Journal of Manufacturing Technology Management

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Received 27 December 2024
Revised 7 April 2025
11 July 2025
Accepted 26 July 2025

The role of human interoperability in achieving sustainable smart manufacturing

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Abstract

Purpose – Using smart manufacturing technologies presents potentials for economic, environmental, and social sustainability objectives. Regarding their contribution to sustainability, these potentials are not mutually exclusive but interrelated. This study investigates these interrelationships of utilizing advanced digital technologies for sustainable smart manufacturing. By identifying the importance of the social dimension and its human factor, this study contributes to the recent research on human-centricity in smart manufacturing.

Design/methodology/approach – We apply a two-step mixed-method approach. First, through 44 expert interviews supported by a literature review, we identify nine key sustainability potentials that influence sustainable smart manufacturing. Second, we analyze the interrelationships and expand our analysis using data from 68 participants.

Findings – We identify the impact of each factor and the cause-and-effect interrelationships. Our findings show that all environmental potentials can be categorized into effect dimensions. Within the economic and social dimensions, only one factor each is classified as an effect factor, whereas two factors in each domain are recognized as cause factors. Interestingly, employee qualification acts as the strongest lever influencing all other key sustainability dimensions.

Originality/value – This study elucidates the interplay between smart manufacturing technologies and sustainability in smart manufacturing, offering valuable insights to navigate the interrelatedness of sustainable potentials, in particular regarding human interoperability.

Keywords Smart manufacturing, Advanced digital technologies, Sustainability, Triple bottom line, Cause and effect, Human interoperability

Paper type Research article

Quick value overview

Interesting Because **-** In smart manufacturing, there has been a shift toward situating the human at the heart of many perspectives. In the context of social sustainability, the human factor is becoming increasingly important. Therefore, the interrelationship of the human factor with other dimensions and possible interrelationships must be understood. This study illustrates the interplay between the economic, environmental, and social objectives of smart manufacturing. It highlights that social approaches can act as a lever in this interplay and that a stronger emphasis should be placed on dealing with the human factor.

Theoretical Value - Previous studies have adopted a linear view of sustainability efforts. We show that this linear view is insufficient because various factors are interrelated. In particular,

Journal of Manufacturing Technology Management
Vol. 36 No. 9, 2025
pp. 197-220
Emerald Publishing Limited
e-ISSN: 1758-7786
p-ISSN: 1741-038X
DOI 10.1108/JMTM-12-2024-0724

the dimension of social sustainability is considered a lever linking economic and environmental objectives. With the correct qualification measures, humans can directly influence sustainability efforts. Further, we provide evidence that social sustainability is essential for achieving sustainable smart manufacturing.

Practical Value - Industrial companies must consider the interoperability of their various sustainability objectives. Focusing on human factors can enable additional sustainability efforts. Managers should recognize the importance of humans in smart manufacturing. This approach can also help achieve efficiency in economic and environmental objectives, particularly through training, such as workshops or development measures.

1. Introduction

Recent developments through advanced technologies in smart manufacturing environments have enabled sustainable production in industrial companies (Marcon *et al*., 2022; Nascimento *et al*., 2019). Transformational changes, such as new customer demands or resource scarcity, require industrial companies to focus on digitalization and sustainability. Traditional manufacturing techniques are becoming automated, and processes are rapidly becoming digitalized through the use of digital technologies such as artificial intelligence (AI), digital twins, or extended reality (XR) (Chiarini, 2021). Digital manufacturing technologies offer several sustainability potentials for the environmental, economic, and social dimensions (Hussain *et al*., 2024; Wei *et al*., 2024). Regarding environmental potential, the use of AI optimizes production programs by selecting the most efficient order, thereby reducing high-emission idle runs (Bai and Sarkis, 2017). Economic sustainability is achieved by reducing costs through digital twin technologies or digital platforms to virtually map production processes and detect unnecessary costs (Arcidiacono and Schupp, 2024; Frank *et al*., 2019). In the social dimension, enhancing transparency facilitates the improvement of working conditions and supports employees (Veile *et al*., 2020). This information can be exchanged across the value chain to facilitate stakeholder integration in a socially sustainable manner. While the environmental dimension was dominant in the past, the social dimension has gained importance in recent studies (Baig and Yadegaridehkordi, 2024; Cillo *et al*., 2022).

Combining digitalization and sustainability marks the beginning of a new stage of industrial development (Dieste *et al*., 2024). Extending the sustainability goals of Industry 4.0, Industry 5.0 focuses on human-centricity and resilience (Baig and Yadegaridehkordi, 2024; Cillo *et al*., 2022). The importance of the human factor in sustainable manufacturing is particularly interesting as human-machine collaboration is being expanded through Industry 5.0 technologies (Langås *et al*., 2025). Previous research has emphasized economic benefits and environmental effects, with less focus on social effects (Arcidiacono and Schupp, 2024). However, industrial companies are changing their perspectives on social development in their manufacturing environments.

Smart manufacturing offers drivers that contribute to all three sustainability dimensions (e.g. Birkel and Müller, 2021). However, the drivers do not operate alone but are interdependent. with mutual interrelationships including cause-and-effect factors. While several articles have been published on this intersection, a substantial research gap still exists. Extant research mostly provides an overview of the sustainability aspects of smart manufacturing (e.g. Bohnsack *et al*., 2022). However, limited attention has been paid to these interrelations and the quantification of these effects (Birkel and Müller, 2021). In particular, the literature lacks a detailed overview of the interrelationships between all three dimensions of the triple bottom line (TBL).

Further, while some authors have discussed the interrelationships of barriers to sustainable manufacturing (e.g. Bag *et al*., 2022), this study considers the key sustainability potentials of digital technologies in smart manufacturing. It analyzes their interrelationships, focusing on previous research on social sustainability. Measuring human interoperability in relation to these potentials allows for the identification of mutually relationships (Flores *et al*., 2020). Hence, we aim to answer the following research question:

What is the role of human interoperability within the interrelationships of key sustainability potentials enabled by smart manufacturing technologies?

To answer this research question, this study highlighted the interrelationships between key environmental, economic, and social potentials within the TBL of sustainability. The selected approach first combined 44 expert interviews with a literature review. Second, a total of 68 experts evaluated the key potentials and their interrelationships in an online survey. Additionally, the analysis helped identify the cause-and-effect factors. The resulting insights can provide concrete recommendations for action in practice, offering an in-depth supplement to the extant literature.

