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Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach

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ABSTRACT

Artificial intelligence (AI) is playing a leading role in the digital transformation of enterprises, particularly in the manufacturing industry where it has been responsible for a profound transformation in key business and production operations. Despite the accelerated growth of AI technologies, knowledge of the implementation of AI by small and medium-sized enterprises (SMEs) remains underexplored. Thus, this study seeks to examine how manufacturing SMEs orchestrate resources for AI implementation. Building on the resource orchestration (RO) theory and recent work on AI implementation, we investigate multiple case studies involving manufacturing SMEs in Sweden operating in the packaging, plastic, and metal sectors. Our findings indicate that SMEs structure a portfolio based on acquiring and accumulating AI resources. AI resources are bundled into learning and governance capabilities to leverage configurations for AI implementation. Through a dynamic process of AI resource orchestration, SMEs effectively leverage AI resources and capabilities by mobilising technologies, coordinating manufacturing processes, and empowering skilled people. This research contributes to existing practice and the academic literature on AI implementation, highlighting how SMEs orchestrate AI resources and capabilities to drive an organisation's digital transformation whilst creating a competitive advantage.

1. Introduction

Artificial Intelligence (AI) is having a significant impact on the digital transformation of organisations (Kraus et al., 2022). In the manufacturing industry, the implementation of AI technologies has become revolutionary (Bokrantz et al., 2023). We define AI as "*a system's ability to interpret external data correctly, to learn from such data, and to use those to achieve specific goals and tasks through flexible adaptation*" (Kaplan & Haenlein, 2019, p. 17). AI implementation is regarded as the process of deploying and using AI technologies within an organisation, which determines its use, return on investment, and trust (Dwivedi et al., 2021). The implementation of AI technologies has produced multiple benefits (Abdallah et al., 2023) and, in the manufacturing industry, companies are benefiting from flexibility in production processes that are facilitating the move towards major levels of customer product customisation (Wan et al., 2021) or accelerating the enhancement of human resources performance in company processes (Li et al., 2023). However, AI implementation is a sophisticated process that involves changes in production practices and management styles, which present significant challenges to companies (Fu et al., 2023; Wang et al., 2023). This challenge is particularly relevant for small and medium-sized Enterprises (SMEs) in the manufacturing industry because these companies are required to make fundamental changes to their internal resources, processes, and capabilities (Dey et al., 2023).

AI can significantly contribute to SMEs' ability to overcome challenges, collaborate and interact with their customers and suppliers (Skare et al., 2023), and increase their productivity (Baabdullah et al., 2021). The growing benefits of implementing AI by SMEs in the manufacturing industry have resulted in supply chain agility (Dey et al., 2023), maintenance cost reduction (Velmurugan et al., 2022), and augmented SME risk prediction (Zhang et al., 2021). However, SMEs integrating AI into organisation and production processes is a

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challenging undertaking. This challenge is amplified further because the majority of SMEs exhibit poor levels of digitalisation, hindering their capacity to apply AI solutions (Andrea et al., 2021). Studies have, for example, highlighted the high cost of AI implementation in a resource-intensive setting, which requires IT expertise and skilled human talent (Sommer et al., 2023). While many studies have focused on the technological implementation of AI technologies (Zhang et al., 2021), there is a need to comprehend how the digital transformation of SMEs takes place when implementing AI as part of their manufacturing processes (Skare et al., 2023).

A greater part of the literature acknowledges that AI implementation can be analysed through the lenses of organisational strategy and organisational capabilities (Weber et al., 2023), with specific reference to dynamic capabilities (Martínez de Miguel et al., 2022; Ogunrinde, 2022), the resource-based view (Kumar et al., 2023), and the resource orchestration (RO) theory (Ma et al., 2023). In particular, RO theory provides a novel theoretical lens to identify how to manage AI technologies, people, and processes to successfully create value by implementing AI applications in organizations (Zhang et al., 2021). The RO theory contributes to a further understanding of resource management because it is an approach that centres on the role of managers in the creation of value through resource transformation (Sirmon et al., 2011). It is a theory that contributes to a broader understanding of AI implementation (Dey et al., 2023) because it reveals the dynamics in which companies identify, acquire, and combine the utilisation of resources. Thus, the RO theory helps us to comprehend the management of a company's resources and capabilities in the process of creating value for owners and customers (Sirmon et al., 2007). However, the literature has yet to focus on explaining how manufacturing SMEs orchestrate resources to implement AI technologies across their processes of digital transformation (Dey et al., 2023). This topic is particularly important since manufacturing SMEs have struggled to understand the impact that AI has on their businesses (Andrea et al., 2021). Therefore, SMEs face multiple challenges concerning AI implementation because of their limited awareness of AI technologies, their scant access to human talent with AI capabilities, and their limited investment capacity for AI applications (Abdulaziz et al., 2020). Considering this gap in the literature, we focus on the research question: *How do manufacturing SMEs orchestrate resources for artificial intelligence implementation?*

We build on RO theory by exploring the underlying processes through which AI implementation occurs in manufacturing SMEs. Drawing on five studies conducted on manufacturing SMEs in Sweden who are undergoing digital transformation through AI implementation, we examine how manufacturing SMEs implement AI to support the processes that underpin their resource orchestration: structuring resources, bundling resources to form capabilities, and leveraging processes to exploit capabilities (Sirmon et al., 2011). We collect data from manufacturing SMEs in the packaging, plastic, and metal sectors. Since we aim to capture how AI implementation contributes to the digital transformation of manufacturing SMEs through the RO lens (Zhu & Li, 2023), we observe the phenomenon as an ongoing process in which plans and resources are deployed and re-adapted on the basis of emerging outcomes. We expand on prior research that examines the influence of AI implementation, and we put forward a framework for digital transformation for AI implementation.

The remainder of this paper is structured as follows. Section 2 follows this introduction with a review of the theoretical background underlying the study. Section 3 then describes the research methodology. The results are presented in Sections 4 and 5; here, Study 1 and Study 2 are introduced to provide a framework for comprehending SMEs' digital transformation through AI implementation. Section 6 presents the discussion, which integrates theoretical contributions, practical implications, study limitations, and future research directions. Finally, Section 7 presents the conclusions.

2. Theoretical background

2.1. *Digital transformation through artificial intelligence in the manufacturing industry*

Companies are pushing digital transformation strategies based on implementing AI to support digital innovation (Kim & Kim, 2022). Notably, companies' digital transformation through AI has become increasingly vital in the manufacturing industry because its implementation boosts productivity and enhances firm performance (Ahmad et al., 2022). The implementation of AI technologies has allowed manufacturing companies to achieve optimal operating conditions and promote efficient operation management processes (Ishfaq et al., 2023). Centrally, AI's rapid expansion is having a transformational impact on businesses by shaping companies' business models and core processes to strengthen competitiveness (Brynjolfsson & Mcafee, 2017). Notably, AI implementation has brought awareness and understanding of the digitalisation of operations management while allowing the identification of challenges and opportunities for businesses (Mypati et al., 2023). Through key components, the data pipeline, and the use of algorithms, experimentation platforms, and infrastructure (Iansiti & Lakhani, 2020), AI's capacity to accomplish highly complex tasks opens up a wide range of applications and future prospects for the manufacturing industry (Frank et al., 2019).

Companies are increasingly identifying the different possibilities that arise from implementing AI through the development and functioning of manufacturing processes in different ways (see Panel A in Table 1). To illustrate, Demlehner et al. (2021) explored how AI enhances car manufacturing through the assessment and identification of general use cases classified in two dimensions: estimated business value and realisability. Their study has raised the call for an exploration of the literature on AI behavioural, managerial, and organisational challenges. Hradecky et al. (2022) explored the perceptions and organisational readiness to adopt AI in the exhibition sector of the events industry. By exploring the Technology Readiness Index and a framework composed of three dimensions – notably, technology, organisation and environment – the authors show that the European exhibition industry is configured as a slow AI adopter, inhibited by issues of data management, organisational technological practices, and financial resources.

Authors such as Dwivedi et al. (2021) acknowledge the role of AI in the manufacturing industry where AI-based applications have demonstrated potential in replacing human workers with intelligent automation. Thus, manufacturing organisations tend to use AI technologies for production where intelligent machines are socially integrated into the manufacturing process, acting as co-workers to solve relevant problems. A line of inquiry that has gained attention in the literature considers the question of how AI technologies enhance manufacturing organisations' performance and sustainability (Jamwal et al., 2022). Their study discusses how deep learning creates job opportunities and shows a connection with the adoption of Industry 4.0[1] practices in the manufacturing industry to achieve sustainable production. Overall, inquiries persist in pursuing an understanding of AI capabilities and how they can be implemented in the manufacturing industry (Mypati et al., 2023), while AI implementation by SMEs is a debate that is still emerging (Skare et al., 2023).

2.2. *AI implementation in manufacturing SMEs*

Different from large organisations, SMEs face relevant challenges in implementing AI to keep up with global competition. Several studies have begun to acknowledge the challenges and difficulties SMEs face

[1] The term Industry 4.0 refers to a methodology for creating a shift from machine-dominant manufacturing to digital manufacturing (Oztemel & Gursev, 2020).

Table 1
Summary of the Seminal Studies on AI Implementation.

Study	Key emerging themes	Limitations	Research gaps	Example citations
Panel A: Studies related to AI implementation in the manufacturing industry				
Demlehner et al. (2021)	Car manufacturing, Automotive industry, Production strategy	• Press releases or grey literature are not included. • Limited panellists participating in the research	There is a need for more research on managerial, behavioural, and organisational AI challenges	"This includes for instance questions like how AI can effectively be managed in organizations, how it can be scaled most efficiently, or how successful change management can foster its acceptance rather than its rejection" (p. 11)
Dwivedi et al. (2021)	Cognitive computing, expert systems, machine learning, research agenda	• Workshop and based opinion paper supported in the non-systematic literature review	There is a need to explore the different levels of testing and applied scenarios to validate AI implementation	"How do we know what levels of testing and applied scenarios have been used to validate an AI algorithm? Are the key logic and execution paths transparent to decision makers to ensure they are comfortable with the performance and likely outcomes of the AI system? Who gets the blame when things go wrong? Academic research is needed to answer these questions to develop a deeper analysis of the potential implications for all key stakeholders." (p. 40)
Hradecky et al. (2022)	Exhibition industry, technology readiness, organisation readiness	• Limited participants' availability • Online interviews • Abstract and lacking real-life evidence responses	There is scant knowledge of organisational readiness to adopt AI	"Field studies, including shadowing and longitudinal studies, can be implemented to investigate the decision-making process of AI adoptions within organizations. Studies on the exhibition sector's readiness regarding AI adoptions can be further investigated in other geographical contexts or smaller venues."
Jamwal et al. (2022)	Deep learning, Industry 4.0, sustainable manufacturing	• Limited to three databases	Limited knowledge of the manufacturing context and its relationship to sustainability	"In future studies, applications of deep learning approaches in the various industry sectors in the different regions of the world can be explored, which will help provide a holistic overview and understanding of the potential of deep learning approaches for sustainable production" (p. 11) "There is a need to conduct an extensive survey to investigate whether the deep learning approaches are contributing to sustainable production" (p. 11)
Panel B: Studies related to AI implementation in SMEs				
Skare et al. (2023)	Digital transformation, digital economy	• Lack of relevant records in the European SME database	The role of digital transformation in SME business activities	"Future studies should consider firm- and industry-level SME indicators" (p. 13) "Future research should focus on specific digital technology instruments, such as CC, ERP, CRM, big data, and advanced cloud computing, and their impact on companies across sectors and sizes." (p. 13)
Wang et al. (2022)	Intelligent manufacturing, Intelligent transformation	• Difficulty in constraining informant identities • Difficulty in analysing hierarchy on intelligent transformations • Focused on SMEs in central China	There is a lack of knowledge on how SMEs achieve intelligent transformation using AI	"It would be a good idea to consider multi-cultural factors and identify common factors and interesting differences. Finally, the models we constructed were not verified through empirical analysis. We will consider the validation of the model in future research." (p. 1155)
Hansen and Bøgh (2021)	Machine learning, Industry 4.0, predictive analytics	• Based on survey results • Limited number of SMEs	There is a lack of knowledge on how SMEs utilise IoT and AI technologies	"Future research should focus on simplifying AI solutions for SMEs and thus make them more directly applicable to them." (p. 370)
Barata et al. (2023)	Agile methods, cognitive mapping, decision-making trial, evaluation laboratory	• Focused on Portuguese SMEs • Research conclusions based on a group panel showed hesitancy when defining determinant's influence on the decision makers' views	There is a gap in the literature that identifies the determinants of e-commerce, AI, and agile methods in SMEs	"Researchers may get interesting results by combining the approach selected for this research with another method or technique. Any contributions that strengthen the existing knowledge about SMEs successful development of e-commerce, AI, and agile method projects will always be welcome." (p. 13)
Kim and Seo (2023)	Machine learning, technological development, utilisation, impact, strategic decision-making framework, artificial intelligence strategy	• Using technology road maps has limitations in understanding SMEs' different positions.	SMEs are experiencing difficulties in developing strategic decision-making to implement AI strategies for AI technology development and utilisation	"For further research, it would be useful to conduct a foresight study to examine AI strategies of SMEs by using this framework and to look into different changes of AI strategies between firms,

(*continued on next page*)

Table 1 (*continued*)

