# Executive Insights Into Emerging Tech: How Decision-Makers of SME+ Organisations Perceive the Business Applications of AI

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# Abstract

***Purpose*:** Although the organisational implementation of artificial intelligence (AI) contains numerous challenges and opportunities for SME+ enterprises (headcount<1.000), the perceptions that SME+ decision-makers have of AI business applications remains underexplored. The primary objective of this study was to explore the perceptions of SME+ decision-maker of AI business applications. Guided by a theoretical framework on AI topology, business value opportunities and AI perceptions of other relevant stakeholders, perspectives on the benefits, barriers, opportunities, human strengths (relative to AI) and anticipated future impacts of AI were investigated. ***Method:*** A qualitative research approach was used in data collection. 14 semi-structured interviews of 60 minutes were conducted with decision-makers of SME+ organisations across a variety of industries. Through inductive coding, perspectives were grouped into common themes and further analysed. ***Results:*** This research provides insights across multiple organisational domains, from operational processes, limitations of AI and effective allocation of human resources. A shift was identified in the processes that generate business value, where effective AI deployment enables insight generation to become an integrated component in operational processes. AI was further identified to increase the quality of the goods and services an organisation is able to produce. Furthermore, while AI is said to democratise data access for organisations of all sizes, this research identifies new limitations that have arisen from AI implementation which challenge this narrative, such as higher costs of labour, choosing suitable applications and low oversight of AI usage by employees. Lastly, humans were identified to excel in areas of creativity, physical labour and interpersonal contact compared to AI, and have crucial roles to supervise decision-making of AI-driven processes. ***Conclusion:*** This research introduces new perspectives to the field of organisational AI and identifies key areas where and how AI is influencing organisational processes. Insights from this research may strategically inform SME+ organisations how AI may benefit their organisation, emerging limitations and human resource allocation.

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# 1. Introduction

The world of artificially intelligent technologies is evolving rapidly. The introduction of commercially available AI tools has democratised generative pre-trained transformers (GPTs) to the general public, which have been met with widespread adoption (El-Bayaa et al., 2025; Maslej et al., 2025). But not only have the general public taken a keen interest in AI, both investors (Candrian & Scherer, 2024) and businesses alike (Maslej et al., 2025) spend large portions of their budgets on AI development, and growth in the global market is expected to rise exponentially (Statista, 2025). This is not without reason, as AI implementation has the potential to drastically improve organisational efficiency in a variety of business processes (Enholm et al., 2022). Recent developments in AI have led to the creation of highly conversational chatbots, advanced object detection, or algorithms that can generate lifelike imagery, video and music (El-Bayaa et al., 2025; Holdsworth & Scappichio, 2024; Peterson & Hashemi-Pour, 2023). In addition, performance on AI benchmarks has sharply increased (Maslej et al., 2025). Not only are these applications technically advanced, but they be implemented in businesses across a wide variety of sectors. For example, chatbots have shown potential as useful assets for companies ranging from ecommerce to legal sectors (Necz, 2024) and image detection has shown use in healthcare—outperforming doctors in the identification of tumours (Brinker et al., 2019; Longoni et al., 2019)—or even in railway maintenance, analysing where and when to clean railways (Ghasemi Parvin & Ghasemi Parvin, 2023).

However, for SMEs it has previously been identified that the implementation of new technologies into business processes is especially troublesome, because they may lack understanding or technological infrastructure (English & Hofmann, 2018; Hattali, 2024; Kgakatsi et al., 2024). By contrast, large enterprises often have well-established technological infrastructure and face lower barriers to recruit new talented staff (Kgakatsi et al., 2024). This results in a tough competitive environment for SMEs.

Furthermore, negative experiences with AI are frequently identified amongst the end-users of AI in business applications (Burton et al., 2020; Dietvorst et al., 2015; Haupt et al., 2025; Longoni & Cian, 2022; Longoni et al., 2019; Yam et al., 2025) and employees that are exposed to AI tooling (Chen & Li, 2024; Chuang et al., 2025; Sadeghian & Hassenzahl, 2022; Schwabe & Castellacci, 2020). The judgement to adopt AI into business processes is up to an organisation's top-level decision-makers, who are in a position to outweigh the positive benefits from AI adoption on organisational efficiency, while risking the negative effects on their end-users.

With global news coverage of AI strongly coinciding with AI-related developments (Ittefaq et al., 2025), only the newest and most complex AI techniques and applications are starting to form a proxy for what defines AI as a whole (Lockhart & Ramos, 2024). This directs the focus of businesses away from more rudimentary AI techniques, even though these applications are often at the core of running a business more efficiently (Lockhart & Ramos, 2024). With AI being an umbrella term encompassing a huge variety of data tools, there exists a disconnect between the perception of AI, and which of its subcomponents may have more strategic impact on businesses (Lockhart & Ramos, 2024).

All in all, in the business landscape of AI, there exist conflicts of interests between company investments and end-users, troubles of implementation for SMEs, and disconnects about the perception and business value of AI. Regardless, little academic research is available on how organisational decision-makers of smaller enterprises perceive the business applications of AI. Therefore, this research focusses on decision-makers of organisations that lie below the category of "large enterprises"—meaning less than a company headcount of 1.000—and their considerations surrounding the implementation of AI within the processes of their respective business. This group of organisations will be referred to as SME+ organisations throughout this paper. As such, the research question this paper aims to answer is as follows: How do decision-makers of SME+ organisations perceive the business applications of AI? In the pursuit to answer this question, this paper aims to answer a variety of sub-questions, such as: "How can

organisations benefit from implementing AI?", "Which opportunities, barriers and prerequisites are associated with the implementation of AI in organisational contexts?", and "Which roles should (continue to) be carried out my humans over AI systems?".

This research provides a new source of perspectives about the implementation of AI, directly from the organisational decision-making level. As such, it provides a realistic insight and contributes to a growing understanding of the considerations that are made when implementing AI in business processes across organisations ranging in size and industry. Practically, the research presents the technical and societal opportunities and hurdles that are experienced by organisations upon implementing AI. This provides the opportunity to reflect on the degrees to which businesses and societal values may be impacted if these barriers were lifted or restricted.

# 2. Theoretical Framework

The theoretical framework is set up to address three components for the research. The first section is devoted to defining and contextualising the different subsets and categorisations of AI and outlines the different AI techniques that have been developed. The second explores how AI is able to generate value for businesses. Lastly, perceptions of AI from are examined from the perspectives of society and employees.

## 2.1 Categorisation of AI

In order to fully contextualise the business applications of artificial intelligence, it is first important to establish concise and consistent definitions of AI and its different categories. Doing so allows for a deeper understanding of how developments in AI have allowed different applications to generate business value. Notably, artificial intelligence is an umbrella term for all simulations that parallel and surpass human intelligence, not strictly the simulations that current technology has been

able to realise. This is reflected in the categorisation of artificial intelligence, which exists on a spectrum, from rudimentary rule-based decision-making all the way to emotional and metaphysical intelligence and beyond. For distinguishing types of AI on this spectrum, there are two leading types of classifications for artificial intelligence: classification by *capabilities* and by *functionalitie*s. Classification by *capabilities* aims to distinguish AI by levels of task complexity, whereas classification by *functionalities* distinguishes the mechanisms by which these tasks are performed. Each classification has their own strengths and weaknesses. While classification by *capabilities* includes the full extent and potential of AI, classification by *functionalities* provides measurable parameters that AI techniques can be held and compared to. The following sections provide a deeper explanation of these classifications, followed by an overview of the different techniques of AI.

### *2.1.1 Classification by Capabilities*

Classification by *capabilities* consists of three subtypes: artificial narrow intelligence (ANI—also referred to as narrow AI or weak AI), artificial general intelligence (AGI—also referred to as general AI or strong AI) and artificial super intelligence (ASI—also referred to as super AI or superintelligent AI) (Gurkaynak et al., 2016; *Understanding the Different Types of Artificial Intelligence*, 2023). Each subsequent type builds on the capabilities of the previous.

ANI operates only on a limited set of data and is specialised to perform a specific task. (Banafa, 2024; Joshi, 2019; *Understanding the Different Types of Artificial Intelligence*, 2023; Xivuri & Twinomurinzi, 2021). Despite this limitation, the task it is asked to perform can still be very complex in nature. Currently, ANI is the only artificial intelligence in existence and the complete realisation of the following types is thus far strictly theoretical (Banafa, 2024; *Understanding the Different Types of Artificial Intelligence*, 2023). Regardless, recent developments in AI technology have led specific AI applications to display various attributes of AGI and ASI to varying degrees of success (Dolan, 2025).

Next, AGI would theoretically be able to use previously learned skills and reasoning to transfer and combine knowledge between different fields without being explicitly taught how, or by humans manipulating their underlying models (Pennachin & Goertzel, 2007; Peterson & Hashemi-Pour, 2023; *Understanding the Different Types of Artificial Intelligence*, 2023). It would apply knowledge, reasoning and creativity, and possess a reasonable degree of metaphysical abilities like self-awareness and autonomy, making it capable of performing all intellectual tasks humans can (Banafa, 2024; Gurkaynak et al., 2016; Pennachin & Goertzel, 2007). Lastly, ASI would theoretically be able to exceed the cognitive capabilities of humans in every field, including but not limited to: social skills, decision-making and experiencing emotions (Gurkaynak et al., 2016; Joshi, 2019; *Understanding the Different Types of Artificial Intelligence*, 2023; Xivuri & Twinomurinzi, 2021). The methods by which it would exceed human capabilities would be incomprehensible or irreplicable by human minds. It also seems widely agreed that systems that employ ASI will have evolved beyond the point of human dependency to function, and in their pursuit to optimise earth, may seek human extinction (Gurkaynak et al., 2016; Kokotajlo et al., 2025; Xivuri & Twinomurinzi, 2021). In simpler terms, in classification of *capabilities*, ANI functions to only fulfil a single specified task, AGI would fulfil several interconnected tasks at a similar level as humans, and ASI would surpass humans on every intellectual level.

### *2.1.2 Classification by Functionalities*

The second classification sorts AI by *functionalities* and consists of four subtypes: reactive AI, limited memory AI, theory of mind (ToM) AI and self-aware AI (Banafa, 2024; Hintze, 2016; Joshi, 2019; Peterson & Hashemi-Pour, 2023; Sharma et al., 2023; *Understanding the Different Types of Artificial Intelligence*, 2023). This classification segments AI based on its operational mechanisms. Each subsequent type has the ability to build upon the characteristics of those before it.

Reactive AIs encompass all machine algorithms that operate in Rule-Based Systems (RBS). They are designed to deterministically perform one very specific task, where the objective is to output an optimal prediction based on the statistical analysis of vast amounts of presently available data (Hintze, 2016; Sharma et al., 2023; *Understanding the Different Types of Artificial Intelligence*, 2023). It is only limited to if-then conditioning and they are not able to learn from previously performed tasks, meaning that repeating an instruction will lead to the exact same outcome every time (Banafa, 2024; Hintze, 2016; Peterson & Hashemi-Pour, 2023; Sharma et al., 2023). This form of AI is also commonly known as symbolic AI, classical AI, or GOFAI (Good old-fashioned AI) (Rahnama, 2025). Limited memory AIs are able to learn from historical data to make decisions and predictions. They are trained by large data sets that they store and can call upon when solving future problems (Banafa, 2024; Joshi, 2019; Peterson & Hashemi-Pour, 2023; Sharma et al., 2023). For example, in image recognition, AI calls upon a huge set of training images in order to identify images itself. However, they are not restricted to images and can be applied in any field that has historical data available, such as linguistics, self-driving cars, robotics or agriculture (Joshi, 2019; Peterson & Hashemi-Pour, 2023; Sharma et al., 2023). The combination of reactive AIs and limited memory AIs make up all of ANI, and thereby all existing AI technology (*Understanding the Different Types of Artificial Intelligence*, 2023). The complete realisation of further categories of functionalities are strictly theoretical and would fall under AGI (Hintze, 2016; *Understanding the Different Types of Artificial Intelligence*, 2023). The next type under *functionalities* is Theory of mind AI. It is a theoretical form of AI that would be able to understand human emotion and reasoning and would personalise its interactions depending on the unique characteristics of their subject (Joshi, 2019; *Understanding the Different Types of Artificial Intelligence*, 2023). It would understand human motives behind an interaction and base its response on these motives (Joshi, 2019; *Understanding the Different Types of Artificial Intelligence*, 2023). Recent technical developments indicate that achieving Theory of mind AI may soon be on the horizon (Dolan, 2025). Lastly, Self-aware AI would

have its own consciousness, sets of emotions, principles, reasoning, opinions and perception of its purpose in life, all of which would influence the way in which it would interact with users (Banafa, 2024; *Understanding the Different Types of Artificial Intelligence*, 2023).

### *2.1.3 AI Techniques*

Both aforementioned classifications are still rather broad and provide limited degrees of depth of the current AI techniques in use. While rule-based systems are sufficiently summarised by the reactive AI category, as systems that operate purely on laws and if-then statements, there are further distinctions that can be made within limited memory AI. Although all limited memory AI techniques are a form of machine learning (ML), different sublevels of complexity exist within machine learning. The following section briefly describes machine learning and its subtypes: deep learning (DL) and generative AI (GenAI).

A machine learning model trains by statistically segmenting existing data and can apply the same statistical processes for predicting unseen data (‘What Is Machine Learning (ML)?’, 2020). An advanced machine learning algorithm can consist of three components: A decision process, an error function and an updating or optimisation process. (‘What Is Machine Learning (ML)?’, 2020). First, the algorithm follows a sequence of calculations intended to predict the desired segmentation from a set of data. (‘What Is Machine Learning (ML)?’, 2020). Next, it compares this prediction with known examples (if available) or with human evaluation to identify the accuracy of the prediction. (‘What Is Machine Learning (ML)?’, 2020). Lastly, it updates the sequence of calculations to make sure the prediction will be closer to the target outcome next time (‘What Is Machine Learning (ML)?’, 2020). This last component; repeated, autonomous optimalisation, may only be a relevant component to select applications, such as language models. Regardless, machine learning models may also operate on only the first or first two components. Depending on the application, repeated, autonomous optimalisation of

the algorithm may not be necessary. Next, deep learning is a subset of machine learning that can produce outputs by combining the knowledge from several, sometimes hundreds of independently learned layers (Holdsworth & Scappichio, 2024; Peterson & Hashemi-Pour, 2023). Each of the layers have varying weights and thresholds to determine which data should be processed for the final output, both of which can be selected by the algorithm itself (Hardesty, 2017). Compared to classical machine learning, deep learning can independently refine the accuracy of different layers within the algorithm, without necessarily affecting the entire algorithm as a whole. For example, when it comes to facial recognition, it can rely on variables (such as colour, shape or the combination of shapes and colours) and use each of these layers in combination to form an accuracy assessment of a face previously unseen (Peterson & Hashemi-Pour, 2023). Lastly, generative AI is the newest technological development and a subset of deep learning. It is the class of machine learning algorithms that is able to produce data, including language, audio and imagery content in response to a prompt or request (El-Bayaa et al., 2025; Holdsworth & Scappichio, 2024; Peterson & Hashemi-Pour, 2023). It can do so by extensive training through deep learning, from large sets of unstructured image, video and language data (Holdsworth & Scappichio, 2024).

