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Capabilities of the Intelligent Manufacturing Enterprise

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Abstract

Manufacturing enterprises encounter pressure to digitalize and increase their intelligence as their environments demand improved productivity and agility. Based on existing research on intelligent enterprises, manufacturing enterprises, and data technologies, the authors developed an explanatory model for the derivation of a definition of the intelligent manufacturing enterprise. This paper expands the formerly developed model by presenting the characteristics of the intelligent manufacturing enterprise and the capabilities needed to become such an enterprise.

Keywords

Intelligent Manufacturing Enterprise; Intelligent Enterprise; Manufacturing Enterprise; Data Technologies; Industry 4.0; Content Analysis; Capabilities; Characteristics

1. Introduction

Today, manufacturing enterprises can no longer have a singular focus on increasing productivity but rather must address changing customer needs and incorporate fast-moving technologies [1–3]. Looking at the manufacturing industry from a historical perspective, various methodologies and paradigms have influenced its development, including lean and agile manufacturing, as well as the Industry 4.0 paradigm [3–14]. Each of these areas supports or affects a particular aspect of the manufacturing enterprise. Still, no universal definition can be found that encapsulates the different perspectives and goals that these enterprises should be striving for [15]. Building on the authors' previous paper on defining the intelligent manufacturing enterprise (IME), this work seeks to elaborate on that definition [15]. It directly addresses the model users, manufacturing enterprises, and outlines steps for companies to work towards becoming IMEs by presenting required capabilities. For this, the characteristics of an IME are derived first from the previously proposed IME definition. Next, the derivation of capabilities from these characteristics is combined with a classification and a mapping of dependencies between capabilities. In summary, this paper addresses the following research question: "*What are the capabilities necessary to become an intelligent manufacturing enterprise?"*

2. Research Design

The authors' previous paper formally addressed the research question *"What is an intelligent manufacturing enterprise?"* [15] As this research question falls under the applied sciences, ULRICH's research process was utilized [16]. This work continues along the same research path to answer a subsidiary research question following the establishment of the IME definition *("What are the capabilities necessary to become an*

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intelligent manufacturing enterprise?”). Figure 1 provides an overview of the research process of applied sciences according to ULRICH [17]. The focus of this paper is the derivation of assessment criteria, design rules, and theoretical models.

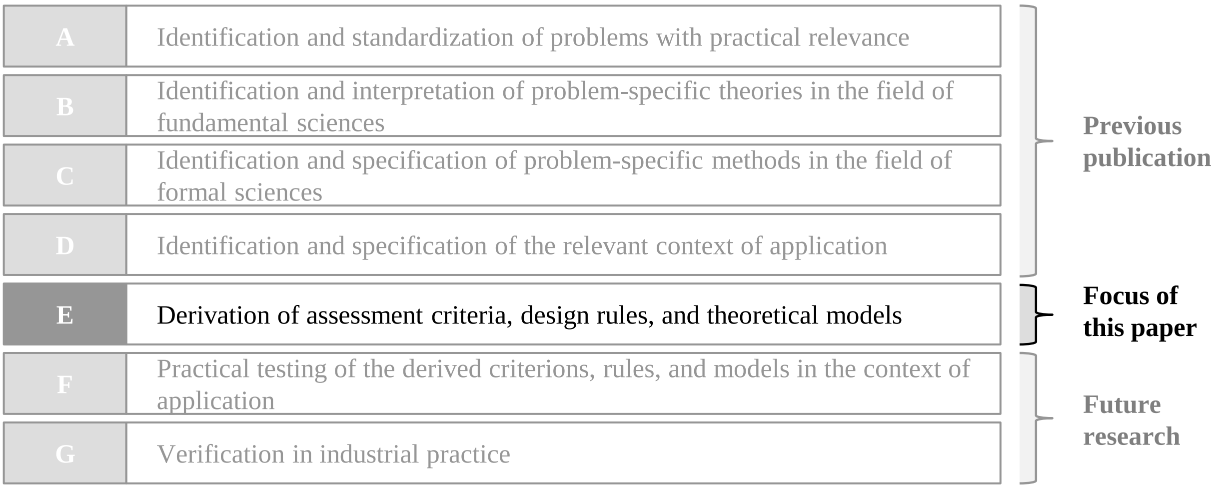

Figure 1: Research Process of Applied Sciences According to ULRICH [16]

Following the assumptions of WEBB ET AL.’s work on defining IT governance, the analysis in this work assumes that the IME is a concept supported by multiple sub-topics [18]. For this reason, the paper builds on the content analysis of existing literature and definitions to elaborate on the unified definition of the term. An application of content analysis involves a six-step process, according to KRIPPENDORFF and KUCKARTZ; including preparation of the data, formation of the coding system and sub-codes, analysis, and validation [19–21]. The coding system is the core feature of content analysis. In general, codes categorize a group of words, phrases, or paragraphs that convey a similar meaning [22]. Literature data is manually or automatically coded by marking groups of words or phrases with unique codes. In each of the research model’s sub-models, the relevant coded segments are converted into the desired outputs (characteristics, challenges, potentials, etc.) via SALDAÑA’s Codes-To-Theory model, which describes how insights locked in codes are revealed by moving up to assertions and theory via themes, concepts, and categories [23].

