the test results have been analyzed. In that way, it was possible to quickly iterate and improve the analytical framework during the design phase.

For engaging in rigorous design evaluation, it is suggested to utilize different techniques such as experiments, simulations, or case studies (Von Alan, March, Park et al., 2004). This is why a mixed-method approach was chosen to achieve the highest rigor as possible. Four simulations with the analytical framework, two Strategy Expert interviews, and one Data Technology Expert interview were conducted.

The simulations took place with four senior consultants, who mimicked the role of a company's management with which they have several years of consulting experience. In that way, they were empowered to act as a user of the analytical framework under experimental conditions. At first, the theoretical framework was introduced to explain the general background. Then, during the simulations, the consultants were guided through the analytical framework. Afterward, they could give feedback related to the framework's usability and the generated results. In the end, the consultant's feedback and the data generated were analyzed for evaluating the analytical framework.

Furthermore, expert interviews were conducted. Firstly, the automatability assessment was simulated with the Data Technology Expert. Afterward, the automatability results from the other simulations were presented to receive his technology expert opinion on the overall data. Additionally, Strategy Expert 1 and 2 were consulted to validate the theoretical model and propose possible improvements.

Each of the three expert interviews á ~40 minutes and four simulations á ~75 minutes have been dealt with as semi-structured expert interviews. Semi-structured interviews are chosen because it is necessary to have the experts explain and build on their responses. In that way, the expert's answers were not too restricted, and they could express their knowledge and motives regarding their specific field of expertise. They could also lead the discussion in an unexpected direction, which they think is important and relevant for the framework (Bryman & Bell, 2011; Saunders, Lewis, & Thornhill, 2009).

To analyze the content of the semi-structured interviews, they were recorded, transcribed, and subject to qualitative content analysis. The analysis followed the summarizing-approach (Saunders et al., 2009), where the key points and arguments are extracted. In that way, the interviews have been condensed from large amounts of text into short central statements. The simulation feedback has additionally been categorized in "positive," "negative," and "ideas" to achieve higher comparability. Derived from the summaries, it was possible to identify recurring patterns and overlapping or contradictory arguments. The summaries can be found in Appendix I and J.

4 Results

The Results Section is structured as follows: at first, the outcome of the theoretical framework evaluation is presented, as it builds the foundation of the analytical framework. It is continued with the analytical framework's design by elaborating its general settings and the individual components. Lastly, the results of the analytical framework simulation are presented.

4.1 Theoretical Framework Evaluation

In general, the feedback from the simulations was that the core competence analysis adds a valuable feature to the discussion about automation use cases. Core competences could serve as a filter for focusing on the strategically relevant business processes.

Both Strategy Expert 1 & 2 support the idea to differentiate between core competences and non-core competences and to illustrate the variables in a two times two matrix. As well, they agree that automatable core competences should be automated in-house and that a third party should automate non-core competences as a service. Strategy Expert 2 stressed the critical difference between make or buy and that they should also be named accordingly. Nevertheless, the strategic implications in the lower half of the matrix leave more room for discussion.

Table 3 ACM Strategic Implications Expert Opinion

	Non-core competence	Core competence
Automatable	Both: Buy the automation solution	Both: Make the automation solution
Non-automatable	Expert 1: Observe Market Expert 2: Ignore	Expert 1: Observe Technology Expert 2: Prepare for Automation

Strategy Expert 1 emphasized that technological possibilities are endless, and hence both the market (new offerings) and technological developments (new technologies) should be observed for further advancements and possible efficiency increases (see Appendix I.1). Strategy Expert 2, on the other hand, has a more practical approach: by adapting, standardizing, and systemizing processes, non-automatable core competences should be prepared for future automation. While this effort is worthy for core competences, non-core competences do not require such investment and might be ignored until an automated solution enters the market (see Appendix I.2).

The feedback to the theoretical model given by the experts is not contradictory and will, therefore, be included in the strategic recommendations. Specifically, the recommendation for preparing non-automatable core competences adds value to the theoretical framework.

4.2 Analytical Framework Design

The following chapters serve to describe the designed analytical framework. Firstly, the general setting is explained by detailing the analytical framework's objectives and structure. Then, each central component is elaborated individually, while, if necessary, the search process is depicted as well (Gregor & Hevner, 2013).

4.2.1 Analytical Framework Objectives & Setting

One primary goal of the analytical framework is to demonstrate and test the validity of the theoretical model on a set of example processes. In this way, the analytical framework raises no claims of being a complete solution for identifying the processes for automation. It shall instead give insights into the general understanding of how to identify automation use cases and provide a rough estimation.

The objective has academic and professional reasons. From an academic perspective, the analytical framework will be used to test the theoretical framework and to generate data. This data can be analyzed to receive insights into the underlying mechanisms. From a professional perspective, such an analytical framework can be utilized to demonstrate a business consulting approach towards potential customers. By exemplarily showcasing the analysis of the firm on a small scale, the interest in a more comprehensive analysis might be created.

As the interview with Strategy Expert 1 has shown, to comprehensively analyze all business processes according to the theoretical model, a several weeks long workshop series with a variety of different attendants is necessary. On the other hand, consultancies often offer a quick "bait-service," which has the target to demonstrate expertise and to attract customers. These services usually take place with a business leader in a timeframe of up to 1.5 hours (see Appendix I.1). Therefore, academic and professional requirements can be best met by designing an analytical framework, which

1. identifies automatable business areas that should be further analyzed,
2. is based on the theoretical framework,
3. can be simulated to produce a set of reliable data,
4. builds upon state-of-the-art knowledge,
5. does not require more than 1.5 hours, and
6. matches the skills and needs of a business manager.

The resulting analytical framework is comprised of three active steps – a process request, core competence analysis, and automatability assessment. The actions follow after each other, and in the end, the results are demonstrated in the Automatability-Competence-Matrix (ACM) and with an ACM score. The setting for the analytical framework is a bilateral exchange between the business manager and the consultant, who is guiding the manager and fills the framework with the provided data.

4.2.2 Process Request

The process request shapes the progress of the analytical framework, as here the business manager states the processes that will be analyzed. The process request consists of one question:

“What processes along the company's value chain are critical to its success? Please, name up to 7 processes!”

As the targeted timeframe is limited to 1.5 hours, it is necessary to limit the amount and type of possible processes. It is barely possible to look at all the business processes of a company during this time. On the one hand, the manager shall not be guided too strongly during the process because his answers need to be unbiased and honest. On the other hand, the answers require to be provided in a way that they apply to the following steps. Asking for processes which are critical for the success already guides the manager into the direction of core processes, without actually naming the term “core competence” and without influencing considerably. Within the framework, processes of the initial validation are demonstrated as a set of example processes. These serve as support to better understand the question. The setup of the Excel worksheet is illustrated in Figure 7.

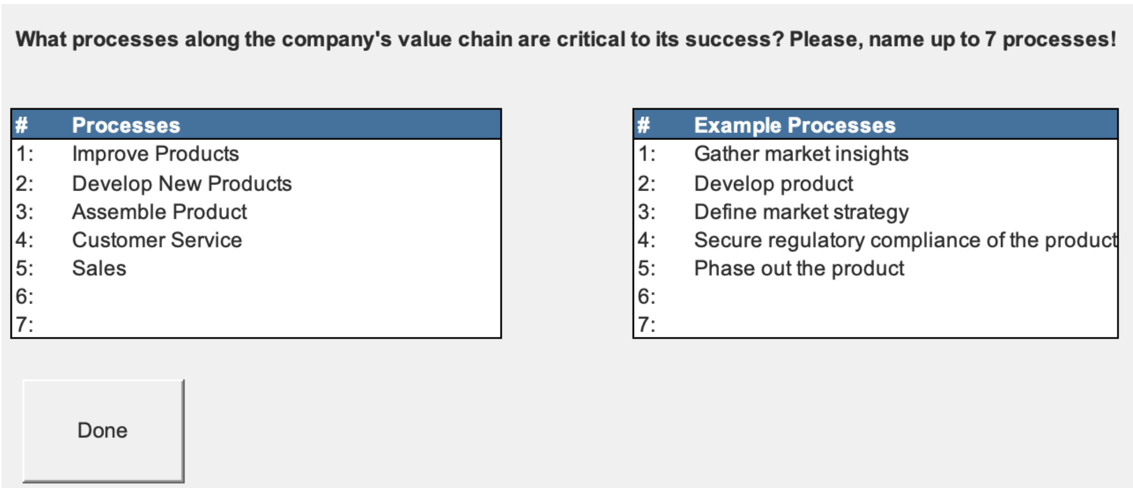

Figure 7 Process Request Worksheet

4.2.3 Core Competence Analysis

The core competence analysis has the target to validate whether the provided processes are indeed essential and whether they make use of the company’s core competences. Six dummy variable question items are used, which are equally weighted and need to be answered with either 'yes' or 'no.' Therefore, the resulting core competence score reaches from zero to six. Within the worksheet, processes and question items form a matrix to enable answering all questions in a structured way. The worksheet and question items are illustrated in Figure 8:

Questions	MRO	Customer Management
1. Does the process contribute to the perceived customer benefit of the end product/service?	yes	yes
2. Are the resources required for the process unique? a) Resources = financial, physical, human & organizational assets b) Unique = valuable, rare, inimitable & non-substitutable	yes	no
3. Is this process flexible and capable of adaption to other products/services?	yes	yes
4. Is this process additionally used across other organizational functions, products or businesses?	yes	yes
5. Does the company heavily depend on a few (1-3) individuals to be able to perform that process?	no	no
6. Does the process allow market domination in a specific sector or is it emphasized as a specialty against competitors?	yes	no
Core Competence Score	**6**	**4**

Figure 8 Extract from Core Competence Analysis Worksheet

All items are derived from the literature regarding core competences and are related to the work by Boguslauskas et al. (2009), who proposed a scheme for the identification of potential core processes in the context of business process outsourcing. The items one to three are grounded in the arguments of Prahalad et al. (1990). Additionally, resource-based theory identifies four characteristics of a firm's core competence (Barney, 1991). This is why item two is extended by the requirement that the resources required for the process need to be unique (valuable, rare, difficult to imitate, and difficult to substitute).