2. Related literature and research gap

2.1 Smart manufacturing

The integration of advanced digital technologies into industrial production is a fundamental aspect of the ongoing digital transformation. Digitalization and connectivity characterize the levers that increase efficiency and productivity in smart manufacturing (Frank *et al.*, 2019). This represents a novel approach to manufacturing in which the real and digital worlds are connected, offering new opportunities for real-time communication and autonomous functioning. The foundation of a smart factory is formed by digital technologies, including sensors, data processing units, and actuators, which enable the transfer of real-time data (Peruzzini *et al.*, 2024). These technologies facilitate networking within industrial production, including human-to-human, human-to-object, and object-to-object interactions (Zhang *et al.*, 2023). Additionally, real-time condition monitoring simplifies the remote diagnosis and control of production plants while assisting in the predictive maintenance of machines and production equipment (Frank *et al.*, 2019).

Incorporating digital technologies establishes a comprehensive network connecting the entire value chain, including machines and data, with people. Smart devices are continuously trackable and locatable (Chiarini, 2021; Kong *et al.*, 2021). Production orders can move autonomously through the manufacturing process, and machines can set themselves up and reorganize production when errors are detected. Consequently, the dependability of a smart factory is enhanced by its ability to predict and automatically circumvent potential production errors (Hussain *et al.*, 2024). Standardized processes and data transparency are required to identify appropriate areas for implementing smart manufacturing technologies (Veile *et al.*, 2020).

To explain the concept of advanced technologies in smart manufacturing, this study encompassed eleven core technologies for smart manufacturing, including *smart sensors and actuators*, *Internet of Things* (IoT), *cyber-physical systems* (CPS), *AI*, *digital platforms*, *cloud computing*, *big data analytics*, *industrial robotics*, *XR*, *digital twin technology*, and *additive manufacturing* (Peruzzini *et al.*, 2024). These core technologies were mentioned by the majority of the experts and are listed in Table 1.

2.2 Sustainability in industrial manufacturing

According to the World Commission on Environment and Development (1987), developing processes and practices without compromising future generations' needs defines sustainability. Traditionally, companies have primarily focused on maximizing profits. However, prioritizing profit maximization without considering the environmental and social impacts of companies' actions is no longer adequate (Glavič and Lukman, 2007). The TBL is a useful tool for understanding sustainability as a multidimensional concept (Elkington, 1997). This concept incorporates the environmental, economic, and social aspects to provide a comprehensive view of sustainability. Further, the TBL is the most frequently investigated construct in research on sustainable development through smart manufacturing (Khan *et al.*, 2021). Therefore, this study incorporates the TBL as a definition of sustainability (Birkel and Müller, 2021).

Table 1. Smart manufacturing technologies

Advanced technologies for smart manufacturing	Description	Reference
Smart sensors and actuators	Smart sensors, actuators, and radio-frequency identification technology can be fitted into machines, products, logistics vehicles, and similar items to monitor and track resources, measure processes, and transmit relevant data	Chiarini (2021) Pacheco *et al.* (2023)
Internet of Things	The IoT utilizes an information technology infrastructure to connect physical devices, facilitating the acquisition and dissemination of data. Moreover, it enables the integration of various services and applications to display information and detect issues	Kiel *et al.* (2017)
Cyber physical systems	The IoT refers to the large network of interconnected objects, whereas CPS connect physical devices to a central processing unit with software integration. This integration enables greater adaptability and enhances the quality of physical processes	Kamble *et al.* (2020a)
Artificial intelligence	AI facilitates the exchange of crucial information, executes necessary actions, and controls machines and processes autonomously. It involves intelligent machines operating independently, responding to changing conditions, and learning from previous tasks and outcomes. AI also enables the visualization and interpretation of the relevant information and meaning of process data	Bai and Sarkis (2017)
Digital platforms	Digital platforms connect actors and machines in manufacturing. Data are collected and made available to every user in real-time	Frank *et al.* (2019)
Cloud computing	Cloud computing allows industrial companies to access cloud provider resources such as data storage or analysis, eliminating the need for the company to invest in its own infrastructure	Frank *et al.* (2019)
Big data analytics	Big data analytics provides data analysis tools and algorithms, enabling better decision-making for industrial production	Müller *et al.* (2018)
Industrial robotics	Industrial robotics describes using robots in manufacturing operations to increase productivity and efficiency. Robots can support humans in hazardous and unsafe tasks	Kamble *et al.* (2020b), Bai and Sarkis (2017)
Extended reality	Augmented reality is a technology that superimposes digital content onto the real environment. Virtual reality is comparable to augmented reality, but instead of being overlaid, it shows a completely virtual process replicating a real one	Masood and Egger (2020), Souza Cardoso *et al.* (2020)
Digital twin technology	The digital twin is a virtual representation of systems or objects, allowing for simulations to be conducted and enabling intelligent decision-making, mapping the entire production process in the industrial metaverse is gaining attention	Hussain *et al.* (2024), Luo *et al.* (2023)
Additive manufacturing	Additive manufacturing, or 3D printing, is a technology directly related to production. It allows for the transformation of digital files into three-dimensional objects, such as spare parts, layer by layer	Hussain *et al.* (2024), Frank *et al.* (2019)

Source(s): Authors' own work based on Frank *et al.* (2019)

Digital technologies in smart manufacturing provide new opportunities to achieve sustainable value (Bohnsack *et al.*, 2022; Wei *et al.*, 2024).

Environmental sustainability. Smart manufacturing has demonstrated its potential to significantly reduce scrap and waste, thereby minimizing environmental impacts (Veile *et al.*, 2020). Digital technologies enhance energy and resource efficiency by producing high-quality parts within the same time frame. Additionally, the transparency achieved through smart manufacturing can facilitate the use of renewable energy and resources, reduce the necessity for transport and logistics processes by avoiding incorrect deliveries, and highlight their positive impacts on the environment (Sarkis and Zhu, 2018). For instance, smart sensors for emissions reduction can serve as early warning systems, making a substantial contribution to the environment (Chiarini, 2021).

Economic sustainability. Regarding economic advantages, smart manufacturing enables companies to enhance cost transparency and optimize their production planning, leading to increased efficiency and flexibility (Frank *et al*., 2019). By reducing lead times and improving their market share, companies can maintain their competitiveness and gain overall profits (Dubey *et al*., 2017). In addition, smart manufacturing facilitates the development of new business models, enhances energy efficiency, and promotes the use of renewable resources (Hussain *et al*., 2024).

