Journal of Production Systems and Logistics
Volume 2 | Article 6
Published: February 2022

Defining the Intelligent Manufacturing Enterprise

Günther Schuh[1,2], Thomas Scheuer[2], Riley Colleen Padovano[2]

[1]*Laboratory for Machine Tools and Production Engineering (WZL) of RWTH Aachen University / Aachen, Germany*
[2]*Fraunhofer Institute for Production Technology IPT / Aachen, Germany*

Abstract

Manufacturing enterprises encounter pressure to digitalize and increase their intelligence as their environments demand increased productivity and agility. Based on existing research on intelligent enterprises, manufacturing enterprises, and data technologies, developing the definition of an intelligent manufacturing enterprise is required. Current research lacks historically derived definitions of these dynamic fields, as well as a model of their overlap. An explanatory model is proposed to define the intelligent manufacturing enterprise, its characteristics, and the capabilities needed to become such an enterprise. This model is derived through qualitative and quantitative methods utilizing content analysis. This paper describes the content analysis methodology as well as the derived definition of the intelligent manufacturing enterprise.

Keywords

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

1. Introduction

Manufacturing enterprises face many challenges, such as responding to changing customer needs and utilizing rapidly evolving technologies, as they continually convert raw materials into finished products [1–3]. Today, companies are especially faced with increasing demands on their productivity and agility that they try to answer by exploiting data and its related benefits [1,4]. Already before intelligence and "smartness" had become popular buzzwords in the manufacturing industry, strategies for collecting, saving, utilizing, and transforming data gave intelligent enterprises access to insights and business knowledge that were previously untapped [5–7]. This term "intelligent enterprise" first gained popularity in the services industry through QUINN in 1992. His theory defines an intelligent enterprise strategy as transforming intellectual resources into service outputs that are most beneficial to customers [7]. At the same time, manufacturing models such as lean manufacturing, agile manufacturing, smart manufacturing, and the Industry 4.0 paradigm gained popularity. Manufacturers established cyber-physical systems to connect their production machinery and collect production data in a central location [1,8,9]. As the amount of stored data increased, data technologies were developed to enable "smart" or "intelligent" processes using these previously untapped data stores [10]. Manufacturing companies just beginning their intelligent manufacturing journeys can be overwhelmed and unable to find a starting point [3]. This phenomenon has already been identified within Industry 4.0, where firms struggle to see the business areas where the paradigm can first be applied [3]. Hence, guidance accessible to manufacturing enterprises needs to be published. The first step to present such guidance is a clear definition of an intelligent manufacturing enterprise (IME), which is the goal of this paper. Based on a word study of the IME term and preparatory research, the first two critical sub-topics for definition derivation are established: intelligent enterprise theory

This Paper has been reviewed by the Certified Reviewer Community of publish-Ing. – 2 reviews – double blind

DOI: https://doi.org/10.15488/11731
ISSN: 2702-2587

and manufacturing enterprise challenges. The increasing use of data technologies to analyze existing data stores and enable new functionality offers a myriad of potentials for manufacturing enterprises. For this reason, data technology potentials are taken as the third sub-topic for definition development.

In summary, this paper addresses the following research question: *"What is an intelligent manufacturing enterprise?"* Accordingly, this research question is formally addressed using the research process for applied sciences, according to ULRICH [11,12]. Following the assumptions of WEBB ET AL.'s work on defining information technology (IT) governance, the analysis in this work assumes that the IME is a concept supported by multiple sub-topics [13]. For this reason, this paper utilizes a content analysis of existing literature and definitions within ULRICH's research process to create a research model for definition development. Following this paper's motivation, an overview of the research design is presented. Second, a short theoretical background on the key terms being addressed in the research model is provided. Third, the research model is discussed in detail, and the IME definition is derived. Lastly, concluding remarks comment on the future of the related research.

2. Research Design

It is presented as a hypothesis that the scientific aim of deriving a definition for the IME is directly related to business and engineering management, information sciences, and enterprise strategy. Hence, this work falls under the classification of the applied sciences. The research is structured by the research process of the applied sciences, according to ULRICH, as shown in Figure 5 in the appendix [12]. Within this research process, the development of the definition is derived using content analysis. The choice was made to utilize the content analysis method because it is able to make inferences from large amounts of data systematically [14–16]. Because this model draws the existing large fields of intelligent enterprise theory, manufacturing enterprise challenges, and data technology potentials, a systematic way of organizing the research and drawing conclusions from qualitative research data is needed. The concrete outputs of content analysis are concepts and categories that detail the investigated research topic [17]. 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 [15,18,19].

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 [20]. The initial formation of a code system can be done either inductively or deductively. Codes are derived from pre-existing data, literature, theories, methods, or the study's research question. As the analysis progresses, codes or sub-codes can also be added based on new insights from the data [21–23]. After their creation, the data is manually or automatically coded by marking groups of words or phrases with unique codes. This paper makes use of an unconstrained code framework that mixes data- and concept-driven methods [17,18,24,25]. This choice involves setting a deductive coding framework but inductively adding codes and sub-codes as the data reveals their need during analysis [17]. The decision to use an unconstrained framework was made so that the existing theory could be used to create an initial coding framework. However, additional insights identified through analyzing the sub-models and their overlaps could be added inductively.

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. It describes how insights locked in codes are revealed by moving up to assertions and theory via themes, concepts, and categories [26]. Summaries of the coded segments are used in each model to derive the desired sub-model outputs. Refinement of the outcomes results in a shorter, usable list in each sub-model. In this work, the MAXQDA software facilitates qualitative and mixed methods research through various features that help researchers collect, transcribe, organize, analyze, visualize, and publish data and their associated findings [27].

3. Literature Review

As demonstrated in the introduction, different sub-topics contribute to developing a definition. To derive a definition of the IME, two sub-topics arise directly from the wording of the term IME: intelligent enterprises and manufacturing enterprises. Specifically of value are the definition and characteristics of intelligent enterprises, collectively referred to as intelligent enterprise theory, and the challenges faced by manufacturing enterprises. Furthermore, data technologies are the primary driver of technological potentials and thus are considered as the third sub-topic.

The concept of intelligence itself must first be derived within the context of **intelligent enterprises (**IEs). The definition is highly dependent on the field in which it is being used. Today, irrespective of a specific scientific field, intelligence can be defined as the ability to understand, learn, reason, and perceive order, trust, relationships, and facts from gathering information to reduce the level of uncertainty for a decision-maker [28–32]. Drawing on this definition and IE literature, an IE is defined by utilizing data technologies to coordinate information, intellect, and knowledge of its systems, competition, products, and employees to create customer value [5,6,33–43]. These skills allow firms to operate more efficiently by making data-driven, real-time decisions based on the knowledge they harness [34]. IE literature misses the mark of addressing the entirety of the IME term. QUINN's elaboration of an IE paradigm comes closest to outlining an enterprise model and the steps needed to become such an enterprise [7]. However, QUINN's intense focus on limiting internal activities to core service and intellectual activities results in manufacturing firms often outsourcing their manufacturing. QUINN does not address how manufacturing firms should approach the IE paradigm if they build up their manufacturing in-house rather than outsource it [7]. Closely related is WIIG's work on knowledge management and the IE. WIIG indirectly addresses a roadmap to becoming an IME by discussing the areas of emphasis of IEs and the challenges to acting intelligently. The work's primary focus is how knowledge management supports the IE. Such a discussion is extremely valuable but much more specific than the goal of this paper, which is to provide an overall model of the IME [34]. Lastly, the 2016 INNOVATION SYMPOSIUM published a set of their insights on IEs. While omitting a precise definition, the symposium addresses trends and technologies that enable the IE in various fields, including manufacturing [5].

Manufacturing enterprises (MEs) are described as multi-faceted chains of value-adding activities that are unique from one another and utilize methodologies such as lean or agile manufacturing [44]. However, a general definition developed from a literature review defines a ME as a firm created to produce physical goods for sale [1,45–49]. ME literature addresses the history of the ME, but primarily focuses on the challenges that these enterprises face. ESMAEILIAN ET AL. provide a robust outline and classification of MEs over time before directly addressing what they label "new manufacturing paradigms originated from data analytics" [1]. These paradigms include smart manufacturing, data visualization, cloud manufacturing, and cyber-physical systems, all considered in the development of the IME definition. ESMAEILIAN ET AL. readily identify the associated challenges of data security, data quality, database integration, and the lack of analysis models [1]. GATES ET AL. take an entirely future-oriented focus and utilize survey data from 360 senior executives to investigate how firms should address competing for growth [47]. Also exploring the future, the WORLD ECONOMIC FORUM draws on case studies and enterprise experiences to identify key drivers and estimate the impact of the fourth industrial revolution [9]. These papers provide a wealth of first-hand, empirically-based predictions and extensive reviews of the published literature but do not address theory building. They are descriptive and do not begin to approach whether a new model of the ME is needed to address the growth and drivers they are predicting.