Quinn et al. (1994) provide another source for the core competence analysis, who describe core competences as

- flexible, long-term platforms, capable of adaption or evolution (item 3),
- embedded in the organization's system (item 4), and
- areas where the company can dominate (item 6).

The approach to identify core competences by Hafeez et al. (2002) is different in the application, but the underlying theories are strongly overlapping. Only what they call "collectiveness determination" is not included in the other methods. Hence, the dependency on a few individuals has been added as a negative criterion for core competences (item 5). According to Hafeez et al. (2002), a competence cannot be a company's core competence, if the execution and knowledge are highly dependent on a few individuals.

4.2.4 Automatability Assessment

The automatability assessment serves to estimate whether current technology is capable of automating a process. The estimates are not binary in the sense that the processes are either automatable or not. Instead, they indicate as to how extensive the development of the automated solution would be. Even though the economic interest in automation is tremendous, the knowledge base in the field of estimating what is automatable is sparse. Hence, the automatability assessment's design was more iterative and experimental than the design of the other components.

The proposed solution heavily relies on the results from Duckworth et al. (2019), who surveyed 150 AI experts to estimate which activities are automatable with today's technology. Duckworth granted access to the complete database (see email communication, Appendix D), which allows the utilization of the features for assessing a process's automatability. The general concept of the assessment is that to perform a process, the acting person requires a particular set of skills, knowledge, and abilities. Therefore, each process can be characterized by a numerical rating of features (skills, knowledge, and abilities).

Duckworth's dataset provides information about the automatability gradient of all skills, knowledge, and abilities that are included in the O*NET database. It then allows for transforming the set of features into automatability estimates by accumulating the numerical rating times the feature gradient:

$$Automatability\ Score = \sum Rating_{Feature} * Gradient_{Feature}$$

Formula 1 Automatability Score, self-developed

In practice, the user has the task to rate each of the given processes according to the degree the process requires each of the skills, knowledge, and abilities. The features contain 120 individual skills, knowledge, and abilities, which makes it impossible to rate all processes within one and a half hours. After validation of several versions with the Medical Technology Expert, it was decided to reduce the number of features through clustering and to average the gradients provided by Duckworth. The O*NET database already offers categories, which are used as clusters. Nevertheless, the feature clusters have additionally been minimized by deleting those with neglectable gradients and those, which are difficult to apply on business processes (e.g., "Multilimb Coordination"). To additionally emphasize business aspects of the features, the cluster "Business and Management" has been split, and each containing feature is equally weighted as the other feature clusters.

In the end, 23 features and feature clusters comprise the automatability assessment, which implies that all processes from the process request are to be rated 23 times. The O*NET database also provides descriptions of each feature and feature cluster, which are additionally presented to the user for explanatory purposes. For those features that are clustered features, it is possible within the framework to display the containing features and feature descriptions. The features, descriptions, and gradients included in the automatability assessment are summarized in Appendix F.

Initially, the features were rated on a scale from one to five, but by rating a feature with the least possible rating, a one, the feature still influences the overall automatability score. As gradients describe the increase or decrease when the rating is increased by one, it should be possible to give a rating without any influence on the automatability score. Hence, the scale was expanded by the answer option zero. This allows to exclude a feature from the calculation entirely and does not profoundly change the responses. According to Allen and Seaman (2007), it is recommended to use as wide a scale as possible, because the answers can always be collapsed afterward. Additionally, the now proposed six-point Likert scale eliminates the neutral option, which forces the user to decide for a tendency.

Skill, Knowledge, Ability	Desciption	MRO
To what degree does each process depend on the following skills, abilities and knowledge? Give Ratings from 0 - 5 0 - no dependency 1 - little 2 - little/medium 3 - medium 4 - medium/strong 5 - strong dependency		
Quantitative Abilities	Abilities that influence the solution of problems involving mathematical relationships	1
Auditory and Speech Abilities	Abilities related to auditory and oral input, e.g. speech recognition or sound localization	2
Administration and other office procedures	Knowledge of administrative and clerical procedures and systems such as word processing, managing files and records, stenography and transcription, designing forms, and other office procedures and terminology.	2

Figure 9 Extract from Automatability Assessment Worksheet

Within the framework, the processes are again presented at the top, the features are written vertically, and the gradients are not displayed to the user for ensuring unbiased responses. Figure 9 illustrates the worksheet setup. For guiding the user along with the feature ratings, the overall question is: “To what degree does each process make use of the following skills, abilities, and knowledge?”. Additionally, the six-point Likert scale is explained with a qualitative description.

Other approaches for the automatability assessment have been trialed and neglected during the design phase. In general, an optimization problem occurred between two contradicting targets, which were, on the one hand, an accurate automatability prediction and, on the other hand, a fast and user-friendly assessment. For example, instead of observing on the skills, knowledge, and ability level, the occupational level might be utilized. Unfortunately, these have shown to be unusable as they are too generic and neglect the substantial varieties of automatability within one occupational group.

4.2.5 Automatability Competence Matrix and Score

For interpreting the results of the core competence and automatability analysis, each process is placed in a matrix, as described in Chapter 2.8. The abscissa represents the core competence score and spans from zero to six, where six represents a 100% core process. The automatability score is placed on the ordinate and has a variable span, depending on the assessments of the processes.

As described in the theoretical framework, those processes which are easier to be automated and which make use of a firm’s core competences should be automated first. For comparing the processes with each other and allow reasoned decision-making, it is necessary to be able to quantitatively evaluate the degree to which each process is in the top right corner of the ACM. Therefore, an ACM score is introduced, which serves the user as a prioritization tool. This ACM score is generated by calculating the Euclidian distance to the bottom left corner of the ACM, where the core competence score equals zero, and the automatability is at the “lowest automatability baseline.” Since in each batch the process with the lowest automatability might have a different score, the process with the lowest automatability score serves as the lowest automatability baseline for the other processes. The formula and description of the ACM score calculation are elaborated in Appendix G. As already mentioned in Chapter 2.5.3, the assessment results and scores are quantified, but the numbers rely on survey results. Hence, a certain degree of deviation from “reality” is most certain and should be remembered.

As an illustrating example, the results of the validation with the Medical Technology Expert are visualized in the ACM, and the processes have been ranked according to their ACM score. The ACM, the schematic calculation of the ACM scores, and the resulting scores can be seen in Figure 10 and Table 4.

The process “Develop product” has been assessed as the least automatable and therefore targets the lowest automatability baseline. Then, the Euclidian distance to each process is calculated from the intersection of the ordinate with the lowest automatability baseline. None of the processes were evaluated to be in the top right corner, and only two of them came close. Here, the ACM score provides a convenient quantitative comparison and prioritization option.

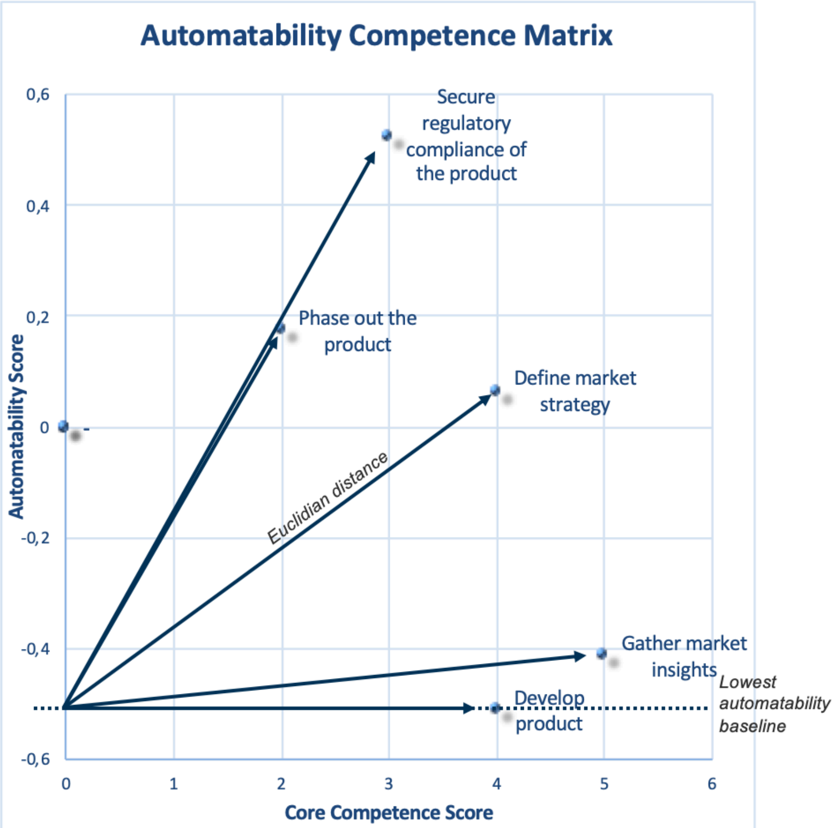

Figure 10 ACM Score Calculation

Table 4 Validation ACM Scores

Rank	Process	ACM-score
1	Secure regulatory compliance of the product	1,118
2	Define market strategy	0,868
3	Gather market insights	0,839
4	Phase out the product	0,740
5	Develop product	0,667

4.2.6 Analytical Framework Overview

The analytical framework is comprised of three steps that are undertaken in less than one and a half hours in cooperation with a business manager or leader who wishes to identify the processes most beneficial to be automated. In step one, the process request, the manager is asked to identify up to six processes, which are critical to the company’s success. These will be further analyzed during the following steps. Step two is the core competence analysis, which utilizes six dummy questions to elaborate the degree to which the processes are core processes. In step three, the automatability assessment, the business manager is asked to rate each process according to the degree it depends on 23 different skills, knowledge, and abilities. In that way, the processes' automatabilities are estimated. In the end, the processes are placed in the automatability-competence-matrix, which allows deriving recommendations about the automation strategy (make/buy/prepare/observe).