Study	Key emerging themes	Limitations	Research gaps	Example citations
				between service and manufacturing industries and between countries in terms of AI technological development and utilization".
Panel C: Studies related to AI Resource Orchestration and AI capabilities				
Dey et al. (2023)	Supply chain resilience; Organisational factors; Circular economy; Agility; Risk management	• Limited sample of SMEs belonging to an emerging economy setting	Lack of knowledge on how optimal leadership enhances SMEs' willingness to invest in and adopt AI	"The proposed model can be further extended in the future to understand the impact of driven systems on SC diligence by introducing new constructs drawn from OSCM literature such as SC robustness, orientation, flexibility and dynamic capability, efficiency, visibility and transparency, resource configuration, culture, and types of partnership, collaboration, and relationship between various stakeholders" (p. 26) "Future studies can also understand the relationship between AI adoption, implied demand uncertainty resulting from customers' needs, product attributes and market competition, and SC resilience." (p. 26)
Kumar et al. (2023)	CRM, Healthcare customer service, Flexibility, Service innovation	• Data collection is limited to Indian healthcare professionals • Study of AI-enabled technology in its developing phase	Lack of understanding of AI-enabled CRM capabilities	"This study established three dimensions of AI-enabled CRM capability in healthcare. However, other dimensions may emerge which should be explored." (p. 13)
Abou-Foul et al. (2023)	Servitization, Social innovation, Dynamic capabilities	• Research results limited to a theoretical lens and a particular context	Limited understanding of AI developments and their impact on a business context	"A good avenue of future research could be to incorporate organizations' AI maturity levels when collecting samples. Further empirical work should also focus on AI governance, technical diligence, affordability, and industry-level capabilities." (p. 11)
Weber et al. (2023)	Machine learning, Resource-based view, Knowledge-based view	• Potential researcher's bias in data analysis • Incapacity to capture specificities about the analysed organisations or their industries in-depth	Limited understanding of how capabilities enable AI implementation	"Scholars could operationalize these organizational capabilities and quantitatively investigate their influence on AI implementation success and failure" (p. 1561) "Future research could explore how organizations arrange and govern their roles, structures, and processes to build the identified organizational capabilities." (p. 1561)
Fosso Wamba (2022)	AI assimilation, Dynamic capability, Organisational agility	• Uses a cross-sectional survey to validate the research model. • Data is collected in an English-speaking developed country	The literature lacks empirical research on how AI assimilation could improve organisational outcomes related to organisational and customer agility and firm performance	"Future studies may consider using case studies or longitudinal survey studies to assess the proposed research model" (p. 9) "The adopted model may be tested and validated through other geographical and linguistic parameters, using data from non-English-speaking countries" (p. 9)
C. Zhang et al. (2022); D. Zhang et al. (2022)	Big data, Sustainability, SDGs, Resilient urbanisation	• Limited to two case studies, which present limitations in generalisability • Limited to studying one city	There is a call for empirical studies on how to leverage AI for sustainability	"Future studies can use different research methods to test and refine the current findings, which would increase both statistical and theoretical generalizability and promote the conceptual development of the phenomenon of AI for sustainability." (p. 13) "Fruitful opportunity for further research to analyse other significant technologies and their specific development process to be leveraged for sustainability, which would provide a more comprehensive understanding of the topic."
Zhang et al. (2021)	E-commerce, Smart warehouse, Resource orchestration	• A single case study that limits generalizability • Focused on business processes in e-commerce not applicable to other industries	There is a necessity to understand AI technologies and to align them with different organisational elements	"Future research can collect data from more businesses and more industries as AI applications grow in practice." (p. 11) "More studies of other warehousing processes are needed to fully understand all of the AI applications in e-commerce fulfilment centres." (p. 11)

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Table 1 (*continued*)

Study	Key emerging themes	Limitations	Research gaps	Example citations
Chen and Lin (2021)	Business intelligence (BI), STD Conceptual model, Dynamic capabilities, Firm performance	• A limited number of recessive constructs (factors) underlying business intelligence and performance • The findings are based on a panel data analysis	The lack of theoretical consensus and measurement of AI technologies embedded in business intelligence	"There may be other recessive constructs or factors underpinning BI capacity and business performance, beyond the three we have extracted within the STD conceptual framework. Future research should yield more interesting findings or evidence if more influential factors or variables are to be taken into consideration."

with AI implementation (Table 1, Panel B). Manufacturing SMEs are particularly exposed to internal pressures, such as elevated implementation costs, higher needs for enterprise development and growth, skilled human resources, and top management involvement, while other external pressures relate to competitive environments, the convenience of AI technologies, and the need for policy support (Wang et al., 2022). The literature has directed attention to the role of digital technologies, such as AI, in enhancing SMEs' productivity and performance and the use of these technologies in dealing with the consequences of extreme events such as the COVID-19 pandemic for securing business continuity (Papadopoulos et al., 2020). Moreover, the central questions of this digital transformation for SMEs continue to focus on how digital technologies affect SMEs' business activities. Based on the Digital Economy and Society Index, Skare et al. (2023) found that SMEs' ability and flexibility in addressing business issues are strengthened.

Hansen and Bøgh (2021) explored how SMEs use the Internet of Things (IoT) and AI technologies in manufacturing. The authors advise that SMEs should pursue machine-wise implementation because it is cheaper compared to full production-wise implementation. Recommendations point to a need for SMEs to focus on using IoT and AI for predictive analytics. The authors reveal that SMEs need to cultivate descriptive, diagnostic, predictive, and prescriptive analytics. However, the literature on AI implementation has not focused primarily on the manufacturing industry. Barata et al. (2023) highlight SME use of AI as a determinant of e-commerce development and the use of agile method projects. Their study demonstrates the relevance of using cognitive mapping, decision-making trials, and evaluation laboratory techniques to evaluate decision-making processes in SMEs.

Although a large part of the research exploring SMEs' AI implementation provides insights into how these companies improve strategic decision making practices (Kim & Seo, 2023), there is scarce understanding of how SMEs embed AI into organisational practices and the organisational capabilities needed to leverage their investment (Mikalef et al., 2021). Past literature has noted that, when assessing AI implementation, it is fundamental to capture the resources and capabilities required to invest in the necessary resources to leverage AI (Mikalef & Gupta, 2021). Moreover, this topic is scantly addressed in the SME realm, where investment and human resources are limited. In the following sub-section, we address this gap.

2.3. Resource orchestration perspective for AI implementation

Resource orchestration (RO) theory constitutes a comprehensive theoretical perspective that explains how companies transform their resources and capabilities to create and maintain value for businesses and customers (Sirmon et al., 2007). RO has emerged as a complementary view of the resource-based view (RBV) and dynamic capabilities (DC) (Teece et al., 1997) by stating how organisations can deliver a new combination of resources and capabilities to produce new outcomes while creating value by examining a company's resource management from internal and external environments (Sirmon et al., 2007). RO essentially explains how companies create value through resource transformation, and it underscores the significance of organising a company's resources to stimulate competitive advantages (Sirmon et al., 2007).

RO theory relates the different processes and the distinctions in resource management, which are divided into three components (Sirmon et al., 2007). Firstly, *structuring* refers to a firm's resource portfolio management and includes the three sub-processes of acquiring (purchasing resources), accumulating (developing resources internally), and divesting (shedding resources controlled by the firm). Secondly, *bundling* consists of a component that relates to the combination of firm resources for the construction or alteration of a company's capabilities. Bundling integrates the sub-processes of stabilising (making minor incremental improvements to existing capabilities), enriching (extending existing capabilities), and pioneering (creating new capabilities for competitive contexts). Third, *leveraging* is the application of capabilities that create customer value through mobilising (capability configurations to support opportunities exploitation), coordinating and deploying (resource advantage, market opportunity, and entrepreneurial strategies) sub-processes. RO has been considered an effective framework for analysing AI-based resources and capabilities (Mikalef & Gupta, 2021; Perifanis & Kitsios, 2023), and it has come to the centre of understanding AI adoption in a manufacturing setting (Ma et al., 2023). We define AI capabilities as "*the ability of a firm to select, orchestrate, and leverage its AI-specific resources*" (Mikalef & Gupta, 2021, p. 4). AI capabilities denote an organisation's capacity to leverage AI technologies to achieve specific objectives. Therefore, AI capabilities comprise the integration of tangible (data, technology, and basic resources), human (technical and business skills), and intangible resources (inter-departmental, organisational change capacity, risk proclivity).

The RO theory has been useful in understanding AI implementation in business settings (Table 1, Panel C). To illustrate, Dey et al. (2023) build on RO and knowledge-based view theories to develop a structural model that examines the antecedents of supply chain resilience and AI adoption. The authors show that managers can drive AI adoption by implementing a data-driven, digital, and conducive culture that strengthens employee competencies. Zhang et al. (2021) utilise the RO perspective to explore how to create value through the management of AI technology, people, and processes. The authors analyse Alibaba's successful e-commerce AI applications and, through their results, they show that AI resources (data, algorithms, and robots) must be coordinated, leveraged, and deployed to work with information systems and warehouse facilities in order to generate strong AI capabilities. The authors identify forecasting, planning, and learning AI capabilities that co-evolve with human capabilities to create efficiency and effectiveness. Zhang, Zhang, et al. (2022); Zhang, Pee, et al. (2022) use RO theory to analyse potential applications of AI in sustainable urbanisation. By analysing two cases of AI implementation in a large city, the authors identify that the purposeful orchestration of well-known AI resources (data, knowledge, algorithms, and information systems) is necessary to develop strong AI capabilities. Based on resource-based theory, dynamic capabilities, and the theory of productivity paradox, Kumar et al. (2023) have explored how AI-enabled customer relationship management capabilities are formed and how they affect service innovation in the healthcare sector. The authors conclude that AI technologies improve clinical understanding and knowledge, which facilitates the fostering of patient relationships.

A capability-based perspective has experienced burgeoning growth in the AI literature. However, pertinent questions remain unanswered. Fosso and Wamba (2022) utilise the dynamic capability framework to demonstrate that AI assimilation is a predictor of firm performance and organisational and customer agility. The authors highlight a lack of empirical research on the geographical aspects that need to be considered to improve organisational outcomes regarding customer agility and firm performance. Chen and Lin (2021) focus on the implementation of AI technologies for business intelligence in the process of optimising business decisions and operations. One of the gaps highlighted by the authors is the lack of theoretical knowledge on the implementation of AI technologies to support business intelligence. Abou-Foul et al. (2023) build on the dynamic capabilities approach and expose academia's limited understanding of AI implementation in the business context. Finally, Weber et al. (2023) build on the knowledge-based view to explore how organisational capabilities allow companies to cope with AI's characteristics. The authors highlight the lack of understanding of how capabilities enable AI implementation. Indeed, the literature reinforces the prevalent view that the orchestration of resources and capabilities for AI implementation is very much an ongoing debate with a specific need to further deepen understanding of the digital transformation that companies are currently enduring (Chen & Tian, 2022).

3. Research design

The literature suggests that a qualitative approach might be used to carry out an in-depth examination of the phenomena under observation (Silverman, 2000). To obtain rich data and discover the dynamics underlying the phenomenon under research, we used an inductive and exploratory multiple-case study approach (Siggelkow, 2007). We built upon a multiple-case study because it is a revelatory methodology (Yin, 2014) that robustly captures rich data from real-life contexts (Yin, 2009). This approach enabled us to gather detailed and in-depth data and to incorporate multiple sources of information (Creswell et al., 2007).

Cases were selected based on a theoretical sampling technique (Patton, 2014), in which the selection criteria were informed by our research question: *How do SMEs in the manufacturing industry orchestrate resources to implement artificial intelligence to support their digital transformation?* Principally, we focused our attention on a group of Swedish SMEs in the packaging, plastic, and metal manufacturing sectors that are introducing AI and currently undergoing the transformation. The SMEs are owned by a large Swedish Holding Company (SHC). In this study, five manufacturing SMEs and their headquarters participated (Appendix 1). The subsidiaries of SMEs operating in the manufacture of packaging were targeted – notably, plastic and metal cans, pails, pots, and tubes. Although the participating SMEs were at different stages of the process, all were actively engaged in AI integration and implementation through their various projects.

The empirical research was carried out across two studies over a period of twenty-one months from March 2022 to November 2023 (Appendix 2). Specifically, we conducted an exploratory study via in-depth interview questions. Then, we validated the data in a second study through organisational meetings. The second study focused on the validation of the results to acquire complementary in-depth views and provide further insights into the findings identified in the exploratory study.

4. Study 1. An exploratory analysis of resource orchestration

4.1. Overview

Building on the empirical data from the analysed SMEs, we identified and conceptualised the resource orchestration underlying resources and capabilities associated with AI implementation. Thus, we identified the set of configurations for AI implementation across the digital transformation process of manufacturing SMEs.

4.2. Methodology

Study 1 was conducted from March 2022 to September 2023 and focused on understanding AI implementation and transformation in the participating SMEs. In line with Bogner et al. (2009), primary data was predominantly collected through a series of semi-structured interviews with key respondents who had privileged knowledge of AI implementation – namely, managers, domain experts, and operative experts. The interviews were supported by an interview guide developed from the RO theory (Sirmon et al., 2007, 2011), focusing on questions that sought to understand resources and capabilities related to AI applications as well as their outcomes (Appendix 3a). Interviews were carried out in person and via Zoom and recorded (with permission) in both English and Swedish. Interviews conducted in Swedish were translated into English. All interviews were transcribed to be analysed subsequently.

A total of 18 exploratory interviews were conducted with management-level and domain-expert respondents who had been involved in setting up the engagement. Study 1 was principally developed with top management seniors, data scientists, domain experts, and IT specialists at the participating SME and the SHC to retrieve rich and in-depth data from the phenomenon under analysis. This approach enabled us to gain an extensive understanding of participants' experiences by engaging with the respondents in a natural setting (Creswell et al., 2007).