Social sustainability. Smart manufacturing considerably affects social sustainability (Marcon *et al*., 2022; Wei *et al*., 2024). Safety can be enhanced by reducing accidents and creating more comfortable working environments for workers with disabilities (Souza Cardoso *et al*., 2020). This is achieved through the provision of training, higher salaries, and a decreased manual workload (Moon *et al*., 2023). Additionally, a qualification gap results from the transformation of manual jobs into those requiring digital expertise. Therefore, training, expanding, or replacing the workforce is crucial.

2.3 Human-centricity in smart manufacturing

In recent studies, the social dimension of sustainability has become particularly important. Originating in Industry 4.0, industrial research is evolving from data transfer and process automation to an even more holistic approach (Lu *et al*., 2022). Under the new paradigm of Industry 5.0, the focus is on human-centricity and resilience (Cillo *et al*., 2022; Ivanov, 2023). The human-centered dimension in particular influences current research streams on the social dimension of smart manufacturing. Recent studies have shown that the human factor is indispensable to sustainable manufacturing (e.g. Langås *et al*., 2025; Zahid *et al*., 2024). This is because employees who work with the new technologies are actively involved in their adoption and implementation through changing workplace settings (Zhang *et al*., 2023). Smart manufacturing structures combine human needs with technological efficiency (Lu *et al*., 2022). Human-machine collaboration occurs in human-robot (Langås *et al*., 2025; Peruzzini *et al*., 2024) and human-AI applications (Baig and Yadegaridehkordi, 2024). Thus, the human position has shifted from task execution to a supervisory role for machines' self-executed activities. Employees observe production processes and intervene as necessary, supported by technological systems (Flores *et al*., 2020). However, the trustworthiness of smart manufacturing applications remains questionable; employees must trust the systems to be able to accept these applications (Zahid *et al*., 2024). Reservations generally come from an emotional and psychological perspective of fearing job loss or replacement by new technologies (Zhang *et al*., 2023).

2.4 Evaluating interrelationships

The dimensions of sustainability potentials in smart manufacturing are interrelated and have partially combined effects (Avrampou *et al*., 2019; Frank *et al*., 2019; Wei *et al*., 2024). They share several complementary goals. For instance, environmental sustainability can enhance economic sustainability because a positive environmental image can attract investors to a company. However, interdependencies between dimensions can also result in conflicts (Kiel *et al*., 2017). For example, the use of digital technologies in industrial production can improve economic sustainability by making processes more efficient. Hence, to assess sustainability potential, the interrelationships between economic, environmental, and social sustainability must be considered. Although this study focused on the positive aspects by examining the sustainability potential of industrial companies to suggest further improvements, the negative aspects should not be underestimated (e.g. Dieste *et al*., 2024; Rocha *et al*., 2025). Environmentally, the use of technology can be detrimental, leading to increased energy consumption (Bohnsack *et al*., 2022). Economically, the introduction of new technologies usually involves large investments and resources such as digital infrastructure and expertise (Peruzzini *et al*., 2024). In the social dimension, trust issues with new technologies may worsen employee well-being (Zahid *et al*., 2024).

Recent studies have identified sustainability potentials through qualitative analyses and literature reviews (e.g. Birkel and Müller, 2021; Khan *et al*., 2021). However, subsequent in-depth analyses have been lacking. Owing to their qualitative or literature-based approaches, the assumptions require a more detailed verification of the identified parameters. This study aims to offer a comprehensive picture of the utilization of digital technologies in smart manufacturing by determining the significance of key potentials and their cause-and-effect factors. It revealed the interrelationships between individual sustainability potentials and simplified future decision-making in the pursuit of objectives (Mangla *et al*., 2018). This methodology presents an opportunity to supplement qualitative data with quantitative analyses.

3. Methodology

Using two consecutive data collection methods, we comprehensively assessed the sustainability potentials of advanced digital technologies in smart manufacturing. First, we adopted a combined approach, including a literature review and 44 expert interviews with German companies, to explore the sustainability potentials that arise from using digital technologies in smart manufacturing.

Second, we utilized the nine most significant sustainability potentials identified through the literature review and expert interviews for a quantitative analysis using a DEMATEL survey with 68 respondents. This approach determined the potentials that can be achieved through digital technologies and their interrelationships. The methodological approach is illustrated in Figure 1.

3.1 Phase 1: identification of key sustainability potentials

To identify the key sustainability potentials, we conducted a literature review and semi-structured interviews with 44 industry experts. We identified industry experts based on their expertise in smart manufacturing and knowledge of digital technologies. Consistent with the recommendations of Gioia *et al*. (2013), we conducted the qualitative analysis in three phases: *data sampling*, *data collection*, and *data analysis*.

Data sampling. Based on the five-step approach of Denyer and Tranfield (2009), we conducted a literature review to gain insights into relevant theoretical studies. We found appropriate studies by scanning several articles using the keywords *advanced digital technologies*, *smart manufacturing* and *sustainability potentials*. We combined these keywords across multiple databases (EBSCOhost, Scopus, and IEEE Explore) with AND/OR connectors. These data bases have been successfully used in recent studies (e.g. Zupic and Čater, 2015). Starting with 3,095 scientific articles, we excluded duplicates (n = 2,475), low-quality articles based on an SJR ranking below Q1 (n = 731), and articles that did not fit our thematic fit, lacking aspects such as manufacturing focus and the sustainability potentials of advanced technologies. Consequently, 117 scientific articles were selected for further validation. We combined various statements into codes, which were then compared with the interviews. The exact procedure for the analysis is described in *data analysis* below.

We also conducted 44 interviews with experts from industrial companies. The companies listed in Table A1 in the Appendix varied in terms of size and manufacturing industry sectors, allowing for the generalization of results and mitigation of potential biases (Edmondson and Mcmanus, 2007). The industry sectors included the automotive, mechanical engineering,