4.3 Analytical Framework Simulation

After completion of the design phase, the analytical framework's application was simulated four times (Simulation A-D). As described in Chapter 3.2, four consultants mimicked the roles of the business managers of four different companies (see Table 5). For each company, they can demonstrate in-depth knowledge and experience, which empowers them to take over that role. The consultants were guided through each step in the analytical framework, and afterward, the results have been presented. In the end, the consultants gave feedback related to the application of the analytical framework and the generated results. The entire analytical framework simulation spreadsheets can be found in the Annex. Resulting ACM matrices are shown in Figure 11.

The simulation results demonstrate the following characteristics:

1. The processes are skewed towards the right, which means all processes tend towards being core processes.
2. The range of automatability scores reaches from -0.63 to 0.91.
3. Only the automatability scores of Company A are balanced between positive and negative, whereas for B, they are solely positive, and for C and D, they are strongly negative.
4. The highest-ranked processes, according to the ACM score, are Assembly (1.302), Drop Shipping (1.302), Sales (1.202), and MRO (1.093).

Table 5 Simulations Company Overview

Company	**Industry**
Company A	Industrial Sewing Machine Producer
Company B	Bedding Goods Producer
Company C	Pipe, Fiber & Cable Producer
Company D	Aircraft Maintenance, Repair & Overhaul

Figure 11 Simulation Results - ACM Matrices

The feedback after simulation A was that the level of analysis is too high, and even though some processes are declared to be not automatable, there still might be sub-processes that are automatable. It was suggested that it might be useful to utilize company process maps to identify which processes are automatable (see Appendix J.1).

During Simulation B, the interviewee intentionally mimicked the situation before a company-wide automation initiative, which he had accompanied in 2018. Hence, the results were directly verifiable. Additionally, the interviewee brought a process map of company B, which was used to identify processes for the analysis. Each of the selected processes was estimated to be automatable, while the order acceptance process had the highest-rated automatability and core competence score. This result is wholly aligned with the interviewee's expectations, as it is a rather simple process that has already been automated end-to-end, and it is the number one core competence of Company B. In total, many aspects of all the given processes have at least partly been automated. In this case, the feedback was that both automatability assessment, as well as core competence analysis, have been accurate (see Appendix J.2).

Simulation C and D both suffered from a process level difficulty. After Simulation C, the feedback was that the acting person for each process was unclear, and hence, different roles had been mixed that take part in the process. The result is that the majority of processes are estimated to be hardly automatable. Even though the automatability scores are negative, the interviewee mentioned that their relation to each other still is accurate and that the core competence scores fit as well (see Appendix J.3)

The results of simulation D draw a comparable picture as simulation C. The core competence scores match the expectation, and the automatabilities are too low, while the order of automatabilities is accurate. The interviewee mentioned that the more specific the processes, the better are the automatability ratings. High-level processes will always lead to high-level answers (see Appendix J.4).

5 Analysis

5.1 Core Competence Analysis

Overall, the core competence analysis has proven to be accurate. Three out of four consultants explicitly mentioned that the analysis result meets their expectations. Nevertheless, an observation is that all processes under investigation have a core competence score of three or higher. Three possible explanations for this phenomenon have been identified.

Firstly, the initial process request is biased as it directly asks for "critical" processes. In that way, minor processes have been ignored from the start.

A second explanation relates to the theory of core competences. Usually, companies do not have more than five core competences, which is why the framework for identifying core competences by Boguslauskas et al. (2009) uses knock-out variables. If one criterion is not met, after their definition, it is no core competence. By applying this logic to the results above, only one out of twenty processes would be assessed to be core, which better reflects theory. Anyhow, it was intentionally decided to give scores from zero to six to provide a more differentiated core competence assessment.

Confirmation bias might induce the third reason for skewed core competence ratings (Nickerson, 1998). As in the beginning, the consultants were asked for critical processes, they might have (unconsciously) given biased answers within the core competence analysis to confirm their initial estimate.

Additionally, minor issues occurred related to questions three[1], four[2] and five[3]. Questions three and four have always been answered with "yes", which indicates that their difference is not relevant to the users. For that reason, both questions should be merged. Question five lead two times to confusion, which is why the item could be reformulated to be less ambiguous. In the end, even though there might be certain limitations to the analysis, the overall performance of the core competence analysis can be validated.

5.2 Automatability Assessment

In general, the automatability assessment demonstrated a valuable performance when comparing the processes' scores among each other. Their relation with each other usual-

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[1] Question 3: "Is this process flexible and capable of adaption to other products/services?"

[2] Question 4: "Is this process additionally used across other organizational functions, products or businesses?

[3] Question 5: "Does the company heavily depend on a few (1-3) individuals to be able to perform that process?

ly reflects the expected outcome, as was the feedback during the simulations and the interview with the Data Technology Expert (see Appendix I.3). Especially during simulation B, all processes that were estimated to be automatable have already been computerized. This leads to the conclusion that the classification of processes by using skills, knowledge, and abilities is generally suitable for determining their automatability. The following figure summarizes the automatability scores of all four simulations and the simulation results from the Data Technology Expert interview:

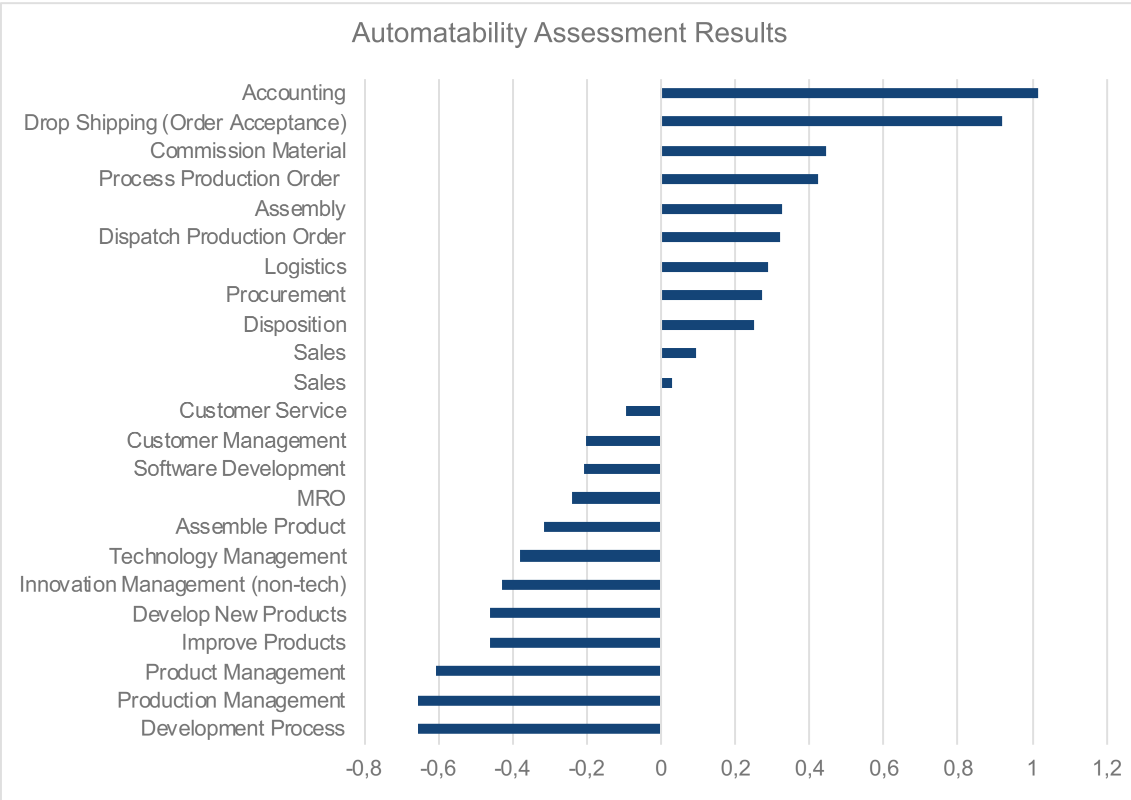


Figure 12 Automatability Assessment Results

In general, repetitive and manual tasks group at the upper end of the automatability scores, which is in line with the theory by Acemoglu et al. (2017). Customer-oriented processes, such as sales or customer service, are found in the middle section. This also appears to be accurate: many aspects of customer-oriented processes are already automated through e-commerce, chatbots, or self-service websites. Nevertheless, social intelligence (a bottleneck of computerization) and other soft skills often are critical skills when dealing with customers, but these are difficult to automate (Huang & Rust, 2018). Therefore, their mid-range automatability scores seem to be justified. Finally, development and management processes represent the bottom part of automatabilities. This, again, is according to findings by Kaplan et al. (2019) or Frey et al. (2017), as these processes are mixtures of creative, social, and cognitive tasks.

Even though the general impression of the results implies accordance to theory, three significant limitations have been identified:

1. Personal backgrounds bias feature ratings
2. The automatability score itself is not informative, because assessment results foremost matter in relation to each other.
3. High-level processes cannot be estimated accurately

Firstly, the evaluation of skills, knowledge, and abilities is a highly subjective task and is influenced by the personal and professional background. During the interviews, it was recognizable that interviewees tended to give higher feature ratings to their own profession. On the one hand, this might be caused by a more profound understanding in one field than the other. On the other hand, there might be a bias to overestimate one's own profession in relation to other professions. For example, the software developer distributed 37 skills, knowledge, and ability points to software development, but only 23 to accounting. As well, a Ph.D. in engineering gave 74 points to an engineering process, whereas procurement only received 22 points.