**Figure 1**

*AI Categories and Techniques Contextualised*

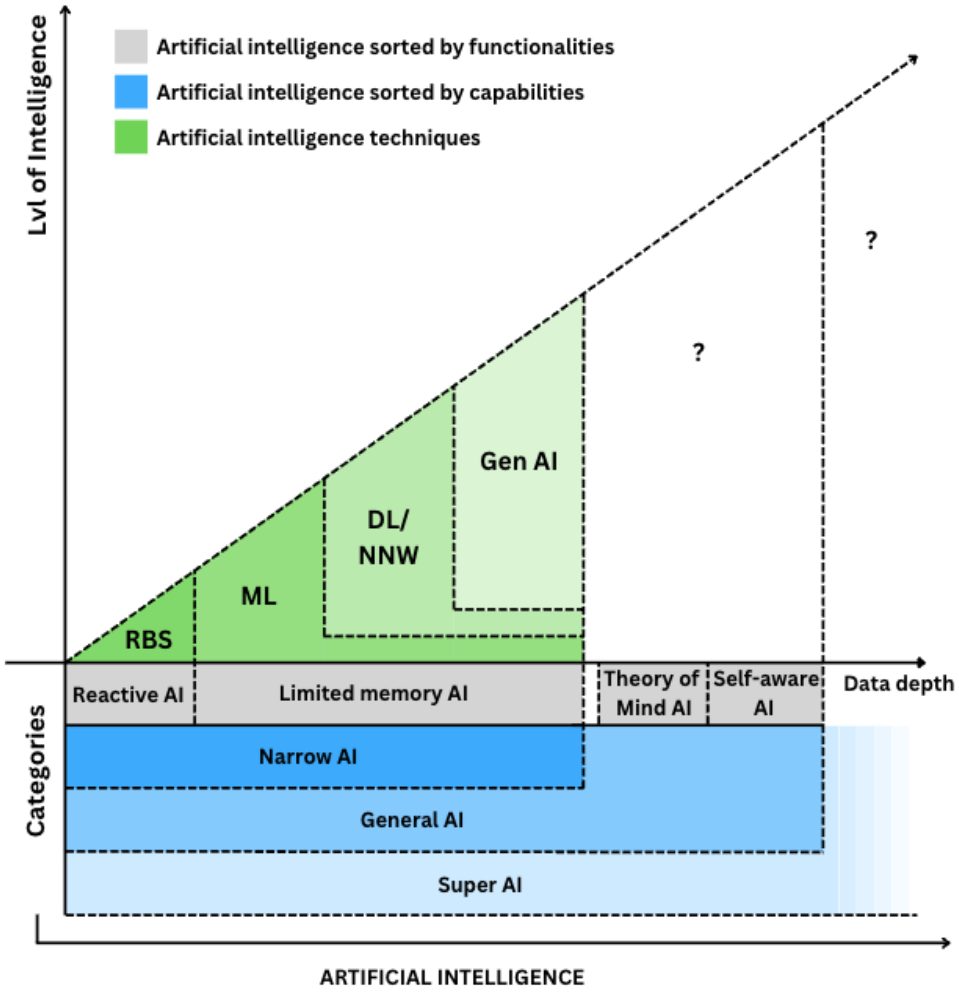


Figure 1 displays the relative relationships across the categorisations of AI and its techniques. While the variables on the axes are always positively correlated—since the accurate simulation of higher intelligence activities requires an increased variety of data and data structures—this relationship may also exist as a curved or exponential relationship, shown by the dotted line. Each technique and category is separated by dotted lines since they are not defined by absolute or fixed terms but have a relative relation to each other instead, except for the distinction between the categorisations of *capabilities* and

*functionalities,* considering these are two distinct types of categorisations. A line fully separates RBS and ML, since these operate under two distinct *functionalities* of reactive and limited memory AI respectively. The horizontal dotted lines within each ML subtype show that instances exist wherein AI applications making use of RBS can display higher levels of intelligence than applications making use of subsequent techniques (like GenAI for example). ToM and self-aware AI are not fully explanatory of the breath of general AI properties, as shown by the gap in the figure. This is because AI with general capabilities is also said to be able to transfer knowledge between different domains and contexts, which as a property is not described by the *functional* categories ToM and self-awareness. Machine Learning (ML) is specified to be named deep learning (ML), neural networks (NNW) or generative AI (GenAI) depending on the complexity and type of intelligent behaviour it simulates. Hence, these categories are regarded as sequential subtypes of ML and do not intersect the axes. Lastly, while super AI is theoretical, current narrow AI applications may already express super AI characteristics. For example, advanced chess bots significantly outperform the cognitive capabilities of human players (Bilalić et al., 2024), displaying super AI qualities in a narrow task. The same may apply to general tasks, which is why both narrow and general AI are regarded as subtypes of super AI.

This figure is a generalised simplification of the ways in which the categorisations and techniques surrounding AI are relatively connected to each other and includes certain assumptions. First, the model assumes that our current definition of generative AI is not suited to enable AI that displays functionalities beyond limited memory. Next, this figure is not suitable for plotting data points, such as different AI applications. Considering all relationships are relative and curves are malleable, plotting data points would provide little explanatory power. Moreover, plotting an AI application would require multiple data points—above and below the x-axis, in order to display both the level of intelligence it simulates and its attributes.

## 2.2 How AI Creates Business Value

Having outlined the different types, capabilities and techniques of AI, this chapter highlights the ways in which AI has proved to be a transformative technology in generating business value for organisations. Paradza & Daramola (2021) identify business value as "the transactional, informational and strategic benefits realised from the adoption of BI (Business Intelligence)" (p. 2), but this paper extends this definition to include the benefits realised from the adoption of AI, in order to address the positive effects enabled by automation.

### *2.2.1 Transformation of Labour*

The first order of impacts of AI on organisations is the transformation of labour. Developments in AI have enabled optimisations in labour and productivity, which has the direct effect on enhancing the operational processes behind generating business value (Enholm et al., 2022; Huang & Rust, 2021). This first section focusses on the methods by which AI has transformed the ways of working through automation and augmentation.

#### Automation

Automation refers to the implementation of systems that replace (human) work and service tasks (Enholm et al., 2022). By automating repetitive tasks, employees are enabled to redirect their focus from routine tasks to higher-value activities that require human attention and expertise (Alessandro et al., 2024; Enholm et al., 2022; Hattali, 2024; Huang & Rust, 2021). When repetitive tasks are automated, they can be processed at higher speeds and accuracy than humans could, drastically reducing both costs of labour and processing time (Gómez Gandía et al., 2025; Kiron et al., 2011). Overall, this means that higher quality output can be created at higher speeds, indicating a boost in productivity (Chuang et al., 2025; Inia et al., 2024). While simple repetitive tasks (e.g. filling Excel sheets) have long been able to be

automated through RBS, GenAI has enabled the automation of tasks that require higher levels of cognition, such as automatically categorising, processing and drafting e-mails, or dynamically responding to customer services inquiries in the form of chatbots (Enholm et al., 2022; Sadeghian et al., 2024).

## Augmentation

Augmentation refers to providing employees with tooling that allows them to work more efficiently or effectively (Enholm et al., 2022). In some cases, this refers to AI tooling that provides an assistive role to human expertise, such as consulting LLM's (Appendix A) to inform and increase the quality of written texts (Enholm et al., 2022). However, augmentation also refers to AI tooling that supplements human work by overcoming cognitive capabilities and inherent limitations (Enholm et al., 2022). For example, it is not feasible for humans to perform real-time predictive data analyses on large, unlabelled datasets, due to constraints in time, availability of resources and cognitive capacity—whereas AI can handle this task effectively through Deep Learning. This ability of AI to generate insights from previously incomputable data has unlocked valuable potential in a variety of organisational processes, which will be further explored in following sections.

**Figure 2**

*The Impact of AI Deployment on Labour and Productivity*

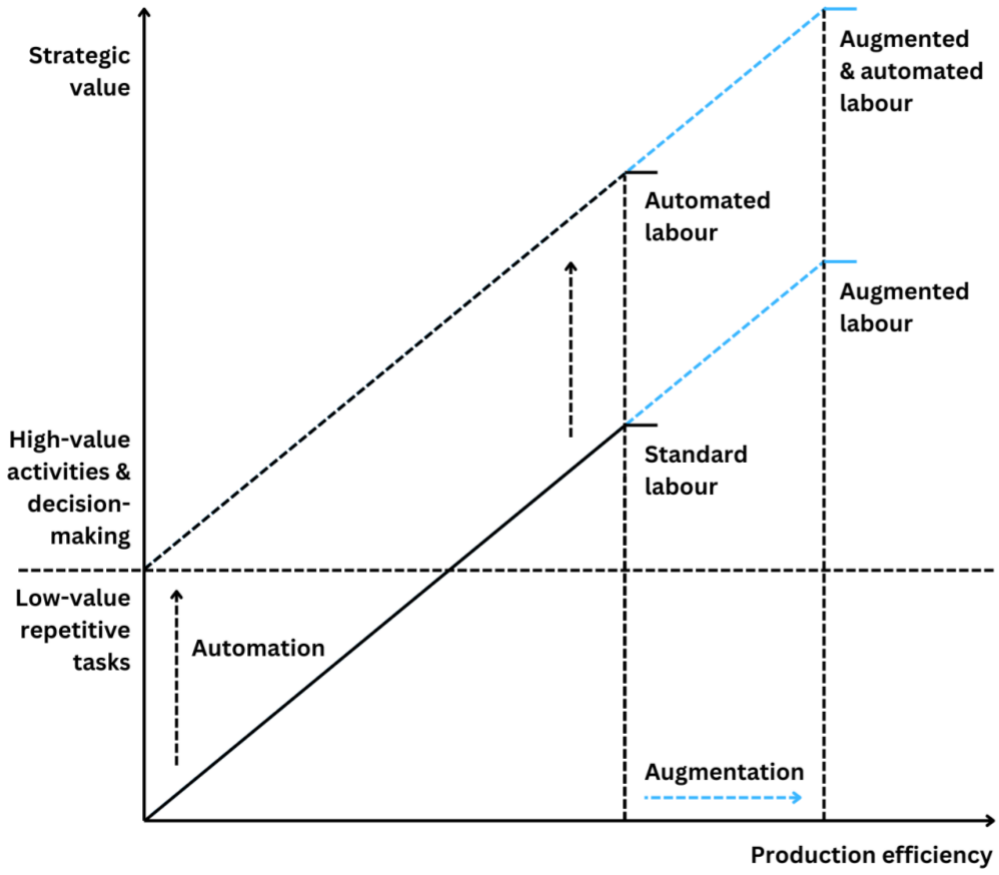


Figure 2 outlines the impact of automation and augmentation on the productive output of employees within an organisation. With no deployment of AI tools, employees may spend a large proportion of their time working on low-value repetitive tasks, and lower amounts of time on high-value activities respectively. Therefore, productivity, represented by the AUC (area under the curve), is relatively low in this instance. Through automation, (portions of) these repetitive tasks are handled by AI, and the labour curve moves upwards relative to the degree of automation. In a perfect scenario, AI handles all repetitive tasks, and automated labour allow employees to exclusively carry out high-value activities & decision-making, maximising productivity. Augmentation increases the efficiency with which employees are able to fulfil their work. Hence, it may extend the curve to the right depending on the

degree of augmentation deployed. The combination of automation and augmentation leads to the highest potential productivity increase.

### *2.2.2 Transformation of Operational Processes*

The transformation of labour, driven by optimisations resulting from AI integration simultaneously impacts the ways in which the operational processes of organisations are carried out. The following section highlights the ways in which AI impacts the operational processes of organisations in terms of their process efficiency and capacity to generate insights.

#### Process Efficiency

Process efficiency refers to the operational efficiency with which the digital and physical products and services of an organisation can be produced (Enholm et al., 2022). Exemplified by the previous chapters, the deployment of AI can enable higher productivity in generating output, thereby achieving higher process efficiency. Automation allows repetitive tasks to be carried out at greater speeds, and it redirects employees to spend higher portions of their attention on high-value activities, increasing quality of output. Augmenting employees with assistive- or transformative tooling allows them to fulfil their current tasks at greater speeds and/or quality and fulfil tasks that were previously impractical or impossible. Higher process efficiency generates business value by reducing cost of labour spent on repetitive tasks, (Gómez Gandía et al., 2025; Kiron et al., 2011) and an increase in product quality by emphasising high-value activities (Alessandro et al., 2024; Enholm et al., 2022; Hattali, 2024; Huang & Rust, 2021). However, in addition to increasing the output of current operational processes, AI developments may also drive business value by providing strategic leverage through generating insights.