In response to many of these challenges, MEs seek to increase or optimize the productivity of their processes and systems [1,4,50]. Paradigms and methodologies such as Industry 4.0, intelligent manufacturing (IM), and operational excellence (OE) can help MEs to do this. Industrie or Industry 4.0 was coined in Germany in 2011 to describe the phenomenon of information and communication technology becoming increasingly more integrated into the industrial manufacturing industry [3,51]. In SCHUH ET AL.' s *Industrie 4.0 Maturity Index*, they choose to define Industrie 4.0 as "real-time, high data volume, multilateral communication and interconnectedness between cyber-physical systems and people" [3]. Intelligent manufacturing is treated as a method and seeks to improve manufacturing systems overall through automatic control of processes and eliminating human intervention [52–54]. BARARI ET AL. clearly distinguish between intelligent and smart manufacturing based on the type of cleverness expressed by each model [55]. Smart manufacturing expresses a set level of inborn cleverness that supports its goal of real-time reactivity through Industry 4.0 digitalization and related technologies [55]. Contrary to this, intelligent manufacturing retains a progressive cleverness that drives its progress through its knowledge management systems [55]. Lastly, operational excellence or, in the specific case of MEs, manufacturing excellence, can be summarized as the state or process of achieving world-class performance [56]. It is both a roadmap of methods to implement and a process to record the performance results that arise from these implementations [56]. RUSEV AND SALONITIS present operational excellence built on culture, continuous process improvement, enterprise alignment, and results [57]. SHARMA AND KODALI derive a nine-columned framework for manufacturing excellence ranging from a globally focused manufacturing strategy to innovative product planning and total quality management [56].

Data technologies (DTs) are the main driver of technological potentials for MEs and can be defined broadly as any technology that takes data as an input to supply a particular output [10,47,58,59]. Artificial Intelligence (AI) and the Internet of Things (IoT) are two examples of the most prominent technologies mentioned in the literature [60]. Specific to this research, data technologies are defined as those technologies that utilize raw or processed data for the sake of uncovering information and insights from that data [61–65]. DT potentials within the context of Industry 4.0 have been addressed by a wide variety of authors [58,59,61,62,66]. Roadmaps for utilizing these technologies have been proposed to address the complexity and wide range of the data technologies available. While OZTEMEL ET AL. and KLINGENBERG ET AL. present strong literature reviews of Industry 4.0 and its related technologies, the data-driven optimization of MEs is disconnected from the concept of intelligence [58,61,62]. SCHUH ET AL.'s creation of the *Industry 4.0 Maturity Index* provides a structured six-step pathway to implement the Industry 4.0 paradigm. The formulated capabilities leave room for a deeper level of detail. This pathway informs this paper's IME model development and challenges it to create capabilities with a higher granularity [3].

Unique from the literature that addresses only one of the three components contributing to the IME definition, both GE ET AL. and CHAVARRÍA-BARRIENTOS ET AL. explicitly use the terms "intelligent manufacturing enterprise" and "sensing, smart, and sustainable manufacturing enterprise" (S^3-ME) in the titles of their research. Despite this use, GE ET AL. develop the concept of an enterprise application of the intelligent manufacturing model rather than defining an IME itself. They address the significant elements of enterprise intelligent manufacturing but do not outline steps to get there – focusing on a descriptive model rather than an explanatory model [52]. Likewise, CHAVARRÍA-BARRIENTOS ET AL. focus on the smart ME and do not outline the characteristics of such an S^3-ME. However, they propose a model to design this enterprise, rather than the capabilities or steps to become one [67]. Lastly, qualitative and quantitative research methods, including content analysis, surveys, and case studies, are not found in the literature related to IMEs. This lack increases this work's effort because the tools used to develop the theory have not been applied in these topic areas in the past.

The above evaluation of relevant terms, theories, and approaches aims to assess the literature gap present, which motivates the creation and completion of this paper. This gap contains the lack of a unified definition of an IME. In addition, there is no clear framework or pathway to becoming such an enterprise, which is a trend seen across multiple manufacturing models such as lean, smart, or agile manufacturing. As a result, those who approach the IME concept focus on describing certain aspects rather than supplying clear steps to reach this definition. Furthermore, the utilization of data technologies in connection with an IME remains limited to particular technologies and is primarily encompassed within Industry 4.0 literature.

4. Results

The next step of ULRICH's research process is the derivation of the research model within traditional, scientific requirements. The research model draws on the three identified key sub-topics to form a unified definition of an IME and addresses the identified literature gap. In addition, the model will be expanded from a descriptive to an explanatory model in future research. The section explains the research model derivation in detail, elaborating on the topic introductions above.

4.1 Model Requirements

To begin developing the model structure for deriving the definition of the IME, a set of formal and content requirements for the composite model are developed based on the work of PATZAK and HAAG [68,69]. PATZAK's formal requirements focus on empirical and formal correctness, manageability, and the quality of results [68]. The model's content requirements are derived systematically from five different aspects as outlined by HAAG [69]. The object under consideration is the IME and its capabilities, which will require data from multiple sub-topics. The scientific goal of the model, definition, supplies the model purpose, guidance, to the model user, MEs. Lastly, the time reference is described as applicable to each development stage on the path to becoming an IME.

4.2 Model Composition

This paper develops a descriptive model that lays out the definition of an IME and prefaces a broader explanatory model addressed in future papers. This model is made up of three sub-models that feed into a transitory definition model and then the final explanatory model. Figure 1 shows the sub-models and their connection to the explanatory model, each derived according to the abovementioned requirements.

The components of the IME explanatory model, the IME characteristics, capabilities, and their connections to data technologies are not addressed in this paper but rather in future research. The organization of the system elements follows PATZAK's requirements for empirical and formal correctness. The sub-model structure allows for clear organization and interfaces within the model and different levels of detail so that each sub-model in the first row can be fully developed without detracting from the final detail of the explanatory model [68]. The presented model structure remains manageable by building off themes already recognized by the manufacturing industry. Large amounts of literature and research have already been published in the three sub-models' areas, which offer a strong starting point and allow the most effort to focus on the development of the IME definition.

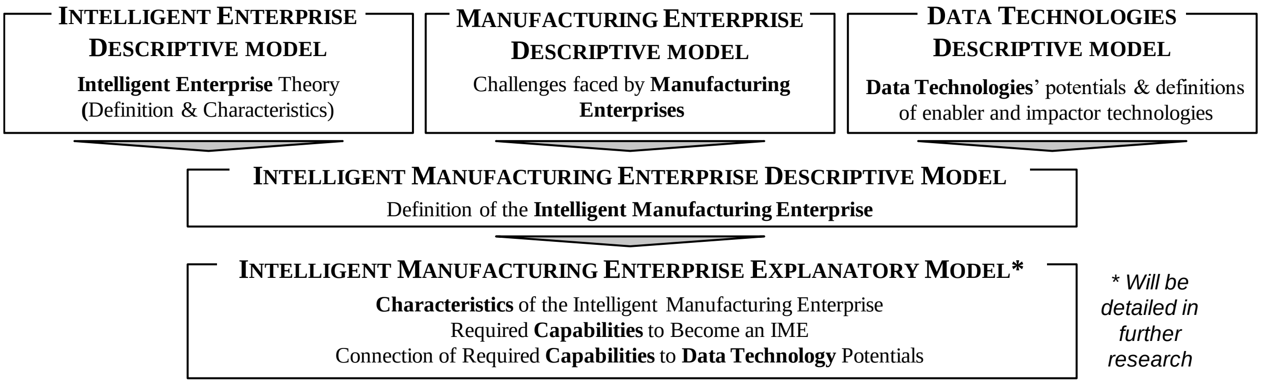

Figure 1: Research Model Structure

After determining that the primary goal of this work would be definition development, WEBB ET AL.'s work on defining "IT governance" serves as the initial inspiration for building a research model. Their research faces similar challenges to this work, as there has not been a clear concept of "IT governance." Still, a large body of literature chronicles the term's evolution and a variety of proposed definitions [13]. As a result, a unified definition of "IT governance" is developed systematically using a content analysis approach with a collection of twelve definitions found in the related literature. Like their method, IE theory, ME challenges, and data technologies' potentials are used as starting frameworks to support the IME definition [13]. Sections 4.3 through 4.5 delineate the three sub-models. All those sections follow a similar structure, starting with possible definitions of the term and ending up in an own partial definition towards the unified IME definition. Section 4.6 describes this IME definition within a descriptive model.

4.3 Intelligent Enterprise Descriptive Model

The term "intelligent enterprise" has been evolving over the past 40 years [5,7,34–37,41]. The goal of this first sub-model is to develop a modern IE theory consisting of a uniform definition and the related characteristics of an IE. Common aspects are to be derived from existing definitions which in turn lead to the creation of a partial definition. This definition is supported by the characteristics of the IE which are derived in a parallel manner. In conjunction with a definition statement, characteristics fully define a term, distinguishing the term from all others [70,71].