Figure 2 provides an overview of the research model structure, formulated in the previous paper. In each sub-model, the relevant coded segments are converted into the desired outputs (characteristics, challenges, potentials, etc.). Summaries of the coded segments are used in each model to derive the desired sub-model outputs. These sub-model outputs are taken as inputs by the definition model to establish an IME definition (the focus of the previous publication) along with IME characteristics and the capabilities needed to become such an enterprise (the focus of this paper). Within the definition model of the previous paper, the topics of intelligent manufacturing and operation excellence were identified within the manufacturing enterprise descriptive model as relevant paradigms. Because these topics help to confirm the correctness of the chosen terminology, they are relevant to be considered additionally in this paper [24–27].

Following the chosen research methodology of ULRICH, the theoretical background is first presented (cf. Section 3). This includes a summary of the previous derivation of the IME definition and an explanation of the terms "characteristic" and "capability.” Second, the development of the characteristics of an IME is examined (cf. Section 4.1), followed by the related derivation of the required capabilities to become an IME (cf. Section 4.2). Third, these capabilities are refined and categorized, which includes their dependencies and relations to data technologies (cf. Section 4.2). Finally, the results of this work are discussed critically (cf. Section 5).

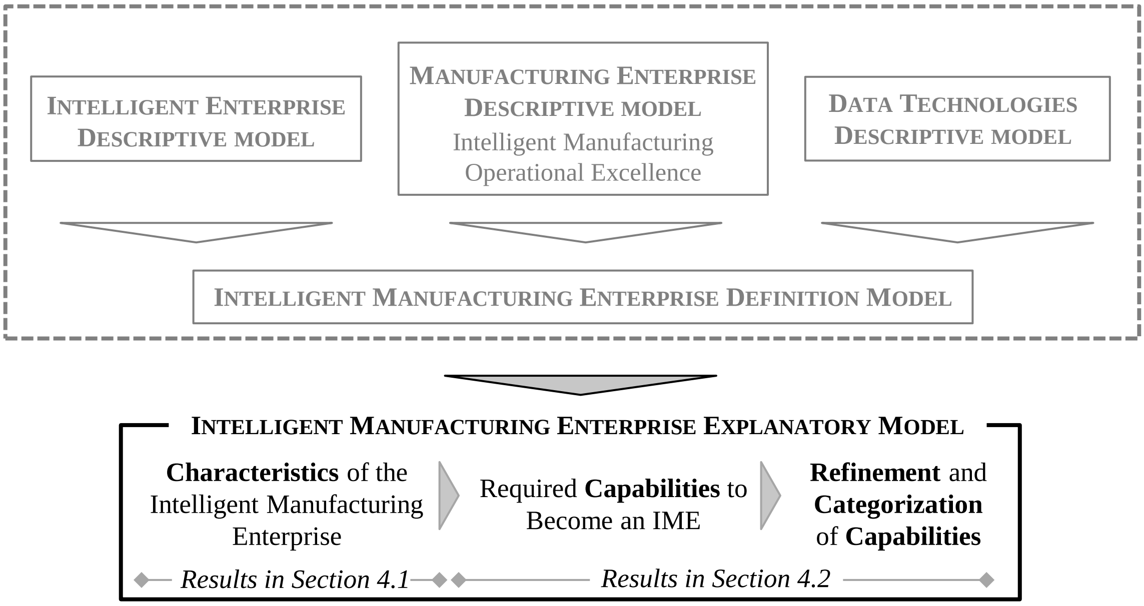

Figure 2: Research Model Structure [15]

3. Theoretical Background

The authors' previous work utilizes ULRICH's research method for applied sciences to derive and detail the definition of an IME [16]. The following section summarizes the outputs of the previous work published in the first phase of this research. In addition, the definitions of 'characteristic' and 'capability' are introduced.

3.1 Intelligent Manufacturing Enterprise

The IME definition is derived within the authors' previous paper using content analyses within three topics: intelligent enterprise theory, manufacturing enterprise challenges, and data technologies' potentials. These analyses are combined, and the following definition of an IME is presented:

> *"An intelligent manufacturing enterprise is an enterprise that produces physical goods for sale and utilizes data technologies to coordinate information, intellect, and knowledge of its systems, competition, products, and employees to achieve operational excellence through continuous improvement. It directly addresses the long-term challenges of manufacturing enterprises through the utilization of impactor data technologies. Intelligent manufacturing enterprises have completed the six stages of the Industrie 4.0 Development Path and are ready to adapt to the fifth industrial revolution to come. In addition to achieving intelligence through data technology usage, traditional manufacturing strategies (TQM, LM, JIT, etc.) are brought to bear in organizational culture to achieve continuous competitive advantage."* [15]

3.2 Characteristic

Characterizing the IME and describing the pathway to reach this vision, is the goal of this research. In conjunction with a definition statement, characteristics fully define a term, distinguishing the term from all others [28,29]. In addition, a "characteristic" is defined as a typical or noticeable quality or feature of an enterprise that serves to identify them [30,31].