This leads to the second important limitation: as everyone has a slightly different rating behavior, perspective, and understanding of the processes and features, it is not generally possible to compare assessment results from separate interviews. This is why, in relation to each other, the assessment was usually appropriate, but the overall score did not always reflect the expectations.

When analyzing processes that contain sub-processes, a third limitation emerges. Even though the general impression of a process could indicate a difficult automatability, there still might be the case that a particular sub-process is highly automatable (see Appendix I.3). This induces the risk of missing out on valuable automation possibilities. Additionally, high-level processes are too vague to be analyzed. During the assessments, the interviewees tended to jump between several sub-processes and intermingled operational and managerial roles. That is why overall automatability scores have been lower, e.g., in Simulation C and D.

Processes, where these limitations took effect, are, for instance, the two assembly processes with highly differing automatability scores (0.33 vs. -0.31). The reason for the tremendous difference is that the interviewee of the lower-rated process did jump between underlying processes and included too many activities (see Appendix J.2). Even though the interviewee's assessment of the process resulted in a relatively low score, concerning the other processes, the process has the right position. This is mainly because she consistently assessed all the processes this way. As a result, the relation is correct, but the scores themselves cannot be compared to other simulation scores. Nevertheless, the Data Technology Expert states, the subjectivity of the ratings is not necessarily detrimental as long as the results are still usable (see Appendix I.3).

5.3 Overall Analytical Framework Evaluation

In the end, the utility and validity of the core competence analysis can entirely be verified. As well, the automatability assessment demonstrated decent functionality as a rough estimation of a process's automatability, even though a few limitations emerged. Unfortunately, both analyses function best on different process levels, which lead to a detrimental overall utility and validity of the analytical framework. This is reflected in the overall feedback from the simulations, which emphasizes a problem with the level of analysis.

Core competences and core processes are best analyzed at a very high level. Their strategic importance is only visible when analyzing the whole company within the context of competition and markets. Automatabilities, on the other hand, should be examined on the lowest process level as possible, since the simulations have shown that high-level processes cannot be estimated accurately. Ultimately, the interplay of core competence analysis and automatability assessment on the same process level does not render valuable results, although each component by itself does function properly.

5.4 Analytical Framework Redesign Options

Based on the previous analysis and the expert interviews, several options emerged how the analytical framework might be redesigned for enhanced performance. In general, an analysis on such a high level, as it was planned, is too generic, and a more comprehensive and time-consuming structure is necessary. For efficiently utilizing the theoretical framework, a possibly better approach is to separate the core competence analysis and automatability assessment. This could be achieved by firstly defining the core competences on a high level and afterward assessing the automatability on a low level. Therefore, the high-level processes are decomposed until a process level is reached, which is more applicable for determining the automatability.

Such an approach requires more personnel and time as the initial analytical framework. Firstly, persons with essential process knowledge should additionally participate in the process, as Strategy Expert 1 also mentioned. Secondly, a comprehensive process map, which shows all actors, activities, and equipment within a company, should be generated. During simulation B, such a process map was used and lead to the most accurate simulation results.

Both the core competence analysis and automatability assessment may be adapted to follow the new approach better. While at the moment, the core competence analysis is designed to assess whether the already chosen processes match the criteria, the questions might be turned around to identify matching ones within all of a firm's processes. For example, the question "Does the process contribute to the perceived customer benefit of the end product/service?” might be changed to “Which processes contribute to the perceived customer benefit of the end product/service?”. In this way, the core competence analysis could guide the manager along the different criteria to identify the core competences. Afterward, those processes, which make use of the core competences, can be marked on the process map. The resulting overview of all processes and core competences then serves as a heatmap.

Afterward, the automatability of all marked processes is assessed on a low process level. The difference to the original approach should be that the assessment does not rely on a single person but happens with a committee and in active consultation with the process owners. This minimizes the automatability assessment’s limitations.

The approach to assess automatability via skills, knowledge, and abilities was mainly due to the limitations given in the analytical framework’s objectives definition, which mentions that a manager quickly receives an overview of what is automatable and what is not. For the described approach with a comprehensive process map, the automatability assessment might be adapted entirely, and Duckworth et al.’s (2019) results on activity level can be applied. With the provided dataset of 2200 different activities and their estimated automatabilities, it is technically feasible to “mine” for the most automatable processes, as the Data Technology Expert confirms (see Appendix I.3). Probably, that required some adaptions of the process map to match with the activities, but the results would be increasingly accurate. Here, future research should be performed to evaluate the possibility of automatically estimating the automatability of all processes within a process map.

6 Discussion and Conclusion

6.1 Main Findings

The goal of this research was to design an analytical framework for the identification of business processes that are most beneficial for AI-enabled automation. Four subordinate research questions have been formulated:

- **Q1: What is AI-enabled automation?**
- **Q2: What are the current capabilities and limitations of AI-enabled automation?**
- **Q3: What theoretical framework might be used to classify business processes and recommend an AI-enabled automation strategy?**
- **Q4: Which components define an analytical framework for the identification of business processes that are most beneficial for AI-enabled automation?**

AI-enabled automation is a new wave of automation, targeting the substitution of human labor at increasingly complex tasks, which conventional automation technologies could not automate. This is enabled by advances in AI, which interprets and learns from data to adapt to new challenges.

For assessing the automatability of processes, it was looked at the current capabilities and limitations of AI-enabled automation. Here, macroeconomic research on job automation provides insights into what is automatable and what is not. In general, the bottlenecks of computerization (perception & manipulation, social intelligence, and creative intelligence), as developed by Frey et al. (2017), are still accountable, which is also confirmed by Duckworth (see Appendix D). Furthermore, the bottlenecks are recognizable in the feature gradients used for the automatability assessment: Primarily, skills, knowledge, and abilities that are related to the bottlenecks of computerization have strongly negative gradients. Apart from these bottlenecks, technology does not seem to have limitations. Instead, the general impression is that seemingly everything is possible (see expert interviews in Appendix I.1 & I.2).

For classifying business processes and recommending an AI-enabled automation strategy, the approach by Thomassen et al. (2014) was adapted, and a matrix was introduced that utilizes the variables automatability and core competence to assess processes. For each of the four quadrants, a distinct automation strategy was developed in consultation with the strategy experts. The resulting ACM and recommendations are illustrated in Figure 13. The ACM only serves as a theoretical framework for the analytical framework and illustrates the relationship between automation and core competences. Additionally, it can be utilized for presenting the results of the analytical framework in a concise and comprehensible way.

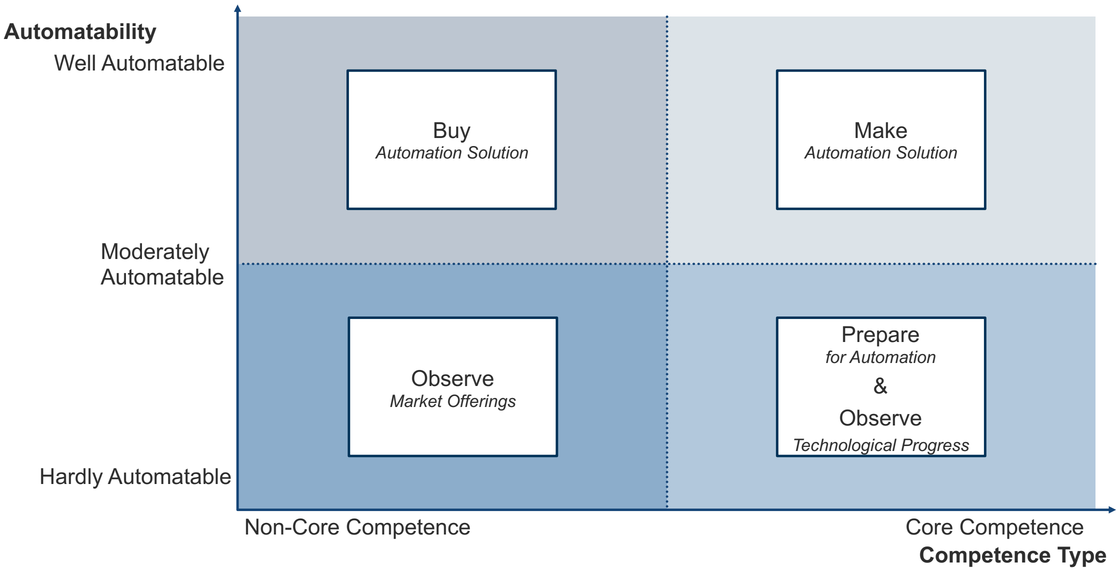


Figure 13 Updated Automatability Competence Matrix

A core competence analysis, an automatability assessment, and an ACM score have been developed as an instantiation of the theoretical framework. Each component was designed in a way that the full analysis does not last longer than one and a half hours. This is why the core competence analysis is comprised of 6 dummy questions per process, and the automatability assessment consists of 23 features, that use skill, knowledge, and ability ratings as proxies for automatabilities. Afterward, the ACM score equally weights both normalized criteria to calculate an overall assessment.

The design evaluation through expert interviews and simulations shows that the individual components function adequately. Minor limitations to the core competence analysis occurred through biased responses, but in general, its functionality is validated. The automatability assessment is prone to more severe limitations, as user rating behavior differs from person to person. Therefore, the results can only be compared with each other, but not with results from another person's rating. Hence, the automatability assessment only serves as a quick tool to order a set of processes according to their automatability, but the automatability score itself is not informative.

Another finding is that the automatability of high-level processes cannot be estimated accurately, because often automatabilities of sub-processes strongly vary. This is contradictory to the core competence analysis, which only adds value at a high level of analysis. As the automatability assessment requires a bottom-up approach and the core competence analysis needs a top-down perspective, it is suggested to split both analyses and conduct them consecutively. The theoretical framework and the automation strategy recommendations remain untouched, solely the analysis process should be approached differently.