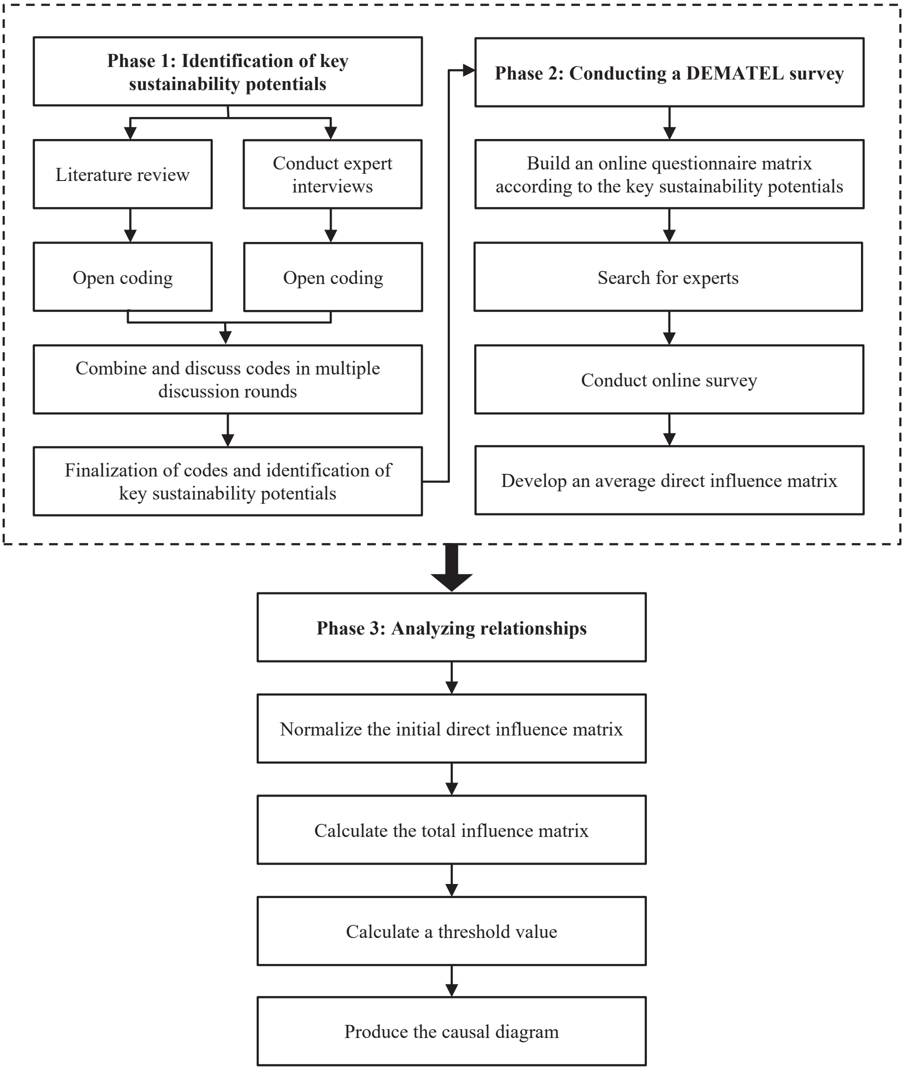

Figure 1. Research approach. Source: Authors' own work

electrical, and metal industries. Thus, we analyzed industry sectors with comparable properties rather than the consumer industry or medical equipment with typically different standards and approaches. We identified appropriate experts from these companies based on their professional knowledge of smart manufacturing, experience with smart manufacturing technologies and positions within the company, such as top-level or manufacturing management. This careful selection process ensured the reliability and validity of our results (Eisenhardt and Graebner, 2007).

Data collection. The semi-structured interviews were conducted between September and November 2023. Anonymity was guaranteed to all the experts. The interview guideline (see Appendix Table A2) comprised open- and closed-ended questions, allowing for the collection of data in a structured manner while capturing unexpected insights through follow-up questions (Yin, 2018). All interviews were recorded and subsequently transcribed.

Data analysis. Based on the recent literature and expert interviews, the coding process entailed the sequential development of first-order concepts and aggregate dimensions (Gioia *et al.*, 2013). To categorize the sustainability potentials of digital technology in the manufacturing sector, we utilized the TBL dimensions to aggregate the theoretical dimensions. After several iterations and discussion rounds between the three researchers, including the coding from recent studies, we identified three of the most significant sustainability potentials for each TBL dimension. These included *energy conservation* (F1), *material saving* (F2), *emission reduction* (F3), *data efficiency* (F4), *process optimization* (F5), *cost reduction* (F6), *employee motivation* (F7), *employee qualification* (F8) and *employee support* (F9).

3.2 Phase 2: conducting a DEMATEL survey

The DEMATEL technique uses matrices and digraphs to visualize the structure of complex causal relationships. Unlike conventional multiple-criteria decision-making strategies, it does not depend on the assumption of independence among the criteria (Mangla *et al.*, 2018). Therefore, the analysis can include criteria with conceptual interdependencies. By utilizing these insights, decision-makers can identify, scrutinize, and confirm direct and indirect connections between all components of a system.

To analyze the interrelationships of sustainability potentials identified in the initial interview study, we created an online questionnaire (see Appendix Table A3). To ensure the validity of the results, a general comprehension question was included. In addition, we gathered the participants' demographic information and their relationships with digital technologies in smart manufacturing. If the participants were familiar with the topic because of their profession, we asked additional questions regarding the size and industrial sector of their companies. Finally, the participants were asked to rate the direct influence of factor F_i on the remaining factor F_j. The factors corresponding to the sustainability potentials from the first study were *energy conservation* (F1), *material saving* (F2), *emission reduction* (F3), *data efficiency* (F4), *process optimization* (F5), *cost reduction* (F6), *employee motivation* (F7), *employee qualification* (F8) and *employee support* (F9).

The online survey was conducted from November 2023 to January 2024, and potential participants were invited to participate via email, LinkedIn, or private contacts. Three criteria were applied to identify potential experts. First, the experts were familiar with smart manufacturing technologies. Second, the experts were aware of sustainability potentials. Third, the experts could identify interrelationships through their work experience. We included practice and research experts to incorporate their perspectives on future developments using the same criteria. After closing the survey, we recorded 79 completed questionnaires. We excluded responses from participants who answered the comprehension question incorrectly, were unrelated to the topic of digital technologies in manufacturing, or had insufficient experience with digital technologies in manufacturing. Through this process, 11 responses were excluded from the sample, resulting in a final sample of 68 valid responses. The sample comprised 29 women and 39 men. A total of 45 participants had regular contact with smart manufacturing technologies at work, and 23 had gained insights through in-depth studies. The sectors included the automotive ($n = 10$), mechanical engineering ($n = 13$), electrical ($n = 11$), chemical ($n = 3$), food ($n = 1$), aviation ($n = 1$), and research and service management ($n = 29$) industries. To enhance the generalizability of the results, we recruited a large sample, compared to extant studies using similar methods having typically less than ten participants (e.g. Samaranayake *et al.*, 2024). In doing so, we aimed to provide results that could be transferred to and would be valid in several contexts.

3.3 Phase 3: analyzing relationships

Following data collection, we used a five-step approach for the analysis (Wu *et al.*, 2015).