To analyse the data, we followed a thematic approach to identifying relevant patterns and themes (Braun & Clarke, 2006). A theoretical coding process was carried out, using an abductive approach based on the framework of reference (Dubois & Gadde, 2002). The coding process was rather iterative, going back and forth between the theory and the collected data (Gioia et al., 2013). This method provides consistent and rigorous analysis across three iterative stages of data analysis, following the approach commonly undertaken in case studies (Yin, 2014). With the support of NVIVO software, data were coded to identify prominent themes that helped us to glean important insights from the phenomenon under observation. This process was conducted through a within-case analysis for each SME, followed by a cross-case analysis with the continuous identification of how SME resource orchestration supports AI implementation as the company makes its digital transformation (Beverland & Lindgreen, 2010). Fig. 1 depicts the data analysis process developed in three stages (Gioia et al., 2013).

The first step in data analysis involved a thorough reading and familiarisation with the interview transcripts. We read and coded the collected data, including interview transcripts, meeting notes, and internal documents. The utilised software facilitated the coding process by identifying common phrases retrieved from verbatim quotations, resulting in first-order categories. In this step, we identified information related to resources, capabilities, and leveraging AI applications, as well as valuable outcomes. We identified the emerging codes that most accurately represented the participants' voices (14 elements). The second step consisted of recognising patterns in the first-order categories through an iterative process between the theory and the data, leading to the generation of second-order themes that allowed a higher level of abstraction. Here, we conceptualised the first-order codes into seven themes. This step was facilitated by thorough discussions of the data, which then led to the third step. This final step involved the generation of aggregate dimensions. We categorised the seven themes into three dimensions: *structuring AI resources*, *bundling AI capabilities*, and *leveraging AI resources and capabilities*. These three dimensions served as the basis for our analysis.

4.3. Results

The themes that we identified in the data collection process represent

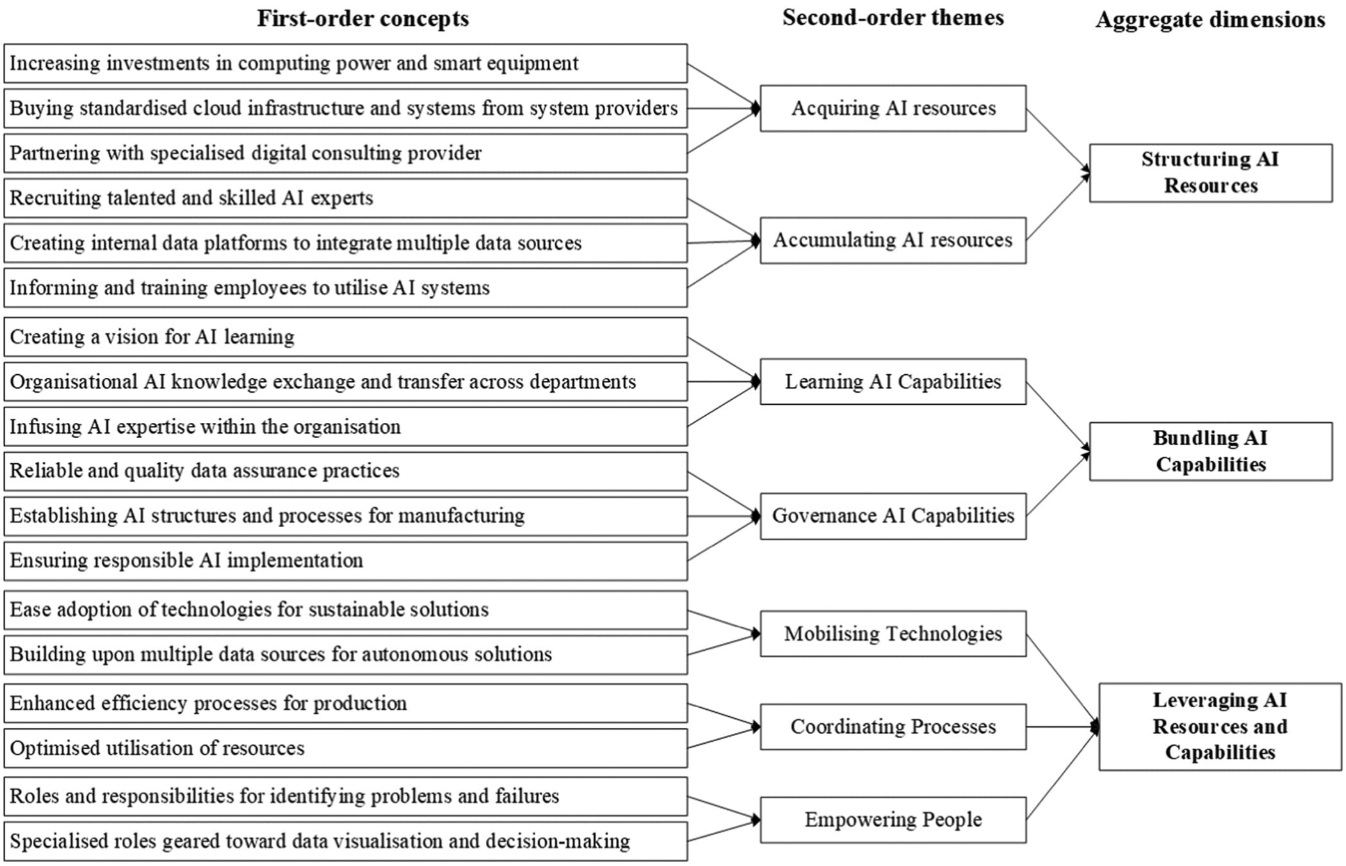

Fig. 1. Data analysis.

the main dimensions of RO for AI implementation by SMEs: (1) *structuring AI resources* into the business portfolio, (2) *bundling AI capabilities*, and (3) *leveraging resources and capabilities* to generate AI outcomes. Table 2 provides examples of illustrative quotations for the second-order themes relating to the orchestration of resources for AI implementation. We also provide a framework for understanding AI implementation across the SMEs' digital transformation.

4.3.1. *Structuring AI resources*

Our analysis reveals that manufacturing SMEs strategically build their portfolio by acquiring and accumulating AI resources. These resources are managed in diverse ways across business processes, acting as a foundation for the development of AI capabilities. The resource portfolio is described in the following sub-sections.

Acquiring AI Resources. In the context of SMEs, acquiring AI resources encompasses a broad range of practices, including investing in computing power and smart equipment, buying standardised cloud infrastructure, and partnering with specialised digital consulting providers. The resource acquisition process requires SMEs to ***increase their investment in computing power by purchasing smart equipment***. To illustrate, Alpha and Beta invested in smart sensors to collect real-time data on packaging manufacturing processes (for ML use). In addition, Alpha, Beta, Gamma, and Delta have invested in smart tracks, and Gamma has invested in new machines that feature embedded AI solutions. However, the analysed SMEs and the SHC must incur significant costs associated with computing resources and infrastructure as AI is implemented in their companies. Several changes will need to be addressed in advance, such as selling off potentially redundant equipment and facilities and divesting underutilised resources. Alpha's production development manager suggested that the investment in new equipment may be problematic:

> "The future of a number of machines in our factory will need to be examined since they are not 'smart'. It is, however, a question of cost and proof of concept that we will see a return on investment."

In addition, a work-in-progress is being carried out to determine what infrastructure can be used to continuously develop, implement, and use AI. The analysed SMEs and the SHC aim to implement a full digital transformation. However, this will require new equipment and investment in computing power. The production development manager at Alpha explains that to fully adopt Industry 4.0 technologies, sensors and other digital tools must be installed. Since data assets are dispersed across multiple systems, SME companies and the SHC require mapping of existing hardware and software to invest in the right amount of computing power. As mentioned by the head of IT at the SHC:

> "I think we should just have a roadmap or no strategy, and no paperwork this big. But what basic prerequisites must be met? That way it's known. It would be good because then we'll know how much time and money it will take".

In the process of AI resource acquisition, SME companies and the SHC are requested to ***buy standardised cloud systems from system providers***.

AI implementation requires the use of different technologies, and the analysed SMEs demonstrated that there was a need to develop in-house database servers. Notably, the evolution of cloud technologies has caused companies to shift towards the outsourcing of these services. Therefore, requiring significant computing resources and infrastructure is seldom costly. Improvements in data platforms are needed because they integrate cloud capabilities, such as database hosting, scaling, code hosting, and machine learning. SME companies and the SHC continuously improve their data platforms by building on their cloud infrastructures. They purchase standardised cloud computing from

Table 2
Resource orchestration for AI implementation: within-case analysis.

		Alpha	Beta	Gamma	Delta	Epsilon
Structuring	*Acquiring*	“To be truly Industry 4.0, sensors and other things need to be implemented. Today, we’re not there. All of the companies have smart tracks, but they aren’t connected to a lot of systems.” Production Manager “So, we fetch data from the ERP system once per week. And the planner has decided which orders are to be in the coming week. And we use these orders. We fetch them to a cloud service on Azure, Microsoft Azure, where we perform the AI planning. Then, we send the results to a SharePoint application. And in this SharePoint application, the user and decision makers at SMEs can see the planning.” Business System Manager	“During our discussion, we discussed different sensors that could be used in the production process to manage energy efficiency, warehouse efficiency, or pick-and-pack operations.” Key Account Manager.	“All new machines have this logging function that we can access. From new machines, we can extract all logging values. It’s possible to do that with old machines, but it’ll only be a matter of time before all machines are replaced. In most cases, we could take out a logging program on all of our machines. We can put it in some IOT sensors and see what it can be, heat, pressure, etc.” Production Manager	“On the plant right now, we have seen a need to improve the efficiency of the machine. So, if you look at investment, we see that we have old machines in the factory, and to be able to cope with the increased volume demands we have on the company, as well as to become more efficient, we need to have other machines to help reduce machine costs. This is one of the most critical investments here, to replace some of the old machines.” Production Manager	"We’ve ordered a new planning system called the EQ-CLAW. Additionally, the program has a function where you can - based on certain criteria, you can set how priority is determined, for example, if one diameter for one order should be the same diameter for the next order to run the machine smoothly. You can then ask the program to set up the best following protocol - how the orders should relate to each other, if you have those features or criteria". Production Manager
	Accumulating	“I need people who are interested in that. Also, I probably need a system base and data in the system so that the machine has something to work with, which is dependable, in other words, and available, so that it can communicate with the machine. In addition, I think that there is also a kind of openness, a willingness from people to put certain projects up for sale by AI. Competence, systems, and data are essential, as are business motivation and willingness.” Production Development Manager	“We see the directive from the top since our data scientist, for example, was hired and so on.” Key Account Manager	“We have a lot of data. Our business system has been logging data since 1999. Do we use the data from our production? […], our basic data in the business system must be correct before we can proceed.” Production Manager	“All production data is being tracked. We are analysing them and taking action. Therefore, you have all the inputs for an AI, a prediction, and we can measure everything within our machines.” CEO	“We asked the make, sure, and we have that in our space that the machine fields have the possibility to extract the most data you have in the HMI system or in the control system of machines.” Strategic Purchaser
Bundling	*Learning*	“I’m absolutely convinced that when we understood how to facilitate it in the printing process, we could take the planning process into different machines within the organisation in different areas.” Production Manager	“Like every department in our company, you have a digitalization plan, and maybe we have a vision for how things should be handled in the future. Our goal is to have less manual work, be able to predict how the weather will affect our customer sales and how we can prepare for those changes, and to have less manual work.” Key Account Manager	“As part of the ‘shift forum’ that we do every 14 days, we cover the theory and the information, but now we need to cover the practical application so they can use it in real life […]. Topics are selected based on team needs.” Production Manager	“Every department has a follow-up with actions. Every month, we have a meeting with the entire management team. Then, we have the quality meetings that we have if we have any claims from customers, internal or external, and we work on improvement. We can bring up issues in many different areas. We also have production management meetings with other plants in the SME, where we discuss if we can use some of the same systems at different companies. […] We considered applications that can be used for the other plants. And AI was one of the issues.” Production Manager	“So, then I would say that we’re building on the first project to enter a new level in a new factory facilitating the same base knowledge that we obtained in the first project.” Production Manager

(*continued on next page*)

Table 2 (*continued*)