3.3 Capability

The term "capability" is key to understanding the explanatory model developed. Within strategic management research, capabilities are regarded from different perspectives. STALK ET AL. and LENOARD-BARTON point out, that capabilities are connected to customer needs, as well as to knowledge and skills of employees or systems [32,33]. In addition, DAY outlines classes of capabilities based on their emphasis, while EISENHARDT AND MARTIN discuss the existence of dynamic vs. stationary capabilities [34,35]. Therefore, it is consensus in the strategic management community that no single list of capabilities applies to every organization. Each enterprise has a unique competition environment, history of actions, and anticipated future requirements. Hence, capabilities are understood as markers for firms to indicate what skills and abilities should be implemented next in their digital journeys to become IMEs. A capability is defined here as the power, ability, or state of being capable or able to do something [36–39].

4. Results

Based on the IME definition derived in the authors' previous paper, the goal of this work is to derive the capabilities required to become an IME (cf. Section 2). To achieve this, the characteristics of an IME must first be derived as an intermediary result. Subsequently, for each of the identified characteristics, capabilities are derived. Those capabilities are finally refined and categorized in a multi-step process.

4.1 Characteristics of an IME

The first goal of this paper's analysis is to identify the characteristics of the IME. The literature review consolidated by the authors' previous model serves as a basis to derive these [15]. The inputs from the three main sub-models are supported by insights from corpora analyses of the main sub-models' literature with Voyant Tools [40]. The Summary Grid Tool of the qualitative and quantitative MAXQDA research software summarizes each topic's coded segments related to characteristics [41]. Relevant points are rephrased as characteristics and sub-characteristics in a parallel way to SALDAÑA's categories and sub-categories in his "Codes-To-Theory" model [23]. First, the initial list of characteristics is determined by taking the most frequently mentioned characteristics from the literature summaries. Then, points that are overly specific to either intelligent or manufacturing enterprises and not wholly applicable to the IME are removed. Unique to the Voyant Tools contributions, no content analysis is involved, rather a synthesis of repeated key terms or phrases from the study are used to form characteristics. Table 1 presents the 17 IME characteristics as results of the first part of the explanatory model.

Table 1: Intelligent Manufacturing Enterprise Characteristics

IME Characteristics
Accesses information easily [3,42–45]
Acts in an environmentally sustainable way [1,24,26,46]
Acts with agility: responds in real-time to changing demands and conditions [1,4,8,14,35,42,47–50]
Communicates clearly throughout the organization [1–3,7,8,34,43,51,52]
Develops and deploys intellectual rather than physical assets and resources [35,45,53–58]
Develops and integrates new technologies [3,35,59–63]
Exercises foresight and prediction [3,24,43,55,64,65]
Focuses on quality, productivity, sustainability [14,24,64]
Integrates all production processes [1,6,8,24,43,51,66]
Invests in special skills, knowledge, and intellect of employees [44,45,67]
Is willing to change, evolve, adapt [3,62,68]

Makes data-based decisions [3,14,43,47,48,69–71]
Possesses resilience: is able to withstand high-impact disruptive events [1–3,72]
Provides personalized manufacturing and services to customers [14,48,51,60,73–76]
Saves and maintains knowledge and expertise [1,3,35,45,77]
Utilizes impactor data technologies [3,4,78]
Utilizes localized optimization and connected assets [3,67]

4.2 Hypothesized Capabilities to Become an IME

The second goal of the explanatory model is to identify the capabilities needed to become an IME. For this, capability assumptions are first gathered by asking the following question for every previously derived characteristic derived: *"To be described by this characteristic, which capabilities does a firm need to implement?"*. This is done by drawing on the coding, summaries, and 95 literature sources assembled in the IME definition model [15]. Second, the capability assumptions are categorized and refined in five further steps to increase the quality and manageability of the final capability list. This process has been influenced by SALDAÑA's "Codes-To-Theory" model (cf. Section 2) [23]. The initial capability identification and refinement process is summarized in Figure 3 (displayed on the following page). The procedure and result of the steps are described in detail within Sections 4.2.1 to 4.2.6.

4.2.1 Derivation of Capabilities based on Characteristics (Step 1)

As displayed in the "Step 1" field of Figure 3, characteristics are the starting point for the derivation of capabilities. For each IME characteristic, the coded literature is searched for abilities that firms must possess to be described with this characteristic. This results in a list of capabilities (the boxes) for each of the IME characteristics (the columns). Across all characteristics, a total of 132 capabilities are identified. The following Steps 2 and 3 are done in a parallel manner.

4.2.2 Literature-Based Categorization (Step 2)

In this categorization and refinement step, categories are sought to organize the initially derived capabilities thematically. This makes them intuitive and recognizable to the target model user, the manufacturing enterprise. The procedure for creating these categories involves first finding sources in the existing manufacturing literature that could provide possible categories. Categories are collected from different literature sources. There are a considerable amount of researchers publishing on capabilities and categorization systems, including EISENHARDT, LEONARD-BARTON, PORTER, SCHUH ET AL., SHARMA AND KODALI, and ULRICH AND SMALLWOOD [33,35,79]. The works of PORTER, SCHUH ET AL. and SHARMA AND KODALI are chosen as inputs from the literature because they are the most extensively elaborated frameworks within the research field of manufacturing enterprises. Furthermore, they are perceived to have the best applicability to the formulation of categories. This results in ten categories from PORTER's Value Chain, six from SCHUH ET AL.'s *Industrie 4.0 Maturity Index*, and eleven from SHARMA AND KODALI's operational excellence framework [3,26,80]. Second, these three sources of categories are combined into a single list of categories by combining similar categories and eliminating categories that are repetitive. This results in seven categories for the 132 hypothesized capabilities: Technological, Organization, Knowledge Management, Customer Relations, Strategy/Management, Personnel, and Processes.