## Insight Generation

Insight generation is the process of mapping business analytics to provide the organisation leverage in strategic decision-making (Enholm et al., 2022). Informed by data, organisations can identify and address key areas of focus, such as customer satisfaction, product quality or cost breakdowns, increasing business value through the improvement of these factors (Borge et al., 2022; Enholm et al., 2022; Mirwan et al., 2023). The deployment of AI enables organisations to generate deeper insights of these factors at higher speeds and accuracy. ML can perform big data processing and analysis on organisational data to calculate KPI's and predict upcoming trends—capabilities that were technically possible to perform by humans, but not at scale and in real time (Hattali, 2024; Mirwan et al., 2023). Unsupervised DL models (Appendix B) exceed the cognitive capabilities of humans by performing analyses on mass amounts of unlabelled data, revealing previously unknown or overlooked trends (Enholm et al., 2022; Hattali, 2024; Mirwan et al., 2023). Recently developed GenAI tooling can even analyse business analytics and provide actionable recommendations on it, both simplifying the presentation of complex data and increasing the speed of analysis (MIT SMR Connections, 2024). Moreover, because of the high processing capacity of AI, it can perform data analysis on open-source data, massively expanding the breadth of variables that businesses can analyse at scale (Mirwan et al., 2023). AI-driven data analytics has enabled deeper insight generation and augmented managers to make strategic decisions informed by real-time data, which allows them to dynamically respond to market changes (Borges et al., 2021; Enholm et al., 2022; Hattali, 2024; Huang & Rust, 2021; MIT SMR Connections, 2024; Paradza & Daramola, 2021). For example, insights from consumer data may identify opportunities in the market and inform the production of new product or services (Huang & Rust, 2021). This organisational agility provides organisations with competitive market advantage, which is consistently identified as a distinct benefit of technologically proficient organisations (Enholm et al.,

2022; Hattali, 2024; Hendrayati et al., 2024; Mirwan et al., 2023; MIT SMR Connections, 2024; Paradza & Daramola, 2021).

### Process Efficiency & Insight Generation

In many use cases, the benefits of refined insight generation and higher process efficiency combine to generate business value. For example, the monitoring of machinery or systems that degrade over time can be performed through computer vision (Appendix C), which can monitor their current conditions and carry out maintenance predictions, reducing downtime and maintenance costs (Kiron et al., 2011; Schmidt et al., 2020). The synergy between process efficiency and insight generation may also prove beneficial for consumer-related processes. In marketing, AI-driven insight generation may enable an organisation to more accurately identify their target audience and strategically determine which marketing approach would best suit this audience (Enholm et al., 2022; Huang & Rust, 2021; Mirwan et al., 2023). AI even allows personalisation at scale, identifying individual consumer behaviour and suggesting personalised recommendations (Hendrayati et al., 2024; Mirwan et al., 2023; Rodenhausen et al., 2024). Next, when creating marketing materials, portions of texts or visuals may be generated through GenAI and refined by employees, after which rollout across media platforms can be automated (Rodenhausen et al., 2024).

## *2.2.3 Barriers and Recommendations of AI Deployment*

The implementation of AI into an organisation will not automatically result in the generation of business value. Although there is a varied array of benefits available that AI can provide for businesses, in some organisations, its implementation fails to deliver on this potential, despite significant investments of time, effort and resources (Enholm et al., 2022; Torres et al., 2018). Whereas some organisations report a decline in competitive performance, others find that their implementation of AI does not fully realise the anticipated positive effects (Torres et al., 2018). This may be attributed to a

variety of factors, including limitations in data management, lack of talent to develop or manage AI, or generalised implementation of the system (Hattali, 2024). These factors can lead to inaccuracies in data processing, limitations in development or misalignment with the organisation, reducing the usefulness of the AI systems (Hattali, 2024). Therefore, deriving meaningful business value from AI and AI-powered business analytics requires thoughtful and strategic implementation. Considering each business has different central focuses and operational processes, organisations will maximise business value from AI by aligning its deployment with their unique personal needs and objectives (Borge et al., 2022; Hattali, 2024; MIT SMR Connections, 2024) The use of AI should enhance the achievement of these goals to generate the desired business value (Borge et al., 2022; MIT SMR Connections, 2024). This means organisations must first understand the requirements necessary for AI to deliver the desired functionalities (Enholm et al., 2022). Developing a structured framework for AI adaptation involves deliberate decisions about inputs, ensuring that the outputs generated can drive strategic, data-driven decision-making.

SMEs are in a unique segment of organisations when it comes to the potential to adopt AI. They have historically been identified to have significantly lower adoption rates of emerging technologies, despite their potential to transform operational processes and drive transform competitive advantages (English & Hofmann, 2018; Kgakatsi et al., 2024). This has previously been identified to be the case for Big Data analytics (English & Hofmann, 2018; Kgakatsi et al., 2024), and recently AI (Hattali, 2024). In their literature review, English & Hofmann (2018) outline that low adoption can be attributed to a combination of understanding, interest and skill shortage. Operating at small scale and in niche markets, SMEs may not be aware or be interested in industry trends outside of their personal domains, letting transformative opportunities pass by (English & Hofmann, 2018). SMEs may also be more likely to be managed from traditional attitudes, hindering technological development (Kgakatsi et al., 2024). From the technical side, SMEs generally face challenges in recruiting IT staff, building infrastructure or struggle

to find suitable software that provides sufficiently valuable insights at reasonable degrees of complexity and costs (English & Hofmann, 2018). By contrast, larger corporations often have well-established IT resources and management, which enable smooth integration of emerging technologies (Kgakatsi et al., 2024). Due to these challenges, SMEs fall behind in the market and are under ever-increasing pressure of being outcompeted by larger organisations (English & Hofmann, 2018). However, according to (Hattali, 2024), the development of AI-powered tools has a democratising effect on the technological capabilities of organisations. AI tooling has developed to become more cost accessible (Maslej et al., 2025) and implementation requires lower levels of technical or specialised expertise, enabling SMEs to implement AI solutions and keep firm positions in the market (Hattali, 2024; MIT SMR Connections, 2024). Upon implementation, Hendrayati et al. (2024) identify how SMEs may proportionally benefit more from the cost-saving benefits of AI, which balances their competitive market position with larger corporations.

## 2.3 Perceptions of AI

Regardless of the theoretical capabilities, advantageous use-cases and applications of AI, whether it generates value for a business ultimately comes down to whether it generates value for stakeholders. If business value is not identified by its external stakeholders or realised by its internal stakeholders, AI implementation has failed to generate value. Therefore, the following section focusses on the perception of AI, and its anticipated societal consequences. These societal perceptions may influence the ways in which stakeholders view AI, given that they themselves are members of society. The section that follows outlines the perspective of employees on AI implementation, as well as implications and recommendations to accommodate employees upon implementing AI.

### *2.3.1 AI Within Society and Its Anticipated Future Consequences*

Developments in AI are met with a combination of anticipated social risks and social values to society, depending on its application and execution. Generally, the social values of AI are praised by the

public for its potential to handle repetitive tasks and optimise processes to become more efficient (Alessandro et al., 2024). Furthermore, it is recognised for its potential to improve areas within society, such as transportation, healthcare, workplace safety or environmental impact (Alessandro et al., 2024). However, AI is also met with public concerns, including job losses, privacy, the implications of biased algorithms and losing decision-control (Alessandro et al., 2024; Haupt et al., 2025). As developments in AI enable more complex repetitive tasks to be automated (advancing closer to AGI), and some job fields show early signs of replacement, the psychological threat of `human labour being substituted by AI' becomes more impending (Alessandro et al., 2024; Chuang et al., 2025; Haupt et al., 2025; Huang & Rust, 2021). Regardless, some scholars indicate a need to redesign current jobs and anticipate emerging ones (Enholm et al., 2022). Others suggest that with increased productivity enabled by AI, societies will be able to close labour shortages within certain populations (Chuang et al., 2025; Inia et al., 2024). Moreover, there exists concerns amongst the public of AI surpassing the capabilities of humans (Alessandro et al., 2024). In extreme scenario's, researchers (and sci-fi media alike) frequently identify human extinction as the biggest threat of developing AI towards superintelligence, since humans may be regarded as a hurdle in the achievement of its motives (Daniel Kokotajlo et al., 2025; Gurkaynak et al., 2016; Xivuri & Twinomurinzi, 2021).

### *2.3.2 Employee Interaction With AI*

In organisational contexts, employees are stakeholders that are highly impacted by AI, both as the end-users of augmenting tools and subjects of potential replacement by automation. As crucial stakeholders to an organisation, the perspective of employees is valuable to take into consideration in the design and implantation of AI business applications. Hence, the next section outlines the perceptions of employees on AI developments in the workplace. Further, it highlights positive and negative usability contexts of AI tooling and provides recommendations for AI implementation with regards for employees.

AI integration in the workplace has a dual effect of positive and negative outcomes on employees (Chen & Li, 2024). On the one hand, higher degrees of automation increase employees' job satisfaction by improving productivity, safety conditions and levels of competence (Chen & Li, 2024). On the other, it has been suggested that AI induces technostress—the psychological feeling that technology develops too quickly to keep up, invades personal life, and threatens job security by replacement (Chuang et al., 2025). Threats of job replacement are identified for employees across the workforce (Chen & Li, 2024; Schwabe & Castellacci, 2020). Low-skill workers, whose routine-based tasks may be primary targets for automation, experience high replacement stress and thereby decreased job satisfaction (Chen & Li, 2024; Schwabe & Castellacci, 2020). However, replacement stress has also been identified to play a major role amongst experienced, high-skill workers (Chen & Li, 2024). Besides threatening job replacement, Chuang et al. (2025) outline how AI integration reduces employees' work-life balance, increases exhaustion, and thereby reduces overall job satisfaction. Generally, when working with AI over humans, employees experience lower motivation, meaningfulness and satisfaction in their work (Sadeghian & Hassenzahl, 2022). Regardless, given the potential for optimisations in productivity and cost cuts, further integrating of AI in organisations may be unavoidable (Sadeghian et al., 2024). In this regard, Sadeghian et al. (2024) found that in cases where humans and AI collaborate, the highest degrees of job satisfaction are identified in interactive collaborations that preserved human accountability and decision-autonomy. Less job satisfaction was experienced when humans excerpted a supervisory role over AI or AI took the role of an advisory partner (Sadeghian et al., 2024). Hattali (2024) indicates that this hybrid approach "is expected to lead to more effective decision-making processes that balance the efficiency of AI with the creativity and strategic thinking of human leaders" (p. 6).

On this topic of usability, much research has been devoted to how users experience AI applications in practice. While AI may have the potential to optimise processes through augmenting employees with AI tooling, if bad user experience prevents them to realise this potential, business value

will not be impacted (Burton et al., 2020; Dietvorst et al., 2015; Haupt et al., 2025; Yam et al., 2025). Generally, when the context that AI is deployed in matches the users expectation of its perceived qualities, its integration is valued (Yam et al., 2025). However, if there is a misalignment between the expected functionalities and the operational context of AI, there forms a reluctance to engage (Yam et al., 2025). Acceptance of AI deployment is generally referred to as *algorithm appreciation*, whereas apprehension is known by *algorithm aversion*.

## Algorithm Aversion

Algorithm aversion is characterised by the reluctance or unwillingness to engage with a system- as opposed to a human operator (Burton et al., 2020; Dietvorst et al., 2015; Haupt et al., 2025; Yam et al., 2025). The term was first coined by Dietvorst et al. (2015) when they observed that participants in their experiment preferred the forecasts of a human forecaster, despite an algorithmic forecaster outperforming them, and has been widely observed since. Similar results were found by Longoni et al. (2019) when it came to a preference for (inferior) human vs. (superior) AI assistance in the context of healthcare. Moreover, Haupt et al. (2025) outline how algorithm aversion is widely observed by organisations upon integrating AI in their customer-facing applications, which may include interaction-based applications such as customer services or sales agents, as well as exposure to generated text- and image-based content. Both customer service assistance and generated content were attributed lower competence and quality when it became apparent (or the suggestion was made) that it was provided by AI (Haupt et al., 2025). A literature review by Burton et al. (2020) identifies that this phenomenon is not limited to AI but has been in effect for more than 50 years in a variety of algorithmic applications.

A variety of reasons have been proposed that algorithm aversion may be attributed to. Haupt et al. (2025) outline that AI is regarded by humans as untrustworthy, non-empathetic and unsuitable for tasks that require subjectivity. Longoni & Cian (2022 and Longoni et al. (2019) suggest that in the context

of personalisation, algorithm aversion may be attributed to the (false) belief that AI assistance would not be personalised to the (supposedly) unique characteristics of humans. In their literature review, Burton et al. (2020) mention how humans may experience low decision-control over the output of algorithms and have low social and economic incentives to use AI. In addition, they explain that users expect perfect outputs from a technology that they simultaneously believe is incapable of generating them (Burton et al., 2020). Lastly, human and machine decision-making operate on fundamentally different mechanisms, which limits its explainability and may fuel fear and distrust (Burton et al., 2020; Haupt et al., 2025). Haupt et al. (2025) summarise that such factors may drive users to regard AI with lower source credibility than humans, acting as a determinant for reduced attributions of output quality.

## Algorithm Appreciation

In some contexts however, it has been found that users tend to *prefer* the use of automated systems over human assistance, referred to as *algorithm appreciation* (Logg et al., 2019; Longoni & Cian, 2022; Wölker & Powell, 2021; Yam et al., 2025). The term was first used by Logg et al. (2019), as a counterview to *algorithm aversion,* when they identified several consumption contexts in which users showed higher reliance on algorithmic assistance compared to human assistance.

The suggestion is made that algorithm aversion occurs when algorithms are used in hedonic contexts, whereas appreciation arises in analytical utilitarian contexts (Longoni & Cian, 2022); (Wien & Peluso, 2021). Hedonic consumption is driven by affective, experiential characteristics and emotional satisfaction (Huang & Rust, 2021; Longoni & Cian, 2022; Wien & Peluso, 2021). Satisfying a hedonic consumption effort cannot be measured objectively, since it requires subjective nuance for a product to be rewarding (Longoni & Cian, 2022). On the other hand, utilitarian consumption is characterised by functional and instrumental goals, where its value lies in the extent that the goal is achieved, not the way in which it was achieved (Huang & Rust, 2021; Longoni & Cian, 2022; Wien & Peluso, 2021). For example,

whether and how an algorithmic- or a human assistant determined the lowest price of a flight on the internet does not matter for the outcome, only its price does. Utilitarian qualities may further be characterised as practical, rational, functional or instrumental (Huang & Rust, 2021; Longoni & Cian, 2022; Wien & Peluso, 2021). Furthermore, it is important to mention that this distinction between hedonistic and utilitarian consumption is not absolute, and different contexts may present a mixture of each objective respectively, depending on its presentation and the consumption goals (Wien & Peluso, 2021). This connection between consumption context and algorithm perception aligns with the sentiment that algorithm deployment is valued when it performs within its expected functionalities (analytical, objective tasks), whereas humans are anticipated to thrive in subjective tasks (Huang & Rust, 2022; Yam et al., 2025). However, this relationship is not always identified. Wien & Peluso (2021) significantly identified algorithm aversion in hedonic contexts, but not algorithm appreciation in utilitarian contexts, and in one of the experiments by Logg et al. (2019), algorithm appreciation was found in the subjective domain of forecasting human attraction- stumping predictions of researchers.