		Alpha	Beta	Gamma	Delta	Epsilon
	Governance	"In the past, printers and operators planned manually for 34 min a week, which took their time away from production. Now, we use the KBA to check data. Compared to what we used to do manually over the years, there has been a total change. In comparison with what we used to do manually historically. If we save about – it varies but an hour or two hours a week in the system. I would like us to use more data from the KBA. Our data helps us learn a lot." Operator	"It is a preparation for switching to more data-based, I suppose, but that's only in some parts of the company. Every now and then, they do some data washing to help strengthen the structure." Key Account Manager	"While we're starting up, we're not actually there yet with Internet of Things sensors installed on our machinery so we can like understand the flow of cooling water in our facility so we can know what is actually going on with temperature differences and what is going on with water flow so we can figure out if there are any quality issues in a certain machine." Technical and Maintenance Manager	"Our skilled people in some areas work with data in a very structured way, but we try to use data in a less structured way. The data we collect from customers is difficult to predict because we are typically part of a chain of suppliers. We try to use production data all the time, but we do not always do so." CEO	"We will be able to extract everything from machines in the future, including temperatures and pressure. Although we have multiple sources of data today, we aren't implementing them in AI processes yet." Strategic Purchaser
Leveraging	*Mobilising Technologies*	"To make the production process as efficient as possible, we have a number of systems in place. [….] There is a purchasing system, a production system, and then there are interfaces that send data from one system to another." Head of Sustainability	"We have our SAP, our business system. The main system already has a solution for most questions and if it doesn't, someone has asked the question before and there is an add-on. Only by asking the right questions and defining our goals can we reach a high level of success." Key Account Manager	"We have investments like sensors. The next is how we can develop machine learning with that technology. A colleague of mine works with IoT sensors, as well as value engineering for continuous improvement in the borough as well." Production Manager	"A digital strategy for the group is important because we are trying to integrate our systems more and more and use the same system." CEO	"We work with Excel sheets today. The Jeeves system allows us to see how many orders we have made and how much we have, which is collected in the SAP system. We have a lot of data, so we plan to use QlikSense to present the data in a better way." Production Manager
	Coordinating Processes	"What we do more or less every day is measure efficiency, so we're always trying to get more efficient, and one way to do that is by using AI or other tools. Efficiency measurement basically, it's in production[…] For example, efficiency counts for using materials, using thinner materials in products, reusing plastics, and so forth." Production Development Manager	"Currently, AI is an ongoing project and only a few people understand its power and necessity." Key Account Manager	"Now we have a robotic cell adjacent to an action moulding machine, and we are using a phonic (machine with AI) between these two products, and they speak the same language. By using the same language, we can communicate more effectively between the robotic cell and the inaction mould machine and be more precise between the interfaces between the robotic and machine technologies." Technical and Maintenance Manager	"It would be helpful if we had a setup. The process is similar to implementing LEAN. It is important to have a plan for it. We invest not only money, we invest time and resources." Production Manager	"Currently, we are trying to implement the Balthazar system for production. Our goal is to get more data into Qlik Sense and make it more presentable." Production Manager
	Empowering People	"If you want a good result in anything you do, you should start from the bottom up. The idea may come from the top down, but if you want good results, and success in what you're doing, it's always bottom up. […] I aim to get people on, if you say so, on a grassroots level to get what we're doing and want to do it, because if they want to do it, they can see the gain and understand their part of it, so the project always runs smoothly. The idea should be transferred to the production leaders and the teams themselves. It should feel as if they came up with the idea themselves.". Production Development Manager	"At the executive level, we have identified the need for education and staff strengthening." Key Account Manager	"We have started up a technician team with two production technicians. We also have the maintenance team or the mechanical team at our facility so that everything is in one place like everything is in the same group of people working on everything […]. Everything that we need will come from them to us, to me, and we will set up a good project and a good start, and then we will develop that, and put it in place […]. It is no longer possible to be a traditional manufacturing company.". Technical and Maintenance Manager	"We have expertise in a variety of areas, I would say. We don't have the expertise when it comes to AI. However, I believe we have technical experts who can work together. So, they can understand each other. But we don't have that type of people working inside the company who have broad experience with many of those types of projects." Production Manager	"There is education in the factory. We have internal courses, but we plan to achieve a goal every year for each new employee. There are various forms of education every year, but they could be anything from machines to equipment." Strategic Purchaser

providers such as Azure and Qlik, allowing domain experts to be assisted by AI solutions. The data scientist from the SHC discussed this issue in connection with the cases of Alpha and Beta:

"We moved our SAP and Jeeves servers to the cloud recently, but we have yet to work on using these platforms for AI. These improvements are continuous improvements that we are and will make, and they will probably be true even in ten years."

To determine what infrastructure can be used to continuously develop, implement, and use AI, Alpha collaborated with an external consultant who is an expert in AI solutions. In this regard, the business system manager highlights the pivotal role played by the cloud across SME companies and the SHC's transformative initiatives on AI implementation, describing it as a key to improvement and change.

Finally, to acquire AI resources, SME companies and the SHC needed ***to partner with specialised digital consulting suppliers***.

These suppliers assist with the deployment of AI models to ensure access to robust data storage systems. SME companies and the SHC acquired external resources and formed alliances with experienced firms to effectively manage the necessary infrastructure in order to utilise computational resources for data storage, providing scalable solutions for storing and accessing data. Furthermore, a lack of knowledge of AI has led SME companies and the SHC to collaborate with an external consultant who is an expert on AI solutions. He works with them to establish data management capabilities for the purpose of building a data-driven organisation. When describing Alpha, Beta, and Delta projects, the head of IT stated:

"In the end, we realised that it wouldn't work because it would just be hugely expensive and difficult to use. We went back and thought again and brought in a consulting firm who worked within a subset of the master data."

Alpha's product development manager stated that the company acquired external resources and formed alliances with experienced firms:

"We have limited resources, but if we have good projects, we use other companies, AI companies, to do the work. That shouldn't be an issue."

The lack of knowledge of AI implementation led SMEs and the SHC to collaborate with an external consultant who had expertise in AI solutions. The consultant worked with them to establish data management capabilities. According to the head of IT at the SHC, the AI implementation project pertains to Alpha, Beta, and Delta, which prompted consideration of external support:

"It was quite early in the process that we asked various consulting firms. 'How can we correct our master data?' We didn't know what we wanted. We received a couple of proposals from consulting agencies for systems and solutions."

Accumulating AI Resources.

AI resource accumulation by participating SMEs and the SHC involves internal resource development by recruiting human talent with AI expertise, creating internal data platforms for the integration of multiple data sources, and informing and training employees to effectively implement AI. Centrally, SME companies and the SHC benefit from ***recruiting talented and skilled AI experts*** to provide knowledge and expertise on AI technologies and systems. This requires human talent with the capacity to understand and apply data analysis skills, programming languages, and machine learning techniques, to name a few. A process of this kind necessitates the identification of experts capable of developing enhanced skills internally – a process that, in the case of all the SMEs analysed, was completed by recruiting a data scientist. In addition to the recruitment of data scientists, certain SMEs developed AI-based applications for factory automation by engaging students to write master's theses on the company's problems. On the Delta project, the CFO explained the potential that the engagement of human talent with AI expertise can bring to the organisation:

"I thought about what if there was simply a machine that was observing everything and making no mistakes, then initiating its by-product? Afterwards, the sales director could focus on other things, like getting new business or, you know, entertaining customers or whatever else they do to get business."

In addition, we noticed that the SMEs recognise the relevance of finding new ways to improve factory operations deploying AI applications. Alpha's production development manager asserted that, as AI advances, there is a greater probability of liberating employees from performing repetitive and manual tasks. As the expert highlighted, employees can instead focus on higher-level, creative, and strategic work.

To accumulate AI resources, the different SMEs and the SHC supported the implementation of AI by ***creating internal data platforms to integrate multiple data sources.*** These platforms allow the integration, classification, and organisation of large numbers of data sources. It was noted that, given their strategic priorities and data-related business objectives, participating SMEs and the SHC strive to create data governance that will lead to long-term value. Since companies have a wide range of unstructured data formats, the creation of data platforms to access a large amount of information is key. In this regard, a process is being developed to determine which use cases can be applied to accessible data. To ensure robust data flow and control of the data landscape, it is necessary to implement a master data management process and investigate the possibility of a more modern data platform.

All the SMEs and the SHC carry out evaluations of the data available across manufacturing processes by classifying the data that can be utilised through AI systems. This process facilitates the development and maintenance of the analysed SME data structures, as well as their integration into architecture-based applications, systems, solutions, and projects. The accumulation of resources by SME companies and the SHC remain an ongoing challenge, and AI implementation is probable to influence different tasks and positions. The production manager at Gamma pointed out:

"Data isn't a problem, but how to arrange the effective utilisation of data for AI implementation comprises a continuous hurdle."

Finally, it was observed that the process of accumulating AI resources required ***information and training on organising and categorising data***. SME companies and the SHC recognise the relevance of investing and developing resources internally by implementing strategies to spread knowledge, such as learning forums. To accomplish this process, the enterprises are required to invest in supporting and sustaining resources while restoring and revitalising weakened resources. By way of illustration, SME companies and SHC employees relied on training programs offered by the SHC Academy to enhance AI skills. Indeed, the SHC Academy continually employs an approach to informing and training their staff to better categorise and classify data for AI purposes. The HR documentation stated:

"It is important for us to create internal development while, at the same time, attracting the talents of tomorrow. One way of growing talent from within is through our SME Academy."

Similarly, the production manager from Gamma and the SHC's CFO emphasised the importance of the communication process in informing and training employees:

"To start, we needed people who would transfer their knowledge and understanding of the process […] To transfer their knowledge to understand the AI team, we needed to get those people in a room together to discuss what they were doing and what they were looking for."

The production manager at Alpha stated that training is viewed as a reciprocal process that involves learning and education. This view stresses that, having informed the SMEs and the SHC, human talent is crucial:

> "AI possibilities come from people within the organisation who have an insight into where we can improve our performance."

4.3.2. Bundling AI capabilities

Through bundling, companies enrol in the process of forming AI capabilities. Thus, capabilities are created by combining AI resources to allow organisations to carry out AI implementation actions. Manufacturing SME companies and the SHC demonstrated the value in bundling learning and governing AI capabilities across the data collection process.

Learning AI capabilities focuses on introducing knowledge exchange to members of the organisations. The concept focuses on developing the company's awareness phase through the promotion of learning capabilities and inter-organisational expertise exchange and knowledge transfer. In this regard, it was observed that top managers in the participating SMEs and the SHC initiated AI transformational processes by ***creating a vision for AI learning***. They formed an AI transformation group, which included CFOs, the head of IT, the data scientist, the production development manager (Alpha), and the business system manager (Alpha). By bringing different competencies together, they were able to design a holistic and inclusive agenda for AI implementation. Special attention was placed on how AI learning could be facilitated and deployed. These practices provided the fundamental grounds for the creation of a widely accepted and clear agenda for AI implementation within the firms. Furthermore, every month, the group discusses how to bundle AI into concrete organisational capabilities. This group aims to explore ideas, identify organisational challenges related to AI, and share knowledge.

The production manager at Epsilon emphasised the importance of those meetings, where they exchange knowledge and learn from each other. As part of the company's vision, investing in a factory is viewed as a way to transfer knowledge about AI implementation to the company's decision makers. Alpha's production manager believes that, when they understand how to facilitate AI in their processes, they can transfer that knowledge to different machines in various fields within the organisation.

To bundle capabilities, ***organisational AI knowledge exchange and transfer*** are required, which consist of applying, sharing, and playing a collaborative part in AI knowledge within the organisation. Curiously, the SMEs and the SHC provided evidence of minor incremental improvements in existing AI capabilities. It involved an exchange of organisational expertise and knowledge transfer. The SHC internalised AI; it developed three pilot projects from which it was able to learn more about AI for use as the basis for production. This will form the basis for other AI activities in the future. The CFO from the SHC stated:

> "[.] so to make sure that not only the production but every other department through the organisation, and every entity or subsidiary has an AI project of their own for that. Because that's when I'm convinced that if you have your project in your organisation in your department, then you will understand the possibilities."

Several methods are used to introduce AI, one of which is the internalisation of practices learned from the SHC Academy. The Academy has played a pivotal role in this process, an aspect that was reinforced by the data scientist:

> "Across the entire company, it is sort of recommended for this program, and maybe 10 or 12 people take this set of modules every year. In one of those modules, we will talk about artificial intelligence and digitalisation. So, I've sort of presented AI there and what it is, and how you can use it. In that way, we are also trying to spread knowledge within the organisation. Therefore, it isn't just for the top but also for other people within the organisation."

Obtaining greater knowledge in the company is encouraged and supported by management. AI activities are clearly communicated within the organisation, as the data scientist noted:

> "We're also trying to spread the knowledge in the organisation. So not just to the top, but also to people who are sort of up and coming, maybe future managers."

Manufacturing SME companies pursue the development of AI learning capabilities by ***infusing AI expertise into the organisations***. This process consisted of asking the data scientist and AI experts to have meetings and knowledge exchange moments with staff members. To illustrate, the data scientist from the SHC meets with the domain experts in all subsidiary companies to identify challenges that are considered AI. These meetings are intended to build learning capabilities and to promote inter-organisational expertise exchange and knowledge transfer. The data scientist of the SHC supporting the subsidiary companies stated:

> "I have meetings with the domain experts and, of course, I would present, for instance, what we are doing related to AI. I talk to operators and their production and developers when we plan a meeting."

The SMEs were able to benefit from AI expertise and know-how derived from the SHC "hub", a platform for AI generation that allows them to develop knowledge transfer routines across the entire organisation. In this regard, Epsilon's production manager described the process of knowledge transfer from the AI project as follows:

> "Each AI project is a learning experience that allows us to enter a new level in a new factory, facilitating the same knowledge that we obtained in the first project."

AI Governance Capabilities integrate the set of policies and principles that SME companies and the SHC use to develop and use AI technologies. Through these capabilities, the observed companies showed interest in ensuring that the use of AI is transparent and trustworthy. The data showed that AI governance capabilities require ***reliable and quality data assurance practices***, which means that, to be accurate, the data used to deploy AI in the manufacturing process have to carry out predictions and perform effectively. The observed SMEs showed that large quantities of data need to be structured. This is assumed since companies are developing internal standards for the gathering, storing, processing, and disposal of that data. The companies can achieve this goal by striving to optimize production processes and supply chains. Since AI is affecting many fields within the organisation, both technologies are expected to substantially change working conditions for many people. It is necessary to connect various systems to develop the capability and resources to use data analytics. The organisation has initiated activities such as order forecasting, which can assist in many areas, such as production planning, purchasing, budgeting, and storage planning. Currently, sales staff and planners have to employ various systems to achieve these, which is time-consuming and difficult.

AI governance capabilities are related to processes in which companies could establish ***AI structures and processes for manufacturing***. Some of these structures included the use of predictive modelling of the process of feeding AI systems with data that allow the SME companies and the SHC to identify patterns in manufacturing processes. For instance, in the process of planning, a production sequence was introduced to replace the manual work involved, such as the timing of production orders, which is a major factor limiting productivity. To effectively operate the printing machines (KBA), data from the KBA of printing orders should be automatically structured. The aim is to reduce the overall setting time, decrease setting times, reduce the manual planning time (by reducing person dependency), and store knowledge in code, which is considered safer. Furthermore, bundling data resources to develop planning production sequences is a heuristic optimisation function, and simulated annealing enables the development of new AI capabilities in this process. An operator from company Alpha explained that they used to plan manually, but now they use KBA to check the data. The way they do things has changed completely; currently, they save one or two hours a week and use KBA data to become more efficient.