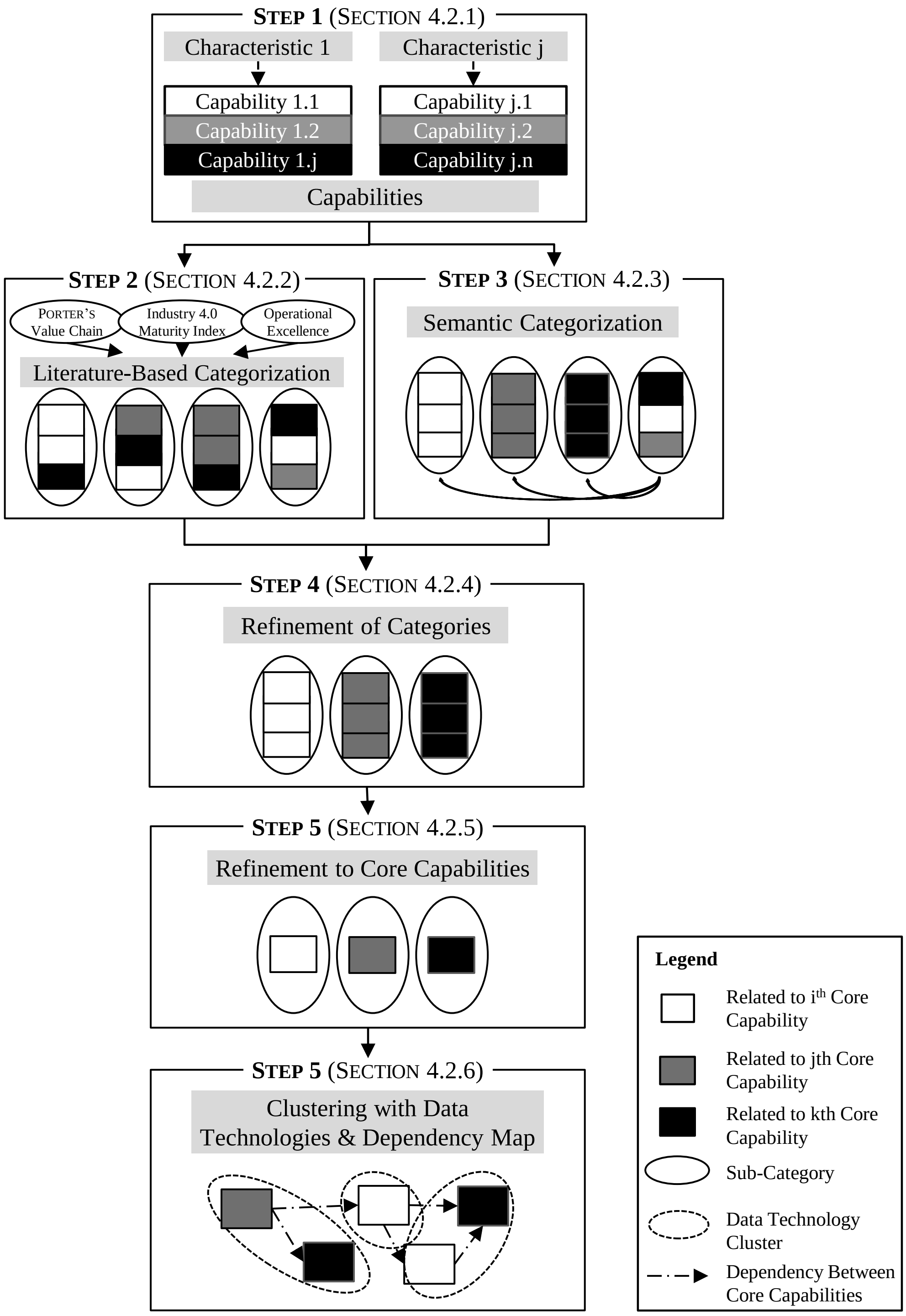

Figure 3: IME Capability Categorization and Refinement

4.2.3 Semantic Categorization (Step 3)

The categories developed in Section 4.2.2 are based on the input from three literature sources. Given the qualitative nature of this choice, these categories are validated by comparison with a second category list based on the semantic and thematic similarity of the capabilities. The goal of this comparison is to identify any missed categories and to determine which categories should be increased in granularity. The comparison method first groups the 132 capabilities by similarity alone. After all the capabilities are grouped, category names are applied based on the capabilities in each category and the relevant literature. The result of this grouping are 19 categories: Green Manufacturing, Data Storage & Processing, Insight Generation via AI, IT

System Structure & Governance, World Class Maintenance, Digital Connectivity, Digital Total Quality Management, Prediction & Foresight, Integrated Supply Chain Control, Customer Relationship Management, Adaptivity, Change Management, Trustworthiness of Insights, Continual Technology Improvement, Knowledge Management, Organization, Strategy, Human Resource Management, and Processes. An inspection of the 19 categories reveals five opportunities to refine the list by combining categories. Insight Generation via AI, Trustworthiness of Insights, and Adaptivity became part of the category Prediction and Foresight because they deal with the generation, evaluation, and purpose of predictions. In addition, Digital Connectivity and Continual Technology Improvement became a part of Processes as they most directly affect the processes a manufacturing enterprise operates. After refinement, a final list of 14 categories results from this step.