It is essential to realise that the expectations of AI functionalities are malleable and may be subject to change as the technology develops with time and humans become subject to more experience and exposure (Longoni & Cian, 2022; Williamson et al., 2025). Since the expectations of AI have a direct effect on the drivers of algorithm aversion and -appreciation, it may be presumed that their respective triggers are not absolute.

## Implications For AI Integration in Organisational Contexts

From a managerial perspective, it is important to understand the implications of algorithm aversion and -appreciation and how to leverage them to favour their business. If AI tooling is not designed or deployed with usability in mind, the employees who are expected to use the application may display algorithm aversion and will not be able to realise the anticipated potential. Likewise,

designing for algorithm appreciation may result in quick and effective adoption that enhances operational processes.

Similarly, businesses are advised to consider when they may best deploy the assistance of their employees over that of an algorithm in the services towards their customers. For example, a consumer may consult a customer services platform for a utilitarian case (how much does x cost) or a hedonic case (could you advise me what to do in case x). The service method should be able to flexibly satisfy either of these objectives in order to be effective, through algorithmic or human assistance respectively. Even for purely hedonic consumption objectives, integrating personification into AI or augmenting human agents through AI may result in algorithm appreciation (Longoni & Cian, 2022; Wien & Peluso, 2021). However, when it comes to recommendations based on unique preferences, there is still a high preference for human over machine assistance (Longoni & Cian, 2022; Longoni et al., 2019).

Regardless, businesses should also be ready to react adaptively in accordance to how the perceptions of AI and its interaction change over time. Businesses are also advised to consider how the framing of consumptions contexts can strengthen the value associated with different sources. For example, the same products may be framed in different contexts with a utilitarian (hedonistic) lens and be recommended by AI (a human employee), to presumably create higher value (Huang & Rust, 2021; Longoni & Cian, 2022; Wien & Peluso, 2021). Overall, it is advised that business should understand and respect the areas in which fostering human connection and ethics is of high importance and look to ensure accuracy while openly acknowledging biases and shortcomings in their algorithms (Jeyapriya & Suganthi, 2025).

## 2.4 Conclusion

In summary, artificial intelligence is a highly diverse concept that has gone through many complex developments in the years since its inception. Although categorisations of AI are available,

these are oftentimes too unknown or niche to be practical in common conversation. Regardless, for accurately referencing different subcomponents and relations within AI, an accurate overview as presented in figure 1 is crucial. Practically, AI is said to have lots of potential to optimise operational processes within an organisation, benefits most accessible to large enterprises given they generally have well-established resources to enable AI integration. Smaller enterprises however are more volatile and face extra challenges to realise these benefits, making this a relevant group of organisations to research. Lastly, although a variety of research has been allocated to the perceptions of AI amongst society and employees, these stakeholders ultimately have little agency in the decision to implement AI into organisational processes. At the forefront of these decisions lie decision-makers within commercial businesses. However, little academic research has been devoted to the perceptions of this exact group. Therefore, this paper focusses on how decision-makers within SME+ organisations perceive the business applications of artificial intelligence.

# 3. Method

## 3.1 Research Design

The aim of this research was to collect the perceptions of decision-makers of SME+ organisations across a variety of industries through qualitative interviews. Perceptions of AI were examined on multiple fronts, including the benefits, limitations, roles, and potential risks of AI in business operations and decision-making processes. The interviews were held in a semi-structured format, to provide the opportunity for interviewees to elaborate on case-specific details. Ethical approval was granted by the ethics committee BMS of the University of Twente and informed consent (Appendix E) was obtained by verbal confirmation of participants in advance of the interviews.

## 3.2 Participants

Interview participants were recruited and personally requested for voluntary participation through LinkedIn Sales Navigator. As the most popular social media channel for business professionals (Zote, 2025), LinkedIn was deemed a suitable platform for collecting participants for this research. Multiple different filters were applied in order to target decision-makers of SME+ organisations. First of all, potential participants were filtered on a required CXO (CEO, CFO, COO, CMO etc.) seniority level, to single out decision-makers within organisations. To distil results to CXO's of SME+ organisations, company headcount filters were applied for <1.000 employees. Further, since perceptions of AI—specifically of its risks and opportunities—may be heavily influenced by local jurisdictions (IAPP research and Insights, 2024), the location of the company's HQ and personal geography of participants was filtered to be within the same geographical location. For this research, the Netherlands was chosen. Moreover, potential participants were filtered to have 3-10 years of experience in their current position. It was deemed that participants below 3 years of experience may not be fully accustomed to their role and responsibilities yet, and participants with 10+ years of experience would presumably be less likely to be highly involved with innovative technology like AI. Potential participants' profiles were filtered on English or Dutch profile languages in order to ensure smooth communication in the interviews and lastly filtered on "Posted on LinkedIn"—a filter that distinguishes participants that have posted on LinkedIn in the last 30 days. It was assumed that the inclusion of this filter would increase the likelihood of response from potential participants. The combination of filters produced a list of potential respondents ranging between ~500-650 people depending on the day of collection. Since LinkedIn Sales Navigator did not disclose on what basis their results were prioritised to be on top of the resulting list, final participants were reached out to by random selection (Appendix D).

The first contact was made through standardised acquisition messages via LinkedIn and any further communication was carried out on a case-to-case basis. This sometimes required contacting their

company directly to request direct or e-mail contact. For scheduling, an interview schedule was sent via a Google Meet link that enabled participants to schedule an appointment based on their personal preference (between May 2025 and June 2025). In total, 190 potential participants were selected by random selection. 74 were reviewed to be unsuitable for participation as they did not fit the target demographic of the study. 73 did not respond to the request. 25 members communicated they were not interested in participation. Reasons for rejection generally fell in the following categories: *Not interested, inconveniences travelling, not being able to accept all requests for interviews* and *no time*. 18 potential participants indicated they were interested in participation, out of which 14 members planned a time slot for the interview and the other 4 did not respond to further communications. 13 interviews were conducted in Dutch and 1 in English. Close to the completion of all interviews, it was deemed that this number of participants had provided sufficient data saturation.

Each of the 14 participants fulfilled a decision-making role at the company they represented, whether as CXO, director or owner. Headcounts ranged from 7 to 1.400 employees, with a mean of 453 employees. 1 Interviewee represented an organisation with a headcount above 1.000 employees (1.400). Regardless, their results were still included because they provided valuable perspectives that applied to the narrative discussion of this research.

**Table 1**

*List of Participants with Roles, Company Industry, and Company Headcount*

| Participant pseudonym | Role | Company industry | Company headcount |
|---|---|---|---|
| Amara Solano | CEO | Healthcare | 7 |
| Jelle Martinek | Owner | Certification | 15 |
| Rens Kovaksen | Owner | Food and beverage | 25 |
| Maartje van Laar | Director | Household | 35 |
| Thijmen Resvink | CFO | Leisure | 200 |
| Bram Alvaers | CEO | Software & IT | 235 |
| Ties van Kessel | CEO | Educational | 325 |
| Teun Veldhuis | CFO | Manufacturing | 400 |
| Cas Broekhuizen | CMO | Software & IT | 435 |
| Luuk Amrani | CEO | Financial services | 700 |
| Joost van Middelkoop | CFO | Healthcare | 750 |
| Sybren Dijkstra | COO | Logistics | 820 |
| Mees Hoogland | CEO | Human resources | 1.000 |
| Anouk Vranekamp | CFO | Construction | 1.400 |

## 3.3 Interview Guide and Procedure

All interviews were carried out between May 2025 and June 2025 and recorded primarily through Google Meet, but in three cases via Microsoft Teams as per the interviewee's preference. Throughout each interview, manual notes were taken. The interview was split up into 4 sections. In the first section, interviewees were thanked for participation and asked to provide verbal consent to the consent form (Appendix E) shown on-screen (and which was previously sent in the Google Meet meeting notes) before the recording was started. Section two focussed on the demographics of the interviewee and the firmographics of the organisation they were employed at. This included their professional background, the company industry and a measure to determine the degree to which the interviewee would describe the organisation as data driven (e.g., *Could you give a brief summary of the company, which industry is it in, and how you would describe your company's activities?*).

In section three, participants were inquired about what they understand by the term AI and the different ways in which their organisation deploys it both internally and in customer-facing applications (e.g., *Can you tell me what AI means to you? To what extent are you currently integrating AI into your business processes?*). Afterwards, they were shown an explanatory video that defined AI techniques in accordance with chapter 2.1.3 and outlined how AI generates business value in accordance with chapter 2.2. The intention behind showing this video was to open up the breadth of AI applications that participants would consider in further questioning. Lastly, section four was directed at the effects that participants (intended to) experience as a result of AI implementation and their future expectations. (e.g., *What are the main benefits that have resulted in implementing AI for your company? How do you foresee the impact that AI will have on your company in the next 5-10 years?*). At the end of the interview, participants were asked whether they had any final thoughts they liked to share, provided contact details of the researcher if they wished to retract information and thanked for their participation. The full interview guide can be found in Appendix F.

## 3.4 Data Analysis

For one of the meetings through Teams, the recording was corrupted and was not retrievable. Hence, its hand-written notes were used to support the results. Each interview was transcribed through GoodTape and verified and adjusted manually where needed. Furthermore, each interviewee was attributed a pseudonymised name, and identifiable company and location details were removed from the transcript for analysis. Interviews were coded through inductive coding with ATLAS.ti. After a primary round of inductively coding the first 5 interviews, the codebook was refined, and each interview was coded again. The final codebook resulted in 6 primary codes and 12 subcodes (Appendix G). The primary codes came out to be: *barriers of AI implementation, (expected) benefits of AI implementation within the organisation, human reliance, future and development of AI, (anticipated) AI use within the organisation* and *viewpoint*. After the coding was complete, all collections of (sub)codes were individually reviewed, whereupon common themes arose. The codes were grouped into these common themes, which formed the structure for the results section.

# 4. Results

This chapter is divided into five sections, each addressing a selection of themes that arose during the interviews. The first sections address how participants viewed AI and the ways in which their organisation used it in their operational processes. Next, the barriers of AI implementation are addressed, followed by the areas in which human labour excels over AI and its anticipated impacts on the labour market. All quotes were translated from Dutch to English by the author, with exception to those by Amara Solano, as their interview was originally held in English. During the interview, every single participant identified and gave examples of how their organisation made use of AI.

## 4.1 Viewpoints on AI

This first section is dedicated to the general views that participants held of artificial intelligence. They relate to the ways in which participants defined AI, the roles they attribute to AI, and its position in the state of their industry's market.

### *4.1.1 Definitions of AI*

The majority of interviewees described artificial intelligence conceptually and by its capabilities and applications. Examples that were mentioned were AI's ability to analyse a large variety of data (Maartje, Rens, Sybren), the processing of repetitive tasks (Anouk, Rens), exceeding current search engine functionalities (Anouk, Bram), its predictive ability (Anouk, Mees) and self-learning abilities (Sybren, Maartje). Some participants described AI metaphorically, such as Sybren, who expressed AI as a "spiderweb, capable of catching data and bringing it into contact with each other". Three interviewees, however, were able to more specifically define AI as the interconnectivity of techniques and models (Thijmen, Teun, Amara). Teun identified AI as an umbrella term that encapsulates a spectrum of applications and techniques, from LLM's to ML and with the inclusion of RPA (Robotic Process Automation[1]). Similarly, Amara explained AI as an umbrella term for a multitude of techniques, and additionally stated the importance of explicitly specifying ML, DL and GenAI as techniques when communicating about AI to avoid misinterpretations.

Some interviewees exemplified that there is a disconnect between the technical definition of AI and how they perceive AI themselves. For example, Jelle defined AI as a whole purely by GenAI. They explicitly referenced the ChatGPT database (and OpenAI's additional models), Co-pilot and Generative image creation software and regarded preceding AI techniques (RBS, ML, DL) as "very advanced

1 *Which is technically not considered AI

computer program[s]" instead (Jelle). Joost mentioned that he did not regard process automation with Co-pilot in the ERP system Microsoft Dynamics as AI. Technically however, each of these processes do make use of AI techniques to operate (Lamanna, 2023). Both Cas and Joost commented on the changing semantics of the term. Cas mentioned to have "been working with it for over 10 years […] despite us (society) thinking it has only existed for two or three years". Joost acknowledged that AI had existed for a long time, predating the 1990s. However, their current perceived meaning of AI seemed largely defined by the modern techniques of DL and GenAI. This was implied by the fact that they specified how they exclusively regarded AI as the analysis and combination of many types of data, as well as the ability to form opinions.

### *4.1.2 The Role of AI (Tool for Hybrid Labour as Means to an End)*

When it came to how the interviewees regarded the role of AI, a shared sentiment was that the preferred method of deploying AI was in hybrid with human labour. This sentiment was brought up by Ties, Thijmen, Mees, Teun and Cas. For example, Thijmen stated: "I do not necessarily believe in the complete replacement of humans with AI. I don't want to say that that's impossible for some functionalities, but I think that the combination is still more powerful than just AI". Furthermore, many interviewees shared that they saw the role of AI as the means to an end for achieving greater outcomes (Teun, Thijmen, Joost). Amara referred to the hybrid collaboration between humans, as well as AI as a means to an end in their interpretation of AI. Specifically, they mentioned that "[AI] is really how the human can actually propagate the intelligence of a machine to accelerate what the output is going to be" (Amara).

### *4.1.3 A View of AI in the Market*

A common sentiment was that value for investors does not simply lie in the use of AI, but rather in realising the value that can be obtained from using AI. As such, many interviewees did not feel

pressure from the market to develop AI specifically. Instead, they felt pressure from stakeholders, or themselves, to optimise and increase efficiency, a goal that they felt could be achieved through the use of AI (Rens, Thijmen, Ties, Mees). Exceptions to this sentiment were generally split into two. Those that felt a direct pressure from the market to specifically develop their use of AI (Maartje), and those that did not experience any pressure (Jelle, Sybren, Rens). In the case of Maartje, they remarked that "it's almost like the only way to get attention from future customers is to keep shouting AI, so there does exist pressure". On the other hand, Rens explained that he did not feel any pressure from the market because "there is often no real strategy for it yet. […] People are very interested in the opportunities and are slowly but surely starting to work with specific applications, but we're still in the early stages of understanding what the opportunities are". Similarly, Jelle did not feel any pressure from the market, because "[they] are far ahead (when it comes to AI implementation)", but they did feel pressure to stay ahead.