In this process, data resources (i.e., the data on orders) are leveraged to develop the analysing capability, based on the production line: optimise a week of production between 30 and 60 orders, reduce salespeople travelling, and develop iteratively in collaboration with machine operators. Furthermore, data resources, machine resources, and human resources are coordinated to generate the learning capability regarding planning, purchasing, budgeting, and storage, and to further enhance human-AI collaboration. In purchasing optimisation, customers buy plastic pails and pots. Approximately 7000 unique labels are purchased by company Delta from an external supplier. The products all have unique artwork and ingredients, and product designs are often changed by customers. The purpose is to reduce the cost of complex price structures and identity labels that can be purchased together. Heuristics and optimisation algorithms are used to improve purchasing orders to obtain a volume discount. Bundling data resources with machine learning resources (i.e., ARIMA/LSTM/Transformers) and then coordinating system resources and human resources enables the development of new AI capabilities in this process. By bundling data resources with system resources, analysing and purchasing capabilities can be developed to reduce the cost of complex price structures and identity labels. A data scientist explained the mechanism of classifying the data:

> "Ordering lower-level assembly products more efficiently. Quantity discounts can be achieved under different conditions when lower-tier products are ordered from a manufacturer for different packages. The design of each lower assembly-level product specifies a fixed number of different colours. Price lists are determined by the manufacturer of lower assembly-level products based on their sizes, types of uses, and applications. Lower assembly-level products with the same price list can be ordered together if the price list does not exceed the maximum number of colours. More colours, however, increase the price per unit."

As seen in the data, SME companies and the SHC were able to enrich AI capabilities by ***ensuring responsible AI implementation***. This means SME companies and the SHC were eager to establish practices for the ethical development of AI systems. Accordingly, by ensuring responsible AI utilisation, SME companies and the SHC can develop transparent practices, minimising bias in data interpretation, while enhancing trust in manufacturing processes. Responsible AI implementation was correlated with the usage of business intelligence practices (such as enterprise resource planning (ERP), supply chain management (SCM), and customer relationship management (CRM systems). As pointed out by the head of IT:

> "Essentially, it's about getting this roadmap about how we should work with data, who should be responsible for data, and then what we should have as a platform for it."

However, ensuring responsible AI implementation is under development as informants from the SHC suggested the need to create business intelligence practices that allowed companies to better understand the ownership of their data by implementing data policies and delivery.

4.3.3. Leveraging AI resources and capabilities

By utilising AI resources and capabilities, implementing AI systems enabled SME companies and the SHC to effectively navigate through their digital transformation while allowing specific performance outcomes in the manufacturing context. The competencies of the manufacturing SMEs and the SHC to leverage AI resources and capabilities were characterised by the mobilisation of technologies, the coordination of manufacturing processes, and the empowerment of people skills.

Mobilising Technologies. To effectively leverage both AI resources and capabilities, SMEs were able to discover that the mobilisation of technologies enables the creation of massive opportunities in manufacturing. By understanding the technological needs of the manufacturing processes, the companies show the capacity to leverage AI resources and capabilities through activities that demonstrate an ***easy adoption of technologies for sustainable solutions***, while supporting their sustainable development outcomes. AI technologies facilitated a more sustainable utilisation of material resources, allowing the SMEs to explore more environmental materials. The focus was placed on the development and testing of new materials and the development of new innovative products. For instance, company Delta was able to reduce its use of plastic in manufacturing bottles. In this context, the CEO of SHC starkly stated:

> "The goal is to eliminate activities in the organisation that do not create customer value. My ideal output is when you can see the effects of the product in reality, which means you know that you are taking away steps that create value in your internal processes[…] We have to make sure that this is as efficient as possible and sustainable."

By adopting technologies for sustainable solutions, SMEs and the SHC can implement AI systems, reducing the use of materials while promoting environmental practices. To support this, the SHCs at the holding organisation were able to establish the 2020 Innovation Centre to develop what the companies call "Tomorrow's Packaging" or the "Packaging of the Future".

Similarly, the mobilisation of technologies was identified through the SMEs' capacity to ***build upon multiple data sources***, leveraging their data intelligence capabilities to expand their platforms for data integration. By implementing and using AI, the SMEs were able to continuously improve their data, making it more reliable and, thus, enhancing their organisation's data management capabilities. The SMEs reacted proactively to issues related to data quality, availability, and completeness. Moreover, technology mobilisation was identified as an incremental process that combines data from multiple sources to create unified sets of information. The data scientist pointed out:

> "Several companies already use data to make production more efficient in many different ways. Production orders, purchasing orders, and customer orders are all digital. It may not always be perfectly organised, but a digital foundation already exists. As far as smaller companies and organisations are concerned, I am less familiar with them. However, AI may also be useful there – for instance, in planning schedules, for example, in one company".

By building upon multiple data sources, the studied SMEs and the SHC were able to employ data integration techniques that merge and combine data from multiple manufacturing processes. Therefore, their capacity to classify "good data" as against "bad data" allowed the SMEs to analyse and utilise data for visualisation and decision-making processes from different systems and formats. By ensuring the reliable use of multiple data sources, the companies were capable of utilising technologies with minimum error, facilitating automated processes.

Coordinating Processes. This relates to enhancing efficiency processes for production and visualising data in the decision-making process. Through ***enhanced efficiency processes in production***, the analysed companies were able to focus on the processes of how goods and materials could be produced in the future. Using different efficient planning strategies can provide a foundation for determining how much of each product to produce. The overarching objective of the observed enterprises is to create more efficient production in product packaging (tubes, pots, cans, metal, and plastic). With the support of AI applications, the analysed SMEs and the SHC aimed to increase market share and revenue, as well as to improve the organisations' product materials across production processes. Moreover, the companies were positive that new processes supported by AI promoted superior overall performance and growth. However, questions remain regarding the extent to which these practices are widespread across organisations, whether they lead to productivity improvement, and whether clusters of complementary organisations may be necessary. Based on the pilot projects, the analysed SME and the SHC were expected to enhance efficiency processes for predicting production using AI. The company has identified several ways in which AI can improve efficiency across its production. Firstly, it can reduce the time wasted in production by using data to optimise behaviour concerning the sequencing of production orders, scheduling workflows and routing, and scheduling the competence of workers efficiently. A second way is to use data to forecast customer demands to ensure that goods can be produced on time when customers need them.

AI resources and capabilities transformed the coordination of manufacturing processes by ***optimising the utilisation of resources*** across the organisation so that decision making is based on a factual, data-driven approach. Resource optimisation was identified in two different processes. The first process was using data to purchase materials at the lowest price possible, while still ensuring that materials are available for production when required. The second process involves the implementation and use of sensors and production data to make sure that machines are running at their optimal level to reduce scrap from faulty manufacturing, and to reduce downtime from machines breaking down. This is achieved by scheduling maintenance before breakdown, a process called predictive maintenance. The production development manager from Alpha placed efficiency at the centre of the production process.

Empowering People. Human capital is one of the central configurations needed to leverage resources and capabilities for AI applications. To empower people, the SMEs and the SHC started by ***ascertaining roles and responsibilities for identifying problems and failures*** in the AI implementation processes. AI improve the accuracy of decision making and supports human operators in identifying problems and failures. The analysed SMEs and the SHC are fully aware that AI is changing the way work is done. By empowering their workforces, they will achieve sustainable production. This process is still in its inception, but it has already transformed some aspects of the way manufacturing SMEs and the SHC work. During a meeting in company Alpha, the researchers observed the activities carried out by operators and the team responsible for the ordering process. Members of the team described how they learnt from the data scientist how to use the data collected from the machine to improve the work they are doing:

> “There is a lot of development we do. It now takes six minutes instead of sixteen. Because we have the data, that’s the basis. But yeah, you can do that manually from the beginning. But, in the end, you have to work with the data, otherwise, it won’t work. Over the past year, we have almost always changed.”

Apart from earmarking human talent capable of ascertaining roles and responsibilities for the identification of problems and failures, the SMEs and the SHC have pinpointed specialised roles geared to ***data visualisation and decision making***. These personnel consist of production managers with support from the system manager and the data scientist. Companies Alpha, Beta, Gamma, Delta, and Epsilon benefited from the SHC policy of developing efficient data analysis to help employees and managers make better-informed decisions based on visual representations of data, making it easier for them to understand and gain better insights, and enabling them to make faster decisions. The CEO (SHC) contends that *“artificial intelligence can play a role in many parts of that value chain to optimise it.”* However, this is an ongoing process of improvement and remains a challenge for the organisation. The data scientist explained:

> “A challenge is the structure of data and how people view data, as well as their understanding of the importance of good data. That’s a very big challenge that can’t be solved easily.”

4.3.4. *Framework for Digital Transformation through AI Implementation*

Based on the empirical results of our study, we observed that manufacturing SMEs implement AI through a process that requires them to identify resources and capabilities before leveraging them and converting them into competitive advantage and value for the customer. Following our observations of the case companies, we propose a process framework on how SMEs implement AI in their manufacturing processes as part of their digital transformation (Fig. 2). The framework illustrates how SMEs can proceed through three different phases of the AI implementation process: (1) *structuring an AI resources portfolio*, (2) *bundling AI capabilities,* and (3) *leveraging AI resources and capabilities* by mobilising technologies, coordinating processes, and leveraging people. Because this digital transformation depends on the capacity to leverage and intertwine AI resources and capabilities, SMEs can use this framework to assist them in their AI transformation path.

During the first phase, SMEs focus on *“structuring AI resources”*, where they identify the relevant resources for AI implementation. These are both tangible and intangible resources – namely, data resources, infrastructure resources, human resources, and capital resources, all of which are important for organisational capabilities. The companies have developed better use of data, invested in new systems, recruited new people with the right skills, and trained employees to better understand data. Moreover, these companies were able to trigger innovation by moving down the AI path.

In the second phase, manufacturing SMEs concentrate on “*bundling AI capabilities*”. The logic is that by building AI resources, SMEs are able to identify current AI capabilities (e.g., big data analytics, which is used to optimise production, plan, and forecast) or to earmark which new capabilities are needed (i.e., recommendation systems and churn analysis). By bundling AI capabilities, SMEs are able to progressively develop a greater understanding of AI technologies while promoting inter-organisational knowledge exchange. In particular, SMEs developed portfolios of projects that enabled them to identify areas that could benefit from AI technologies, determine the feasibility of each project, and estimate the return on investment. Analytics from data, relevant competencies, capital, and infrastructure resources increasingly become crucial resources to bundle AI capabilities.

The final phase is *“leveraging AI resources and capabilities”* where SMEs integrate both capabilities and resources to implement AI in the best possible way and to obtain measurable outcomes to gain a competitive advantage. During this phase, AI capabilities should be scaled up and interchangeably evolved, grown, and expanded, resulting in leveraged gains. These capabilities are linked to organisational performance and value creation resulting from AI. AI implementation is aimed at improving the internal processes of SMEs and enabling them to gain a competitive advantage. Through incremental transformation, SMEs are deploying AI technologies as part of their daily operations. AI has enhanced efficiency in production, operation, and optimisation processes. Data, as part of the foundational decision-making process, has progressively become more important, as has leveraging AI resources and capabilities for employees’ empowerment, learning, and education. We observe that the transformation of SMEs results from the complex interplay of resources given organisational structures and processes. For SMEs, AI implementation is a journey to improve performance by reducing unexpected breakdowns, interruptions, and costs. Achieving this is accomplished by making use of AI technologies that are easy to implement and by building on current capabilities that allow for improved efficiency of the production processes.