The procedure for this model's analysis takes IE literature as an input to a targeted content analysis method. 26 sources relating to "intelligence" and 13 relating to IE were analyzed using five content analysis codes, pattern recognition, and general literary analysis [5–7,28–32,34–36,39,41,50,72–91]. In addition, corpora analyses conducted with Voyant Tools, an open-source, web-based platform for analyzing and reading texts, provide additional insights into terms relevant to the IE definition [92,93]. Specific to the derivation of the IE characteristics, MAXQDA's Summary Grid Tool is used to summarize the segments that are coded in the literature [94]. 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 [26].

The definition analysis first results in three aspects derived from historical "intelligence" definitions and four elements from the 13 IE definitions that are repeated most often in the literature. Beginning with the intelligence definitions, the relevant context of intelligence in this model is manufacturing. This involves the intelligence of manufacturing systems, but also the aspect of human psychological intelligence within the systems' employees [72,73,86]. Intelligence's first two aspects are gathering internal or external information and using reasoning to transform that information into knowledge [28,29,32]. Intelligence is most useful it is applied to areas where it decreases the level of decision uncertainty [30,31]. A review of historical definitions of "intelligence" results in the following insights to support IE theory building:

- Intelligence involves collecting data and information from somewhere [28]
- Analysis is required to transform collected information into knowledge [29]
- Intelligence should decrease uncertainty in decision-making [32]

Four definition aspects are repeated across IE definitions in the literature. First is the use of data technologies to drive or monitor processes. For example, BYRUM situates his full definition on the enterprise being designed for AI utilization. SNYDER ET AL. feature AI algorithms as a vital part of an intelligent factory's shop floor [39]. Additionally, the importance of leveraging DT combinations between AI, IoT, cloud computing, and others is noted, rather than just implementing one technology on its own [95]. Second, integrated processes are used by IEs in combination with best practices and data technologies to increase efficiency and lower work intensity [41,52]. Thirdly, IEs have a unique customer focus that seeks to manage information to create products that are most useful for customers while serving their stakeholders well [7,34]. Lastly, IEs focus on their adaptability to customer requirements and external environmental changes so that required process changes take place immediately [40,88].

These results of seven definition aspects occurring with increased frequency in the literature underscore their particular relevance to the formation of a partial definition of the IME. To summarize the contributions from "intelligence" definitions, "intelligence" in the context of manufacturing is the ability of a manufacturing system or machine to operate autonomously under conditions of uncertainty, rapidly adapt to continuous demand, market, and technology changes, and to provide decision support through making data visible and usable by transforming it into knowledge [6,30,50,96–98]. From this definition and the additional four IE definition aspects the first partial definition of the IME definition, the IE follows, as shown in Figure 2 below.

The result of the IE characteristics derivation is first an initial list of 30 characteristics, which is ranked by the frequency they are mentioned in the literature using the MAXQDA summaries. Next, artifacts from QUINN's overly-specific IE theory are removed to create the final IE characteristics list, which consists of 13 different characteristics. Because these characteristics appear most frequently and are supported by multiple literature sources, they are particularly relevant to the support the partial definition derived above. Figure 2 depicts all outputs of this first sub-model.

INTELLIGENT ENTERPRISE DESCRIPTIVE MODEL

Intelligence Contributions…

- Collection of data and information
- Analysis to transform information into knowledge
- Decreases the uncertainty in decision-making

Intelligent Enterprise Contributions….

- Data technologies control processes
- Combinations of data technologies are leveraged
- Management of information to create most useful products for customers
- Focus on rapid adaptation to external changes

IME Partial Definition: Intelligent Enterprise

An intelligent enterprise *utilizes data technologies to coordinate information, intellect, and knowledge* of its systems, competition, products, and employees *to create customer value*. These skills allow them to operate more efficiently by making *data-driven, real-time decisions* based on the knowledge they harness.

Intelligent Enterprise Characteristics

- Concentrate around a core set of *knowledge* skills
- Develop core competencies that are "best-in-world" and *value-adding for customers* and use employee knowledge to drive these competencies
- Invest in special skills, *knowledge, and intellect* of employees
- Exercise *foresight and prediction*
- Access *information* easily
- Save and maintain *knowledge* and expertise
- Willing to change, evolve, adapt
- Make *data-based* decisions
- Communicate clearly throughout organization
- Develop capabilities continually
- Develop and integrate *new technologies*
- Develop and deploy intellectual rather than physical assets and resources
- Act in an environmentally sustainable way

Figure 2: Results of the IE Descriptive Model [1–3,5–7,33–36,39–41,47,48,52,56,58,61,65,67,88–91,95,99–107]

4.4 Manufacturing Enterprise Descriptive Model

This work's second sub-model addresses the need to understand MEs' challenges in practice. Common challenges are to be derived from literature which in turn lead to the creation of a second partial IME definition. This second content analysis determines the top challenges MEs face by analyzing 25 sources with 14 underlying codes. Literature review, coding, word frequency, and summary methods are all utilized in this analysis. Using the same code-to-summary pathway as the first sub-model, the relevant texts are coded with all manufacturing codes and sub-codes. MAXQDA's Summary Grid Tool is used on ME coded segments to create summaries. The raw summaries are consolidated into a list of challenges experienced by MEs, and similar items are combined to form hybrid challenges. This results in a ranked list of 29 challenges that ME face [1,3,7,9,45,46,48,49,108–114]. Additionally, in contrast to the previous sub-model, this sub-model takes the consensus in the literature to present a ME definition. Repeating from the literature review in Section 3, a general definition of a ME is a firm created to produce physical goods for sale. Such enterprises that operate in the global economy possess and coordinate resources worldwide [1,45–49].

The resulting challenges list reveals five challenges that occur over five times each in the 25 literature sources used:

- Responding to changing individual customer needs and customer demand [1,46,48,109,110,112,114]
- Operating in a global competition environment [9,45,46,48,49,114]
- Expectation of fastest time-to-market, highest quality, lowest cost, best service, cleanest environment, greatest flexibility, and highest knowledge [46,48,49,109,110,115]
- Increasing supply chain complexity [9,46,113,115]
- Operating in dynamic and uncertain environments [3,46,49,55,114]

As these occur at the highest frequency of the challenges identified, they are especially relevant to the ultimate IME explanatory model, especially to the connection between IME characteristics and ME challenges. All 28 challenges identified are relevant to the target user of this model and are presented in Table 1 in the appendix. It should be underlined that these challenges are not mutually exclusive. Hence, connections between them can cause the presence of one challenge to increase the difficulty of another. These connections, however, are not explored within this research model due to the structure of the chosen content analysis method. This sub-model's result reveals the problem context for where and why an IME is required in the first place. The IME is needed to help MEs cope with their top challenges, which are derived in this sub-model. Therefore, this context and its parts are summarized in Figure 3.

MANUFACTURING ENTERPRISE DESCRIPTIVE MODEL

Manufacturing Enterprise Definition…

a firm created to produce physical goods for sale. Such enterprises that operate in the global economy possess and coordinate resources worldwide

Top Manufacturing Enterprise Challenges…

- Responding to changing individual customer needs and customer demand
- Operating in a global competition environment
- Expectation of fastest time-to-market, highest quality, lowest cost, best service, cleanest environment, greatest flexibility, and highest knowledge
- Increasing supply chain complexity
- Operating in dynamic and uncertain environments

We need the intelligent manufacturing enterprise to cope with the top challenges that manufacturing enterprises face today.

Figure 3: Results of the ME Descriptive Model

4.5 Data Technologies Descriptive Model

Data technologies (DT) are a rapidly growing and adapting topic area that has confounded researchers in defining it, categorizing it, and dealing with its dynamic development [10,58,59,62,116]. The goal of this third and final sub-model is to define a DT and identify the potentials data technologies offer. It must be noted that many DT terms, like AI and Big Data, are used interchangeably in both theory and in practice. For this reason, the authors first establish definitions for each technology through a review of those published in the literature and then use these definitions throughout their research process. The developed definitions for this research can be found in Table 2 in the appendix.

The procedure for this sub-model again involves a content analysis of 32 sources through the use of 16 related codes [1,3,5,9,10,58,61–63,65,105,117–137]. Documents imported into MAXQDA from the literature are initially coded under a general DT code and then under codes for individual technologies. Using the MAXQDA Summary Tools, coded passages from all DT types are considered. Within these summaries, repeated or similar terms are collected that are used to derive a definition for DTs as a whole. During this first part of the procedure, it becomes clear that some DTs create value while others only process data into other, usable forms. A search for this phenomenon in the existing literature identified KLINGENBERG ET AL.'s systematic literature review of Industry 4.0 technologies. Within their review, they present a hypothesis that some DTs are enabling, while others are value-creating [62]. To keep the number of potentials to be identified low, only value-creating technologies are considered in the final part of the procedure. To emphasize the impact these technologies have on ME's intelligence, they are referred to as impactors in this research. The nine codes relating to the impactor data technologies are synthesized into additional MAXQDA summaries. From these summaries, a list of the potentials of impactor DTs is parsed. Potentials are ranked by the number of associations they have with DTs in the collected literature. The ten DT potentials related to three or more DTs are considered the top ten DT potentials. To summarize, the results of this three-part procedure are the definition of a DT, the recognition of two types of DTs: enablers and impactors, and the potentials of impactor DTs.