A few participants addressed that AI had caused democratisation when it came to access to data, deeming it had increased competitiveness in the market. Amara explained how a distinct focus on AI processes had allowed their start-up to become disruptive and competitive against industry giants, stating: "Even though they're big, they're not ahead". Similarly, Ties noted that "[we were able to solve x] with chatbots and smart technology. There we truly have competitive advantage". Anouk referred to this phenomenon as well, stating: "it's fairly possible that there's a smaller company that outcompetes you in the span of a day, because they áre doing it (using technology) in a different way. So, I do think you should start working with [AI], even as the industry's leader". Rens aldo addressed this democratisation of data, stating: "The competitive advantage of a start-up compared to a large company mainly comes down to speed. I think AI is able to provide access to data and opportunities that were previously only available for large companies". Besides company size, a few interviewees also commented on industry dependency when it came to the state of AI developments. Bram mentioned how "the financial sector is

not the most progressive" and Anouk explained that "construction is not the most innovative sector". Ties called the education industry "very traditional still" and Luuk shared the same sentiment about their industry of pensions and insurances. In the start-up world, Rens noted that they sometimes felt that the term AI was used purely as a gimmick to garner interest from investment parties. Regardless, as exemplified by Rens and Amara in the previous section, start-ups can significantly and uniquely benefit from the implementation of AI.

## 4.2 Usage of AI

Having covered how participants viewed the concept of artificial intelligence, the following section highlights how the organisations of participants made practical use of AI, including the benefits that resulted from its implementation and participants' future ambitions to implement it further.

### *4.2.1 Current AI Usage*

Interviewees identified a multitude of business applications AI that they actively made use of. The most common examples included using GenAI for coding (Maartje, Joost, Ties, Bram) and language (creation and translation) purposes (Rens, Jelle, Ties, Maartje). When it came to internal use, other examples that were mentioned included the use of AI in ERP systems (Joost, Anouk), using LLM's for market research (Joost, Rens), using GenAI for the creation of promotional materials (Cas, Thijmen, Jelle), using GenAI for the creation of presentations (Rens, Jelle) and AI for (predictive) data analyses (Jelle, Ties, Bram, Mees, Joost). For customer-facing applications, interviewees mentioned their use of chatbots (Thijmen, Ties, Bram). As a whole, Thijmen remarked: "we make a lot more use of AI than we think, because it is fully integrated into tools that we make use of", a remark that was expressed by Ties as well. For two interviewees, AI was a core business element. Cas explained that every AI technique that their company used was designed in-house and ran locally, alleviating any form of third-party

dependency. Amara commented: “for every component that we do—the whole model, the whole setup, is built on AI, […] that’s essentially how we’re structured”.

### *4.2.2 Realised Benefits of AI Implementation*

Interviewees expressed three major benefits they had experienced from implementing AI. First, increased efficiency, in particular when it came to repetitive tasks. Second, an increased quality of output, and third, how AI had a positive transformative effect on job compositions, increasing job satisfaction by shifting focus from repetitive tasks to higher-value activities.

#### Process Efficiency

Starting with the degree to which AI implementation had impacted production efficiency, Cas mentioned: “I’m a lot better equipped to [write] vision documents, that usually require a lot of time to think and discuss. But now I am able to write a seriously good white paper within two days”. Further, Rens mentioned: “Start-up scouting is a good example. There’s no need to hire IT-staff for it. I don’t have to invest in data-infrastructure […]. I can just use it, ask specific questions, give orders, and I get the results back”. Two interviewees explicitly mentioned how the implementation of AI had led their teams to work at greater productivity per employee. For example, Thijmen identified an increased efficiency when it came to customer services, stating the ability to “handle larger portions of business with a smaller team”. In the same vein, Amara recalled: “so, what used to be, you know, that you would have a group, a team of 10 people to review data, now you just need that one person to be able to review it who's really an expert”. Some interviewees also hinted that the increase in processing speed resulted in a higher organisational agility. Thijmen expressed that “(higher) speed is a form of quality in itself, allowing quicker response and content renewal”. Ties explained that the use of AI agents allowed them to quickly establish themselves in a new international market. As they were able to “set up, translate, and redesign their platform for local use within a month”. Multiple interviewees identified that the

increased efficiency brought on by using AI positively impacted their costs of labour. Amara shared that "when you accelerate with the integration of AI, ML and GenAI, we see that with speed and with training the algorithms, we reach a point where you can actually reduce costs and accelerate the outcomes that you're trying to achieve" (Amara Sybesma). Bram exemplified this sentiment when they mentioned: "we have been able to […] bring the accuracy for documentation up from 75% to 95% (by using pre-trained algorithms and LLM's), decreasing the costs of the lender. Analysis […] by a human costs €10,- and by AI costs 25c, and the output is of the same quality, so that has a costs and a speed advantage". Similarly, Cas commented on two ways in which AI can be used to enhance quality and output. They explained that their programmers tended to spend 25% on programming and 75% on researching where to tackle bugs and error codes. They suggested that if AI is deployed to improve the skills of their programmers (by 50% let's say), then one programmer would produce at 37,5% output (an additional 12,5%). However, if deployed to reduce time spent on research by 50%, their programmer would have 37,5% more time to program, essentially making them 1,5 times more productive (up to 57,5% of time spent on programming), saving costs (Cas, paraphrased by author). Rens explained that it can be especially important to save costs when it came to start-up companies, since each individual employee makes up a relatively large proportion of the total labour costs in the organisation.

### Improved Quality of Output

With regards to quality, the augmented capabilities that AI offered had resulted in increased quality of output for a variety of participants. Joost mentioned how LLM's enabled a more complete overview of data and variables, stating: "whereas [collecting] information used to really take time, now you can really collect market information well". Cas remarked how "the uniformity in tone of voice that you can achieve with AI is much greater than I could achieve with one or multiple copywriters". Sybren commented that AI usage had increased the quality of internal communication. "From the operation

department, [unlike before], I am suddenly seeing properly formatted e-mails, with a greeting, introduction, story, conclusion and request […] and that is definitely an advantage" (Sybren). The benefits of automation were also widely observed and exemplified by the following statement from Amara: "we look at regulatory submissions and that reduces the administrative burden. So less human beings needed because we then minimize the risk of human error." (Amara). Furthermore, for Maartje, AI had offered improved tooling which increased their service's quality. They stated: "we have already seen that if we input [the product that we offer] into ChatGPT, it sometimes turns out nicer than from our render engine" (Maartje).

#### Effects on Job Composition and Satisfaction

Similar to how Amara mentioned a reduction of administrative burden, multiple interviewees mentioned positive effects on job compositions. "What remains are the tough questions, which makes that [our employees] get the more interesting cases" (Ties). Similarly, Teun mentioned: "I think you allow people to be more human. And that some tasks that currently have no or little added value, that you can [start to] focus on activities that are of higher value for the customer" (Teun). Lasty, some interviewees mentioned how they appreciated that AI was able to make their job somewhat easier or more comfortable. For example, Sybren mentioned that "if you have [a lot of things] circling around your head […] then you can almost write an authentic message (by using AI) without having to think about it".

### *4.2.3 Anticipated Use of AI and Its Associated Benefits*

Participants also spoke about the benefits they anticipated that AI would be able to realise if implemented further into their organisation. Some interviewees anticipated that further implementation of AI would allow their organisation to become more data driven (Joost, Thijmen). Other interviewees had ambitions to use AI in the future for strategic decision-making (Joost), to develop their product and service package (Rens, Maartje), run predictive analyses (Thijmen), explore opportunities for coding

(Thijmen), analyse data from a greater breath of sources (Jelle), turning tacit knowledge into explicit knowledge (Anouk) and increasing information transparency and access to both customers and employees (Sybren). For example, Maartje imagined a scenario in which they had optimised their process to such an extent that they would be able to tackle a completely new market segment. Anouk saw potential in AI to turn tacit knowledge into explicit knowledge. They mentioned "that when people have worked here for 30 years, […], that you hold an interview with them, they tell you how the process works, and that ChatGPT can help us with a process description of how that works. Meaning you can extract the knowledge from these people" (Anouk). They implied that this knowledge base would help new, young employees to quickly learn the required skills and knowledge. Sybren imagined how fluid information transparency, enabled by AI, could have great benefits for their organisation. They explained: "[Currently,] when we run into busy workloads […] then it's often on the day itself, or two days beforehand, that we talk about these peaks, think about solutions, and communicate with our customer. Obviously, there is a lot of potential there. If both are aware in the moment of: I have this many resources, this amount of capacity, and I have certain customer demand to meet […]—if you would be able to link those, that would be incredible" (Sybren).

## 4.3 Perceived Disadvantages and Barriers of AI Implementation

Outside of its benefits, interviewees mentioned a multitude of disadvantages, risks, perquisites, limitations or hurdles of AI implementation. The following section outlines these barriers that were identified across several themes. Themes range from inherent limitations of AI models and considerations that come with technological development to strategic and managerial challenges that have arisen from AI.

### *4.3.1 Model Constraints and Reliability*

AI models have inherent limitations due to the ways they are built and how they operate. As such, Jelle recommended to always review AI's output with "a healthy conscience and expertise". A disadvantage that was identified by two interviewees was the limitation that AI models were only able to look back and learn from a collection of existing information. Cas commented: "It's as if you would drive in your car and only look in the rearview mirror, as if you would make your decisions based on that". Thijmen was cautious about the long-term usage of predictive models based on current data, saying: "when the market changes, or there are influences in the market that cause it to change, will the model still hold predictive power? Or have you just created a model that only works very well on the *current* standings of the market, because then it is a lot less valuable" (Thijmen). Next, participants commented on the explainability of AI, and the risk of a 'black box'. Thijmen stated: "in its totality, if you combine […] big data […] with the self-learning aspect of LLM's, then it becomes very complicated to see what happens exactly". Moreover, Cas mentioned the risk of using AI to handle a variety of tasks at the same time, since "single task agents have a way higher chance to succeed and to be accurate". Furthermore, they, as well as Thijmen, expressed their concerns for bias and stereotyping, and how it can lead to misrepresentation. "There is a lot of bad influence […] from the internet, because that is not an accurate representation of the real world. […] The big danger is that we believe that AI always tells the truth" (Cas). Sybren often experienced uncertainty of the truthfulness of the output from GenAI, especially when it came to high stake activities like legal and financial cases. Likewise, on this topic of output reliability, Rens found GenAI unreliable for certain applications. They mentioned that "when we ask AI to create a sales presentation, a document, or an image, the chance that there are strange things in the output, that we won't be able to remove, is quite big. So, before you can reliably make a GenAI tool reduce your workload well, you still need to take some steps" (Rens). Maartje similarly mentioned that

“you still cannot trust it with 100% certainty […] it still makes such obvious mistakes. […] If you truly [want to] tailor your process to it, these need to go, otherwise you will get stuck”.

### *4.3.2 Enterprise Data Model Structure and Data Quality*

Cas, representing an IT company, identified that implementation of AI is often limited by the data quality and structure of organisations. Multiple interviewees referred to the importance of data quality, mentioning “garbage in is garbage out” (Joost), “AI doesn’t do anything without data” (Mees) or “you need tons of data to be able to really train the algorithms to perform at a high level” (Amara). Teun explained that “If your data is in silo’s, you have less possibility to experiment with AI at scale”. Thijmen experienced the disadvantages of poor structure first hand, as they noted their outputs were often inconsistent due to their organisations disorganised infrastructure. Sybren explained why organised infrastructure was hard to achieve from their perspective. “Our history is as diverse as our products. Throughout the years, we have had multiple initiatives and planned to compile this into […] more integrated [ERP] systems. […] But I think, partially because of our product diversity, that has always been especially tricky” (Sybren). On the other side of the coin, Ties experienced that when upscaling, more advanced forms of AI required more sophisticated data management. They explained that: “We have had to change our platform a few times already, to increasing levels of cloud complexity, with more memory and different forms of database management” (Ties).

### *4.3.3 Data Ownership, Security, Trust and Geopolitical Risk*

Openly sharing company information with third party AI providers was a theme that arose often. “We still find it challenging to openly share information” (Sybren). Regardless, Anouk mentioned that innovation capacity of a company can be greatly held back by being too reserved about data sharing. Three interviewees suggested that the use of third-party cloud services places company data at risk, as its security is no longer entirely within the organisation’s control but is subject to the practices and

resilience of the third party. Multiple participants noted that this was impacted further by the current state of geopolitics, which had a negative impact on the willingness to share organisational information. Mees emphasised that this was an especially important consideration for their organisation, given that they have large collections of personal demographic data of employees, such as home addresses, and many employees were located near zones of war. Cas had the suspicion that the current state of geopolitics was reducing societal and interpersonal trust. They suggested this leads to apprehension in sharing information, because of the risk of losing data ownership, greatly limiting the applications that can be realised with AI (Cas, paraphrased by author).

### *4.3.4 Finding Value and Appropriateness of Use*

A recurring aspect was the ability to understand where to implement AI properly. Maartje mentioned that "the biggest hurdle is a clear formulation of the task. […] That you're still uncertain what solutions you are looking for". This sentiment was shared by Anouk, who specified that an important prerequisite of AI development is "not to automate […] until you have fully thought through your process, [otherwise] you will not get the benefits that you expect". Similarly, a prerequisite for Sybren was: "we first need to understand [AI] ourselves before we send it out (to the customer)". Joost and Cas mentioned the importance of checking the validity of the prompts and requests that are put into AI, not only the output. Mees noted that although AI is very capable of achieving certain outcomes, sole reliance on AI may not be desirable. "[With AI] I can make the most optimal planning of work, transport and accommodation [for my employees]. However, that leads to [my employees needing to frequently switch between these] […]. I know one thing for certain, the average employee thinks you'll have gone crazy, so finding the balance to what is economically the most optimal outcome and what is the most responsible emotional- or social ordering, that's where I do not see where AI […] will help us to [determine] the most accepted optimalisation" (Mees). With regards to deploying AI in social contexts,

Jelle mentioned that “the handling of [human interaction by AI] is worthless”, explaining that “every time [you are] confronted by it […] you are always disappointed”. Chatbots were brought up often in this negative regard by participants. While understood by many as a logical implementation, there was a collective distaste for its ineffectiveness. Mees posed that an important aspect of implementing AI chatbots is to consider what its implementation communicates about the organisation. “Even though the answer might be better, does [the implementation] deliver on the same ‘closeness’? […] if you look at the emotional dimension, it might be a lot more valuable—despite getting a worse answer, [that] I had *you* (a person) on the line, and that has meant more to me than the accuracy of the answer” (Mees).