6.2 Contribution to Literature and Theory

A significant contribution to literature and theory constitutes the developed automatability assessment. Until now, there is no widely accepted framework for assessing the automatability of business processes. The automatability assessment constitutes a valuable approach by using the dataset provided by Duckworth et al. (2019), and it proves that skills, knowledge, and abilities are utilizable as proxies for process automatability. The automatability assessment also represents a knowledge spillover from macroeconomic research on job automation to microeconomic process analysis. Finally, through the possibility of being applied during other researches, the automatability assessment itself might contribute to literature and theory when the automatability of processes needs to be estimated.

Furthermore, the matrix for automation initiative selection developed by Thomassen et al. (2014) was developed further and adapted to serve the needs of AI-enabled automation. The hitherto undefined variables strategic importance and ease of implementation have been concretized through the use of core competences and analysis of current capabilities and limitations of AI-enabled automation. Additionally, the four strategic recommendations in the ACM supplement the matrix with concrete implications. Therefore, the ACM contributes to Thomassen et al.'s call to further develop their methodology.

The last significant contribution is related to the process level of analysis. The research has shown that it is impractical to assess the automatability of a process with a top-down approach. This is why future analysis processes based on automatability and core competences should be separated, and new options for the design of the analytical framework have been proposed.

6.3 Contribution to Practice

The contribution to practice is threefold. First of all, the theoretical framework gives recommendations on how to analyze internal processes for automation initiatives and proposes strategies on how to deal with all four process categories. In this way, the theoretical framework can be applied by business managers and consultants when searching for valuable automation use cases.

Secondly, the automatability assessment serves as a rough and fast estimation, whether a process is automatable or not. It can, therefore, be utilized as a first indicator when applying the theoretical framework.

Lastly, the proposed analytical framework, which separates between core competence analysis and automatability assessment, is a promising approach to execute the theoretical framework. For practitioners, it should be possible to perform the core competence analysis and automatability assessment successively and thus achieve well-applicable results.

For UNITY, the thesis results are directly applicable. The theoretical framework is already in use during customer workshops to illustrate strategic considerations when deciding for automation initiatives. Additionally, the automatability assessment was further adapted with this research's findings and now serves as an "AI Potential Tool," which compares different processes regarding the possible impact AI-enabled automation might have.

6.4 Limitations of the Research

The first limitation relates to the simulations of the analytical framework. As they have been conducted with consultants who *mimicked* the role of a business manager, the analytical framework has not been tested under real-world conditions. However, even though the consultants did not always have a perfect company or market knowledge, it was sufficient to identify the strengths and weaknesses of the analytical framework.

Another limitation results from the company selection, as the simulations have been majorly focused on assembly or maintenance companies, which have a strong focus on manual work. No simulations have been executed for companies with entirely dissimilar value chains, such as IT, retail, media, or logistics companies.

Besides, there are limitations to the argument that core competences should be automated through in-house development, and third-party solutions should automate non-core competences. As Strategy Expert 1 states, a company should automate a non-core competence, when it is easy to do so, and the efficiency increase is valuable (see Appendix I.1). This, of course, holds for low-investment developments, but not for more complex projects. If due to resource restrictions, a company had to decide whether to start a significant investment into the automation of a core competence or a non-core competence, then the decision should fall onto the former for the reasons given in Chapter 2.8.

The automatability assessment has its limitations in such a way that personal backgrounds bias the estimation, the results foremost matter in relation to each other, and that high-level processes cannot be estimated adequately. Also, the automatability estimates have not been comprehensively validated by experts. Even though an expert did analyze the results, the opinion and expertise of one expert are still limited and lack representativeness.

Lastly, a limitation of the automatability assessment's usability is due to the progress in automation technology. Over the months, the gradients will most-certainly rise, and additional activities will be automatable. For ensuring the assessment's utilization in the future, the gradients require updates through new expert surveys. For example, annual surveys could be established to track the progress continuously.

6.5 Future Research

Future research might focus on empirically testing whether the theoretical framework holds. For instance, historical data might indicate that firms that primarily automated their core competences have been more successful in the long-term. Additionally, the analytical framework might be simulated or tested with more companies, especially with ones that have different value chains. Thus, the results can increasingly be generalized. Future research could furthermore focus on designing a new analytical framework, which separates between the core competence analysis and automatability assessment, as it is elaborated in Chapter 5.4.

Especially the automatability assessment provides further possibilities for future research. Firstly, the current version of the automatability assessment requires additional expert validation. For instance, the process automatabilities might be challenged by an expert panel or through the Delphi technique. Secondly, scholars focused on process mining or process modeling might develop the automatability process mining software, which makes use of the automatability estimates on activity level by Duckworth et al. (2019). In conclusion, this thesis research project followed a few novel approaches to solving current academic and professional challenges, which could be further improved and validated.

List of References

Acemoglu, D., & Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics* (Vol. 4, pp. 1043-1171): Elsevier.

Acemoglu, D., & Restrepo, P. (2017). Robots and Jobs: Evidence from US Labor Markets. *MIT Department of Economics Working Paper No. 17-04*. doi:https://dx.doi.org/10.2139/ssrn.2940245

Acemoglu, D., & Restrepo, P. (2018). *Artificial Intelligence, Automation and Work*. Retrieved from

Aksoy, S., & Haralick, R. M. (2001). Feature Normalization and Likelihood-based Similarity Measures for Image Retrieval. *Pattern recognition letters, 22*(5), 563-582.

Allen, I. E., & Seaman, C. A. (2007). Likert Scales and Data Analyses. *Quality progress, 40*(7), 64-65.

Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the Risk of Automation. *Economics Letters, 159*, 157-160. doi:10.1016/j.econlet.2017.07.001

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives, 29*(3), 3-30. doi:10.1257/jep.29.3.3

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of management, 17*(1), 99-120.

Barney, J. (1995). Looking Inside for Competitive Advantage. *Academy of Management Perspectives, 9*(4), 49-61.

Bischke, J. (2018). Welcome To The Age Of Recruiting Automation. Retrieved from https://www.forbes.com/sites/forbestechcouncil/2018/07/12/welcome-to-the-age-of-recruiting-automation/#1e913c161865

Boguslauskas, V., & Kvedaraviciene, G. (2009). Difficulties in Identifying Company‘s Core Competencies and Core Processes. *Engineering Economics, 62*(2).

Bruun, E. P. G., & Duka, A. (2018). Artificial Intelligence, Jobs and the Future of Work: Racing with the Machines. *Basic Income Studies, 13*(2). doi:10.1515/bis-2018-0018

Bryman, A., & Bell, E. (2011). Ethics in Business Research. *Business Research Methods, 7*(5), 23-56.

Brynjolfsson, E., & McAfee, A. (2012). *Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*: Brynjolfsson and McAfee.

Brynjolfsson, E., & Mcafee, A. (2017). The Business of Artificial Intelligence. *Harvard business review*.

Bughin, J. (2018). Wait-and-See Could Be a Costly AI Strategy. *MIT Sloan Management Review*. Retrieved from https://sloanreview.mit.edu/article/wait-and-see-could-be-a-costly-ai-strategy/

Bughin, J., Chui, M., & McCarthy, B. (2017). How to Make AI Work for your Business. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/how-to-make-ai-work-for-your-business

Caetano, A., Silva, A. R., & Tribolet, J. (2010). Business Process Decomposition-an Approach Based on the Principle of Separation of Concerns. *Enterprise Modelling and Information Systems Architectures (EMISAJ), 5*(1), 44-57.

Crook, T. R., Ketchen Jr, D. J., Combs, J. G., & Todd, S. Y. (2008). Strategic Resources and Performance: a Meta-Analysis. *Strategic management journal, 29*(11), 1141-1154.

DiPaola, S., Gabora, L., & McCaig, G. (2018). Informing Artificial Intelligence Generative Techniques Using Cognitive Theories of Human Creativity. *Procedia Computer Science, 145*, 158-168.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial Intelligence for Decision Making in the Era of Big Data – Evolution, Challenges and Research Agenda. *International Journal of Information Management, 48*, 63-71. doi:10.1016/j.ijinfomgt.2019.01.021

Duckworth, P., Graham, L., & Osborne, M. A. (2019). Inferring Work Task Automatability from AI Expert Evidence.

Frey, C. B., & Osborne, M. A. (2017). The Future of Employment: How Susceptible are Jobs to Computerisation? *Technological Forecasting and Social Change, 114*, 254-280. doi:10.1016/j.techfore.2016.08.019

Grant, R. M. (1991). The Resource-Based Theory of Competitive Advantage: Implications for Strategy Formulation. *California management review, 33*(3), 114-135.

Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. *MIS quarterly*, 337-355.

Hafeez, K., Zhang, Y., & Malak, N. (2002). Core Competence for Sustainable Competitive Advantage: a Structured Methodology for Identifying Core Competence. *IEEE transactions on engineering management, 49*(1), 28-35.

Hain, J. S., Rutherford, B. N., & Hair Jr, J. F. (2019). A Taxonomy for Financial Services Selling. *Journal of Personal Selling & Sales Management, 39*(2), 172-188.

Hevner, A. R. (2007). A Three Cycle View of Design Science Research. *Scandinavian journal of information systems, 19*(2), 4.

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research, 21*(2), 155-172. doi:10.1177/1094670517752459

Jarrahi, M. H. (2018). Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making. *Business Horizons, 61*(4), 577-586. doi:10.1016/j.bushor.2018.03.007

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence. *Business Horizons, 62*(1), 15-25. doi:10.1016/j.bushor.2018.08.004

Kline, R. (2010). Cybernetics, Automata Studies, and the Dartmouth Conference on Artificial Intelligence. *IEEE Annals of the History of Computing, 33*(4), 5-16.

Koch, C. (2016). How the Computer Beat the Go Player. *Sci Am Mind, 27*, 20-23.