The first of this sub-model's results, the definition development results, show that the inputs and outputs of DTs are critical to their definition. The majority of technologies take in raw data and then process it. For example, blockchain is a distributed ledger technology that stores inputted data without changing it [129]. In contrast, AI, including machine and deep learning, can complete exercises that typically require human intelligence. For example, human minds pre-process data via pattern recognition before consciously analyzing it [135,138]. In the same way, AI can work with raw data if necessary but primarily takes processed data as input [65]. Other technologies, like cloud technologies or cloud computing, sit in the middle, actively working with both raw and processed data [61,125,127]. The second part of the definition involves the outputs of DTs. Here phrases like "interpret," "extract value" and "transform into valuable knowledge" point to DTs delivering new knowledge and insights that derive from the inputs they receive [61,63,65]. The definition of a DT emerges from the combination of these input and output insights. From this follows the definition of a DT as a technology that utilizes raw or processed data for the sake of uncovering information and insights from that data [10,47,58,59].

Second, by looking at both the works of KLINGENBERG ET AL. and SCHUH ET AL. the initial categorization as enablers and value-creating technologies are mapped onto the *Industrie 4.0 Development Path* (see Figure 6 in the appendix) [3,62]. This results in enabler technologies and technologies that create an impact for the company and help them move to the next development stage. This mapping also allows for the possibility for technologies to be both enablers and impactors. Enablers analyze raw data and organize it into a processed form for further analysis. At the same time, impactors utilize data sources that are either cleaned by enablers or are raw data to find insights, make predictions, and ultimately make decisions with and without human interaction. Depicting the DTs in reference to the Industrie 4.0 stages, the overlap between enablers and impactors becomes apparent. As an example, Machine to Machine (M2M) communication builds on the computerization of machines by allowing them to connect. However, only communication is enabled, and no intelligent processing of any data is broadcasted, so the data sent only enables further analysis [58]. A step further, cyber-physical systems (CPS) utilize M2M and offer analysis of the connected data. Furthermore, CPS can operate autonomously to receive data and send back control commands [131]. Because it both processes data and can react autonomously to the insights it generates, CPS is considered both an enabler and an impactor. Lastly, on the opposite side of the spectrum, AI primarily provides deep insights from data already processed and stored by precursor technologies like IoT, cloud, or Big Data [65].

Thirdly, the ranking of impactor DT potentials, based on how many DTs they are related to, reveals which are most available to MEs. These potentials can be used to directly address the challenges derived in the second sub-model. Particularly relevant are improving quality control through real-time inspection and process control through real-time monitoring of production lines [5,9,58,61,65,133]. Figure 4 summarizes the results of this third sub-model, including the list of the top ten potentials of DTs and the DTs they are related to.

DATA TECHNOLOGIES DESCRIPTIVE MODEL

Data Technology Definition…

a technology that utilizes raw or processed data for the sake of uncovering information and insights from that data

Enabler Data Technologies…

Machine-to-Machine (M2M) Communication, Enterprise Resource Planning (ERP) Systems, Cybersecurity, Internet of Things (IoT), Virtual Reality, Cyber-Physical Systems (CPS), Blockchain, Cloud Technologies

Potentials of Impactor Data Technologies

Potential to….	*Related Impactor Data Technologies*
…improve product development	Artificial Intelligence (AI), Big Data, Virtual Reality
…optimize energy consumption & management	AI, Big Data, IoT
…perform predictive maintenance	AI, Big Data, IoT, CPS
…improve quality control	AI, Big Data, IoT, CPS, Virtual Reality
…have human-free manufacturing environments	AI, IoT, Blockchain
…utilize predictive models & analytics	AI, IoT, CPS, Cloud
…enable green manufacturing	Big Data, IoT, CPS, Cloud
…collect, analyze, and store data in real time	Big Data, Cloud, IoT
…improve process control & monitor in real-time	AI, Big Data, CPS, Cloud, Virtual Reality
…increase supply chain visibility & improve its management	Big Data, IoT, CPS

Figure 4: Results of Data Technologies Descriptive Model [1,3,5,9,10,58,61–63,65,105,117–137].

4.6 Intelligent Manufacturing Enterprise Descriptive Model

After the derivation of IE theory, the challenges faced by MEs, and the potentials of DTs, these outputs are interfaced with the IME definition model. The goal of this descriptive model is to establish a definition of the IME. The results of the previous three sub-models are analyzed within the context of the mass of literature collected thus far in the research process. The result is a combination of the partial definitions developed in the sub-models and additional insights from the literature.

The procedure begins with combining the previously derived definitions for MEs and IEs. The first half of the IME definition is formed by combining the beginnings of the IE and ME definitions. The critical points from each definition are that MEs produce physical goods for sale, and IEs use data technologies to coordinate information [39,41,46,52,95]. Initially, the IME definition also included that its purpose for utilizing data technologies was to create customer value. A focus on customer value is included in the IE definition and stems from QUINN's original work and its focus on IEs in the services industry [7,33]. Because the identified manufacturing challenges are conceivably linked to the potentials offered by impactor DTs, the second part of the IME definition adds the use of impactor DTs to address manufacturing challenges. Lastly, there is the need for a distinction between IMEs and the Industry 4.0 paradigm.

SCHUH ET AL. outline six stages in their *Industrie 4.0 Development Path*. The implementation of impactor DTs characterizes the completion of the final three stages of the *Development Path:* Transparency, Predictive Capacity, and Adaptability [3]. Because an IME is defined as utilizing impactor DTs, such enterprises have completed the *Industrie 4.0 Development Path*. IMEs are located on the other side of the 6th stage and are situated to face the next industrial revolution. Therefore, distinguishing IMEs concerning the *Industrie 4.0 Development Path* offers the opportunity to specify the foundation required to begin developing into an IME. Development starts with applying impactor DTs; this necessitates the previous application of enabler DTs. These precursor technologies, like M2M communication and ERP systems, are essential prerequisites to running automatic processes and monitoring systems via impactor technologies. In addition, even the automatic collection and storage of data can only be relied on if the data is confirmed to be accurate and dependable [132]. Therefore, firms that want to work towards the IME definitions presented here need to assess their current condition and determine if their focus should be on the IME capabilities or on establishing reliable and accurate data creation and collection systems.

In addition, the topics of intelligent manufacturing and operational excellence are identified repeatedly in the development of the ME sub-model. Although stand-alone themes, they exist at the same level as many of the other paradigms and methods that MEs implement to address relevant challenges and increase their productivity [52–54,56,57,139–145]. First, understanding the distinction between "smart" and "intelligent" manufacturing confirms the correctness of defining the researched term as an "intelligent" manufacturing enterprise. Historically, rather than focusing on meeting changeable customer needs, MEs focus on semi-stable customer demands like low-cost, high-volume goods, increased quality control, and agility to react to internal and external disruptions [48]. Operational excellence encapsulates these identified focuses well with its development of internal capabilities through continuous improvement. Ultimately, this way of operating does produce customer value and competitive advantage [139]. Operational excellence identifies superior implementation of well-known manufacturing strategies like Total Quality Management (TQM), lean manufacturing (LM), and Just-In-Time (JIT) as critical to increasing customer value and competitive advantage [140]. Because the topic of intelligent manufacturing helps to confirm the correctness of the chosen terminology and operational excellence encapsulates the goals of MEs, they are relevant supporting topics interesting to consider in this model development, but not requiring their own sub-models.

Drawing on the above-mentioned themes and the results of the previous three sub-models, the following definition of an IME follows:

> *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.*

5. Discussion

Critical reflection on the detailing of the research model reveals both strengths and weaknesses. The ability of the model to combine complex themes from multiple research topics in a structured and traceable manner is a strength. Conversely, a large amount of data and over 350 sources makes traceability difficult as the derivations are deep and complex. This results in broad citing at times when researcher documentation is weaker. Additionally, the significant planning of the research model makes it easy to track and meet the requirements of the model. With an inclusion of practical feedback from the industry in the course of the modeling process, the practical relevance of this model could be further increased.