### *4.3.5 In Search of Knowledge, Information and Qualified Talent*

For knowing where and how to implement AI into an organisation, information and qualified talent was frequently mentioned as a hurdle. Mees noted that there is little knowledge within their organisation about which AI tools are available and how to use them effectively. Likewise, Rens identified that one of the biggest hurdles was “not knowing what is available and how it can help […]. Often you see that for something basic, like making a presentation, you get eight, nine, ten suggestions that all claim they are the best […]. I don’t have the time and energy to try all ten of them out. It’s a jungle of what’s available and what’s not, which holds me back from diving in”. With regards to the difficulty of finding talented staff that brings knowledge into the organisation, Joost attributed this to the semantics of the term AI. They mentioned that “[AI] is an umbrella term. Everybody thinks they can enter [the organisation] with AI knowledge. […] People often overestimate themselves” (Joost). They later clarified: “AI is clearly a specialty. If you want to achieve something big, you will need somebody with 5-10 years of experience. […] The market is relatively limited, in the sense that everybody who ever had a course in prompt engineering thinks they are an AI specialist” (Joost). Op the topic of recruiting talented staff, Ties mentioned: “If you collect the right team of people, people with knowledge, and you implement [AI]

well, I believe it can only lead to improvements, no resistance". Jelle mentioned not to feel any resistance from their employees, attributing it to the fact that they "only work with highly educated employees".

### *4.3.6 Pricing and Costs of Labour*

Another downside surrounding AI was identified to be its costs. Ties commented that the implementation of AI requires suitable tooling, which comes with additional (licencing) costs. Other participants rather emphasised increasing costs of labour. For example, Amara mentioned that "[they] can design something in GitHub or another platform like Azure. It costs nothing for us to have the membership to do that. But you need to hire somebody who's an expert on it to be able to build it for you. And that's where the labour comes in. It gets very expensive" (Amara). They later clarified that this was because the costs of labour had changed for experts in this field: "[before], you could pay a data scientist a minimal amount and now they're hard to find" (Amara). Similarly, Thijmen commented on the cost of labour and mentioned: "I would very much like to admit one or two data scientists, but if I admit two, I have already increased my employee base by 2%, and those are just costs" (Thijmen).

### *4.3.7 Resistance to Change (From Traditionalist or Older Employees)*

A multitude of interviewees commented that traditional mindsets, ways of working or scepticism negatively impacted the speed and ease with which AI could be implemented into their organisation. For example, Maartje stated: "The developers are very sceptical about AI developments. […] You need to nudge them to actually start exploring". They further mentioned that "[their] 3d modellers are quite stuck in their existing workflows". Such a mindset was identified by Mees as well: "Breaking old habits is tough". Joost identified these traditionalist mindsets as a negative influence on the organisation because it slows development. Some participants specifically attributed age to traditionalist mindsets. Anouk explained that for them, "the challenge lies mostly with the factory manager who's 60 years of age […].

To also get *this* person on board". Likewise, Joost mentioned: "With the 30-plussers that are already working somewhere, they will not be able to absorb it (AI) as quick [as younger employees] because they are stuck". On the topic of younger employees, Ties mentioned: "it's also age dependent. If you're young, you like it, you think it's cool. And if you ask older people, they think it's a threat. I don't think that will ever change". On the contrary, Anouk later shared that "the good news is, luckily that there are many people amongst the older generation who are open minded for it". Maartje had experienced that a traditionalist mindset could be swayed by the slow introduction and experimentation of use cases.

### *4.3.8 Strategic Considerations, Culture and Leadership*

The next disadvantage of AI were the strategic aspects that come with such a transformative technology. Sybren mentioned how AI development initiatives may sometimes be haltered by their devotion to their clients. They explained that the implementation of data-driven AI projects requires their clients to share specific data and information, which their clients would often be apprehensive about. "Change management is a real deal […]. But it is especially important to take your internal and external stakeholders along" (Sybren). They later identified that the implementation of AI required very "rigid choices" and that "at a certain moment, you have to just make the call and say that you're going to tackle it differently" (Sybren). Similarly, Teun mentioned leadership as an important prerequisite for properly implementing AI. When it came to implementing AI well into an organisation, they mentioned that "if it is not carried from the top of the company, you get a lot of bottom-up approaches. But then you run the risk that you take well-meant initiatives that eventually don't lead—like an orchestra, to a beautiful symphony" (Teun). Instead, they remarked that "you need a tech-savvy or a digital savvy board. […] And that means you also need to have a culture [to invite AI], or create it, that's based on trust. If you have more trust, you take more risks. More risk leads to innovation, innovation leads to progress" (Teun).

### *4.3.9 Low Barrier to Entry for Using AI*

Lastly, multiple interviewees expressed that the accessibility and ease of use of AI can form disadvantages and risks. Maartje mentioned that their organisation did not have a structured process for using AI yet. As a result, they observed that employees were unhindered and openly shared company information, risking a giant data leak (paraphrased by author). This risk was similarly identified by Thijmen: “One of the biggest problems that I see is the low barrier to entry. The speed with which people will just start using tools, […] without you having any control over it, is one of the biggest concerns for me. […] The fact that, when people make use of GenAI tools, that with most of those tools you lose intellectual property rights on everything that you feed the model with, that’s very dangerous”. Teun summarised many aspects of the risks and disadvantages from this chapter when they referred to the low barrier to entry of AI. “If everybody [in the organisation] is going to work with data and AI, and we are all going to prompt. How will we keep it manageable? How will we make sure that we actually get outcome? […] If you get to the point that you are used to using it, then you’ll get an upwards curve, but that carries a cost. Although these are small costs, if you do it at scale, if 40.000 people at [company] would prompt each day […] then the costs become uncontrollable. So how do you make sure it’s meaningful, that you deploy responsible AI, that you don’t have hallucinations, discrimination. You need to think about that framework properly” (Teun).

**Table 2**

*Perceived Barriers of Implementing AI Into SME+ Organisations*

| Limitations | Explanation |
|---|---|
| Model constraints and reliability | Inherent limitations of AI models that affect reliability, accuracy and explainability of the output |
| Enterprise data model structure and data quality | The degree to which the data in the underlying data infrastructure is structured and of quality |
| Data ownership, security, trust and geopolitical risks | The required measures to alleviate the risk of a data leak and prevent its financial, personal and geopolitical consequences. |
| Finding value and appropriateness of use | The ability to identify the places, and deploy the right methods to realise the potential of AI effectively and reliably |
| In search of knowledge, information and qualified talent | Finding relevant information and qualified staff that enables proper, strategic integration of AI into the organisation |
| Pricing and costs of labour | Increased financial burden as a result of increasing costs of labour from talented and qualified professionals |
| Resistance to change (from traditionalist or older employees) | Internal cultures or motives that resist the deployment of AI, hindering its integration within an organisation |
| Strategic considerations, culture and leadership | The leadership and vision required for integrating a new and dynamic technology into a long-term business strategy |
| Low barrier to entry for using AI | Low control over the intention and input of employees' AI usage throughout the organisation weakens top-down oversight |

## 4.4 Human Strengths Relative to AI

Within the interview, certain questions were directed to understand perspectives on the roles that were regarded to be better suited to humans as opposed to AI. Regardless, outside of direct lines of questioning, interviewees would bring this theme up naturally.

### *4.4.1 Product Physicality and Physical Labour*

One topic that was brought up by two interviewees was that of physical evaluation. For example, Anouk, whose organisation operated in the construction industry, mentioned: “an architect really wants, they want to have the product in their hands, see it, feel it, see the real colour, see how the light interacts with it. […] In that sense we are still a business where people come to visit us to see and handle products” (Anouk). Ties made a similar mention when they stated: “I think that you will get a digital twin online. […] And maybe I will only chime in whenever you answer a question that the digital twin really cannot answer, because it has to do with the physical world” (Ties). Sybren anticipated that physical labour would continue to be performed by humans. “I work in a production setting. If I look out my window, I see cranes driving, I see forklifts driving. I don’t see that getting replaced by AI any time soon” (Sybren). They later specified that they felt this way because these jobs required a certain degree of uniqueness and interpretability.

### *4.4.2 Creativity*

Next, creativity was often mentioned as an inherent strength of humans over AI. Four interviewees explicitly mentioned this factor with varying examples. For example, Cas mentioned: “With AI you can create quite a few fun things that are good for bulk. But if you really want sophisticated creativity, use a human still. […] Ultimately, the true lightbulb happens in the human brain”. Maartje shared a similar sentiment about AI being good for bulk work and added that humans are useful for

proactivity on top of creativity. Teun addressed the combination of creativity and AI tooling when they mentioned: “I think a certain degree of creativity lies with humans […]. The creativity is decided by how good you are at making a certain prompt that leads to a different outcome […]. If you’re very creative […] and you give a different prompt than me […], then you get a different outcome than when I make it because I’m less creative for example”. Ties explained creativity as: “There where you need to combine many things from different sources, and also sources that are not online yet”. They continued: “You have a lot of companies that still have a lot offline. And where there is a lot of knowledge and experience and specific context […], that people still play a role there, supported by AI tooling. I think that will disappear at some point as well” (Ties), hinting at the importance of data documentation.

### *4.4.3 Human to Human Contact (in Business and Emotionally Oriented Settings)*

Furthermore, amongst a variety of participants, interpersonal contact was identified to be an important human role. This topic arose implicitly in many of the aforementioned quotes throughout this entire chapter, but this section highlights the cases where participants explicitly mentioned this attribute. Some interviewees referred specifically to the importance of interpersonal connection in business-related settings. When asked which tasks should ideally be carried out by humans, Rens commented: “selling products where you especially need human interaction. To talk with customers, approach customers. The whole reporting, maybe the market research, developing and testing, that you can remove- automate, […] which allows people to occupy themselves more with tasks that have more added value”. Similarly, Jelle referred to the potential of hybrid labour, but highlighted the importance of human interaction. “I can imagine [that] in the business-to-business, you base your service offer on AI-generated data: analyses, alternatives. But the last step in business-to-business is a human interaction, and that is uniquely human. I don’t see that happening any other way” (Jelle). Outside of the scope of business, multiple participants mentioned the importance of emotional availability by humans. For

example, when it came to handling a distressed customer as a service desk employee, Ties believed that effective, calming reassurance was only achievable by humans.

### *4.4.4 Expert Validation*

Another frequently mentioned role where human dependency played an important role was in the verification of decisions and data. Amara commented: “I think no matter what, the validity of the data needs to be reviewed by a human who is an expert in the field”. They later added that “what [they] use the human resources for are the experts that are going to really look at the data to make sure of its accuracy” (Amara). Mees exemplified the effect of expert verification when they posed the following hypothetical: “Within the planning department, I just mentioned optimisers, they make a very optimal planning and then at the last moment, an operational employee looks over it and thinks: hold on, we planned Patrick and Richard together, but they work horribly together, I’ll plan them in separately instead”. Lastly, Sybren reflected on his trust perceptions of human employees vs AI output. “The guys from finance, if I receive something (produced by AI) and I let my finance guys take another look at it and calculate it again, then I might have a lot more trust. Maybe that says more about me personally than the reliability of the information that comes out of AI” (Sybren).

### *4.4.5 Agency, Responsibility and Accountability*

Finally, multiple interviewees remarked that humans played an important role in (strategic) decision-making (within an organisation). Ties and Rens shared a similar sentiment. “I think that the process of making decisions should stay with us (humans)” (Rens). Bram exemplified this sentiment when commenting on responsibility, stating that: “if the software has made a mistake, that is the responsibility of the CTO”. Rens further offered an explanation for why they suggested decision-making should have human oversight. “The system may arrange a quick overview of everything that is out there. […] But the eventual decision to talk with start-up A or B, that remains with us. That I wouldn’t delegate

to the system, because […] it is not just a rational process, but also the human factor of: what team do they have, what kind of people they are, how much experience do they really have—is just as important as the business idea that [the company] works on. […] So, the decision-making, human interaction, […] to start up projects, to sell orders, that I wouldn't automate" (Rens).

**Table 3**

*Roles in Which Human Labour was Identified to Excel Over AI-driven Automation*

| Human strengths relative to AI | Explanation |
|---|---|
| Product physicality and physical labour | The experience of physically handling and evaluating products and performing physical labour |
| Creativity | The ability to create new and innovative ideas or concepts |
| Human to human contact (in business and emotionally oriented settings) | The interpersonal communication between humans, which forms uniquely emotional connections |
| Expert validation | Using expert knowledge to critically think, evaluate and validate any form of output |
| Agency, responsibility and accountability | The agency and power to make important decisions, and carry responsibility and accountability of its consequences |

## 4.5 Impact of AI on the Labour Market

Lastly, interviewees shared many of their expectations and anticipations for the impacts that AI would have in the future. Cas compared its impact with the introduction of the internet, and noted that "when Google was originally introduced, that was revolutionary to us (society). […] But this (AI) is existentially different than just a search engine. This is so multidimensional, that we cannot imagine in which ways it will be relevant, or applicable". Many interviews specified how AI would impact the labour market and change labour demands. A popular opinion was that many jobs and occupations would become obsolete or subject to change. "I think many jobs will disappear" (Joost). Cas explained how this concept wasn't anything new when they stated: "progress is of all times, so some functions will go extinct. […] We don't need the milkman that puts a bottle at your door anymore. So, it's been of all times that some things are not functional anymore because they've been replaced". Jelle anticipated that "repetitive work, work requiring lesser education, that's the first to go. That has been the same with all forms of automation, and it will not be any different for automation supported by AI, that's what I expect". While it was acknowledged that retraining and replacement would likely not be well-received by the workforce, participants saw this as an unavoidable consequence of this technological revolution. Moreover, Bram commented that organisations need to mindful of other stakeholders besides their employees : "As company management, you are responsible for a variety of stakeholders, but your shareholders are an important part. So, I think that if you can increase the efficiency of your company, supported by new technology, than you should essentially do so" (Bram).