Step 1: Creating the direct influence matrix. To examine the relationships between the nine ($n = 9$) factors $F = \{F_1, F_2, \ldots, F_9\}$, each of the 68 respondents ($k = 68$) was asked to indicate the degree of the direct influence of factor F_i on factor F_j. The degree of influence was measured using an integer scale of "no influence (0)", "low influence (1)", "medium influence (2)", "high influence (3)", and "very high influence (4)". Subsequently, we created tan individual direct influence matrix $A_k = [a_{ij}^k]_{n\times n}$ for every k th expert, where a_{ij}^k represents the judgment of the corresponding expert regarding the influence of factor F_i on factor F_j. Owing to the pairwise comparison, all entries where $i = j$ equaled 0. We obtained group direct influence matrix A by calculating the average for every entry a_{ij}^k for all 68 experts using Equation (1).

$$a_{ij} = \frac{1}{k}\sum_{k=1}^{k} a_{ij}^k, i,j = 1,2,\ldots,n = 9 \tag{1}$$

Step 2: Normalizing the initial direct influence matrix. Using Equations (2) and (3), the group direct influence matrix A was normalized to produce the normalized direct influence matrix $D = [d_{ij}]_{n\times n}$:

$$D = s\times A \tag{2}$$

$$s = \frac{1}{\max\left(\max\limits_{1\le i\le n}\sum_{j=1}^{n} a_{ij}, \max\limits_{1\le i\le n}\sum_{i=1}^{n} a_{ij}\right)} \tag{3}$$

Step 3: Calculating the total influence matrix. The total influence matrix T is obtained using Equation (4), where I represents the identity matrix:

$$T = D(I - D)^{-1} \tag{4}$$

Step 4: Calculating a threshold value. Because the total influence matrix T shows all effects between the factors of the system, negligible effects must be filtered out. Therefore, we calculated the threshold value α using Equation (5) and highlighted all values in the total influence matrix T that exceeded this threshold. These represent the most critical influences of system factors. Although other methods exist, we defined a threshold value consistent with extant studies (Pan and Nguyen, 2015) by calculating the average value of all elements within matrix T, where N represents the total number of elements ($N = n^2 = 81$).

$$\alpha = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}[t_{ij}]}{N}, i,j = 1,2,\ldots,n = 9 \tag{5}$$

Step 5: Producing the causal diagram. The vectors R and C were obtained by summing the rows and columns of the total influence matrix T separately using Equations (6)-(8). First, the horizontal axis vector $(R + C)$ called "Importance" was calculated by adding vector R to vector C. In the vector representation, each row $(r_j + c_j)$ indicates the importance of the corresponding factor F_j. Second, the vertical axis vector $(R - C)$ called "Relation" was obtained by subtracting vector C from vector R. The results indicated the net effect of each factor on the system. If the result of $(r_j - c_j)$ is positive, factor F_j has a net influence on the remaining factors in the system and belongs to the cause group. Conversely, a negative result for $(r_j - c_j)$ indicates that factor F_j is primarily influenced by the other factors in the system and, therefore, belongs to the effect group. Finally, we mapped the dataset of $(R+C, R-C)$ onto an influential relation map, making it easy to identify the importance and relationships of all the factors within the system.

$$T = \left[t_{ij}\right]_{n\times n}, i,j = 1,2,\ldots,n = 9 \tag{6}$$

$$R = [r_i]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \tag{7}$$

$$C = \left[r_j\right]_{1\times n} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n} \tag{8}$$

4. Findings

Based on the interviews, we identified nine key potentials according to the TBL's sustainability dimensions (Section 4.1), followed by an analysis of their interrelationships (Section 4.2).

4.1 Key sustainability potentials

First, we identified sustainable potentials through the qualitative analysis, including a literature review and 44 expert interviews. The key sustainability potentials represented the three most important factors in each dimension of the TBL. Environmental potentials included *energy conservation* (F1), *material saving* (F2), and *emission reduction* (F3). Economic potentials included *data efficiency* (F4), *process optimization* (F5), and *cost reduction* (F6). Social potentials comprised *employee motivation* (F7), *employee qualification* (F8), and *employee support* (F9). Table 2 shows the nine key sustainability potentials, which are briefly described below.

F1: Energy conservation. The heat generated during production is re-utilized for heat recovery. Digital technologies facilitate optimal distribution and limit external energy requirements (E18). Further, processes with high energy consumption are identified and optimized. Real-time data from production enables successful quality management and reduces unused energy (E27). Energy is a significant cost element for businesses, making it a key consideration in the manufacturing sector (Cao *et al.*, 2020).

F2: Material saving. Material saving involves the reliable use of resources, beginning in the design phase of a product through the use of digital twins (E1, E25). This is because a substantial portion of the future material consumption is already determined during the design phase (Khan *et al.*, 2021). Additionally, well-planned production programs can ensure the efficient use of required materials (E39). A recycling system supported by AI enables the reuse of surplus materials from production (Nascimento *et al.*, 2019), ensuring the responsible use of materials (E25).

F3: Emission reduction. To reduce emissions, companies can use advanced digital technologies to optimize transport routes between production steps and achieve optimum capacity utilization, thereby eliminating empty runs (E3, E34). Additionally, machine emissions can be reduced by optimizing them in the industrial metaverse or using smart sensors with an early warning function (E36).

F4: Data efficiency. Data possess a different meaning in smart manufacturing, forming the basis for using various technologies such as generative AI (E12, E44). Digital technologies support the generation, collection, and analysis of data as the first step (E38). This enables the

Table 2. Nine sustainability potential dimensions derived from interviews and the literature

Dimension	Key sustainability potentials		Exemplary literature sources	Number of interviews mentioned
Environmental sustainability	F1	*Energy conservation*	Cao *et al.* (2020) Veile *et al.* (2020)	21
	F2	*Material saving*	Hussain *et al.* (2024) Khan *et al.* (2021)	12
	F3	*Emission reduction*	Avrampou *et al.* (2019) Veile *et al.* (2020)	11
Economic sustainability	F4	*Data efficiency*	Bohnsack *et al.* (2022) Kong *et al.* (2021)	35
	F5	*Process optimization*	Bai and Sarkis (2017) Kamble *et al.* (2020a) Oliveira Santos *et al.* (2020)	33
	F6	*Cost reduction*	Veile *et al.* (2020) Yadav *et al.* (2020)	17
Social sustainability	F7	*Employee motivation*	Kreye (2016) Salimian *et al.* (2021)	15
	F8	*Employee qualification*	Wei *et al.* (2024) Luthra *et al.* (2020) Aldieri *et al.* (2021)	12
	F9	*Employee support*	Souza Cardoso *et al.* (2020) Moon *et al.* (2023)	11

Source(s): Authors' own work

creation of added value beyond the production of products (Bohnsack *et al.*, 2022). For instance, efficient data handling can help to develop specific recommendations for production and increase customer satisfaction (E14, E20).