Koschmider, A., & Blanchard, E. (2007). *User Assistance for Business Process Model Decomposition.* Paper presented at the Proceedings of the 1st IEEE International Conference on Research Challenges in Information Science.

Manyika, J. (2017). A Future that Works: AI, Automation, Employment and Productivity. *McKinsey Global Institute Research, Tech. Rep.*

Markoff, J. (2011). Computer Wins on 'Jeopardy!': Trivial, it's not. *New York Times, 16*.

McCarthy, J. (1989). Artificial Intelligence, Logic and Formalizing Common Sense. In *Philosophical Logic and Artificial Intelligence* (pp. 161-190): Springer.

McCorduck, P. (2004). Machines who Think.

Nason, R. S., & Wiklund, J. (2018). An Assessment of Resource-Based Theorizing on Firm Growth and Suggestions for the Future. *Journal of management, 44*(1), 32-60.

Nedelkoska, L., & Quintini, G. (2018). Automation, Skills Use and Training.

Nickerson, R. S. (1998). Confirmation Bias: A Ubiquitous Phenomenon in Many Guises. *Review of general psychology, 2*(2), 175-220.

Osterwalder, A., & Pigneur, Y. (2010). *Business Model Generation: a Handbook for Visionaries, Game Changers, and Challengers*: John Wiley & Sons.

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems, 24*(3).

Perigal, H. (1873). On Geometric Dissections and Transformations. *Messenger of Mathematics, 2*, 103-105.

Peteraf, M. A., & Barney, J. B. (2003). Unraveling the Resource-Based Tangle. *Managerial and decision economics, 24*(4), 309-323.

Pfeiffer, S. (2018). The" Future of Employment" on the Shop Floor: Why Production Jobs are Less Susceptible to Computerization than Assumed. *International Journal for Research in Vocational Education and Training (IJRVET), 5*(3), 208-225.

Porter, M. E. (2001). The Value Chain and Competitive Advantage. *Understanding Business Processes*, 50-66.

Porter, M. E. (2008). The Five Competitive Forces that Shape Strategy. *Harvard business review, 86*(1), 25-40.

Prahalad, C., & Hamel, G. (1990). The Core Competence of the Corporation. *Harvard business review, 68*(3), 79-91.

Quinn, J. B., & Hilmer, F. G. (1994). Strategic Outsourcing. *MIT Sloan Management Review, 35*(4), 43.

Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D., & Spira, M. (2018). Artificial Intelligence in Business Gets Real. *MIT Sloan Management Review, September, 17*.

Russell, S. J., & Norvig, P. (2016). *Artificial Intelligence: a Modern Approach*: Malaysia; Pearson Education Limited.

Saunders, M., Lewis, P., & Thornhill, A. (2009). Research Methods for Business Students *Harlow: Pearson*(5).

Skewes, J., Amodio, D. M., & Seibt, J. (2019). Social Robotics and the Modulation of Social Perception and Bias. *Philosophical Transactions of the Royal Society B, 374*(1771), 20180037.

Soliman, F. (1998). Optimum Level of Process Mapping and Least Cost Business Process Re-Engineering. *International Journal of Operations & Production Management, 18*(9/10), 810-816.

Thomassen, M. K., Sjøbakk, B., & Alfnes, E. (2014). *A Strategic Approach for Automation Technology Initiatives Selection.* Paper presented at the IFIP International Conference on Advances in Production Management Systems.

Thuan, N. H., Drechsler, A., & Antunes, P. (2019). Construction of Design Science Research Questions. *Communications of the Association for Information Systems, 44*(1), 20.

Triznova, M., Maťova, H., Dvoracek, J., & Sadek, S. (2015). Customer Relationship Management Based on Employees and Corporate Culture. *Procedia economics and finance, 26*, 953-959.

Van Aken, J. E. (2005). Management Research as a Design Science: Articulating the Research Products of Mode 2 Knowledge Production in Management. *British journal of management, 16*(1), 19-36.

Von Alan, R. H., March, S. T., Park, J., & Ram, S. (2004). Design Science in Information Systems Research. *MIS quarterly, 28*(1), 75-105.

Von Rosing, M., Von Scheel, H., & Scheer, A.-W. (2014). *The Complete Business Process Handbook: Body of Knowledge from Process Modeling to BPM* (Vol. 1): Morgan Kaufmann.

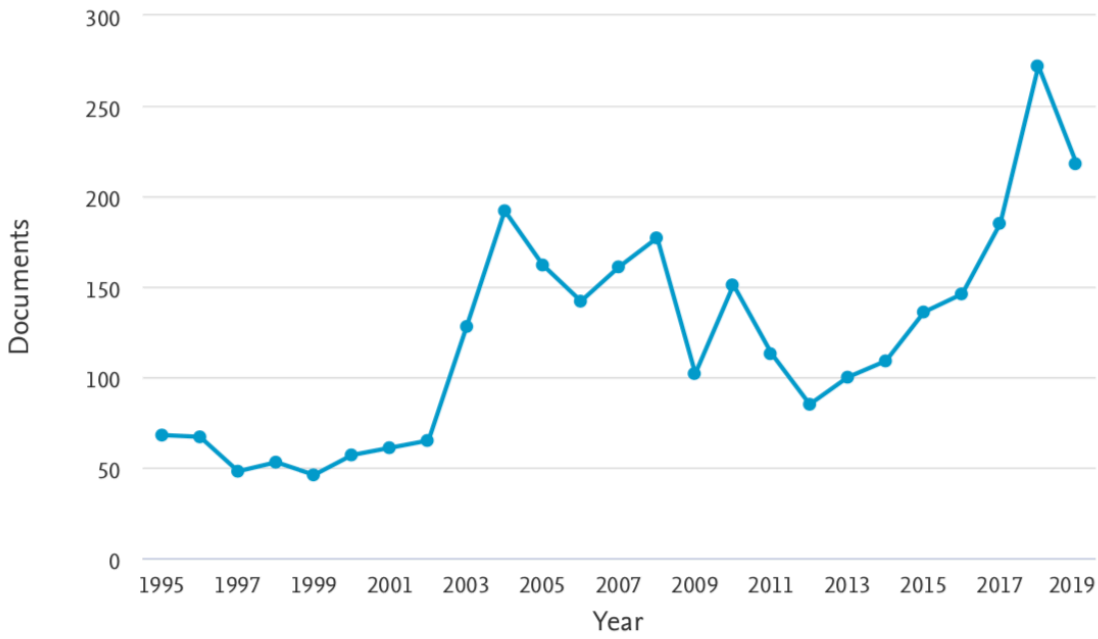
Wright, S. A., & Schultz, A. E. (2018). The Rising Tide of Artificial Intelligence and Business Automation: Developing an Ethical Framework. *Business Horizons, 61*(6), 823-832. doi:10.1016/j.bushor.2018.07.001

Yang, C.-C. (2015). The Integrated Model of Core Competence and Core Capability. *Total Quality Management & Business Excellence, 26*(1-2), 173-189.

Yüksel, I. (2012). Developing a Multi-Criteria Decision Making Model for PESTEL Analysis. *International Journal of Business and Management, 7*(24), 52.

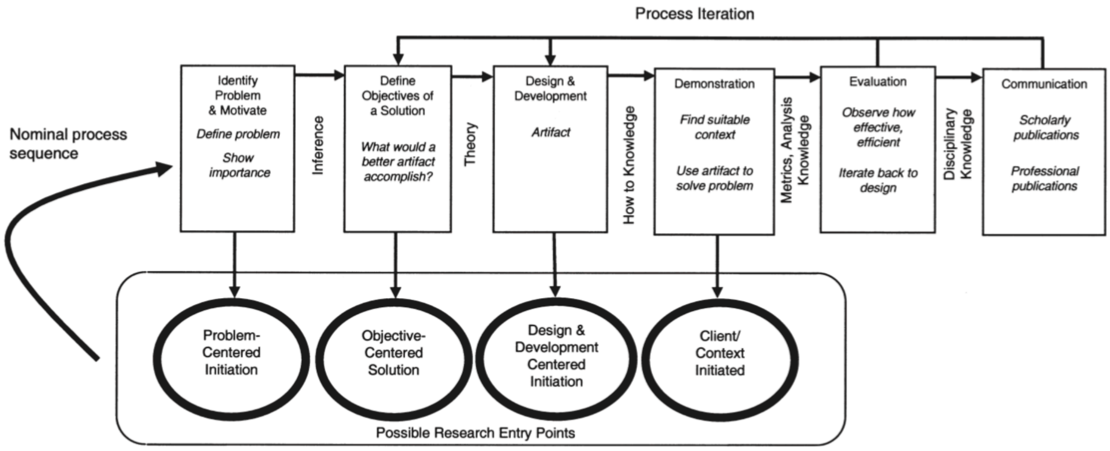
Appendix

A. Publication Histogram: "Job" AND "Automation



Source: Scopus

B. Design Science Research Methodology



Source: Peffers et al. (2007)