5. Study 2: Implementing AI through a Dynamic Framework

5.1. *Overview*

Building on a more concise stage of data gathering, Study 2 aimed to revisit Study 1 results adopting a more nuanced approach to the data derived from the participating SMEs. We explored the aggregate

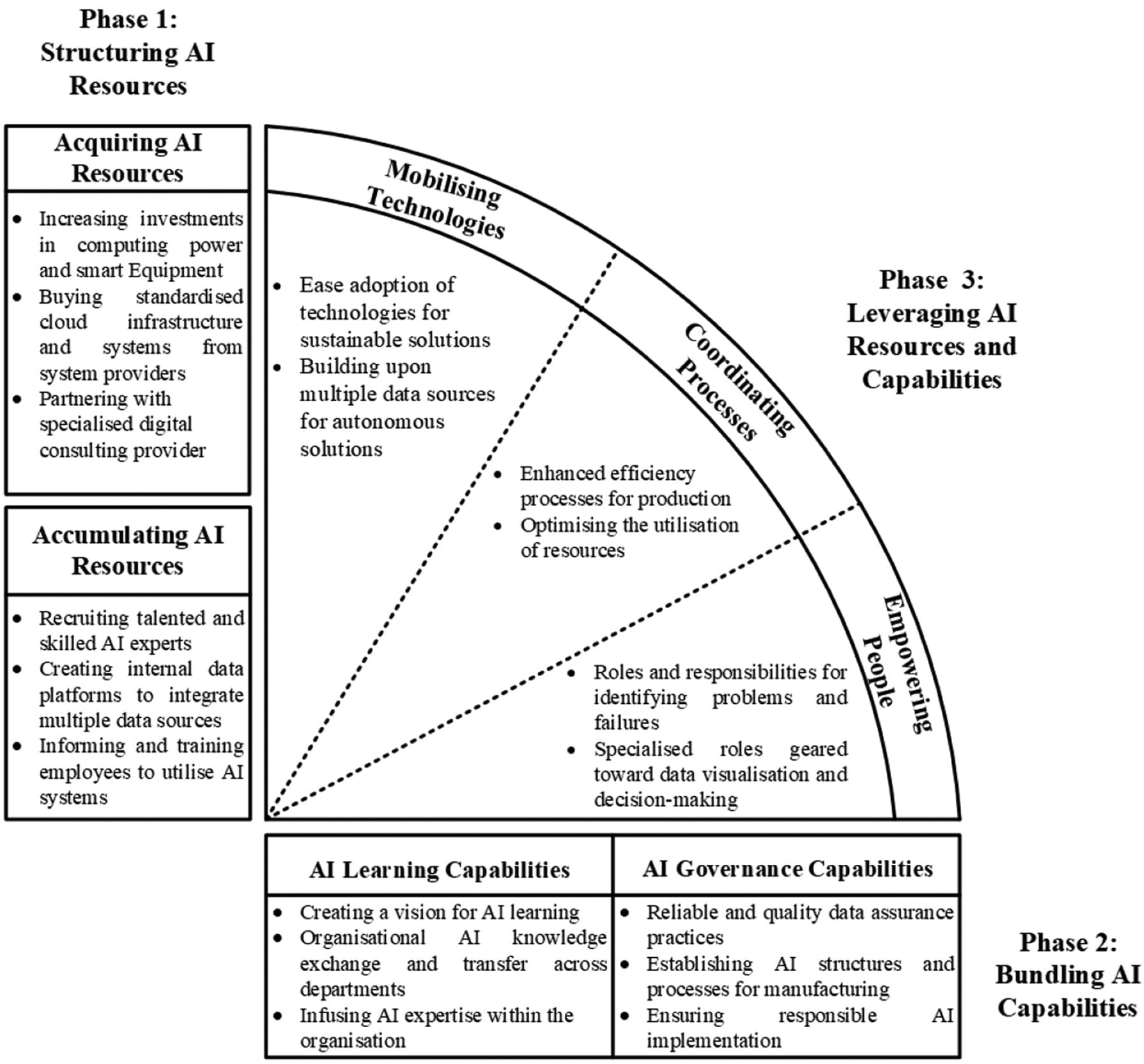

Fig. 2. Framework for Digital Transformation for AI Implementation.

dimensions one by one and provided a new and revisited framework for AI digital transformation in manufacturing SMEs.

5.2. Methodology

In Study 2, we validated our conceptual model using a novel process of data collection. Based on guidance regarding design validity (Stuart et al., 2002), Study 2 aimed to validate the results and conclusions developed in Study 1 by triangulating the multiple sources of evidence to identify alternative explanations for the observed analysis. Study 2 enabled us to strengthen and validate the framework for AI implementation in manufacturing SMEs. By increasing our sample size, we are able to provide a broader perspective and potentially increase the reliability of our findings (Yin, 2014). The approach of having a second study has allowed a more comprehensive view of *how SMEs in the manufacturing industry orchestrate resources to implement AI to support their digital transformation*, adding fresh nuances to those captured in Study 1. We added seven additional semi-structured interviews with managers and operational-level respondents and organised eleven AI reconciliation meetings to gain better insights into AI implementation from their individual perspectives.

To carry out the validation process, we briefly introduced the research context according to the interview protocol (Appendix 3b). The interview questions were refined given what we had learned and the feedback from the findings of Study 1. New informants were selected on the basis of their involvement in the introduction and implementation of AI in their companies. Study 2 included interviews conducted with the maintenance and automation manager (Delta), the CEO (Delta), the strategic purchaser (Epsilon), the key account manager (Gamma), the technical and maintenance manager (Gamma), the key account manager (Beta), and the innovation manager (Beta).

Secondly, we encouraged respondents to answer the questions and express their views based on the analysed categories: *structuring AI resources*, *bundling AI capabilities*, and *leveraging AI resources and capabilities*. The purpose of the meetings was to discuss the status of current AI projects at the SHC, the inventory potential of AI projects, and the upcoming roadmap processes to prioritise AI implementation projects (based on current capabilities and resources). Reconciliation meetings were used to discuss with the different managers and AI domain experts the proposed framework derived from Study 1. Participants were invited to discuss and amend the framework and to provide feedback according to the empirical implementation of AI in SMEs. In addition, meetings with external stakeholders were carried out to develop data strategies to improve SHCs' competitiveness and customer value. Secondary data were considered to triangulate the data (Appendix 2). Finally, we categorised the qualitative data into refined themes that represented primary constructs from the former study. This process consists of a bridge approach that strengthens the findings in Study 1 from the results in

Study 2. A new framework was developed from the validation process.

5.3. Results

To further explain the constructs in the proposed framework, we relied on a set of quotations from the validation process. Some of the constructs developed in Study 1 remained, while others were refined. New dimensions were identified. A summary of the refined themes is presented in Table 3. The researchers proceeded on the basis that the three dimensions of RO were maintained. In that order, each aggregate dimension was refined on the basis of the new findings.

Considering the dimension of ***structuring AI resources***, it was noted that the observations on the different sub-themes related to *acquiring AI resources* remained unchanged as in Study 1. Moreover, it was stressed by the respondents of Study 2 that acquiring AI resources is not a static, standalone process. The different SMEs discussed how to create a structured approach to adapting AI to meet the evolving needs of their organisations and to surmount potential setbacks in the competitive landscape. Therefore, the acquisition of technologies and resources that support the implementation of AI must be aligned with technological innovation and the ability to offer efficiency in SME manufacturing. In addition, the complexities facing SMEs in acquiring AI technologies were also much in evidence in Study 2. In support of this asseveration, Epsilon's production manager highlighted:

> "To be truly Industry 4.0, sensors and other things need to be implemented. Today, we're not there. All of the companies have smart tracks, but they aren't connected to a lot of systems."

The respondents confirmed that initiation should begin by identifying the company's specific needs for AI implementation and that the process should start with small steps. Gamma's technical and maintenance manager reinforced this idea by stating:

> "While we're starting up, we're not there yet with IoT sensors installed on our machinery, so we would like to understand the flow of cooling water in our facility, so we can know what is going on with temperature differences and what is going on with water flow, so we can figure out if there are any quality issues in a certain machine.".

In the category of *accumulating AI resources*, two new sub-themes emerged. "Creation of internal data platforms" was refined by the idea of "increasing the quality of data sources". Discussions were more concrete and focused on implementing AI on a daily basis. Aside from improving internal processes, particular interest was placed on learning about customers' needs and behaviours. Therefore, buying standardised cloud infrastructure and systems places the customer's need to forecast acquisition of these goods to the back. The AI monthly reconciliation meetings discussed the available resources and capabilities in the various plants, the knowledge required, and how it can be translated into customer value.

A second sub-theme on "informing and training employees to utilise AI systems" is a nuanced category, defined as "educating and training employees for AI integration across systems". This modification highlights the idea that education enhances AI implementation in SME systems and machines. Gamma's production manager indicated the importance of employee engagement in knowledge transfer, stressing that employee expertise is key to successfully accumulating AI resources in the company. He concisely stated:

> "To start, we needed people who would transfer their knowledge and understanding of the process [...] To transfer their knowledge to understand the AI team, we needed to get those people in a room together to discuss what they were actually doing and what they were looking for."

Developing skills and optimising resources is a dynamic process that requires continuous attention and investment. Thus, the monthly reconciliation AI meeting serves as an essential forum for organising, defining, and managing the various skills, resources, and competencies in the organisation.

On the dimension of ***bundling AI capabilities***, a new sub-theme emerged regarding *learning AI capabilities* as we ascertained that "organisational AI knowledge exchange and transfer across companies" is necessary to promote learning across organisations. For example, the organisation of monthly meetings was identified as a central routine that would enhance organisational learning capabilities. The objective of SMEs is to expand and enhance their capacity to acquire, apply, and adapt AI knowledge and insights effectively. Moreover, the monthly meetings provide SMEs with a platform for knowledge transfer and exchange between SHC companies. In this process of acquiring and retaining knowledge, the goal is to facilitate AI adaptation, improve performance, drive innovation, and gain a competitive advantage. Therefore, the monthly meetings were observed as an opportunity for knowledge exchange and coordination as part of the digital transformation. As stated by SHC's data scientist:

> "We start by reviewing all projects briefly. Company Delta has been going on for a while, and I would say that we are on track [....] Beta is currently working on the data in the ASP, so I expect an email here

Table 3
Construct refinement from Study 2.

Aggregate dimensions	Second-order themes	First-order concepts	Status
Structuring AI Resources	Acquiring AI Resources	Increasing investments in computing power and smart equipment	R
		Buying standardised cloud infrastructure and systems from system providers	R
		Partnering with specialised digital consulting providers	R
	Accumulating AI Resources	Recruiting talented and skilled AI experts	R
		Increasing the quality of data sources	C
		Educating and training employees for AI integration across systems	C
Bundling AI Capabilities	Learning AI Capabilities	Creating a vision for AI learning	R
		Organisational AI knowledge exchange and transfer across companies	N
		Infusing AI expertise within the organisation	R
	Governance AI Capabilities	Scaling capabilities for organisational learning	N
		Establishing a manufacturing 4.0 company	N
		Ensuring responsible AI implementation	R
Leveraging AI Resources and Capabilities	Mobilising Technologies	Ease adoption of technologies for sustainable solutions	R
		Building upon multiple data sources for autonomous solutions	R
	Coordinating Processes	Enhanced efficiency processes and continuous value creation for customers	C
		Develop a resource matrix to optimise resource utilisation	C
	Empowering People	Develop an understanding of AI among people in the organisation	R
		Specialised roles geared toward data visualisation and decision making	R

Note: R: Remained as in Study 1; C: Changed (was refined); N: New (was identified).

anytime to complete it [….] Alpha just had sick people, but we got an email that now seems to be a little bit back."

Regarding *AI governance capabilities*, new sub-themes were identified. As we observed, AI implementation is primarily focused on evaluating the current activities in the organisation and creating a priority order to ensure that resources are allocated correctly. This is also known as "scaling capabilities for organisational learning". The CFO of the SHC suggested: .

"A little prioritisation of the next project then, and or the next, and maybe what we're doing right now also fits under that as well."

It was centrally agreed that "ensuring responsible AI implementation" is implicitly linked to the use of reliable and quality data practices. In addition, it introduced the sub-theme of "establishing a manufacturing 4.0 company". SMEs have automated manufacturing processes and central manufacturing processes, such as control systems and energy efficiency. However, since SMEs are in the early stages of adopting a data-driven approach to manufacturing, they are taking the necessary steps to improve data governance because poor-quality data is still being gathered. Beta's key account manager illustrated this idea:

"It is a preparation for switching to more data-based, I suppose, but that's only in some parts of the company. Every now and then, they do some data washing to help strengthen the structure."

Regarding the dimension of ***leveraging AI resources and capabilities***, novel nuances and refinements were implemented. Two sub-themes were refined on the aggregate dimension of *coordinating processes*. On the one hand, it seems that SMEs have shown "improved efficiency processes for the organisation and continuous value creation for customers". The implementation of AI by SMEs in the manufacturing industry is a rather dynamic process. SME companies strive to achieve their strategic objectives and become more effective and efficient. A regular assessment of the current state of resources and capabilities is necessary for SMEs to implement and adapt AI. In addition, major discussions take place on the different scenarios that affect SMEs and the SHC, such as war and inflation. The participating SMEs and the SHC emphasised the importance of inter-company collaboration because this leads to a more efficient use of resources and the solving of problems. As Epsilon implemented a Balthazar system for AI-powered manufacturing, customer value was created through improved product quality and the provision of personalised products. Similarly, the production manager from Gamma starkly stated:

"Let's talk about efficiency, a subject that's close to my heart, where we have a target efficiency and if we aren't reaching it, it's yellow, and if it's 3% below, then it's red. We are monitoring this and showing it live on TVs in the production area. [….]. On average, we have five to ten setups per day. Can we collect data to determine which fragments the section is in? Is this the best way to improve our efficiency and uptime?"

On the other hand, it was found that SMEs "develop a resource matrix to optimise resource utilisation". SMEs plan to increase the efficiency of their resources through a metric. The intent is to ensure that resources are used appropriately (not wasted or underutilised) and that they are allocated correctly. Beta's key account manager illustrated this point:

"We will conduct a full competency matrix on everyone in 2024, and AI will have to be included."

The use of data and analytics to allocate resources, as well as the continuous review and refinement of those decisions, is essential for cost control and maximising returns on investment in SMEs and the SHC. Gamma's production manager stated:

"On a weekly basis, we report to the management group how the machines are performing, what we're getting from them, and what problems we're encountering. On a monthly basis, we collect this data and put it in the KPI and report to the management group."

The sub-theme of *empowering people* retained the definition employed in Study 1, with nuanced statements supporting the results from Framework 1. Such is the case of Gamma's technical and maintenance manager who stressed the importance of engaging employees who are attracted to AI – therefore, highlighting the need to encourage employees to keep learning about AI applications:

"We as a company need to learn more about how young people or those who are interested in these types of questions draw them to the actual industry (work like that internally as well) to get more information and to acquire more knowledge about it because I believe that will benefit them, but it will benefit us more, but we're not working with it because yeah, it's in the future and so forth."

5.4. Modified Framework for Digital Transformation through AI Implementation

The validation process of Study 2 – gathering confirmatory and in-depth qualitative data – has enlarged the exploratory findings that manufacturing SMEs orchestrate AI resources and capabilities by means of a dynamic and reinforcing process that self-nurtures across the digital transformation space. Study 2 contributes to our analysis in that it examines the dynamic environment within which organisations operate, their customers, and their business value. The analysed SMEs and SHC try to align their resources and capabilities so that they can provide value to their customers whilst ensuring the sustainability and profitability of their businesses.