It is also important to question whether the model developed here with its definition is the correct answer to this work's research question. The research process and model presented here is believed to be an authentic and systematic derivation from the existing literature for four reasons. First, the research model is highly structured based on established research methods and requirements according to ULRICH, PATZAK, HABERFELLNER, and ZELEWSKI [11,68,146,147]. Second, content analysis is the main method used to detail each sub-model and is a well-established methodology with a long scientific history outlined by KRIPPENDORFF [15]. Third, within the use of SALDAÑA's Codes-To-Theory method, the focus on confirming results using multiple bodies of literature leads to robust connections within the developed partial definitions [26]. Finally, a critical reflection on the interpretation of the quantitative content analysis methodology reveals that the analysis is based on the pure number of mentions of concepts, terms, and codes. This disregards the relevance of the individual contributions. The research question could have been addressed in various ways ranging from more quantitative to more qualitative than the methods utilized here. However, the initial choice of how the boundaries of this research are set determines the final model results. For example, the early determination to qualitatively divide the IME term into "intelligent enterprise" and "manufacturing enterprise" sets the first two focus areas. The pre-existing assumption of the vital role of DTs finalizes the third sub-model theme.

It could be argued that SCHUH ET AL. present capabilities for Industry 4.0 development and ARMAȘ presents the capabilities of the IE, which together could have been combined to form the capabilities of an IME [3,35]. The research presented here is still required for two reasons. First, the possible overlap between SCHUH ET AL., ARMAȘ or any other authors to develop the idea of an IME has not been addressed by researchers. Second, the choice to terminologically examine the IME term brings additional detail into the model. This detail includes the additional domain of identifying the challenges of MEs and how the potentials of DTs related to Industry 4.0 could solve them. Because a historical definition approach is taken in this research by looking at the three sub-model topics since their inception, the ultimate capabilities could not simply be taken and combined progressively from existing literature sources. Therefore, the decision is first made to derive definitions and characteristics that would form capabilities using HABERFELLNERS's "From Broad to Detailed" approach [146]. Because of the heavily qualitative nature of this work, it is impossible to guarantee that there is no other possible solution to the research question this work addresses. Regardless, the scientific methodology grounding this work should ensure that the solution presented here remains a highly viable option.

6. Concluding Remarks

Deriving a comprehensive definition of the IME is only the first of three portions of the IME definition model. This paper introduces this first portion to preface the papers to be published on the remainder of the model. Future articles will present the characteristics of the IME and the capabilities needed to become an IME. In addition, a validation of the research model will be presented. This validation is critical, as content analysis studies should be conducted in connection with a validation study that verifies the derived content and categorizations [17,19]. Finally, the authors hope that this IME definition and the related capabilities, to be presented in future publications, offer a pathway for MEs on their digitalization journeys to approach this new and necessary enterprise model.

Acknowledgements

This research was supported by the European Commission through the H2020 project EPIC (https://www.centre-epic.eu/) under grant No. 739592.

Appendix

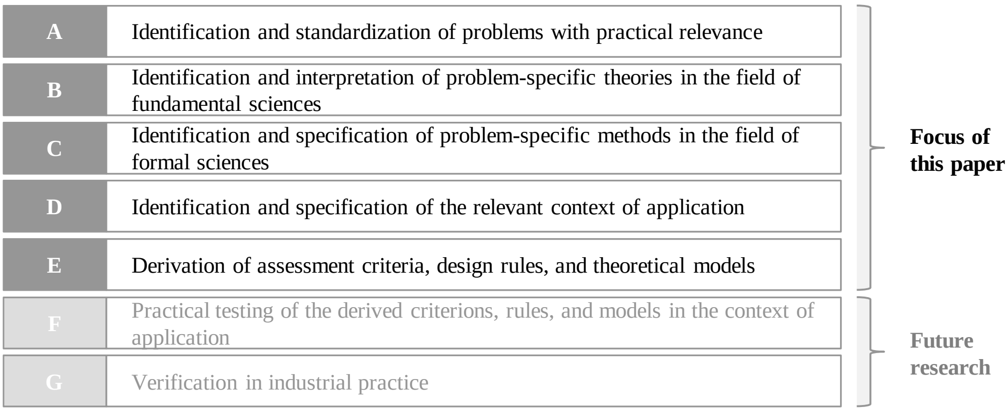

Figure 5: Research Process of Applied Sciences According to ULRICH [12]

Table 1: Top ME Challenges and Their Frequencies

Challenge	Frequency
Responding to changing individual customer needs and customer demand	7
Operating in a global competition environment	7
Expectation of fastest time-to-market, highest quality, lowest cost, best service, cleanest environment, greatest flexibility, and highest knowledge	6
Increasing supply chain complexity	6
Operating in dynamic and uncertain environments	5
Developing collaborative and reconfigurable manufacturing control systems	4
Challenges are too big for single firms alone	4
Outdated control systems	4
Requirements for lower costs and shorter life cycles	3
Utilizing rapidly developing technologies	3
Responding to changing product requirements	3
Continually maintaining competitive advantage	3
Forecasting market, economic, and supply chain disruptions	2
Responding to changing production conditions	2
Educating employees	2
Improving flexibility and agility while maintaining productivity and quality	1
Adapting traditional manufacturing control systems to current needs	1
Meeting expectations to reduce or eliminate environmental impacts	1
Responding to internal stochastic demand	1
Maintaining profit margins despite higher costs	1
Maintaining organic growth	1
High levels of technology transfer	1

Motivating employees	1
Maintaining resiliency and robustness of systems	1
Enhancing human safety	1
Outlining organizational requirements	1
Creating new pools of value for customers	1

Table 2: Derived Definitions of Data Technologies

Data Technology	**Definition**
Artificial Intelligence	is a learning system that can complete tasks that traditionally require human intelligence [65,117].
Machine Learning	involves algorithms that can automatically learn from patterns existing in data without being programmed [65,117].
Deep Learning	takes its name from the deep levels of neural networks that work together to allow these advanced machine learning algorithms to analyze and interpret data the way a human brain would [65,117].
Internet of Things	is a network of uniquely identified physical and digital assets that can collect and exchange data, self-configure its capabilities, and collect, process, and report data from all sources in an enterprise [58,64,118–122].
Big Data	is a bundle of technologies that work with high-volume, velocity, and variety data to extract value through storing, organizing, and processing this data into knowledge [61–63,124].
Cloud Computing	is a collaborative and flexible infrastructure that integrates resources and provides on-demand data analysis and network access - it can host multiple software applications on its flexible infrastructure [61,125–127].

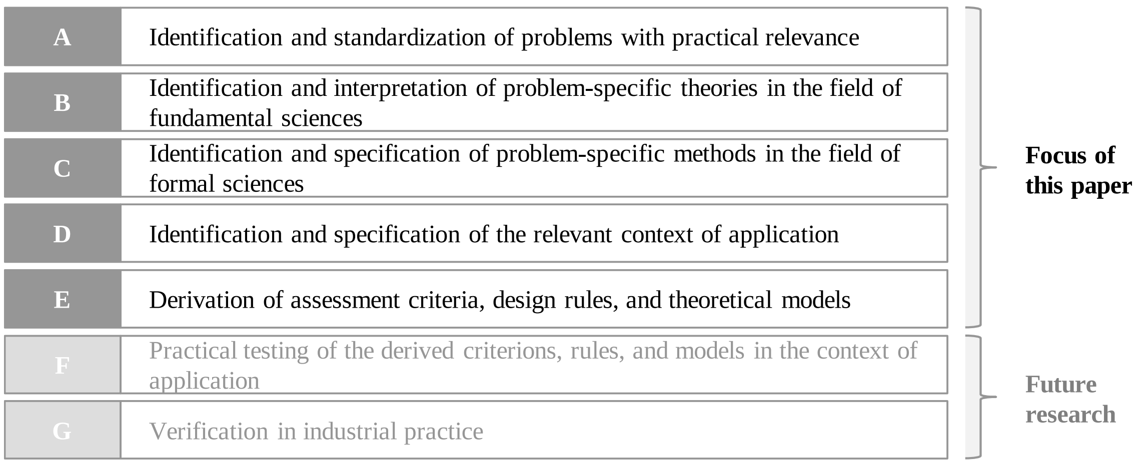

Figure 6: Data Technologies in SCHUH ET AL.'s Industrie 4.0 Development Path [3]

References

[1] Esmaeilian, B., Behdad, S., Wang, B., 2016. The evolution and future of manufacturing: A review. Journal of Manufacturing Systems 39, 79–100.

[2] Hu, Y., Li, J., Holloway, L.E., 2008. Towards Modeling of Resilience Dynamics in Manufacturing Enterprises: Literature Review and Problem Formation. 4th IEEE Conference on Automation Science and Engineering, 279–284.