4.2.4 Refinement of Categories (Step 4)

In Step 4, the two lists of categories identified in the beforementioned steps are compared. The goal of this step is to ensure that the final list of categories includes both those categories taken directly from the literature and those derived via a semantic review of the capabilities themselves. Instead of just taking one of the previous derived category lists (from Steps 2 or 3), this final comparison and refinement ensures the most applicable and fitting categories from both lists are included. The categories considered here are the seven categories generated by the literature analysis in Step 2 and the 14 categories generated by semantic analysis in Step 3. Of the seven categories in the Step 2 list, three are the same as categories in the Step 3 list: Processes, Knowledge Management, and Strategy. An additional two are directly replaced with Step 3 categories, namely Personnel with Human Resource Management and Customer Relations with Customer Relationship Management. Lastly, both the Organization and Technological categories from the Step 2 list relate to three and five categories from Step 3 respectively. The 14 final categories and a graphical depiction of the refinement done in this step are shown in Figure 4.

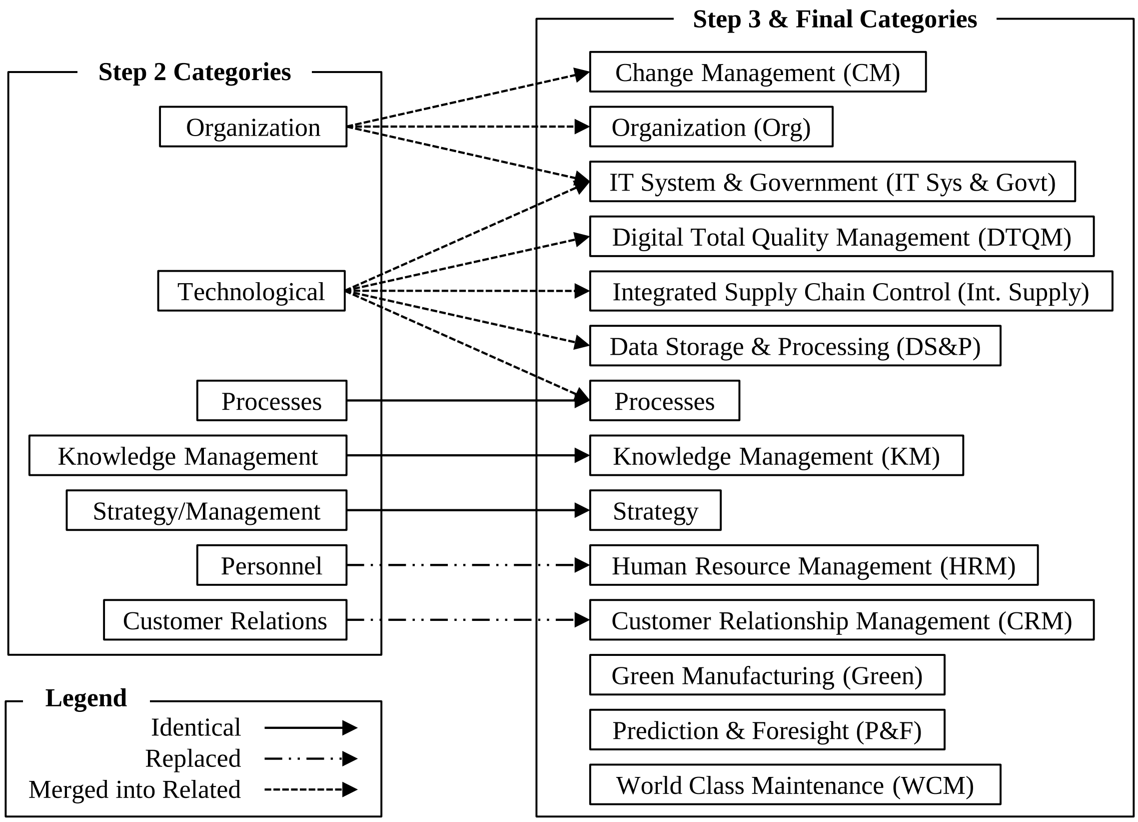

Figure 4: IME Capability Category Refinement

After this refinement, the 14 categories from Step 3 remain into which the 132 capabilities are categorized. Even though the final list of categories is identical to the list generated in Step 3, this refinement step confirms that the categories derived from the literature are also included in the final list, meaning the list is both theoretically and qualitatively derived. These categories can be used as target areas for firms to focus on specific aspects of their enterprise when looking for capabilities to implement along their intelligence journeys.