A central lesson on framework refinement refers to customer value creation as the main outcome sought from AI resource orchestration capabilities. According to the respondents, providing value to customers is a fundamental objective, and AI plays a significant role in this process. The SMEs mentioned the possibility of increasing sales and revenue when resources are allocated to AI projects by engaging customers and enabling data-driven decision-making that aligns with their customer preferences. Alpha's CFO clearly illustrated this point:

"It would have been cool to find something like you said, something that creates customer value, so our clients feel like, wow, this was cool, I'd pay for it. As a result, you become more competitive and more attractive as a supplier."

In addition, Alpha's head of marketing and sales excellence asserted:

"We are perhaps most passionate about production-driven customer offers, so it is also more customer-focused than cost-oriented. It is also possible that we have a forecast that only some customers will order. We say that we have a decent order forecast, then we know that a customer will order something within a month, and this fits well into II Production Planning within 2 weeks. The customer will receive an offer with a reduced price if they order this now, and it will be easier to plan production if they do."

The statement above shows AI implementation by SMEs in the manufacturing industry as part of their digital transformation process. These observations provide feedback for further refinement of the proposed framework for AI implementation. The study validation shows how SMEs manage AI resources and bundle their existing capabilities, maximising the potential of resources and capabilities that their organisation processes. This is a dynamic flux of continuous modifications and enhancements (or acquisitions) of existing structures, which create or renew capacities to leverage AI implementation. Fig. 3 represents our new framework on SMEs' AI implementation as part of the digital transformation process.

The validated framework shows that the three dimensions of *AI resource orchestration* are a dynamic and self-nurturing process. The

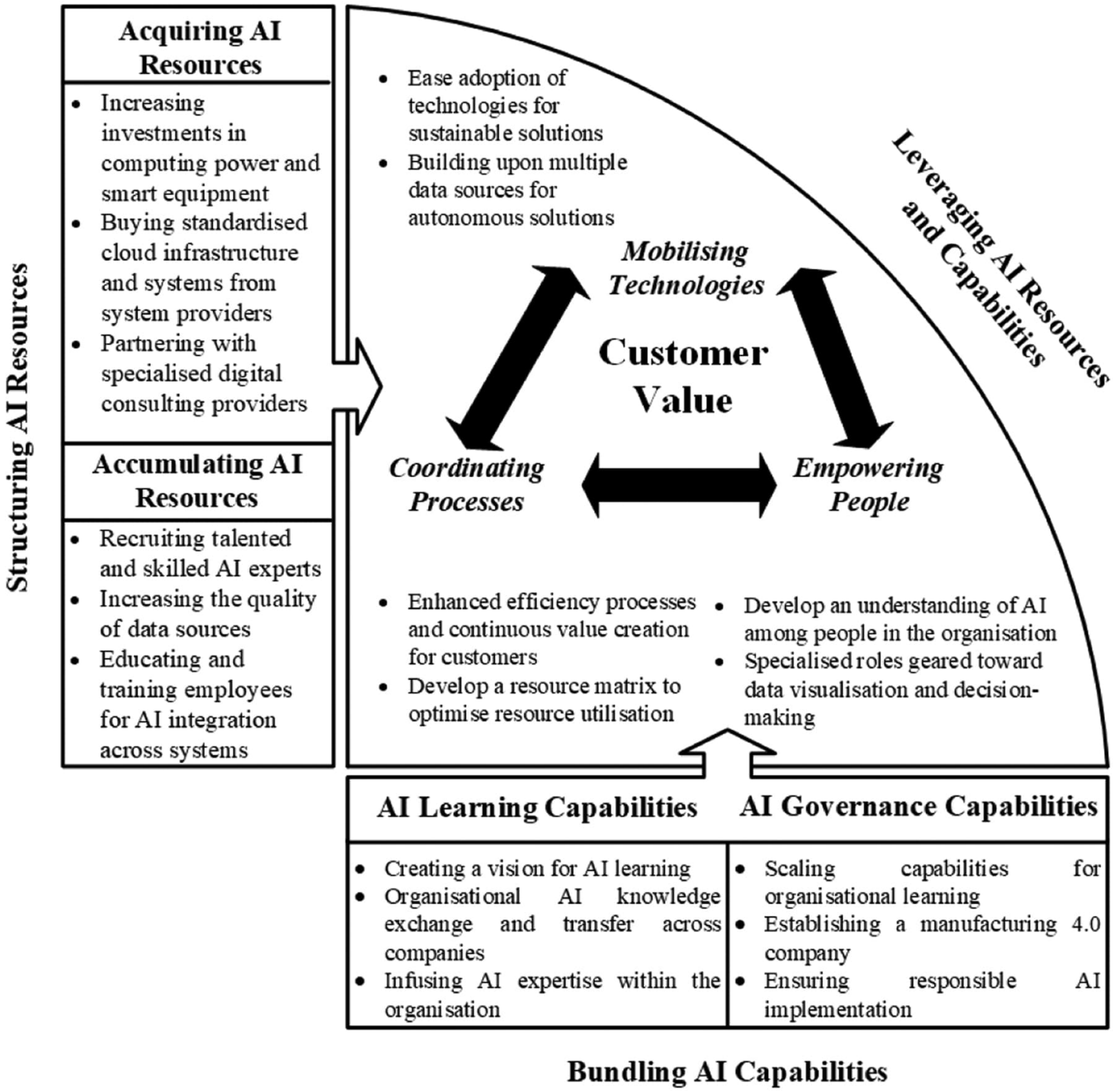

Fig. 3. Modified Framework for Digital Transformation for AI Implementation.

framework reflects that both *structuring AI resources* and *bundling AI capabilities* are iterations of the process of *AI leveraging resources and capabilities*. The latter is the process in which AI resource orchestration occurs as the interaction between the mobilisation of technologies, process coordination, and people empowerment occur, and where value for the customer is generated. The modified framework indicates that the process of digital transformation is constant and permanent because the company is continuously providing new inputs of resources and capabilities to increase its competitive advantage. Therefore, our framework shows that SMEs are undergoing AI implementation and transformation, which is a dynamic and evolving process.

6. Discussion

6.1. Reflection on the theoretical gap and theory extension

In this paper, we shed light on the intricate path that SMEs in the manufacturing industry undergo when implementing AI. By delving into the research question: *How do manufacturing SMEs orchestrate resources for AI implementation?* The study highlighted that this process requires the development of a wide range of capabilities that are necessary within the organisation while adding novel interpretations that are necessary to implement AI. Despite mounting interest in the AI-driven digital transformation of companies, research on SMEs has received scant attention in the literature (Skare et al., 2023). By adopting a qualitative approach guided by a multiple-case study methodology, our study researches the process of AI implementation in five Swedish SMEs in the packaging, plastic, and metal sectors. Building upon RO theory (Sirmon et al., 2007), as suggested by previous authors (Mikalef & Gupta, 2021; Perifanis & Kitsios, 2023), we propose analysing the process of leveraging resources and capabilities, mobilising technologies and empowering skilled personnel to implement AI capabilities by looking interplay of these capabilities. This allowed us to extend previous research on AI implementation in the manufacturing sector (Jamwal et al., 2022).

This capability approach to AI implementation allows us to propose a conceptual framework (Fig. 3) that links organisational capabilities to digital transformation (Sirmon et al., 2007). Research has mostly concentrated on the potential that AI implementation has for performance enhancement (Ishfaq et al., 2023) and improved organisational outcomes (e.g., customer agility or firm performance) (Fosso Wamba, 2022). We position our study as suggesting that AI implementation is crucial to the successful development of companies in transforming towards a smart industry (Ahmad et al., 2022), which is of particular relevance to European SMEs' business activities and performance (Skare et al., 2023). As reported in the framework, our data show that AI implementation requires the interplay of three elements to promote customer value, notably, coordinating processes, mobilising technologies, and empowering people. Our framework offers a nuanced perspective on AI implementation, shedding light on digital transformation as a process in which organisations enhance their competitive advantages by adding customer value. As a result, we can conclude that:

Proposition 1. Implementing AI enhances SMEs' competitive advantages by adding customer value across the interplay of three elements, notably, coordinating processes, mobilising technologies, and empowering people.

A key message from our framework (Fig. 3) suggests that AI implementation by SMEs results from the entanglement of AI resources and capabilities – notably, structuring AI resources, bundling AI capabilities, and leveraging AI resources and capabilities – that are leveraged across the digital transformation of a company. By *structuring AI resources*, we found that SMEs in an emerging state of AI implementation focus on two process-based resources – namely, acquiring and accumulating AI resources – which unfold through investment and talent recruitment. Structuring AI resources as a precondition for SMEs to adequately implement AI capabilities, companies proceed with *bundling AI capabilities*, which is achieved by integrating AI learning capabilities with AI governance capabilities, promoting organizational knowledge, and facilitating quality data assurance. Our results align with previous research that has focused on the role of AI resources (digital resources) in achieving digital catch-up in intelligent manufacturing (Ma et al., 2023).

Although former studies have stressed forecasting, planning, and learning as key AI capabilities for successful AI implementation in SMEs (Zhang et al., 2021), we showcase that AI capabilities are a condition for developing superior capabilities that allow SMEs to leverage both AI resources and capabilities and, ultimately, create value for customers; in other words, *leveraging AI resources and capabilities*. We note that the key resources and capabilities essential for the implementation of AI are human, technological, and procedural; also called, coordinating processes. For SMEs to remain competitive in the marketplace and to maximise their growth potential, they must effectively utilise AI resources and capabilities to add value to their businesses. We named this process AI resource orchestration, in which companies unfold an iterative process of structuring, bundling, and leveraging AI resources and capabilities. Thus, SMEs can optimise resource utilisation by generating new knowledge and achieving improved results as they progress through the process. From this, we can determine that:

Proposition 2. SMEs in the manufacturing industry follow a process-based approach to carry out AI-driven digital transformation through AI resource orchestration, a process that integrates the development of specific organisational capabilities – notably, structuring AI resources, bundling AI capabilities and leveraging AI resources and capabilities.

Finally, our results draw our attention to the role of AI implementation in promoting outcomes beyond those traditionally discussed in the literature. We argue that AI implementation can benefit SMEs by making them not only more efficient across manufacturing processes but also more sustainable (Zeba et al., 2021). Indeed, AI is gaining relevance in organisations for the possibility of automating time-consuming tasks while bringing efficiency and at the same time promoting sustainable and circular economy outcomes (e.g., reduction in the use of materials). Studies have extended results on the role that AI plays in SMEs adopting sustainable practices and enhancing supply chain resilience (Dey et al., 2023). We add to this discussion as part of the process of leveraging AI resources and capabilities, framing how mobilising technologies allows the development of sustainable solutions in the manufacturing processes of packaging, plastic, and metallic materials. As a result, we can conclude that:

Proposition 3. SMEs that leverage AI resources and capabilities effectively in the manufacturing industry are prone to carry out sustainable and circular economy outcomes in their operations.

In addition, we encourage scholars to test our propositions and the claims that we have made in our description of the current state of research in future studies.

6.2. Theoretical implications

This study makes three significant contributions to the literature. Firstly, *we contribute to the nascent literature on AI implementation as a process of digital transformation* (Dwivedi et al., 2021; Hansen & Bøgh, 2021). A key contribution of this study is our examination of the processes that reveal a company's potential to maintain the pace of digital transformation. In analysing AI implementation as a process of digital transformation (Ahmad et al., 2022), we confirm with empirical evidence that companies implementing AI move along an evolving and dynamic path of AI adoption. In contrast with previous studies stressing that AI implementation typically belongs in the realm of experimental projects (Davenport & Ronanki, 2018), we show that adopting AI is a planned endeavour in pursuit of ongoing digital transformation (Weber et al., 2023), which is embedded in a company's vision and business portfolio. Therefore, our research concludes that AI-driven digital transformation is not a one-step journey. Although it is expected that organisations will develop different trajectories in implementing AI (Ma et al., 2023), our study provides a process-based perspective of AI digital transformation in which companies integrate their resources and capabilities dynamically in a mutually enriching manner. As part of this process, our findings pinpoint the need to explore the potential that inter-organisational partnerships have when implementing AI to complement and activate internal resources (Sjödin et al., 2021).

Secondly, *our study contributes to the literature on resource orchestration for AI implementation* (Sirmon et al., 2007). By providing a breakdown of the AI implementation process, we uncover the groundwork for managing resources and building capabilities (Zhang et al., 2021). The RO theory allowed us to provide a micro-foundational approach to AI implementation by exploring how organisations are expected to transform their internal resources and capabilities. We pinpoint the organisational dynamics that consolidate AI as an organisational strategy to create customer value and enhance competitive advantage. In line with Zhang et al. (2021), our approach shows that business performance can be enhanced through the interaction between AI resources and AI capabilities. Such leveraging of AI resources and capabilities results from the interplay between the mobilisation of technologies, the coordination of processes, and the empowerment of human capital. We propose a framework for AI implementation leading to digital transformation (Fig. 3), adopting elements from the original RO theory at the outset of our study. Through the process of leveraging AI resources and capabilities, SMEs can create added value for customers by mobilising technologies, empowering people, and coordinating manufacturing processes – a process that we call *AI resource orchestration*. These three activities describe the overarching process of AI implementation as firms move towards AI-driven digital transformation. Our results corroborate previous research stating that AI technologies, people, and processes can be managed to successfully integrate AI into businesses (Zhang et al., 2021).