C. Most Automatability-Increasing and Decreasing Features

Feature	Average Gradient (std)
Telecommunications	0.16 (0.03)
Clerical	0.14 (0.03)
Wrist-Finger Speed	0.13 (0.02)
Number Facility	0.11 (0.02)
Mathematics	0.09 (0.02)
Depth Perception	0.08 (0.01)
Mathematical Reasoning	0.08 (0.02)
Economics and Accounting	0.07 (0.02)
Response Orientation	0.07 (0.02)
Building and Construction	0.07 (0.04)
Control Precision	0.07 (0.02)
Arm-Hand Steadiness	0.06 (0.02)
Equipment Selection	0.06 (0.02)
Finger Dexterity	0.06 (0.01)
Perceptual Speed	0.06 (0.01)
Visual Color Discrimination	0.06 (0.01)
Static Strength	0.05 (0.01)
Sales and Marketing	0.05 (0.06)
Far Vision	0.04 (0.01)
Spatial Orientation	0.04 (0.02)
Flexibility of Closure	0.04 (0.01)
Night Vision	0.04 (0.02)
Manual Dexterity	0.03 (0.01)
Multilimb Coordination	0.03 (0.03)
Production and Processing	0.03 (0.02)
Installation	−0.18 (0.08)
Programming	−0.14 (0.04)
Technology Design	−0.14 (0.03)
Fine Arts	−0.11 (0.05)
Gross Body Equilibrium	−0.10 (0.07)
Dynamic Flexibility	−0.10 (0.03)
Speed of Limb Movement	−0.10 (0.02)
Psychology	−0.10 (0.02)
Personnel and Human Resources	−0.09 (0.02)
Sociology and Anthropology	−0.09 (0.03)
History and Archeology	−0.09 (0.03)
Science	−0.09 (0.04)
Food Production	−0.08 (0.07)
Management of Personnel Resources	−0.07 (0.02)
Glare Sensitivity	−0.07 (0.03)
Troubleshooting	−0.07 (0.02)
Gross Body Coordination	−0.06 (0.03)
Coordination	−0.06 (0.01)
Learning Strategies	−0.06 (0.02)
Law and Government	−0.06 (0.02)
Negotiation	−0.06 (0.01)
Management of Financial Resources	−0.06 (0.02)
Social Perceptiveness	−0.06 (0.01)
Chemistry	−0.06 (0.02)
Explosive Strength	−0.06 (0.04)

Source: Duckworth et al. (2019)

D. Email Communication with Paul Duckworth, University of Oxford

On 12. Jun 2019, at 15:48, Paul Duckworth <paul.duckworth@eng.ox.ac.uk> wrote:

Dear Andre,

Many thanks for your email. I am happy you have chosen such a topic for your Master's thesis, and came across our work.

Apologies for the delayed reply.

Regarding your request, I am happy to answer your questions.

>>Are the bottlenecks of computerization still valid?

The three bottlenecks identified by Frey and Osborne (Perception/manipulation, creative and social intelligences) are still very much relevant challenges to automation. In their original 2013 paper (re-published in 2017), they manually selected 9 occupational features from the O*NET database and represent each occupation as a vector of 9 numeric values. That is, how much of each feature is required to perform the occupation.

>> Did you find new criteria similar to the bottlenecks of xiicomputerization?

We decided to not restrict ourselves to only those 9 features. We used all 120 occupational features available in the database. So we have a vector of 120 numeric values to represent each occupation. This is therefore more representative, but perhaps some of the features are not as relevant. However, we allowed out machine learning algorithm to use all 120.

Importantly however, we then transformed these occupational features (with some basic assumptions) into vectors that represent each *task* that an occupation performs. This process is described in "Automation by Work Activity" section of the paper (here: http://www.aies-conference.com/wp-content/papers/main/AIES-19_paper_166.pdf)

>> How would you give a quick/rough estimation about a process's automatability?

Our work did not focus on understanding processes, or how automatable they might be. One potential idea might be to compare what tasks a process involves, look at how automatable each task might be (using our task automatability results), and draw conclusions about what that means for the entire process? Perhaps there is one task along a process that cannot be automated. Or perhaps every task is highly automatable.

My availability for a skype call is limited at the moment. But I am happy to converse via email, and would be super excited to be kept up-to-date about your work.

Kind regards,

Paul

University of Oxford | Machine Learning Research Group

Oxford-Man Institute of Quantitative Finance | Eagle House · Oxford · OX2 6ED

E · paul.duckworth@eng.ox.ac.uk

W· www.www.robots.ox.ac.uk/~scpd/

From: Hubert, Andre <andre.hubert@campus.tu-berlin.de>

Sent: 14 June 2019 08:08:52

To: Paul Duckworth

Subject: Re: Activity Automatability Assessment

Dear Paul,

thank you so much for your support and your answers! It really helps to have someone who actually is researching in that field.

Regarding the analysis of processes:

My idea is to look at high level business processes and to estimate whether the tasks required for that process increase or decrease the process's automatability. Here, it is not important to have a fully automatable process, but rather to find potential use cases for beneficial automation projects.

In the section "Question 2: What makes work automatable?" you describe the average derivatives of automatability. I believe those could be very helpful for estimating a process's automatability, what do you think? Would you allow me to get access to the whole set of gradients? That would be great!

Many thanks and have a nice weekend!

Best regards,

André

From: Paul Duckworth <paul.duckworth@eng.ox.ac.uk>
Subject: Re: Activity Automatability Assessment
Date: 14. June 2019 at 12:21:21 CES
To: "Hubert, Andre" <andre.hubert@campus.tu-berlin.de>

Hi Andre,

>> In the section "Question 2: What makes work automatable?" you describe the average derivatives of automatability. I believe those could be very helpful for estimating a process's automatability, what do you think?

You have to be careful here. The derivative of automatability is taken with respect to the occupational features required to perform activities. This can be interpreted as "if the required amount of a feature were to increase, by how much would the automatability score change?".

How you proceed depends upon how you define a process.

1) A process could be represented as a set of (potentially ordered) activities. In this situation I would recommend using the inferred DWA automatability scores from our paper (Table 4) to estimate the automatability of a process. Here you could interrogate which particular activities within a process could be easily automated, improving that process.

2) Alternatively, a process could be represented as a collection of skills/knowledges/abilities required to perform the entire process. (Arguably – you could achieve this representation by averaging over the activity vectors from the activity representation in 1).

Then the gradient information of the features (Table 8) might be useful – as you could see the impact on a process's automatability, by changing the required amount of a feature.

I have attached a CSV file of the complete version of Table 8. Table 4 data can be found here:https://drive.google.com/drive/folders/1OvyuhhM8W5SrBp0arfZ1iH2XNSXYUcz

Kind regards,

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E. Business Processes

E.1.Process Categories

Processes can be categorized according to their role in the firm. The three main categories are management processes, main processes, and support processes (Von Rosing, Von Scheel, & Scheer, 2014). Together they build the architecture of the firm, as management processes control the organization, main processes produce the products and services, and support processes provide the resources for the main process. Examples for each process within a manufacturing company are given in Table 6 (for other company types such as platform companies process examples differ accordingly).

Table 6 Process Type Examples (Von Rosing et al., 2014)

Management Processes	Strategy and Planning
	Budgeting
	Compliance
Main Processes	Design and Development
	Manufacturing
	Delivery
Supporting Processes	Accounting
	IT Services
	Recruitment

Additionally, it needs to be clarified that tagging processes with their category is unrelated to the core competence classification. Management, main and supporting processes can all be part of core competences and in that way be sources for a competitive advantage (Von Rosing et al., 2014). Often the main processes are treated as equal to the core processes, but this research follows the definition by Boguslauskas et al. (2009), who argue that core processes are those processes that make use of a firm's core competences.

E.2.Process Levels and Decomposition

Process models (or process maps) are visual representations of business processes used to detail processes and to focus on the essential elements. Usually, they are utilized for business process re-engineering, which has the target of simplifying a company's process landscape to increase efficiency and reduce costs (Soliman, 1998).

Business process models can have different levels of abstraction, which depend on the purpose and scope of the model. High-level process models usually give an abstract overview of the activities, while low-level process models provide more detailed descriptions (Koschmider & Blanchard, 2007). Decomposable processes consist of processes and its subprocesses and allow a compact and modularized business process model. By decomposing high-level processes, it is possible to go through all the underlying business process levels. Usually, business process models require to maintain particular modeling requirements and need to be consistently on one process level, because elsewise they are non-uniformly modeled and can lead to false analysis results (Caetano, Silva, & Tribolet, 2010; Koschmider et al., 2007).

F. Automatability Assessment Features

Feature	Description	Gradient
Administration and other office procedures	Knowledge of administrative and clerical procedures and systems such as word processing, managing files and records, stenography and transcription, designing forms, and other office procedures and terminology.	0,138
Quantitative Abilities	Abilities that influence the solution of problems involving mathematical relationships	0,091
Economics and Accounting	Application of economic and accounting principles and practices; analysis and reporting of financial data.	0,068
Sales and Marketing	Knowledge of principles and methods for showing, promoting, and selling products or services. This includes marketing strategy and tactics, product demonstration, sales techniques, and sales control systems.	0,044
Construction, Electronics, Technical Plans and Drawings	Knowledge of Building & Construction, Computers & Electro and designing technical plans or models	0,034
Selecting, monitoring and maintaining equipment	Determining the kind of tools and equipment, make sure a machine is working properly and perform routine maintenance	0,027
Production and Processing	Knowledge of raw materials, production processes, quality control, costs, and other techniques for maximizing the effective manufacture and distribution of goods.	0,025
Education and Training	Knowledge of principles and methods for curriculum and training design, teaching and instruction for individuals and groups, and the measurement of training effects.	0,012
Transportation	Knowledge of principles and methods for moving people or goods by air, rail, sea, or road, including the relative costs and benefits.	0,004
Strategic Management	Knowledge of business and management principles involved in strategic planning, resource allocation, human resources modeling, leadership technique, production methods, and coordination of people and resources.	-0,004
Complex Problem-Solving Skills	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.	-0,009
Auditory and Speech Abilities	Abilities related to auditory and oral input, e.g. speech recognition or sound localization	-0,012
Monitoring individuals or Organizations, Critical Thinking, and Learning	Procedures that contribute to the more rapid acquisition of knowledge and skill across a variety of domains	-0,031
Communications and Media	Knowledge of media production, communication, and dissemination techniques and methods. This includes alternative ways to inform and entertain via written, oral, and visual media.	-0,032
Customer and Personal Service	Knowledge of principles and processes for providing customer and personal services. This includes customer needs assessment, meeting quality standards for services, and evaluation of customer satisfaction.	-0,033
Mathematics and Science	Knowledge of the history, theories, methods, and applications of the physical, biological, social, mathematical, and geography	-0,040
Arts and Humanities	Knowledge of facts and principles related to the branches of learning concerned with human thought, language, and the arts.	-0,051
Social Skills	Developed capacities used to work with people to achieve goals (e.g. negotiation, social perceptiveness)	-0,051
Controlling, analyzing, repairing and installing equipment	The ability to control, inspect, repair, analyze, troubleshoot and install equipment	-0,052
Resource Management Skills	Developed capacities used to allocate resources efficiently	-0,053
Law and Public Safety	Knowledge of regulations and methods for maintaining people and property free from danger, injury, or damage; the rules of public conduct established and enforced by legislation, and the political process establishing such rules.	-0,054
Technology, Machines and Programming	Knowledge of technology, machines and programming, including design, uses, repair and maintenance	-0,085
Personnel and Human Resources	Knowledge of principles and procedures for personnel recruitment, selection, training, compensation and benefits, labor relations and negotiation, and personnel information systems.	-0,092