F5: Process optimization. The digital mapping of processes enables the optimization of various production steps. Unused times are uncovered and filled with optimum production programs (E39). Error-prone processes are identified and monitored separately (E34). Relocating production to the industrial metaverse allows processes to be tested virtually before being executed in the real world (E1).

F6: Cost reduction. Incorporating digital technologies can achieve cost savings in production by reducing the number of workers through the use of robotic systems or planning for optimum capacity utilization (E3, E9). Information systems can also be used to monitor ongoing production and identify unnecessary costs (Veile *et al.*, 2020).

F7: Employee motivation. Digital technologies make employees more comfortable in their work environment through additional support functions (E27, E29), which foster a positive working atmosphere. This increases productivity and the employer's attractiveness (E37). Accordingly, employees feel valued and motivated to complete tasks (E5).

F8: Employee qualification. Digital technologies upskill employees. Augmented and virtual reality make it possible to perform tasks on a machine from any location (E7). Errors can be detected more quickly, by integrating other experts using these systems (Luthra *et al.*, 2020). Generative AI also supports employees in their decisions (E33) and offers innovative solutions based on a wide range of data (E35, E38).

F9: Employee support. The use of digital technologies, such as CPS, assists employees in performing their tasks (E9) by making difficult tasks easier or eliminating them (E25). This allows the employees to focus on other tasks. Human error is also minimized, thereby reducing the pressure on individual employees (E19, E27).

4.2 Analysis of interrelationships

Once the key potentials were validated by the experts, the second step was to examine their interrelationships. Potentials can only be realized once the relationships are explored. The average direct influence matrix presented in Table 3 is based on 68 datasets from an online survey of industrial companies and research institutions. According to the average direct influence matrix (Table 3), the normalized direct influence matrix (Table 4) was built. Finally, in a further step the relationships are presented in the total influence matrix (Table 5).

The total influence matrix shows the importance of the individual key potentials (rj + cj). It also allows conclusions to be drawn about the relationships based on the cause-and-effect groups (rj−cj). A detailed illustration of the individual key figures is presented in Table 6.

Importance. According to the rank of the key potentials based on expert opinions, *process optimization* (F5) was the highest ranked potential with a value of 6.9366, followed by *cost reduction* (F6) 6.2280, *energy conservation* (F1) 5.55163, *employee motivation* (F7) 5.4986, *data efficiency* (F4) 5.4139, *material saving* (F2) 5.3629, *emission reduction* (F3) 5.2397, *employee qualification* (F8) 5.2114, and *employee support* (F9) 4.8457.

Unsurprisingly, the industrial focus is still on economic potentials, with optimized processes and low costs being the main drivers of sustainable smart manufacturing. This is due to the cost-driven approach of companies, whose main goal is to generate as much profit as possible by minimizing costs.

The importance of environmental aspects appears relatively low, which is surprising because sustainability goals typically focus on environmental sustainability. However, energy savings are particularly significant compared with the other two potential areas. This is likely

Table 3. Average direct influence matrix

	F1	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*	*F8*	*F9*
F1	0	1.6912	2.9706	1.2059	2.0441	2.9265	1.2500	0.8529	0.8824
F2	2.8382	0	2.8824	1.1176	1.9412	2.9559	1.1912	0.8971	1.5000
F3	2.5735	1.7794	0	1.2647	1.9118	2.0147	1.5441	0.7647	0.8824
F4	2.3971	2.0294	2.0882	0	2.9706	2.5588	1.6471	1.4853	2.0735
F5	2.9559	2.8382	2.7794	2.6324	0	3.1618	2.3676	1.9265	2.9118
F6	2.3235	2.3088	1.9412	1.7647	2.7059	0	1.8529	1.5147	1.5147
F7	1.6618	1.6176	1.4706	1.6618	2.5441	1.9118	0	2.3824	2.2794
F8	1.8676	2.0588	1.7647	2.3235	2.8529	2.2500	2.5441	0	2.1176
F9	0.9853	0.8235	0.7794	1.3971	2.0735	1.8088	3.2794	1.7353	0

Source(s): Authors' own work

Table 4. Normalized direct influence matrix

	F1	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*	*F8*	*F9*
F1	0	0.0784	0.1377	0.0559	0.0948	0.1357	0.0579	0.0395	0.0409
F2	0.1316	0	0.1336	0.0518	0.0900	0.1370	0.0552	0.0416	0.0695
F3	0.1193	0.0825	0	0.0586	0.0886	0.0934	0.0716	0.0354	0.0409
F4	0.1111	0.0941	0.0968	0	0.1377	0.1186	0.0763	0.0688	0.0961
F5	0.1370	0.1316	0.1288	0.1220	0	0.1466	0.1097	0.0893	0.1350
F6	0.1077	0.1070	0.0900	0.0818	0.1254	0	0.0859	0.0702	0.0702
F7	0.0770	0.0750	0.0682	0.0770	0.1179	0.0886	0	0.1104	0.1057
F8	0.0866	0.0954	0.0818	0.1077	0.1322	0.1043	0.1179	0	0.0982
F9	0.0457	0.0382	0.0361	0.0648	0.0961	0.0838	0.1520	0.0804	0

Source(s): Authors' own work

Table 5. Total influence matrix with $\alpha = 0.3104$

	F1	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*	*F8*	*F9*
F1	0.2333	0.2747	*0.3448*	0.2278	*0.3262*	0.3726	0.2524	0.1890	0.2209
F2	*0.3694*	0.2179	*0.3606*	0.2384	*0.3424*	0.3958	0.2677	0.2033	0.2597
F3	*0.3232*	0.2633	0.2078	0.2176	0.3044	*0.3211*	0.2498	0.1757	0.2091
F4	0.3866	*0.3354*	*0.3620*	0.2184	*0.4210*	*0.4197*	*0.3201*	0.2538	*0.3161*
F5	*0.4650*	*0.4154*	*0.4429*	*0.3704*	*0.3609*	*0.5053*	*0.3989*	0.3095	*0.3933*
F6	*0.3645*	*0.3290*	*0.3384*	0.2783	*0.3896*	0.2921	0.3092	0.2413	0.2780
F7	*0.3308*	0.2968	*0.3111*	0.2729	*0.3803*	*0.3663*	0.2311	0.2756	0.3073
F8	*0.3744*	*0.3446*	*0.3565*	*0.3245*	*0.4282*	*0.4174*	*0.3651*	0.1984	*0.3284*
F9	0.2628	0.2306	0.2435	0.2328	*0.3219*	*0.3171*	*0.3323*	0.2274	0.1823