4.2.1 Refinement to Core Capabilities (Step 5)

Reducing the number of capabilities is the goal of Step 5. For this, the capabilities are reformulated to not directly mention any specific data technology first. This increases the opportunities for capabilities to be combined to form higher-level core capabilities.

Second, these non-technology-specific capabilities are reformulated as challenges in order to directly match the capabilities with the manufacturing challenges identified in the first part of the research model. By highlighting the challenges being addressed, additional connections are drawn from the previous manufacturing enterprise sub-model. Also, further opportunities are created to combine capabilities into core capabilities. For instance, the capability “create multi-skilled employees,” is reformulated as “create multi-skilled employees to increase organizational flexibility.” This reformulation addresses the challenge of manufacturing enterprises to maintain flexible organizational structures and processes [81–83].

Third, these challenges are combined to form broader core capabilities. A reduction in granularity is needed to increase the manageability of the model, according to PATZAK’s formal model requirements [84]. Forming core capabilities is similar to deriving characteristics and potentials from content analyses summaries in the sub-models. Any potential repetitions or overly similar core formulations are combined, and the duplicates are removed, resulting in 36 categorized core capabilities listed in Table 3 in the appendix.

4.2.2 Clustering of Capabilities with Data Technologies & Dependency Map (Step 6)

The final step in deriving the hypothesized IME capabilities involves depicting their relationships with data technologies and illustrating their hierarchical nature. This is done to increase the usability and applicability of the model for manufacturing enterprises by organizing them in a way that allows for clear implementation starting-points.

Each capability is marked as either being directly, indirectly, or not related to data technologies. Capabilities are considered directly related to data technologies if applying a data technology would result in the implementation of the capability. Partial capability implementations are then labeled as indirectly related, while those not implementable with data technologies are considered unrelated. Of the core capabilities, seven are classified as unrelated, 14 as partially related, and 15 as directly related to data technologies. Evaluating the relationships between capabilities and data technologies focuses primarily on impactor data technologies because they create value for companies, rather than just enable other technologies [15,78]. Table 2 shows the capabilities directly related to impactor data technologies. The connection to data technologies is determined using 32 data technology literature sources and the 16 associated content analysis codes [1,3,14,43,46,48,63–65,75,78,85–105]. Because a smaller number of capabilities (15) are found to be directly related to impactor data technologies, this smaller list is utilized later during the model validation, so as to keep the number of capabilities to be validated feasible for the survey format.

Table 2: Data Technology Related Core Capabilities of IMEs

Core Capability	Related Data Technologies
Ability to automatically collect and store data	Cloud, IoT, CPS, Blockchain, Big Data
Ability to automatically identify root causes of failures	AI, IoT, Blockchain, Cloud, CPS, Big Data
Ability to automatically pre-process data	IoT, CPS, Blockchain, Big Data
Ability to centrally distribute stored knowledge	IoT, Cloud
Ability to centrally store knowledge from processes, data, and employees	Big Data, IoT, CPS
Ability to collect and analyze relevant customer data	Big Data, IoT, AI
Ability to conduct analyses in real-time	Big Data, AI, CPS, IoT, Cloud
Ability to create insights by transforming data into knowledge	AI, Big Data
Ability to digitalize quality inspections and processes	IoT, VR, CPS, Big Data, AI
Ability to digitally connect all factory assets	IoT, Big Data, CPS
Ability to evaluate data-derived suggestions	AI, Big Data
Ability to hire and/or train employees to be specialists in data technologies	All impactor technologies
Ability to track demand in real-time	Big Data, IoT, AI
Ability to use enabler technologies	All enabler technologies
Ability to utilize predictive maintenance	Big Data, IoT, AI

As an example of how data technologies and capabilities are connected, the capability, "the ability to conduct analyses in real-time," is identified by WANG as enabled through a combination of IoT, cloud computing, and Big Data analytics implementation [96]. In addition, ESMAEILIAN ET AL. discuss the ability of CPS to make autonomous decisions through real-time data to information analyses [1]. Similarly, the CAPGEMINI RESEARCH INSTITUTE highlights the use of AI for real-time quality inspection analyses [64]. In contrast to this, "the ability to foster open communication at all levels" is classified as not related to data technologies. Although there is the potential that data technologies could be used to increase communication, without culture and management changes, this capability cannot be realized. SCHUH ET AL. identify the associated need for change management and a desire from employees to improve. Without the commitment of all stakeholders, no amount of technology will improve communication [3]. The 15 core capabilities and which data technologies are related to them will be validated in future research.

Lastly, the final phase of Step 6 seeks to increase the usability of the results generated thus far. EPPINGER AND BROWNING's Design Structure Matrix (DSM) is used to map the dependencies between capabilities [106]. By creating transparency over dependencies, the nodes, connections, and capabilities without any relationships can be identified. If companies do not know where to start, the outputs of this model are not accessible. Thus, organizing the core capabilities in a dependency map derived from the DSM highlights which capabilities should be starting points for those firms at the earliest stages of their digitalization journeys. Figure 5 (in the appendix) depicts the results of the DSM as a dependency map of the core capabilities and additionally depicts the relation of each capability to data technologies, as discussed above.