[3] Schuh, G., Anderl, R., Dumitrescu, R., Krüger, A., ten Hompel, M., 2020. Industrie 4.0 Maturity Index: Managing the Digital Transformation of Companies. Update 2020. acatech STUDY, Munich. https://www.acatech.de/publikation/industrie-4-0-maturity-index-update-2020/. Accessed 1 April 2021.
[4] Gunasekaran, A., 1999. Agile manufacturing: A framework for research and development. Int. J. Production Economics 62 (1999), 87–105.
[5] The Innovators Forum, 2016. 2016 Innovation Symposium: The Intelligent Enterprise: Insights from the 2016 Innovation Symposium at Harvard. https://theinnovatorsforum.org/sites/default/files/ie_whitepaper_updated_march_21.pdf.
[6] Wang, F.-Y., 2010. The Emergence of Intelligent Enterprises: From CPS to CPSS. IEEE Intelligent Systems 25 (4), 85–88.
[7] Quinn, J.B., 1992. Intelligent Enterprise: A New Paradigm for a New Era. How Knowledge and Service Based Systems are Revolutionizing the Economy, All Industry Structures, and the Very Nature of Strategy and Organizations. The Free Press, London.
[8] Herčko, J., Slamková, E., Hnát, J., 2015. Industry 4.0 as a factor of productivity increase, in: TRANSCOME 2015 Conference Proceedings. TRANSCOME 2015, Žilina, Slovak Republic. 22-24 June.
[9] World Economic Forum, 2016. Manufacturing Our Future: Cases on the Future of Manufacturing 00020233. World Economic Forum, 17 pp. http://www3.weforum.org/docs/GAC16_The_Future_of_Manufacturing_report.pdf. Accessed 28-Apr-21.
[10] Raguseo, E., 2018. Big data technologies: An empirical investigation on their adoption, benefits and risks for companies. International Journal of Information Management 38 (1), 187–195.
[11] Ulrich, P., Hill, W., 1976. Wissenschaftstheoretische Grundlagen der Betriebswirtschaftslehre. Wirtschaftswissenschaftliches Studium: Zeitschrift für Ausbildung und Hochschulkontakt 5 (7+8), 304–309.
[12] Ulrich, H., Dyllick, T., Probst, G.J.B., 1984. Management, Bern & Stuttgart: Haupt.
[13] Webb, P., Pollard, C., Ridley, G., 2006. Attempting to Define IT Governance: Wisdom or Folly? Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06), 1-10.
[14] Holsti, O.R., 1969. Content Analysis for the Social Sciences and Humanities. Addison-Wesley, Reading, MA, USA.
[15] Krippendorff, K., 2004. Content Analysis: An Introduction to Its Methodology, 2nd ed. Sage Publications, Inc., California.
[16] United States General Accounting Office, 1996. Content Analysis: A Methodology for Structuring and Analyzing Written Material, Washingon, D.C.
[17] Elo, S., Kyngäs, H., 2008. The qualitative content analysis process. Journal of Advanced Nursing 62 (1), 107–115.
[18] Kuckartz, U., 2019. Qualitative Text Analysis: A Systematic Approach, in: Kaiser, G., Presmeg, N. (Eds.), Compendium for Early Career Researchers in Mathematics Education. Springer International Publishing, Cham, pp. 181–197.
[19] Stemler, S., 2000. An overview of content analysis. Practical Assessment, Research, and Evaluation 7 (7).
[20] Weber, R.P., 1990. Basic Content Analysis, 2nd ed. Sage Publications, Inc.
[21] Hsieh, H.-F., Shannon, S., 2005. Three approaches to qualitative content analysis. Qualitative Health Research 15, 1277–1288.
[22] Polit, D.F., Beck, C.T., 2004. Nursing Research. Principles and Methods. Lippincott Williams & Wilkins, Philadelphia, PA, USA.

[23] Sandelowski, M., 1995. Qualitative analysis: what it is and how to begin? Research in Nursing & Health 18, 371–375.

[24] Chinn, P.L., Kramer, M.K., 1999. Theory and Nursing a Systematic Approach. Mosby Year Book, St. Louis.

[25] Kyngäs, H., Vanhanen, L., 1999. Content analysis (Finnish). Hoitotiede 11, 3–12.

[26] Saldaña, J., 2013. The Coding Manual for Qualitative Researchers, 2nd ed. SAGE Publications, Los Angeles, London, New Delhi, Singapore, Washington DC.

[27] MAXQDA, 2021. What is MAXQDA? https://www.maxqda.com/what-is-maxqda.

[28] Cebotarean Elena, Titu Maiorescu University, Romania, 2011. Business intelligence. Journal of knowledge Management, Economics, and Information Technology 1 (2), 1–10.

[29] Dictionary.com, 2021. intelligence. Dictionary.com. https://www.dictionary.com/browse/intelligence.

[30] Mashingaidze, S., 2014. Harmonizing intelligence terminologies in business: Literature review. JGR 3 (4), 156–162.

[31] Pellissier, R., Nenzhelele, T.E., 2013. Towards a universal definition of competitive intelligence. S. Afr. j. inf. manag. 15 (2).

[32] Rouach, D., Santi, P., 2001. Competitive Intelligence Adds Value: Five Intelligence Attitudes. European Management Journal 19 (5), 552–559.

[33] Quinn, J.B., 1992. The intelligent enterprise a new paradigm. Academy of Management Executive 6 (4), 48–63.

[34] Wiig, K.M., 1999. The Intelligent Enterprise and Knowledge Management. Article prepared for UNESCO's Encyclopedia of Life Support Systems. Knowledge Research Institute, Inc., Arlington, TX.

[35] Armaş, I., 2014. Intelligent Enterprises - A Capabilities Oriented Model. Hyperion International Journal of Econophysics & New Economy 7 (1), 89–100.

[36] Schoemaker, P.J.H., Tetlock, P.E., 2017. Building a More Intelligent Enterprise. MIT Sloan Management Review 58 (3), 27–37.

[37] Byrum, J., 2019. Engineering the Intelligent Enterprise. ISE Magazine (January 2019), 40–43.

[38] Zebra Technologies, 2019. The Intelligent Enterprise Index: October 2019. https://www.zebra.com/content/dam/zebra_new_ia/en-us/campaigns/brand-campaign/harvard-symposium/how-intelligent-enterprise-survey-index-en-us.pdf. Accessed 8 April 2021.

[39] Byrum, J., 2020. Leading the Intelligent Enterprise. MIT Sloan Management Review. https://sloanreview.mit.edu/article/leading-the-intelligent-enterprise/. Accessed 29 June 2021.

[40] Byrum, J., 2021. How the intelligent enterprise will drive innovation. ISE Magazine 53 (4), 26–30.

[41] SAP, 2021. The Journey to the Intelligent Enterprise. SAP, 22 pp. https://www.sap.com/documents/2020/03/e258345b-8a7d-0010-87a3-c30de2ffd8ff.html. Accessed 1 July 2021.

[42] Schwaniger, M. Prof. Dr., Flaschka, M., 1995. Intelligent Organizations: Building Core Competencies Through Information Systems. Newsletter of the Competence Centre Electronic Markets July (16).

[43] Murtuza, A., 1993. Intelligent Enterprise: A Knowledge and Service Based Paradigm for Industry. Management Accounting September 1993, 84.

[44] Doll, W.J., Vonderembse, M.A., 1991. The evolution of manufacturing systems: Towards the post-industrial enterprise. Omega 19 (5), 401–411.

[45] Carlsson, B., 1988. The evolution of manufacturing technology and its impact on industrial structure: An international study IUI Working Paper, No. 203. The Research Institute of Industrial Economics (IUI), Stockholm, 47 pp. https://www.econstor.eu/bitstream/10419/95188/1/wp203.pdf. Accessed 28-Apr-21.