Source(s): Authors' own work

Table 6. Given and received influence between factors

Factors (F_n)	TBL dimensions	Sustainability potentials	(ri + cj)	Rank	(ri−cj)	Cause/ Effect
F1	Environmental	Energy conservation	5.5516	3	−0.6683	Effect
F2		Material saving	5.3629	6	−0.0527	Effect
F3		Emission reduction	5.2397	7	−0.6956	Effect
F4	Economic	Data efficiency	5.4139	5	0.6519	Cause
F5		Process optimization	6.9366	1	0.3868	Cause
F6		Cost reduction	6.2280	2	−0.5869	Effect
F7	Social	Employee motivation	5.4986	4	0.0456	Cause
F8		Employee qualification	5.2114	8	1.0635	Cause
F9		Employee support	4.8457	9	−0.1444	Effect

Source(s): Authors' own work

because energy consumption is also a cost driver; therefore, unnecessary energy usage should be avoided.

Employee qualifications, motivation and support should not be considered less important than the other aspects. However, the social sustainability dimension has not yet been fully realized by industrial companies and is given less importance based on their rank.

Effect group. The factors *emission reduction* (F3) (−0.6956), *energy conservation* (F1) (−0.6683), *cost reduction* (F6) (−0.5869), *employee support* (F9) (−0.1444), and *material saving* (F2) (−0.0527) categorize the effect key sustainability potentials.

The key potentials of the cause group influence the effect group potentials. The environmental potentials are particularly prominent as effects but not as causes. This is surprising because companies could be expected to prioritize these aspects owing to current demands from customers and society. However, because of the network of relationships, other potentials strongly affect these potentials.

Moreover, cost reduction is considered an important factor of the effect group. Companies generally view cost reduction as a means of unlocking further potentials within the company. However, this is often based on other cause factors.

The only social benefit categorized as an effect dimension is employee support. Advanced digital technologies in manufacturing are expected to provide relief to employees. By contrast, employee qualification serves as a strong cause factor.

Cause group. The cause group of the key sustainability potentials includes *employee qualification* (F8) (1.0635), *data efficiency* (F4) (0.6519), *process optimization* (F5) (0.3868), and *employee motivation* (F7) (0.0456).

The qualifications of employees are a strong factor for the cause group and influence all other key sustainability potentials. Training employees using digital technologies can unlock additional potentials. First, the virtualization of production processes can enhance training by introducing multiple scenarios. Second, it is possible to train without harming oneself and practice making errors without wasting material. For example, when using XR, employees can prevent contact with the contained material and remain safe in hazardous situations.

Data efficiency affects other factors in sustainable smart manufacturing in several ways, highlighting the importance of data generation and analysis using advanced digital technologies. For example, optimizing processes can increase production efficiency and reduce costs.

Employee motivation is the second key social sustainability potential. We argue that intrinsically motivated employees are more open to new technologies, and thus, are more willing to accept them.

Single-sided and multisided connections. Considering the total influence matrix (Figure 2), this study identified both single-sided and multisided connections. The threshold value classifies multisided (higher) and single-sided (lower) connections. In this study, the threshold value represented the average ($\alpha = 0.3104$).

Employee qualification offers only a single-sided connection with all other attributes. Therefore, this key potential has a strong influence on other potentials, but other potentials have little influence on employee qualification. The other two social sustainability potentials (employee motivation and employee support) have predominantly one-sided connections. However, both have a two-way relationship with process optimization.

Regarding economic potentials, data efficiency has the most one-sided connections, influencing other potentials. Only process optimization is multi-directional in this TBL dimension. Cost reduction and process optimization have almost exclusively multilateral connections with all other key sustainability potentials. This emphasizes their importance in industrial contexts. Regarding environmental potentials, almost exclusively multilateral connections with other environmental potentials were observed, disregarding the social and economic TBL dimensions.

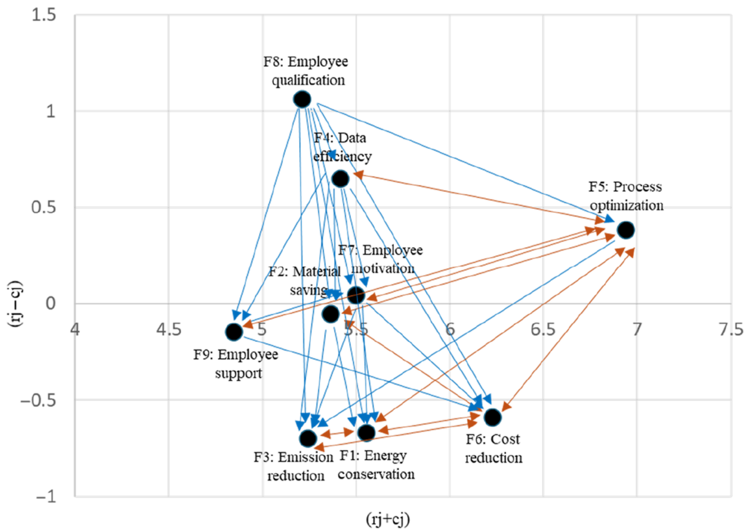

Figure 2. Single-sided and multisided connections. Source: Authors' own work

For all three environmental potentials, only a one-sided connection was observed with employee support. Regarding material saving, the only multisided connection is with cost reduction. Figure 2 shows the single-sided and multisided connections.

5. Discussion

Smart manufacturing unlocked the possibility of performing several processes in a digital environment. The digitalization of processes offers several potential benefits for sustainability that are interrelated as cause-and-effect factors (e.g. Birkel and Müller, 2021; Varriale *et al.*, 2025). Interestingly, all environmental TBL factors were identified as effect dimensions. For the economic and social TBL dimensions, only one factor was identified as an effect dimension, whereas two factors each were identified as causes. Thus, by classifying causes and effects, we contribute to a better understanding of TBL dimensions.