As an example, the capability "determine employees' strengths and weaknesses" is considered. This core capability is one of four nodes, meaning that it supports other capabilities but does not have any capabilities that support itself. Knowing employees' strengths and weaknesses allows to correct motivation of employees and facilitates targeted employee education. SCHOEMAKER AND TETLOCK emphasize the need to determine what experts and employees do and do not know. By identifying the strengths and weaknesses of first employees and then technologies, humans and technologies can be partnered in a way that covers each other's weaknesses [107]. Additionally, WIIG suggests using SWOT (Strengths, Weaknesses, Opportunities, and Threats) analyses of enterprise processes and knowledge assets during the development of knowledge management systems. As employees are a primary source of knowledge within an enterprise, employee SWOT analyses are also critical [45]. As a second example, some capabilities do not have any dependencies, making them additional possible starting points for companies on their IME journey. For example, beginning optimization practices at all company levels or thinking strategically about quality management can be implemented without data technologies but will support additional capabilities in the future.

5. Discussion

This paper details an explanatory model to answer the research question: *"What are the capabilities needed to become an IME?"*. The nature of scientific discovery and research practices bases itself on the building of models. Accordingly, this work is patterned after the research process of ULRICH, the model requirements of PATZAK, and the systems engineering theory of HABERFELLNER [17,84,108]. Within this structure, the identified content requirements of the model are fulfilled: The model is developed based on intelligent enterprise theory, manufacturing enterprise challenges, and data technology potentials. The structured research and content analysis methods used, assure an objective database of sources and a definition derivation process with limited subjectivity. Understanding that an IME remains a state which manufacturing enterprises are still working towards allows this model to be applied to manufacturing enterprises at any development stage. To fulfill its purpose, guiding manufacturing enterprises to become IMEs, the developed characteristics and capabilities are formulated in simple terms and organized using categories from existing manufacturing theory to be practically applicable. The capabilities are also mapped with their dependencies to indicate which should be implemented first. Companies can approach these capabilities by either starting with the roots of the dependency mapping or with the category of capabilities that they have internally identified as an area they wish to improve in.

One major limitation of this work is the high number of capabilities developed in the initial step of Section 4.2. It necessitates a refinement into a manageable number of broader capabilities. This compromise between a manageable model and its level of detail requires the firms having to perform their own customization. A CEO could potentially have the vision to see all of the aspects addressed by this model's capabilities. If not, a level of refinement would need to be done by leaders in each activity area of the value chain to determine which capabilities are accessible to them.

Because expert validation is not included in the theory-building portion of this work, it is not yet possible to decide if the capabilities' level of detail would apply to a broad spectrum of manufacturing firms. For this reason, further empirical research is suggested to determine if a lower level of detail is needed.

Finally, the IME capabilities are organized into a dependency map to convey how the capabilities relate to each other, and which ones would be best implemented first. A combination of ranking the capabilities by importance and utilizing the dependency net could result in a more precise roadmap for the exact order in which the capabilities should be implemented. Additional research is needed to determine if this ranking would be universal across the manufacturing industry or specific to individual enterprises.

6. Concluding Remarks

Presenting a hierarchical list of capabilities to become an IME is the second of three phases within the authors' research on IMEs and their development. Future articles will present a validation methodology of the results present in this and previous works. This validation is critical, as content analysis studies should be conducted in connection with a validation study that verifies the derived content and categorizations

[20,109]. Therefore, the capabilities presented here are the first step for firms to identify how to become an intelligent manufacturing enterprise. It also leaves room for firms to identify unique capabilities for their firms with increased granularity. Due to the abstract form of capabilties, companies will need to concretize them in projects for practical implementation. In this context, the impact of the capability buidling is to be assessed and ultimately supports the selection of the suitable capability bundles. This could be done by evaluating their productivity potential [110].

Acknowledgements

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Appendix

Table 3: IME Core Capabilities

Categorization	Capability
CM, Org	Ability to lead teams in an adaptive and effective way
CM, Processes, Int. Supply	Flexibility and adaptability
CRM	Ability to collect and analyze relevant customer data
CRM	Ability to customize product offerings
CRM	Ability to manage customer relationships
DS&P	Ability to automatically collect and store data
DS&P, P&F	Ability to automatically pre-process data
DTQM	Ability to automatically identify root causes of failures
DTQM	Ability to digitalize quality inspections and processes
DTQM	Ability to think strategically about quality management
Green, P&F, Strategy	Ability to reduce environmental impact (waste, energy use, water consumption, etc.)
HRM	Ability to supply employees with opportunities to learn and improve
HRM	Ability to determine employee strengths and weaknesses
HRM	Ability to empower employees to independently innovate
HRM	Ability to hire and/or train employees to be specialists in data technologies
HRM	Ability to identify multiple/flexible employee roles
HRM, CM	Ability to manage and adapt to change
Int. Supply	Ability to track demand in real-time
KM	Ability to centrally store knowledge from processes, data and employees
KM, HRM, Processes	Ability to centrally distribute stored knowledge
Org	Ability to motivate employees effectively
Org	Ability to operate in a flat hierarchy