[46] Davis, J., Edgar, T., Porter, J., Bernaden, J., Sarli, M., 2012. Smart manufacturing, manufacturing intelligence, and demand-dynamic performance. Computers and Chemical Engineering 47 (2012), 145–156.
[47] Gates, D., Mayor, T., Gampenrieder, E.L., 2016. Global Manufacturing Outlook: Competing for growth: How to be a growth leader in industrial manufacturing 133493-G. KPMG International, Switzerland, 36 pp. https://assets.kpmg/content/dam/kpmg/tr/pdf/2017/01/global-manufacturing-outlook-competing-for-growth.pdf. Accessed 28-Apr-21.
[48] Jin-Hai, L., Anderson, A.R., Harrison, R.T., 2003. The evolution of agile manufacturing. Business Process Mgmt Journal 9 (2), 170–189.
[49] Leitão, P., 2009. Agent-based distributed manufacturing control: A state-of-the-art survey. Engineering Applications of Artificial Intelligence 22 (2009), 979–991.
[50] Zhou, Y., Chuah, K.B., 1999. Human Intelligence the key factor for successful intelligent manufacturing. Integrated Manufacturing Systems 11 (1), 30–41.
[51] Kolberg, D., Zühlke, D., 2015. Lean Automation enabled by Industry 4.0 Technologies. IFAC-PapersOnLine 48 (3), 1870–1875.
[52] Ge, J., Wang, F., Sun, H., Fu, L., Sun, M., 2020. Research on the maturity of big data management capability of intelligent manufacturing enterprise. Syst Res Behav Sci 37 (4), 646–662.
[53] National Institute of Standards and Technology, 2018. Product Definitions for Smart Manufacturing. NIST. https://www.nist.gov/programs-projects/product-definitions-smart-manufacturing. Accessed 8 July 2021.
[54] Wang, B., Tao, F., Fang, X., Liu, C., Liu, Y., Freiheit, T., 2020. Smart Manufacturing and Intelligent Manufacturing: A Comparative Review. Engineering.
[55] Barari, A., Tsuzuki, Marcos de Sales Guerra, Cohen, Y., Macchi, M., 2021. Editorial: intelligent manufacturing systems towards industry 4.0 era. Journal of Intelligent Manufacturing.
[56] Sharma, M., Kodali, R., 2008. Development of a framework for manufacturing excellence. Measuring Business Excellence 12 (4), 50–66.
[57] Rusev, S.J., Salonitis, K., 2016. Operational Excellence Assessment Framework for Manufacturing Companies. Procedia CIRP 55, 272–277.
[58] Oztemel, E., Gursev, S., 2020. Literature review of Industry 4.0 and related technologies. J Intell Manuf 31 (1), 127–182.
[59] Chiarello, F., Trivelli, L., Bonaccorsi, A., Fantoni, G., 2018. Extracting and mapping industry 4.0 technologies using wikipedia. Computers in Industry 100, 244–257.
[60] Davis, R.C., 2021. ("data" AND "technologies") AND "manufacturing" Literature Study Corpus, Aachen.
[61] Ghobakhloo, M., 2018. The future of the manufacturing industry: a strategic roadmap toward Industry 4.0. Journal of Manufacturing Technology Management 29 (6), 910–936.
[62] Klingenberg, C.O., Borges, M.A.V., Antunes Jr, J.A.V., 2021. Industry 4.0 as a data-driven paradigm: a systematic literature review on technologies. JMTM 32 (3), 570–592.
[63] Bansal, M., Chana, I., Clarke, S., 2021. A Survey on IoT Big Data. ACM Comput. Surv. 53 (6), 1–59.
[64] Lee, J., Ardakani, H.D., Yang, S., Bagheri, B., 2015. Industrial Big Data Analytics and Cyber-physical Systems for Future Maintenance & Service Innovation. Procedia CIRP 38, 3–7.
[65] Capgemini Research Institute, 2019. Scaling AI in Manufacturing Operations: A Practitioners' Perspective. Capgemini Research Institute. https://www.capgemini.com/wp-content/uploads/2019/12/AI-in-manufacturing-operations.pdf.
[66] Schlund, S., Baaij, F., 2018. Describing the technological scope of Industry 4.0 - a review of survey publications. LogForum 14 (3), 341–353.

[67] Chavarría-Barrientos, D., Batres, R., Wright, P.K., Molina, A., 2018. A methodology to create a sensing, smart and sustainable manufacturing enterprise. International Journal of Production Research 56 (1-2), 584–603.

[68] Patzak, G., 1982. Systemtechnik - Planung komplexer innovativer Systeme: Grundlagen, Methoden, Techniken. Springer Berlin Heidelberg, Berlin, Heidelberg.

[69] Haag, C., 2009. Werthaltigkeitsprüfung technologiebasierter immaterieller Vermögenswerte. Zugl.: Aachen, Techn. Hochsch., Diss., 2009, 1st ed. Apprimus-Verl., Aachen, 153 pp.

[70] Dictionary.com, 2021. characteristic. Dictionary.com. https://www.dictionary.com/browse/characteristic#. Accessed 1 July 2021.

[71] Merriam-Webster, 2021. characteristic. Merriam-Webster. https://www.merriam-webster.com/dictionary/characteristic. Accessed 1 July 2021.

[72] Witmer, L., Ph.D., 1922. Intelligence - A Definition. The Psychological Clinic 14 (3-4), 65–67.

[73] Goddard, H.H., 1947. A Suggested Definition of Intelligence. The Training School Bulletin 43 (10), 185–193.

[74] Britannica, 2021. Invention of the modern computer. https://www.britannica.com/technology/computer/Early-business-machines#ref216032.

[75] Binet, A., Simon, T., 1905. Methodes nouvelles por le diagnostic du niveai intellectuel des anormaux. L’Ann´ee Psychologique 11, 191–244.

[76] Bingham, W.V., 1937. Aptitudes and aptitude testing. Harper & Brothers, New York.

[77] Fatmi, H.A., Young, R.W., 1970. A definition of intelligence. Nature 228 (5266), 97.

[78] Hyde, G., 1971. Definition of intelligence. Nature 229 (5280), 143.

[79] Muller, P.M., Barlow, H. B., Cook, H. A., 1970. Definition of intelligence. Nature 228 (5275), 1008.

[80] Neisser, U., Boodoo, G., Bouchard, T.J., Jr., Boykin, A.W., Brody, N., Ceci, S.J., Halpern, D.F., Loehlin, J.C., Perloff, R., Sternberg, R.J., Urbina, S., 1996. Intelligence: Knowns and unknowns. American Psychologist 51 (2), 77–101.

[81] Simonton, D.K., 2003. An interview with Dr. Simonton. Human intelligence: Historical influences, current controversies, teaching resources. www.indiana.edu/~intell.

[82] Slatter, J., 2001. Assessment of children: Cognitive applications, 4th ed. Jermone M. Satler Publisher Inc., San Diego.

[83] Sternberg, R.J. (Ed.), 2000. Handbook of Intelligence. Cambridge University Press.

[84] Sternberg, R.J., 2003. An interview with Dr. Sternberg. Human intelligence: Historical influences, current controversies, teaching resources. http://www.indiana.edu/~intell.

[85] Wechsler, D., 1958. The measurement and appraisal of adult intelligence, 4th ed. Williams & Wilkinds, Baltimore.

[86] Legg, S., Hutter, M., 2007. Universal Intelligence: A Definition of Machine Intelligence. Minds & Machines 17 (4).

[87] Solis, J., 2019. Data Visualization is Key. The Journal of Private Equity 22 (3), 102–107.

[88] Keller, B., 2019. Digital Innovation to Drive Intelligent Utility Enterprise. 2019 IEEE International Conference on Energy Internet (ICEI), 484–486.

[89] Arthur, M.B., Claman, P.H., DeFillippi, R.J., 1995. Intelligent enterprise, intelligent careers. Academy of Management Executive 9 (4), 7–20.

[90] Felin, T., Powell, T.C., 2016. Designing Organizations for Dynamic Capabilities. California Management Review 58 (4).

[91] Forbes Insights, 2016. How To Win at Digital Transformation: Insights From a Global Survey of Top Executives. https://images.forbes.com/forbesinsights/hds_digital_maturity/HowToWinAtDigitalTransformation.pdf. Accessed 1 July 2021.

[92] Sinclair, S., Rockwell, G., 2016. About. https://voyant-tools.org/docs/#!/guide/about.