Finally, *we contribute to the growing literature on AI implementation by SMEs* (Skare et al., 2023). To the best of our knowledge, few studies have examined AI implementation by SMEs (D. Zhang et al., 2022; C. Zhang et al., 2022), and the evidence from the manufacturing industry is indeed scant. This aspect is relevant to SMEs because they continue to struggle with digital transformation processes (Schuster et al., 2021) as they seek to develop and cultivate specific AI capabilities (Hansen and Bøgh, 2021). We provide empirical evidence on how Swedish SMEs in the manufacturing industry implement smart technologies and how these organisations carry out the necessary changes required using emerging technologies such as AI. We contribute to the previous literature on AI adoption by SMEs (Dey et al., 2023), proposing that these companies can pursue an AI-driven digital transformation by developing internal capabilities, routines, and competencies for AI implementation (Ma et al., 2023). We show that understanding AI resources and capabilities contributes to SME innovation, performance, and human talent growth (Zhang et al., 2021). We add to the literature by exploring the different factors that contribute to the successful adoption of AI technologies by focusing on the process of digital transformation for AI implementation in SMEs. In our proposed framework, we highlight the critical dimensions that manufacturing SMEs must consider in moving progressively towards more mature stages of AI digital transformation, which, in the case of SMEs, is revealed as a progressive and iterative path.

6.3. Practical implications

As SMEs have historically been slow to implement innovation in manufacturing, our results have important implications for SMEs and offer some guidelines that managers can follow when implementing AI. The use of AI to solve organisational challenges has increased in SMEs, but many AI projects fail or experience setbacks (Davenport et al., 2018). In terms of their resources and size, a challenge and an opportunity exist for SMEs. Their size and flexibility can provide them with business advantages and opportunities to adopt innovative technologies. The conceptual framework presented in this study (see Fig. 3) offers practical guidance for managers and practitioners on how SMEs can orchestrate their resources to implement AI. We describe how AI resources are used and needed, and how, in interaction with AI capabilities, organisations can leverage a wide range of AI resources and capabilities to maintain the pace of AI-driven digital transformation. In pursuit of more efficient and smart manufacturing, CEOs and production managers can justify their AI investments by referring to our digital transformation framework for AI implementation.

We observe that SMEs are striving to enhance their competitiveness in the marketplace and to improve their productivity by discovering new ways and methods (Maroufkhani et al., 2020). From the AI implementation perspective, the results of this research are of interest to SMEs intending to embark on the digital transformation journey. To achieve AI-digital transformation objectives, SMEs may consider developing the relevant strategies that are outlined here. The goal is to increase market share and revenue and to improve the organisation's products and production processes. There is evidentiary support that technology is correlated with superior operational performance and growth.

Moreover, our findings apply to plants with a variety of initial conditions and products. While there are challenges associated with resources and constraints, those with ample resources can also benefit from AI, albeit in different ways. When considering AI implementation, manufacturing managers need to consider their conditions and attitudes towards it. In practice, the data showed initially that AI implementation developed a pool effect, where employees expressed an interest in and a need for AI technologies. Later, the transformation was extended to a variety of AI-based projects, such as order forecasting, purchasing optimisation, and sequence planning. AI was initially used to cut costs and improve efficiency but, as time progressed, the plan was to use it for failure detection, product recommendation, and self-driving trucks. As resources can be orchestrated in different ways by AI implementation, different outcomes may result. Therefore, AI implementation should be evaluated and measured quantitatively. Using AI for manufacturing should be evaluated both quantitatively and qualitatively in terms of return on investment for decision-driven orchestration. Moreover, its effectiveness and efficiency should be assessed. Again, this demonstrates the importance of understanding the driving force before committing to any implementation plan or set of AI tools and techniques.

Finally, the practical implications for SMEs in the manufacturing industry must be considered according to the three context elements that result from the leveraging of resources and capabilities for AI implementation: technology, processes, and people (Madanaguli et al., 2024). A comprehensive strategy and synchronized orchestration of capabilities are essential to successful AI adoption. Firstly, on the mobilisation of technologies, we highlighted the massive opportunities for the manufacturing industry, making production more sustainable and efficient, especially in the management of more environmental materials. Existing challenges to mobilise technologies for AI implementation lie in the need to take the time to experiment and test using new materials for product innovation. Mobilising technologies can help managers to increase a company's data intelligence and improve its data management capabilities. Secondly, important practical implications for AI implementation come with coordinating processes in manufacturing. By putting into practice the set of AI resources and capabilities that we present in this study, SMEs can pursue resource optimisation through the purchase of materials and running machines at optimal levels. Therefore, organisations have the potential to enhance efficiency in their manufacturing processes while boosting the organisational decision-making capacity. Thirdly, empowering people is at the top of the SME digital transformation agenda because AI implementation inevitably requires collaboration between humans and technology. Specifically, SMEs will need to recruit and train human capital to be ready to perform increasing AI-related tasks and to introduce specialised roles with expertise in data interpretation, problem-solving, and decision-making.

Nevertheless, because SMEs are organisations with limited financial muscle, the configuration of these three conditions – mobilising technologies, coordinating processes, and empowering people – will require different efforts depending on the capacity of the company and sector. Practitioners will need to adapt this information to their contexts and interpret it prior to internalising it in the organisation. As AI becomes more prevalent, organizations should consider AI threats related to all aspects of their business, including ethical issues, legislation, cybersecurity, and information security, as well as sustainability. An integrated approach to AI will enable organizations to deploy AI responsibly.

6.4. Limitations and future research directions

Even though this research provides relevant contributions to the literature, some limitations must be acknowledged. Firstly, since the present study relies on a multiple case study of five SMEs in the manufacturing industry that are part of an SHC, the results may not be generalisable. Thus, the findings should be considered specific and applicable to similar contexts. SMEs' AI-driven digital transformation may also diverge across industries. For instance, SMEs implementing AI technologies in a business-to-customer (B2C) context could be expected to interact differently throughout the process of AI implementation. Research studies on sectors other than the manufacturing industry are necessary to fully understand the process of AI resource orchestration in AI implementation.

Secondly, the analysed SMEs were all at an early stage of AI implementation. Therefore, studies that focus on SMEs with more mature stages of AI implementation may add fresh nuances to this study. It should also be noted that AI implementation may be supported by other smart technologies (e.g., robotics and automation, additive manufacturing, 3D printing, IoT, advanced materials, and blockchain). Further research could provide a more comprehensive understanding of AI implementation as a feature of digital transformation maturity in SMEs by analysing other technologies, which may also complement the process of AI implementation.

Thirdly, the findings of this study are based on qualitative methodologies, demonstrating the progressive nature of AI-driven digital transformation in SMEs. However, our conceptual framework can be used to gather new insights or to act as a starting point for reflection and evaluation. To validate and strengthen our findings based on the categories and sub-themes analysed (see Fig. 3), future studies could explore AI implementation in SMEs using quantitative and mixed-methods approaches. Additionally, scholars could consider a broader range of AI resources and capabilities, which incorporate the least number of AI applications and outcomes that are consistent with SMEs maintaining a competitive base.

Finally, our analysed sample of companies presented a continuous and dynamic process of AI implementation, which meant that our results showed progression in the digital transformation process. However, other dynamics might arise through this process. For instance, studies could identify *organisational inertia* during AI implementation or a *reluctance* to continue building on an organisation's AI resources and capabilities. Further studies could explore SME cases in which AI implementation has resulted in *digital transformation failure* because of the perceived need to avoid paradoxes and tensions arising from the AI implementation processes. Such divergent studies may complement traditional successful cases, such as those discussed in our study, to offer a more thorough and inclusive understanding of the topic.

7. Conclusions

This study has been developed to understand *how manufacturing SMEs orchestrate resources for artificial intelligence implementation.* As highlighted in this paper, there has been a rapid implementation of AI in the manufacturing industry in recent years. However, the pace of AI implementation in SMEs differs from larger enterprises. We revealed that SMEs in the manufacturing industry implement AI in an interplay between AI resources and capabilities – what we call, *AI resource orchestration* – which leads to a company's digital transformation. Based on the RO theory, we identified three key dimensions that determine AI resource orchestration for SMEs' digital transformation: a) *structuring AI resources* through a process of acquisition and accumulation, b) *bundling AI capabilities* through a process of learning and governing, and c) *leveraging AI resources and capabilities.* These produce three interactions: mobilising technologies, coordinating manufacturing processes, and empowering people. Notably, our research shows that AI implementation in manufacturing SMEs is a dynamic and self-enriching process. AI digital transformation requires continual adaptation, adjustment, and organisational commitment to stay at the forefront of AI development and drive digital transformation. The implementation of AI requires an organisation's commitment to long-term strategic transformation and the effective use of its resources and capabilities. Nevertheless, it is faced with many challenges, including those related to data management, organisational technological practices, and financial resources, as well as employee learning and development. Indeed, AI resource orchestration goes beyond mere technological development to impact the pace and rhythm in which organisations allocate and manage resources.

CRediT authorship contribution statement

Sabrina Tabares: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Patrick Mikalef:** Writing – review & editing, Validation, Supervision, Conceptualization. **Einav Peretz-Andersson:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vinit Parida:** Writing – review & editing, Validation, Supervision, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Case and data description

Company	No. of Employees	Main Product	Secondary sources	Number of Interviews and Respondent Position	
				Study 1	Study 2
Alpha	200	Packaging solutions in plastics, aluminium, and metal	Presentations, Company Documents, Annual Report, Meeting Observation	Production Developer (2), Business System Manager (1), Production Development Manager (2), Domain Experts (2)	Monthly Reconciliation AI Meeting Participants: Data Scientist, CFO, Technical Manager, Head of Marketing and Sales Excellence, and Head of Sustainability
Beta	140	Jars and Buckets	Presentations, Company Documents, Meeting Observation, Site Visit	Production Manager (1), Domain Experts (1)	Innovation Manager (1), Key Account Manager (1)
Gamma	60	Capsules	Presentations, Company Documents, Meeting Observation, Site Visit	Production Manager (1), Domain Experts (1)	Production Manager (1) Technical and Maintenance (1) Manager
Delta	65	Bottles and Cans for Chemical Products, Medicines, and Food	Presentations, Company Reports, Meeting Observation, Site Visit	Production Manager (1)	CEO (1), Strategic Purchaser (1)
Epsilon	160	Plastic and Metal Tubes	Presentations, Company Documents, Meeting Observation, Site Visit	Production Manager (1)	Maintenance and Automation Manager (1)
SHC	28	Headquarters	Presentations, Documentation, Annual Report, Meeting Observation	CEO (1), Head of IT (1), Data Scientist (2), Business Developer (1)	CEO (1)

Appendix B. Research phases

	Study 1	Study 2
Timeline	March 2022-September 2023	October-November 2023
Purpose	Understanding the implementation of AI within manufacturing companies	Strengthening and validating our framework for AI implementation and data triangulation
Data Collection Methods	Exploratory semi-structured interviews	Validation semi-structured interviews and Reconciliation meetings
Informant	Managers and Domain Experts: 18 Interviews	Managers and Operative Experts: 6 Interviews 11 Reconciliation Meetings
Secondary Data	Company documents, company presentations, annual reports, meeting observations, company visits, company websites	Company documents, company presentations, annual reports, meeting observations, company visits, company websites

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Appendix C. Interview questions

Appendix 3**a.** Interview Questions Study 1.

1. ***Structuring***

- Could you please describe your company’s portfolio of resources needed to implement AI?
- How do you describe your company’s purchasing process of resources for AI implementation?
- How do you develop resources internally?

2. ***Bundling***

- How does your company use or combine the different resources to create capabilities to implement AI?
- How do you describe your company’s capabilities to implement AI?
- How does your company make improvements on its current capabilities?
- How are new capabilities and skills created in your company to support AI implementation?
- Has your company created a particular vision for AI learning within the organisation?

3. ***Leveraging***

- How does AI implementation lead to value creation for your customers?
- How do you describe the capabilities your company needs to exploit market opportunities through the implementation of AI?
- How does your company identify and integrate efficiently its capabilities to implement AI?
- How do your capabilities to implement AI support your business strategy?

Appendix 3**b.** Interview Questions Study 2.

1. ***Structuring AI resources***

Acquiring AI resources.

- Could you please elaborate on the investment process of your company for the acquisition of computing power or smart equipment to utilise AI for manufacturing?
- What is the process of purchasing standardised cloud systems from system providers? How do you describe these systems?
- How does your company partner with specialised digital consulting suppliers for AI implementation?

Accumulating AI Resources

- Could you please describe the recruitment process for talented and skilled AI experts?
- Does your company create internal data platforms to integrate multiple data sources? How do you describe this process?
- How does your company inform or train employees and staff to organise and categorise data that enrich the implementation of AI?

2. ***Bundling AI Capabilities***

Learning AI Capabilities.

- How do you describe your company's vision for AI processes?
- How do you describe your company's organisational AI knowledge exchange and transfer?
- How do you infuse AI expertise within your organisation?

AI Governance Capabilities

- How does your company ensure reliable and quality data assurance AI practices?
- What kind of structures and processes does your company implement for supporting AI manufacturing?
- How does your company ensure responsible AI implementation? How do you describe this procedure?

3. ***Leveraging AI Resources and Capabilities***

Mobilising Technology.

- Can you describe the multiple adoption of technologies for sustainable solutions with AI implementation?
- How does your company build upon multiple data sources to implement AI processes?

Coordinating Processes

- Does AI implementation lead to enhanced efficiency processes for production? Please provide some examples.
- Does AI implementation lead to optimising the utilisation of resources? Please provide some examples.
- Does AI implementation lead to any other outcome associated with its implementation? Please provide some examples.

Empowering People

- How does your company choose roles and responsibilities for identifying problems and failures through AI implementation?
- How do you describe the roles and skills of human talent in charge of data visualisation and decision making?

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