Org, KM	Ability to assess assets accurately
Org, KM, HRM	Ability to foster open communication at all levels
Categorization	**Capability**
P&F	Ability to conduct analyses in real-time
P&F	Ability to create insights by transforming data into knowledge
P&F, IT Sys & Gov	Ability to build reliable and resilient IT systems
P&F, Processes	Ability to actively search for new opportunities to use data technologies
P&F, Processes, Org, HRM	Ability to evaluate data-derived suggestions
Processes	Ability to digitally connect all factory assets
Processes	Ability to maintain internal technical competitive advantage
Processes	Ability to use enabler technologies
Processes, P&F	Ability to proactively plan data technology expansion
Processes, P&F	Willingness to make changes based on data-derived suggestions
Strategy	Ability to optimize at all levels
WCM	Ability to utilize predictive maintenance

Legend: Change Management (CM), Customer Relationship Management (CRM), Data Storage & Processing (DS&P), Digital Total Quality Management (DTQM), Green Manufacturing (Green), Human Resource Management (HRM), Integrated Supply Chain Control (Int. Supply), Knowledge Management (KM), IT System & Government (IT Sys & Govt), Organization (Org), Prediction & Foresight (P&F), World Class Maintenance (WCM), Processes, Strategy

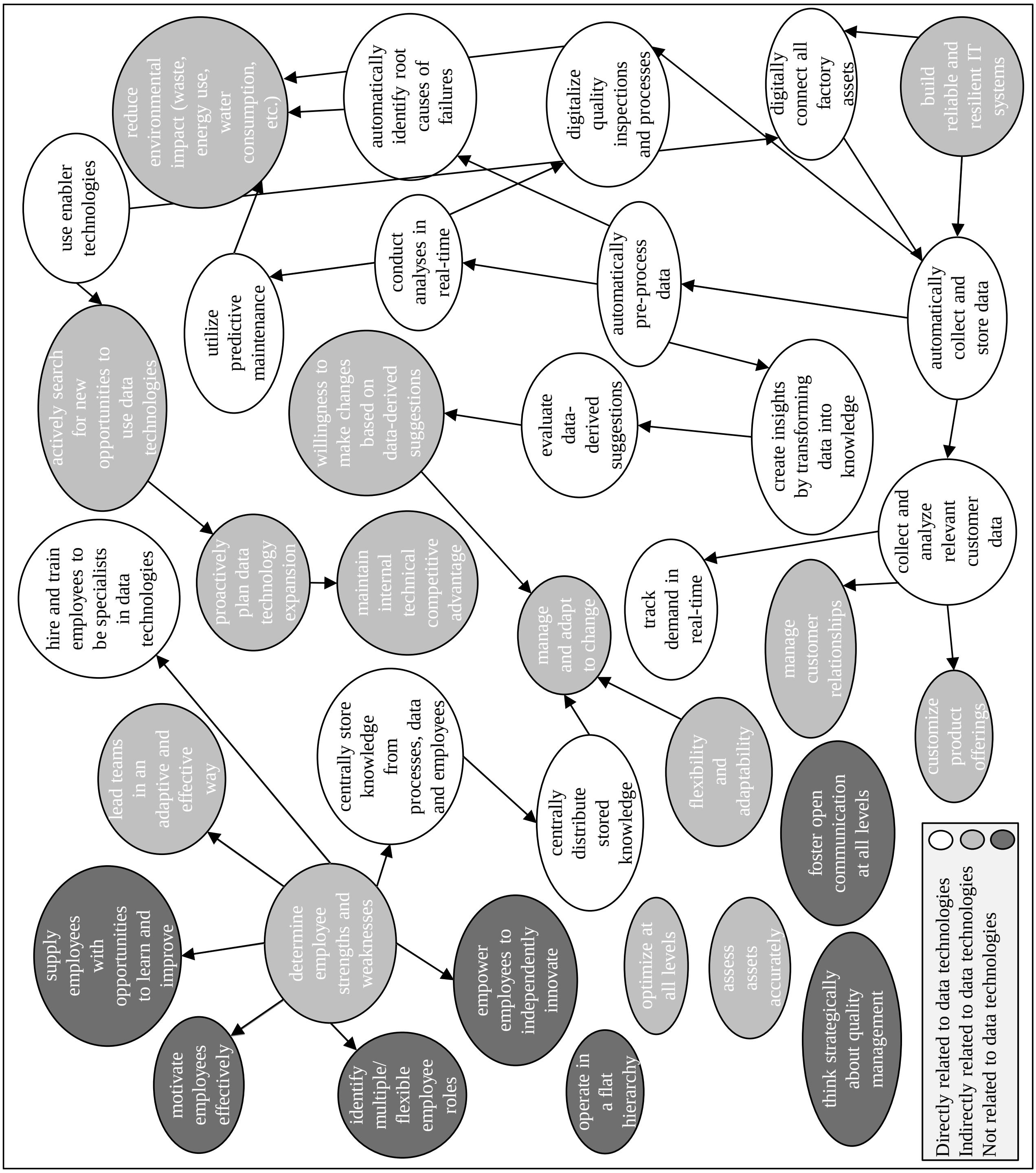

Figure 5: IME Capability Dependency Map and Data Technology Clusters

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