[93] Sinclair, S., Rockwell, G., 2016. Voyant Tools. http://voyant-tools.org/.
[94] Gizzi, M.C., Rädiker, S. (Eds.), 2021. The Practice of Qualitative Data Analysis: Research Examples Using MAXQDA, 1st ed. MAXQDA Press, Berlin.
[95] Snyder, S., Meek, D., Lehtonen, T., Kiradjiev, P., 2020. Expert Insights: Smart Manufacturing: AI technologies, intelligent insights. IBM Institute for Business Value, Armonk, NY, 16 pp.
[96] Albus, J.S., 1991. Outline of a theory of intelligence. IEEE Trans. Syst. Man Cybern, Syst. 21, 473–509.
[97] Rzevski, G., 1997. A framework for designing intelligent manufacturing systems. Computer in Industry 34, 211–219.
[98] Suh, N.P., 1995. Design and operation of large systems. Journal of Manufacturing Systems 14 (3), 203–213.
[99] Quinn, J.B., 1993. Managing the Intelligent Enterprise: Knowledge & Service-Based Strategies. Planning Review September/October, 13–16.
[100] Venkatraman, N., 1993. Intelligent Enterprise, James Brian Quinn: Book Review. Sloan Management Review 34 (3), 122–123.
[101] Brock, D.M., 1995. Intelligent Enterprise: A Knowledge and Service Based Paradigm for Industry: Book Review. The International Journal of Organizational Analysis 3 (1), 105–107.
[102] Warren, K., 1994. Book Reviews: Quinn, J.B. Intelligent Enterprise. Journal of Management Studies 31 (2), 275–277.
[103] Da Xu, L., He, W., Li, S., 2014. Internet of Things in Industries: A Survey. IEEE Transactions on Industrial Informatics 10 (4), 2233–2243.
[104] Dumitrache, I., Caramihai, S.I., Stanescu, A., 2013. From mass production to Intelligent Cyber-Enterprise, in: 19th International Conference on Contorol Systems and Computer Science. 19th International Conference on Contorol Systems and Computer Science. IEEE, pp. 399–404.
[105] Klie, L., 2019. Data Dominates Marketing Innovations: New technologies will continue increasing what companies can do with the data they have. Customer Relationship Management (July/August), 32–35.
[106] DalleMule, L., Davenport, T.H., 2017. What's Your Data Strategy. Harvard business review (May-June 2017), 112–121.
[107] Björkdahl, J., 2020. Strategies for Digitalization in Manufacturing Firms. California Management Review 62 (4), 17–36.
[108] Bird, M.M., 1973. Major Problem Areas As Percieved By Presidents of Small Manufacturing Firms: A Case Study. Academy of Management Journal 16 (3), 510–515.
[109] Camarinha-Matos, L.M., Afsarmanesh, H., Galeano, N., Molina, A., 2009. Collaborative networked organizations – Concepts and practice in manufacturing enterprises. Computers & Industrial Engineering 57 (1), 46–60.
[110] Leitão, P., Restivo, F., 2006. ADACOR: A holonic architecture for agile and adaptive manufacturing control. Computers in Industry 57 (2), 121–130.
[111] Meade, L.M., Sarkis, J., 1999. Analyzing organizational project alternatives for agile manufacturing processes: An analytical network approach. International Journal of Production Research 37 (2), 241–261.
[112] Shen, W., Norrie, D.H., 1999. Agent-Based Systems for Intelligent Manufacturing: A State-of-the-Art Survey. Knowledge and Information Systems 1 (1999), 129–156.
[113] Stock, G.N., Greis, N.P., Kasarda, J.D., 2000. Enterprise logistics and supply chain structure: the role of fit. Journal of Operations Management 18 (5), 531–547.
[114] Wang, J., Xu, S.X., Xu, G., 2020. Intelligent decision making for service and manufacturing industries. J Intell Manuf 31 (8), 2089–2090.

[115] Tao, F., Zhang, L., Venkatesh, V.C., Luo, Y., Cheng, Y., 2011. Cloud manufacturing: a computing and service-oriented manufacturing model. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 225 (10), 1969–1976.

[116] Philip Chen, C.L., Zhang, C.-Y., 2014. Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. Information Sciences.

[117] Jakhar, D., Kaur, I., 2020. Artificial intelligence, machine learning and deep learning: definitions and differences. Clinical and experimental dermatology 45 (1), 131–132.

[118] Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., Ayyash, M., 2015. Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications. IEEE Commun. Surv. Tutorials 17 (4), 2347–2376.

[119] Chen, M., Mao, S., Zhang, Y., Leung, V.C., 2014. Big Data: Related Technologies, Challenges and Future Prospects. Springer.

[120] Djellal, F., Francoz, D., Gallouj, C., Gallouj, F., Jacquin, Y., 2003. Revising the definition of research and development in the light of the specificities of services. Science and Public Policy 30 (6), 415–429.

[121] Duan, L., Da Xu, L., 2012. Business Intelligence for Enterprise Systems: A Survey. IEEE Transactions on Industrial Informatics 8 (3), 679–687.

[122] Fenn, J., Lehong, H., 2011. Hype Cycle for Emerging Technologies. Gartner, Stamford. https://www.gartner.com/en/documents/1754719/hype-cycle-for-emerging-technologies-2011.

[123] Lee, J., Lapira, E., Bagheri, B., Kao, H., 2013. Recent advances and trends in predictive manufacturing systems in big data environment. Manufacturing Letters 1 (1), 38–41.

[124] Oussous, A., Benjelloun, Fatima-Zahra, Lahcen, A.A., Belfkih, S., 2018. Big Data technologies: A survey. Journal of King Saud University - Computer and Information Sciences 30 (4), 431–448.

[125] Badger, L., Patt-corner, R., Voas, J., 2012. Cloud computing synopsis and recommendations: NIST Special Publication 800-146. https://www.nist.gov/publications/cloud-computing-synopsis-and-recommendations. Accessed 8 July 2021.

[126] Storey, V.C., Song, I.-Y., 2017. Big data technologies and Management: What conceptual modeling can do. Data & Knowledge Engineering 108, 50–67.

[127] Wang, L., 2019. From Intelligence Science to Intelligent Manufacturing. Engineering 5 (4), 615–618.

[128] Ivanov, D., Dolgui, A., Sokolov, B., 2019. The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. International Journal of Production Research 57 (3).

[129] Underwood, S., 2016. Blockchain beyond Bitcoin. Communications of the the ACM 59 (11), 15–17.

[130] Kopetz, H., 2011. Internet of Things, in: , Real-Time Systems. Design Principles for Distributed Embedded Applications, 2 ed. Springer US, pp. 307–323.

[131] Papazoglou, M.P., Elgammal, A. The manufacturing blueprint environment: Bringing intelligence into manufacturing, in: , 2017 International Conference on Engineering, pp. 750–759.

[132] Khan, N., Yaqoob, I., Hashem, I.A.T., Inayat, Z., Ali, W.K.M., Alam, M., Shiraz, M., Gani, A., 2014. Big data: survey, technologies, opportunities, and challenges. The Scientific World Journal 2014, 1–18.

[133] Li, J., Tao, F., Cheng, Y., Zhao, L., 2015. Big Data in product lifecycle management. Int J Adv Manuf Technol 81 (1-4), 667–684.

[134] Elia, V., Gnoni, M.G., Lanzilotto, A., 2016. Evaluating the application of augmented reality devices in manufacturing from a process point of view: an AHP based model. Expert Systems with Applications 63 (1), 187–197.

[135] Caelli, T., Rentschler, I., Scheidler, W., 1987. Visual pattern recognition in humans. Biological Cybernetics 57, 233–240.

[136] Gilchrist, A., 2016. Industry 4.0: The Industrial Internet of Things. Springer, Heidelberg.

[137] Wang, Y.-M., Wang, Y.-S., Yang, Y.-F., 2010. Understanding the determinants of RFID adoption in the manufacturing industry. Technological Forecasting and Social Change 77 (5), 803–815.
[138] Schwab, E.C., Nusbaum, H.C. (Eds.), 1986. Speech Perception. Academic Press, Orlando, San Diego.
[139] Roth, A.V., Giffi, C.A., Seal, G.M., 1992. Operating strategies for the 1990s: elements comprising world-class manufacturing, in: Voss, C.A. (Ed.), Manufacturing Strategy - Process and Content. Chapman & Hall, London.
[140] Hall R. W., 1987. Attaining Manufacturing Excellence: Just-in-Time, Total Quality, Total People Involvement. Dow Jones-Irwin, Homewood, IL.
[141] Garvin, D.A., 1988. Managing Quality: The Strategic and Competitive Edge. The Free Press, New York, NY.
[142] Peters, T.J., Waterman, R.H., 1982. In Search of Excellence: Lessons from America's Best Run Companies. Harper & Row, London.
[143] Kepner-Tregoe, Inc., 1999. The Path to Manufacturing Excellence 700-10-P173099. Kepner-Tregoe, Inc., Princeton, New Jersey.
[144] Thoben, K.-D., Wiesner, S., Wuest, T., 2017. “Industrie 4.0” and Smart Manufacturing – A Review of Research Issues and Application Examples. Int. J. Automation Technol. 11 (1), 4–16.
[145] Kusiak, A., 2018. Smart manufacturing. International Journal of Production Research 56 (1-2), 508–517.
[146] Haberfellner, R., 2012. Systems Engineering: Grundlagen und Anwendung, 12th ed. Orell Füssli, Zürich.
[147] Zelewski, S., 1999. Grundlagen, in: Corsten, H., Reiß, M. (Eds.), Betriebswirtschaftslehre, 3 ed. Oldenbourg, München, pp. 1–125.

Biography

Prof. Dr.-Ing. Dipl.-Wirt. Ing. Günther Schuh (*1958) holds the chair for Production Systematics at RWTH Aachen University. Furthermore, he is director of the FIR e. V., member of the board of directors of the WZL of the RWTH Aachen University and the Fraunhofer Institute for Production Technology (IPT).

Thomas Scheuer, M.Sc. (*1992) holds a M.Sc. in Mechanical Engineering and Business Administration from RWTH Aachen University. He currently works at as a research associate in the department of Technology Management at the Fraunhofer Institute for Production Technology (IPT).

Riley Colleen Padovano, M.Sc. (*1996) holds a M.Sc. in Management and Engineering in Computer Aided Mechanical Engineering from RWTH Aachen University and B.Sc. degrees in Mechanical Engineering and Global Languages and Culture from the Massachusetts Institute of Technology (MIT). She currently works as a research assistant in the department of Technology Management at the Fraunhofer Institute for Production Technology (IPT).