Regardless, multiple interviewees viewed AI's impact on the labour market as positive, on the basis that it allowed humans to carry out more meaningful work—or work that was in higher demand—and that it would address national labour shortages. "I am in support that that type of work (repetitive), […] is 'removed' from people and that you can deploy those people in a more useful way than this. I am a supporter, that is a positive development" (Jelle). Sybren regarded that reallocation of resources would

ultimately be beneficial for their employees. They mentioned that: “If you currently need to carry out your work in convoluted ways, and it is very labour-intensive, and you need to do lots of actions […], [but] you would be able to work a lot smarter with AI for example, then it would make your work better. And that also means you have happier employees. So, I’d rather have less, happy people (employees), than a lot of employees because our systems [cannot function otherwise]” (Sybren). Around five interviewees explicitly mentioned how they expected AI to have a positive effect on relieving pressure on the local labour market. “In the Netherlands, we have a raging shortage of labour. So, I think it (AI) can create a solution for this by automating certain actions, which frees people to take up different actions or jobs. And maybe it will also make jobs more interesting—because you’re not asking somebody to stand at a production line or answer standard questions the entire day. To provide them a more interesting and meaningful job” (Rens).

When it came to changing labour demands, some interviewees expected an increasing emphasis on physicality in labour. For example, Anouk implied an increasing need for interpersonal contact when they mentioned: “I think that eventually, characteristics where you as a human are truly authentic, that that will generate a lot of value, because people are going to want that feeling again. Regardless of how sweet and nice a robot may be—because an AI can also be very empathetic—we can’t really call it authentic, because it has no soul”. Besides an increasing demand for emotional satisfaction, Ties instead referred to the need for trade workers. “I think there will always be jobs that you need humans for. […] I think there is a lot of demand for people who *do* certain things, a computer will never replace that [type of work]. It’s becoming harder and harder to find a good construction worker” (Ties).

# 5. Discussion

## 5.1 Main Findings

Results of this study seem to partially align with the suggestion of Lockhart & Ramos (2024), that the perceived meaning of AI is skewed to be representative of the most recent AI developments. This is characterised by the fact that the capabilities and applications that were most frequently mentioned by participants were characteristic of GenAI and DL techniques. Moreover, some participants explicitly expressed that they disregarded some rudimentary forms of AI as belonging to AI.

An interesting finding is that some decision-makers anticipated that AI would be able to increase the data drivenness of their organisation. While this assumption is not necessarily faulty, it requires an important nuance. The degree of data drivenness consists of the quality of the data analysis and the quality of the data itself. When AI tooling is used to analyse data that is inherently of bad quality, data-driven analyses will not result in effective outcomes. However, AI tooling can also be used to clean up data or enrich data by introducing additional relevant variables, which may strengthen the predictive quality of analyses. Therefore, the degree to which AI is able to assist an organisation in becoming more data driven is largely dependent on the exact area of application.

As for creating business value with AI, the benefits that were identified by participants closely aligned with theory. Participants globally identified the redirection of labour from repetitive tasks to higher value activities as a valuable effect of AI implementation. Gómez Gandía et al. (2025) and Kiron et al. (2011) identified that the automation of tasks can reduce costs of labour and processing time, benefits that were equally identified and realised by the participants of this study. Furthermore, whereas the theory identified the main beneficial effects of AI to be of process efficiency and insight generation, comparatively, the participants of this study brought up process efficiency with much higher frequency and variety of examples than insight generation. Instead, participants emphasised an increase in the quality of output alongside process efficiency. This suggests a shift, where insight generation may

nowadays be regarded as a means to an end for achieving output, rather than a goal in and of itself. Such a perspective was also suggested by a participant, when they mentioned: “where in the past, reporting was a goal, it has now become a means, thanks to AI” (Joost, translated by author). As such, the results may indicate that insight generation has become an integral component of business processes, and process efficiency nowadays refers in-part to the efficiency with which organisations can generate and employ their data insights. Something similar may be said for organisational agility. Whereas the theory suggests that organisational agility is mainly a product of insight generation (Hattali, 2024; Mirwan et al., 2023; Borges et al., 2021), participants of this study shared how AI-driven production efficiency enables dynamic market responses. As such, this indicates that production efficiency plays an important role in organisational agility.

Limitations of implementing AI aligned for the most part with theory on technological development within organisations. Similar to the findings by Kgakatsi et al. (2024), participants of this study identified a traditionalist attitude as a limiting factor of implementing AI into their organisation. The results also indicate that this effect may be industry dependent, as participants identified some industries as relatively more traditional than others. Other limitations align with the findings of Hattali, (2024), where participants identified data management and lack of talent to develop or manage AI as limitations of implementing AI. Next, English & Hofmann, (2018) suggested SMEs are limited in their implementation of big data by a lack of understanding, interest and skill shortage. The results of this study indicate that a lack of understanding and skill shortage translate as limitations for implementing AI among SME+ organisations. However, a lack of interest was not identified as a limitation in this study. This may be attributed to the fact that the potential of AI has been a persistent theme in the business landscape for multiple years, with adoption rates of AI amongst organisations rising yearly (Maslej et al., 2025). English & Hofmann, (2018) further identified that SMEs may struggle with finding suitable tooling at reasonable degrees of complexity and costs upon implementing big data. The results of this study

indicate that these limitations do not seem to translate to AI implementation and are rather in-line with the suggestion of Hattali (2024), that AI has a democratising effect**.** In fact, the barrier of implementing and using AI tooling was identified to be so low that it poses a limitation in and of itself. Both in terms of determining which tooling (of the many available) to adopt and the security risk of unmanaged AI usage by employees. Regardless, participants indicated that the democratising effect of AI showed notable benefits for start-up organisations, similar to findings by Hendrayati et al. (2024) and MIT SMR Connections (2024). When it comes to cost, the main limitation that was identified in this study was the cost of labour of talented and knowledgeable professionals. As such, while the costs of AI tooling itself may have reduced (Maslej et al., 2025), which democratises the market, the access to successful AI implementation may still be reserved for organisations that are capable to overcome the costs required for talented labour. As such, the increasing information and talent requirement and associated costs of labour may negate the benefit of democratised access to AI tooling. Whether this will persist may be dependent on increased knowledge availability or ease of use of AI tooling, or changes in the supply of AI professionals in the labour market. None of the participants identified cases in which their AI implementations had failed to deliver on their anticipated benefits, as Enholm et al. (2022) suggested may occur. Instead, the results indicate a strategic apprehension among many participants, where implementation is carefully explored and strategised before its deployment, as advised by Enholm et al. (2022).

The results of this research suggest that there is a preference amongst decision-makers to deploy AI for augmenting labour as opposed to automating labour in their organisation. This is beneficial news for the workforce given that these collaborative forms of labour generally produce the highest degrees of job satisfaction under automation (Sadeghian & Hassenzahl, 2022). Given the areas where human input was regarded as superior to AI, the assumption is made that in augmented/hybrid work settings, a preference would go out to human labour taking the form of creativity, interpersonal communication,

decision-making and verification. Still, when inquired about their future expectations in the development of AI, many participants indicated a loss of jobs, as well as a need to re-educate the workforce. As such, a large portion of participants remarked how they anticipated AI would have a positive effect on relieving pressure on the local labour market, much like suggestions by Chuang et al. (2025) and Inia et al. (2024).

Algorithm aversion was observed amongst participants when it came to the use of chatbots for consumer-facing applications. A feasible reason for why may be because interpersonal communication, as a hedonic service, was identified to be a role better suited for humans. Participant Mees even explicitly commented that using AI may reduce the perceived value of a service, not because of the objective value it offers, but because of the fact that it's a human-oriented service is carried out by AI.

In this regard, another interesting finding is that expert verification was identified as a fitting role for humans. The results indicate a certain degree of distrust in the output of AI tools, which may be the result of a combinations of limitations. With low output reliability (from ill-written prompts), low explainability and a low barrier to produce output all being identified as limitations, low trust may be a result of model limitations, certainty of whether employees make use of AI effectively and accurately, or a combination of factors. This leads to an interesting discussion of whether trust in human verification will remain as AI agents further develop reasoning and generalisable skills. Regardless, as competence of AI continues to grow, it is expected that soft skills from humans will become more important (Karin Kimbrough, 2025). Critically, humans act on ethical and moral compasses that can be important in decision-making, reasoning or justification, which is why humans are still regarded as essential in AI implementation (AI HLEG, 2024; Jeyapriya & Suganthi, 2025). Participants also anticipated that the future holds a growing demand for physical labour and products, and higher degrees of product interaction. It would be interesting to measure the difference in value that people associate with a product in a digital vs a physical context, and the variables that this may be dependent on.

### *5.1.1 Theoretical Contribution*

This research makes an important contribution in the growing academic literature on AI. First, it introduces distinctions of AI terminology into a structured academic context. It further contextualises these terminologies, clarifying their relation to each other and presenting figure 1, that summarises these characteristics. This presents a clear taxonomy that may be used to specifically reference different aspects of AI within the broader umbrella of AI and highlight future changes as the technology develops.

Furthermore, it outlines the position of AI in the business landscape from key influential perspectives on the matter, where it provides practical insights into the benefits that AI can bring into organisations and uncovers new barriers to its implementation. Notably, the emphasis of increasing output quality as a result from implementing AI and the new barriers that have arisen from the democratising effects of AI are new and relevant takeaways. The research also raises new questions and concerns about the implementation of AI into organisational practices when it comes to accessibility and ethics. Both with regards to creating a future workforce that is efficient and motivated and designing AI applications to optimally serve societal goals.

### *5.1.2 Practical Implications*

Practically, understanding the perceptions of decision-makers on the business applications of AI can inform more effective implementation strategies and policy recommendations tailored to SME+ contexts. By presenting the practical benefits that AI has realised for participants, organisations may seek inspiration for new areas or applications to adopt AI in. The presentation of Figure 2 further assists in presenting the beneficial effects of AI on productivity in a clear, comprehensible format. This allows decision-makers to easily be able to identify the benefits of AI implementation into their organisation and strategically evaluate the individual benefits of automation and augmentation respectively.

Furthermore, by providing a coherent overview of the barriers of implementation, organisations and consultancies alike can design strategies for circumventing or minimising these barriers, which is especially important since participants expressed that they felt a strategic pressure to optimise their internal processes. For example, the results exemplify that adequate data quality and enterprise data model structures are valuable prerequisites for effective AI implementation—providing a clear starting point to the process of integrating AI, and the hunch that interconnectedness and physicality may become more important may inform new products or services that highlight these attributes. Furthermore, the uncertainty over data ownership caused by the state of geopolitics suggests a future in which organisations may look to become less dependent on singular third parties in order to become more resilient to geopolitical turbulence.

## 5.2 Limitations and Suggestions for Future Research

While this research presents valuable insights, it is important to acknowledge its limitations and address directions for future research. First of all, the sampling frame of this study consisted exclusively of individuals who were active users of LinkedIn. Regardless, it was deemed that alternatives platforms would have resulted in more narrow sampling frames. Second, there is an inherent limitation in using a company's headcount for assessing the degree of organisational processes and technological advancement, since these factors are dependent on a complex combination of additional variables. This was characterised by participant Anouk, who represented an organisation with 1.400 employees, but provided highly valuable insights for SME+ companies in their interview. Regardless, because participants in this research represented a varied spectrum of company headcounts, it serves as a good exploratory basis for the research matter. Regardless qualitative researched that is purely focussed on start-up organisations may be better suited to identify a democratising effect of AI on access to data for businesses of all sizes. As previously explained, if the cost benefits of cheaper access to tooling are

outweighed by the costs of labour required to work with the tooling effectively, the market for AI may not be democratised. This could make small enterprises still face the same struggles to be competitive in their respective markets.

Since this research was conducted with Dutch organisations only, it would be interesting to see if the same perceptions would be identified amongst decision-makers across different cultures and organisations with varying levels of technological advancement. Given different media representations and stages of development of AI across cultures, differences would be expected. Furthermore, this research aimed to have each participant define AI by the same parameters by introducing the suggested AI topology during the interview. While it did encourage some participants to reconsider and expand their previously given answers, it may be that subjective associations with AI are too engrained to be subject to new interpretations in the short time span of an interview. It would be interesting to conduct quantitative research that surveys the degree to which decision-makers subjectively regard specific business applications as AI and objectively compare their answers to the technical definition of AI. As artificial intelligence is further integrated into society and public understanding grows, its meaning is expected to evolve alongside it. As such, it would be interesting to see how different applications and techniques of AI will evolve to be referred to in common lexicon, which present etymological research and documentation opportunities. In the same vein, a literature review on the changing role of insight generation may contextualise whether organisational business processes are indeed becoming more data driven at their core, as the results of this research suggest.

Next, this research strengthened the notion that traditional cultures and attitudes can hinder the degree of technological innovation of an organisation. Regardless, it would be interesting to explore whether there are overlaps or differences in the barriers of technological innovation across different industries that are commonly referred to as traditional. For example, the pension sector may be regarded as traditional because they may have employees with a higher average age, whereas the

construction sector may struggle with modernising their enterprise data models. Lastly, this research identified that expert verification is regarded as a crucial role to be performed by humans. However, this research did not focus on participant's reasoning for why in detail. Further research could clarify the prerequisites for an AI-verified process to be regarded as trustworthy. This would allow organisations to reliably optimise critical processes at higher efficiencies.

## 5.3 Conclusion

AI usage is increasingly becoming more prevalent in the organisational landscape. However, little is known about how decision-makers of SME+ companies balance the limitations with the advantages of implementing AI business applications.

In this paper, a comprehensive overview of AI terminology presents a clear topology of the different techniques and categorisations of AI. This overview introduces relevant distinctions within AI as an umbrella term, allowing for accurate referral to and specific techniques and categories. Furthermore, interviews with SME+ decision-makers identified multiple areas wherein the business landscape may be changing alongside developments in artificial intelligence. Key areas include the semantics associated with the term AI, democratisation of access to data, the core importance of insight generation in organisational processes and changing demands in the labour market. The findings of this paper have several implications for effectively designing organisational strategies on implementing AI. By presenting an exploratory collection of benefits, limitations and future opportunities, organisations can tailor their strategies to optimise their AI implementation. Lastly, this paper presents an array of directions for future research that may deepen the understanding of the AI and business landscapes respectively.