G. ACM Score Calculation

By normalizing the core competence and automatability scores to reach from zero to one, it is ensured that both features have the same impact on the ACM score. While the core competence score (x) is straightforwardly normalized by dividing it by six ($x_{normalized} = x/6$), the automatability score (y) has a variable span from the lowest automatability score in the batch (y_{min}) to the highest automatability score (y_{max}). Each automatability score is then normalized with the formula:

$$y_{normalized} = \frac{y - y_{min}}{y_{max} - y_{min}}$$

Formula 2 Feature Normalization (Aksoy & Haralick, 2001)

When both scores are normalized and hence have equal weight, the ACM score is the Euclidian distance to the point x=0 and $y=y_{min}$. (or: $x_{normalized}=0$ and $y_{normalized}=0$). A process's ACM score (ACM(P)) is calculated with the theorem of Pythagoras:

$$ACM(P) = \sqrt{x_{p,normalized}^{2} + y_{p,normalized}^{2}}$$

Formula 3 ACM Score Calculation, derived from the theorem of Pythagoras (Perigal, 1873)

H. Expert Short Profiles

Strategy Expert 1	Strategy Expert 1 is a co-founder and board member of the NEXT Data Services AG, a big data and analytics company specialized in data-driven services and strategies. He has more than 17 years of experience as a management consultant and is specialized in strategy development and corporate transformation.
Strategy Expert 2	Strategy Expert 2 is a partner and branch manager at UNITY AG and is specifically focused on corporate foresight, strategy, innovation management, and artificial intelligence.
Data Technology Expert	The Data Technology Expert is the CTO of NEXT Data Services AG and leads the operational activities. He is a data technology specialist, founder of another IT startup and was 5 years director of a research and data analytics branch.
Medical Technology Expert	The Medical Technology Expert holds a Ph.D. in medical technology and is a consultant specialized in automation within the medical industry

I. Expert Interview Summaries

I.1. Strategy Expert 1; 04.06.19 – Skype Interview

Feedback to Theoretical Framework

- The approach of the analytical framework is good, but might be too simple
- For efficiency reasons, everything should be automated when possible
- Commodity processes should be automated due to efficiency increases; core competences due to efficiency increase and differentiation potential
- If a solution is highly standardized, it can be bought, and if it is unique, it should be self-made
- Strategic implications should be made more clear: top left – automate and buy; top right – automate and develop
- If something is difficult to automate it should be observed and not ignored (observe market and technology)
- The benefit of automating easily automatable processes might be high. For example, accounting: It's a waste of time and money, get out of it

Proposals for Analytical Framework Setting

- Middle management has to implement the changes
- C-level needs to give the mandate for automation. Automation also often means restructuring and hence the worker's council should be involved as well
- Three types of experts are necessary for automating a process: Management experts, AI/Data experts, product manager
- An online tool for self-assessment could be possible. Comparable to a survey within the company
- External experts should join the workshop to challenge the core competences
- High-level managers should be part of the workshop, so that middle managers cannot block their abolition
- The optimal size of the workshop is between coaching and workshop size
- Self-assessment could be done by middle management as part of the change management. It can be identified who supports or blocks the change
- Automatability can be roughly estimated, and core competences should be analyzed in detail
- A comprehensive workshop would require several days or weeks
- A rough management check would also be possible. It should be done within a concise period of time

General

- There are no limits to technical disruptions at the moment

- "I am deeply convinced that the potential for automation with AI is tremendous."

I.2. Strategy Expert 2; 27.08.19 – Skype Interview

Feedback to Theoretical Framework

- In any case, it is essential to concentrate on the top right corner. That is the survival field.
- The top right corner should be called "Make" because both target automation
- "In my world, nothing exists that is not automatable; it is only a matter of how complex the model will be in the end."
- The strategic implication in the bottom right corner should be to prepare for automation through standardization and systemization. The better a process is systemized and understood, the better it can be automated
- No attention should be on the bottom left corner
- The market should also be observed for core competences
- Probably an aspect such as build automation capability is missing
- Example given by expert: an insurance company, which only does actuary (risk calculation) can easily be automated through AI by startups. In contrast, chemical companies focused on machinery cannot be automated that easily.

Comments on Simulation Results

- The analytical framework should not start with critical processes but with major end-to-end processes. In that way, not all processes are labeled core processes
- Separation of core competence analysis and automatability assessment could function very well but would require more than 1,5 hours.
- The analytical framework will be well applicable when looking at all processes and not a small selection

I.3. Data Technology Expert; 15.08.19 – Skype Interview

Comments on Automatability Assessment

- Features are broad, within one feature there might be very different aspects with strongly varying automatabilities.
- In relation to each other, the tool predicts automatability accurately
- High-level processes cannot be assessed without defining the underlying processes
- The perspective, who does the assessment, profoundly influences the results
- The approach is comparable to the user story assessment within the scrum framework. The evaluation alone has no value, instead the relation between

them matters and the indication of what is more automatable than other processes

- There might be cases where the general automatability is low, but a specific process is automatable. Therefore, the applicability is in doubt.
- The subjectivity of the assessment is no problem as long as the results can still be used
- Process mining on task level should generally be possible.

J. Simulation Feedback Summaries

J.1. Simulation A; 24.07.19, Hamburg

Feedback to Theoretical Framework

- If something is automatable does not directly mean it is beneficiary
- Two characteristics are not enough. Cost & benefit should be included. It is possible to roll through matrices with different assessment variables

Feedback to Analytical Framework

Pos.:

- An interesting and probably valuable approach

Neg.:

- Core competence question 3 and 4 are not clear
- Dependency on a few people is not explicit.
- The person's background might influence the answers to the questions
- The clustering for Arts and Humanities is detrimental
- The level of the analysis is too high. Even though generally something is declared to be not automatable, there still might be processes that can be automated. Then whole processes might be ignored

Ideas:

- The approach itself is beneficiary, but the process level needs to be lower. The idea is to analyze an entire process model
- 1.5 hours are not enough, the level of detail should be higher

J.2. Simulation B; 29.07.19, Hamburg

Feedback to Analytical Framework

Pos.:

- Core competence analysis is well applicable; results are as expected
- The tool estimates processes to be automatable that have been automated in a later project. That proofs the tool's functionality
- Accurate automatability assessment
- Little time necessary to identify processes for further analysis

Neg.:

- The framework requires in-depth process knowledge
- Aggregate processes are difficult to analyze

Ideas:

- Customer needs to be defined before core competence question 1
- I would map the processes first and then use the framework

J.3. Simulation C; 01.08.19, Hamburg

Feedback to Analytical Framework

Pos.:

- The specific production process is not highly automatable (correctly predicted), but yet the estimation seems to be too low
- The order of the automatability score makes sense, but in general, the automatability should be higher
- The questions are well comprehensible
- The matrix is a good approach, especially because it is quantified
- The approach delivers good advice about where to analyze further

Neg.:

- Usually, a process depends on a few individuals, but it is difficult to say whether they could be adequately replaced
- The results differ when thinking about a specific person or the whole process
- It is not the final solution, because the assessment is very subjective
- It might be difficult to identify core competences on a process level because a USP could result from different sources

Ideas:

- The acting person was unclear, and hence an average estimate was used. The focus needs to lie on the person who is doing something because otherwise, it gets fuzzy
- It takes a little while to get into the way of thinking. It could be useful to start with a self-explanatory example
- Cluster the items per topic without explicitly naming them
- When using the tool in a real-world case, it should be done with two or three people to achieve a more comprehensive company picture
- Why not focus on the non-core competences for automation?

J.4. Simulation D; 05.08.19, Hamburg

Pos.:

- Core Competence score fits the expectations
- Automatability assessment order is correct

- The questions were clear most of the time

Neg.:

- Core competence question regarding dependency on a few people: Process analysis is too high-level because only a bottleneck of subprocesses depend on few individuals and the majority of the processes do not
- Total automatability score too negative
- Sometimes it was necessary also to have market knowledge apart from company knowledge
- The more detailed the process, the better the results. High-level processes lead to high-level answers.

Ideas:

- It was difficult to choose for processes in the beginning. This could be a good homework to prepare
- If it is clear from the beginning that a particular process is relevant, it could directly be started on a lower level. Else, one needs to begin high-level and find out that a process is relevant.

K. Other Simulation Findings

#	**Issue**	**Possible Mitigation**
	Core Competence Analysis	
1	Q3+Q4 have always been answered with yes; the difference is not relevant	Merge Q3+Q4; the theoretical importance is still valid and might be necessary for future analyses
2	Q5 is ambiguous and leads to confusion	Reformulate Q5
	Automatability Assessment	
3	The feature clusters “Arts & Humanities” and “Monitoring individuals or Organizations, Critical Thinking, and Learning” contain ambiguous features	Split or delete the cluster
4	Mechanics of automatability assessment are complicated in the beginning	Reorder clusters, sort by topic and begin with a trivial one

Annex

Excel files of the simulations are digitally attached to the thesis report.