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# Appendix

## Appendix A: Large Language Models (LLM's)

### Large Language Models (LLM):

Large language models (LLM) are holistic systems behind the processing and generation of human speech and text. They consist of three stages. Natural language processing (NLP) processes natural language into machine-readable data that can be used for further processing ('Understanding NLP vs NLU vs NLG', 2023). Next, natural language understanding (NLU) analyses relationships, properties, patterns and semantics in language data (Gillis, n.d.). Lastly, natural language generation (NLG) is the process by which a system outputs language back to a user, staying within the parameters of user requests and previously identified language patterns to mimic human speech (Gillis, n.d.). LLMS's, as an application of GenAI, can form the underlying algorithms behind advanced chatbots for example.

### Natural Language Processing (NLP):

Human text and speech is unreadable to computers, since they only operate in a binary environment. Therefore, a process is required that translates this language into machine-readable data ('Understanding NLP vs NLU vs NLG', 2023). This process is necessary both for translating training data and real-time requests.

### Natural Language Understanding (NLU):

A computational analysis of the relationships, properties and patterns in human language. In addition, when prompted in real time, it is the process in which context is assigned to language. By contextualising the linguistic elements of a user request, it knows the parameters that their output needs to satisfy (Gillis, n.d.).

### Natural Language Generation (NLG):

The process by which a system outputs language back to a user, staying within the parameters of user requests and previously identified language patterns to mimic human speech (Gillis, n.d.).

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## Appendix B: Machine Learning Methods

### Supervised Algorithms / Supervised Learning:

A key element of supervised algorithms is that the data provided to train the model has been labelled beforehand by humans. The algorithm uses these different labelled datasets to make statistical predictions on how to classify the data or perform regression analyses (Klubnikin, 2024).

### Unsupervised Models / Unsupervised Learning:

These models are exposed to and trained by unlabelled data (Klubnikin, 2024). In practice, an algorithm is exposed to massive amounts of raw data and automatically is able to identify relationships without the need for humans to direct it towards the desired outcomes (Holdsworth & Scappichio, 2024; 'What Is Machine Learning (ML)?', 2020). The two applications of unsupervised models may be clustering or anomaly detection. In clustering, the model computes advanced statistical analyses required to identify segments and relationships within large data sets. Anomaly detection aims to find outliers in datasets, that are too far removed from potential clusters of data.

### Semi-Supervised Learning:

Semi-supervised learning is the concept of a model trained both on labelled data and unlabelled data. The inclusion of labelled data points the AI in the right direction. In addition, it is able to teach the algorithm to label the unlabelled data ('What Is Machine Learning (ML)?', 2020).

### Reinforcement Learning:

Reinforcement learning is the process where the results of an algorithms computations are either rewarded or punished for being right or wrong. In some applications, the result of the algorithm's analysis inherently can inherently be classified as a positive or negative outcome, such as in stock trading, but sometimes these classifications must be dictated by humans. This process is referred to as RLHF, or Reinforced Learning by Human Feedback (Klubnikin, 2024; 'What Is Machine Learning (ML)?', 2020).

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## Appendix C: Computer Vision

### Computer Vision:

Computer vision is a process by which AI applications are trained with images and video footage to identify or analyse recurring visual patterns (Betz & Urwin, 2024). Applications may include object identification and classification, object trajectory predictions, object detection, object tracking, facial recognition, content-based image retrieval or semantic segmentation (Holdsworth & Scappichio, 2024; *Understanding the Different Types of Artificial Intelligence*, 2023). Computer vision is the underlying mechanism behind driver-assisting technology such as lane assist, adaptive cruise control or automatic parking. In healthcare, it has been implemented in radiology to assist radiologists with tumour detection and diagnosis.

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## Appendix D: Random Selection of LinkedIn Sales Navigator List

A random number generator was asked to produce a number ranging from 0 to the total number of potential participants that the LinkedIn filter resulted in. This was completed over the course of 5 sessions total, since the process required a significant amount of time from the researcher. 25 times in a primary session (0-516), 75 times in a secondary session (0-519), 25 times in sessions 3 and 4 (0-600; 0-601) and a final 40 times in session 5 (0-614). The number that resulted from the random number generator would correspond with a position in the search result list, and that member would be reached out to as a potential participant.

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## Appendix E: Informed Consent Form

**Research Title:** The Perceptions of Decision-Makers of SME+ Organisations on the Business Applications of Artificial Intelligence

You have been invited to participate in a research study that explores how C-level decision-makers in SME+ organisations perceive the business applications of Artificial Intelligence (AI). The purpose of this study is to better understand your views on the adoption, opportunities, challenges, and strategic implications of AI in your organisation.

If you choose to take part, you will be asked to participate in a one-on-one, online interview lasting approximately one hour. There are no anticipated risks or burdens associated with participation. You are free to decline to answer any question and may withdraw from the study at any time without any negative consequences.

Confirmation of your understanding of this form, and consent to participate will be obtained through verbal confirmation at the start of the interview. At the bottom of this page, you will find the contact details of the researcher, should you have any questions or wish to follow up at any point.
If requested, you will receive a written explanation of how your data will be handled, as well as a summary of the research findings after the completion of the thesis.

All data collected during the interview will be anonymised through pseudonymisation in transcription and for reporting. This means that your name, the name of your organisation, and any other identifying details will be replaced with number codes or fictional names in the research materials and outputs.
The interview will be video recorded to support accurate transcription. This recording and transcript will be securely processed and stored on Google drive cloud storage, protected under ISO 27001, and will be permanently deleted after data collection and analysis are complete- which will be no later than **August 31st, 2025**

Thank you for considering participation in this research and kind regards,

Bennett Hofland

E-mail: B.j.hofland@student.utwente.nl

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# Appendix F. Full Interview Guide (EN)

## Interview Guide EN:

- = Interviewer instructions
  - = (Follow-up) questions
    - = Purpose of the interview questions (checklist)

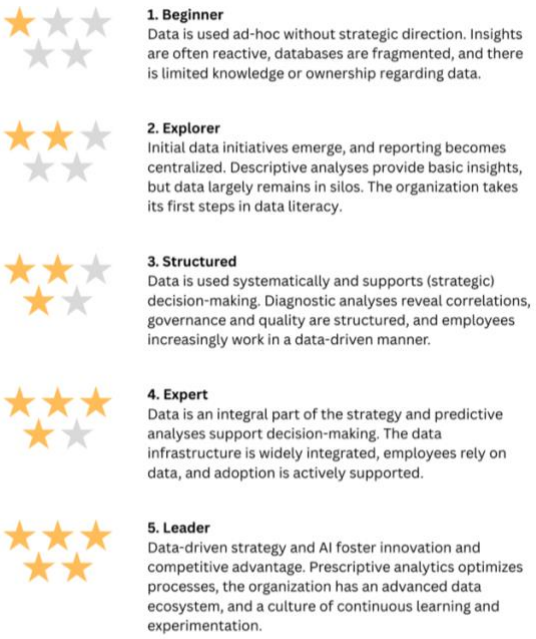
## Welcome, Informed Consent, Meeting rec. (5 min)

- Welcome the participant
- Agreement to the informed consent form (in meeting notes)
  - If not read in advance, this is the opportunity to read and provide consent
  - Start meeting
  - Questions before interview

## Demo/Firmographics (10 min)

- Could you give a brief summary of the company? Which industry is it in, and how you would describe your company's activities?
  - Industry
  - Company activities
- How many employees work at your company?
- Can you tell me something about how you have grown into your current role within the company?
  - Personal role
  - Professional background
- To what extent would you describe your company as data-driven based on these five levels?

- **The image below will be sent to participant via meeting chat**



**1. Beginner**
Data is used ad-hoc without strategic direction. Insights are often reactive, databases are fragmented, and there is limited knowledge or ownership regarding data.

**2. Explorer**
Initial data initiatives emerge, and reporting becomes centralized. Descriptive analyses provide basic insights, but data largely remains in silos. The organization takes its first steps in data literacy.

**3. Structured**
Data is used systematically and supports (strategic) decision-making. Diagnostic analyses reveal correlations, governance and quality are structured, and employees increasingly work in a data-driven manner.

**4. Expert**
Data is an integral part of the strategy and predictive analyses support decision-making. The data infrastructure is widely integrated, employees rely on data, and adoption is actively supported.

**5. Leader**
Data-driven strategy and AI foster innovation and competitive advantage. Prescriptive analytics optimizes processes, the organization has an advanced data ecosystem, and a culture of continuous learning and experimentation.

## AI-Opinions: Pre-Explanation (10m)

- Can you tell me what AI means to you?
  - General impression
- From which source(s) do you gather your knowledge about AI?
  - Competitors
  - Colleagues
  - LinkedIn
  - (Online) Courses
  - News
- To what extent are you currently integrating AI into your business processes?
  - Internal processes
- In what way(s) is AI used for internal processes, such as employees' workflows or data processing?
  - Consumer-oriented
- In what way(s) is AI integrating into the service offering to consumers?

## Explanation of AI-Techniques (5m)

- Brief introduction of the explanatory video about AI techniques[2]
- Were there any moments in the video that you would like me to clarify, or was the information complete?

## AI-Opinions: Post-Explanation (5m)

- After watching this video, do you feel you would like to supplement your answers to the previous questions?
    - What does AI mean to you?
    - Business processes that use AI?

## (Future) AI-Ambitions and Opinions (25m)

- What are the main benefits that have resulted in implementing AI for your company?
    - Or that could arise upon implementation
    - Process optimisation
    - Insight generation
    - Disadvantages
        - Do you ever encounter disadvantages upon implementing AI?
- What are the biggest hurdles you face when it comes to AI implementation?
- Why is this a hurdle for implementation?
    - Talent (knowledge/workforce capacity)
    - Technical infrastructure

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2 The explanatory video covers AI techniques (figure 1 (simplified)) and summarizes the business applications of AI.

    - Goal of implementation
- Which tasks are best suited for AI, and which should continue to be performed by humans?
    - Why?
- How do employees within the organisation regard the integration of AI into their everyday work?
- Automation through AI can offer market and production advantages for the company, but it can also have significant consequences for employees, such as replacement or retraining. How do you view this trade-off?
    - Inevitable consequence of technological innovation
    - The company comes first
    - Employees come first
    - Conflicts in the trade-off
- How has your perspective on AI changed in the past 5-10 years?
    - Technical development
    - Perception in society
- Do you see AI more as a hype or as a revolution?
- How do you foresee the impact that AI will have on your company in the next 5-10 years?
- To what extent does your company feel pressure from the market to develop in the field of AI?
- To what extent is your company capable of implementing AI independently?

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# Appendix G. Codebook

| Primary codes | Subcodes | Definitions |
|---|---|---|
| Barriers of AI implementation | 1. Disadvantages<br>2. Risks<br>3. Hurdles<br>4. Prerequisites | Any considerations that may be made before the implementation of AI, or that hinders the implementation. This code includes disadvantages, risks, hurdles and prerequisites for implementing AI |
| (Expected) Benefits of AI implementation within the organisation | 1. Realised benefits<br>2. Expected benefits | The self-reported benefits that have resulted in the implementation of AI. In addition, the benefits that are anticipated from further expansion of AI in the business |
| Human reliance | | The role of human labour when compared to AI automation. Advantages that human labour may have over AI |
| Future and development of AI | 1. Societal impact<br>2. Business landscape | The expected ways in which the adoption of AI will develop and influence the needs of societies and businesses |
| (Anticipated) AI use within the organisation | 1. Current AI use<br>2. Anticipated AI use | Both the current ways in which AI is used by the organisations of the interviewees and the anticipated ways in which it will be used in the future |
| Viewpoint | 1. Conceptual view of AI<br>2. The role of AI within the market | How AI is regarded by the interviewees, both conceptually and with regards to their industry's market. |

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# Appendix H. Artificial Intelligence Statement

During the preparation of this work, the author used a multitude of AI tools to assist in different stages of the research and writing process.

| | |
|---|---|
| ***Microsoft Editor*** | Grammatical error detection and grammatical suggestions for improvements throughout the entire writing process. |
| ***ChatGPT*** | To evaluate the accuracy of self-written definitions of AI terminology.<br><br>To generate suggestions of words pertaining to certain contexts.<br><br>To translate the interview questions and acquisition messages to potential participants between Dutch and English.<br><br>To translate script of explanation video to Dutch to accomplish consistent tone of voice.<br><br>To provide reasoned suggestions on the structural order of subchapters.<br><br>To generate pseudonyms for each interviewee, excluding the real names of interviewees in the prompt.<br><br>To inform about APA guidelines |
| ***HeyGen*** | To generate an AI avatar that read out the script of the explanation video, to be shown to the participants during the interview. The script itself was fully self-written and strictly based on chapters 2.1 and 2.2. |
| ***GoodTape*** | While not explicitly described as an AI tool, it uses AI techniques to accomplish the goal of transcription.<br><br>To transcribe the interviews. Each transcription was manually listened back to and corrected accordingly. |

No text, reporting or analysis used for the final product or sections of the paper submitted was (fully) created by any AI tool. After using AI tools to assist in the writing process, the author carefully selected which wording conveyed the intended nuances and used this as inspiration to adjust the text accordingly. After using the aforementioned AI tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

**Declaration of academic integrity - M-COM Master Thesis**

I herewith declare that my master thesis is the result of my own work and that materials regarding the works of others, contributing to my master thesis, have been correctly cited and/or acknowledged.

I furthermore declare that I have taken notice of the principles and procedures regarding research ethics and academic integrity as presented in the UT Student Charter and on the website of the BMS Examination Board, or as mentioned otherwise during the course of my studies.

I finally declare that below actions regarding research ethics and academic integrity have been followed through:

1. In the case human test subjects were involved for data collection, I have filed a request for ethical review and my request has been approved by the BMS Ethics Committee
2. I have safeguarded the transmission of research files and documents, using my personal folder on the secure university network drive (P:\bms\cw\theses) or other means of safe data transmission.
3. I have stored my final master thesis and (raw) research data on my personal university network folder (P:\bms\cw\theses) or made it otherwise digitally available to my supervisors.
4. I have uploaded my draft master thesis, prior to the "green-light" meeting, for a plagiarism / similarity check on the M-COM Master Thesis Canvas website and I have shared the plagiarism / similarity report with my supervisors prior to the "green-light" meeting.
5. In the case AI generated content has been used, an appendix has been added in which I explain where and how AI generated content has been used for my master thesis (see info on University of Twente website).

Student name and signature:

Student name: Signature:

Bennett Josey Hofland