Our findings indicated that the anticipated environmental sustainability outcomes associated with smart manufacturing were contingent on several other factors. These potentials were identified as effect factors and were mutually influenced by other factors. For instance, by qualifying employees for optimal technology use, waste can be reduced, and materials can be saved. This contributes to the understanding of human-centricity in achieving further sustainability potentials (Ivanov, 2023). Besides reducing resource consumption, smart manufacturing technologies can enhance the cost-effectiveness of production (Avrampou *et al.*, 2019; Souza Cardoso *et al.*, 2020). Cost was identified as an effect factor; therefore, it was affected by other factors. For instance, when processes are optimized, costly errors can be detected early.

Despite the increasing prevalence of autonomous digital technologies, which are often driven by AI, humans are a crucial element in the execution and monitoring of these systems, highlighting the concept of human-centricity as an enabler of further sustainability potentials (Ivanov, 2023; Peruzzini *et al.*, 2024). The social dimension has been comparatively less regarded in previous research on smart manufacturing (Zhang *et al.*, 2023). However, recent research has highlighted the importance of the human factor in smart manufacturing environments (e.g. Rocha *et al.*, 2025; Zahid *et al.*, 2024). Our findings confirm the importance of this dimension. Complementary to recent Industry 5.0 approaches, the human dimension strongly affects other dimensions (Ivanov, 2023). Employee motivation and qualification were identified as cause factors. Targeting employee training offers potentials for other sustainability dimensions, reinforcing the necessity to prioritize qualifications; thus, humans act as decision-makers in technology adoption and implementation (Wei *et al.*, 2024).

Human interoperability serves as the cornerstone for realizing the sustainability benefits of smart manufacturing. Standardizing interfaces, ontologies, and cross-functional communication protocols reduces cognitive load, shortens training cycles, and strengthens collaboration in human-machine teams. As human interoperability improves, decision-making becomes faster and more inclusive, transforming process optimization into environmental savings, along with the economic rationale for smart manufacturing (Flores *et al.*, 2020).

6. Conclusion

This study identified nine key sustainability potentials in accordance with the TBL dimensions through a qualitative study, including a literature review and expert interviews. The interrelationships between these potentials were comprehensively analyzed, and the cause-and-effect factors were determined. These findings indicated that the human factor is crucial for effectively using advanced digital technologies.

6.1 Theoretical contribution and propositions for further research

This study contributes to the literature by demonstrating the interrelationships between the key sustainability potentials of advanced digital manufacturing technologies (Hussain *et al.*, 2024;

Wei *et al.*, 2024). It provides a cross-dimensional perspective on all three TBL dimensions. The findings extend the research that focuses on environmental or economic aspects but not on the interrelationships with social sustainability between all three dimensions (Birkel and Müller, 2021; Ivanov, 2023).

In detail, employee qualifications influenced other key sustainability potentials but was not influenced by other potentials. Hence, we extended the view that employee qualification is a crucial factor in smart manufacturing technologies (Müller *et al.*, 2018; Wei *et al.*, 2024). Further, employee support and employee motivation mutually influenced process optimization. Hence, by extending the findings on social sustainability, we found the human factor is decisive in realizing the potential of smart manufacturing technologies (Frank *et al.*, 2019; Peruzzini *et al.*, 2024). A further analysis of the impact of human operators can be conducted through field studies in smart manufacturing environments (Ivanov, 2023). Tus, we propose the following.

Proposition 1. The impact of employee motivation and qualification acts as an enabler for output and green production techniques by enhancing human interoperability.

Regarding data efficiency, we found that several one-sided connections were influenced by other potentials. Hence, to achieve data efficiency, several other factors act as enablers (Kong *et al.*, 2021). Further, process optimization mutually influenced with data efficiency, highlighting that the extant process must be optimized to enhance data efficiency, and vice versa. Thus, we extended existing research by quantifying this relationship, which has mostly been described qualitatively (Bohnsack *et al.*, 2022; Müller *et al.*, 2024). We suggest investigating the drivers of data efficiency, leading to the following proposition.

Proposition 2. Data handling remains a core activity in smart manufacturing.

Cost reduction and process optimization had multilateral connections almost exclusively. This confirmed that many industrial companies focus on cost efficiency as an enabler and outcome of many decisions in smart manufacturing technologies, thus extending the extant research (Yadav *et al.*, 2020). Further, cost-driven approaches are at the core of many industrial firms' decisions (Peruzzini *et al.*, 2024). Thus, enhancing economic aspects while enabling environmental and social potentials is the second core contribution of this study (Chiarini, 2021; Marcon *et al.*, 2022; Sarkis and Zhu, 2018). Hence, we suggested the validation of our results in the following proposition.

Proposition 3. Cost-driven logics must be regarded as interrelated with further sustainability potentials.

6.2 Managerial implications

In managerial practice, following a specific sustainability potential can lead to the optimization of other potentials. These findings can assist decision-makers in industrial companies to effectively plan their sustainability efforts by considering the human factor. We summarized our recommendations for managers as follows.

First, this study highlights how companies can efficiently achieve their sustainability goals by including advanced technologies in smart manufacturing. Managers should recognize the connection between digital technologies and sustainability. Digital technologies can bring transparency to value chains, which can help improve processes and workplace settings. Simultaneously, addressing multiple potentials can help managers effectively implement advanced digital technologies in their smart manufacturing environments. Although cost-driven logics must be considered, the human factor should not be overlooked.

Second, companies are forced to become more sustainable and use advanced digital technologies. The optimal pursuit of objectives creates synergies between economic, environmental, and social potentials, as highlighted by the results. By emphasizing the interrelationships between the sustainability dimensions and the human operators' importance, the synergies impact each other. Therefore, positive and negative interactions should be considered.

Third, our results demonstrated that digital technologies can enhance employee well-being and improve economic and environmental efficiencies. So far, many companies have prioritized economic potential over social factors; however, our results indicated that both are interrelated. Thus, managers should consider these interrelated potentials and support employee training on the use of advanced technologies to unlock further potential. Employee qualifications unlock several potentials in other TBL dimensions. Hence, they should be developed simultaneously, emphasizing their interrelationships.

6.3 Limitations and future research

Our results highlighted the complex interrelationships between key sustainability potentials when using advanced digital technologies in smart manufacturing as well as the importance of the human factor. Our sample was limited to German manufacturing firms and contained a self-reported cross-sectional dataset. This led to several limitations regarding generalizability. Hence, for future research, we recommend a longitudinal study in additional countries that potentially integrate secondary data, such as performance, supplier, or customer data, to validate our findings. Furthermore, additional decision-making techniques such as the analytic hierarchy process, the technique for order of preference by similarity to ideal solution, and the best-worst method can be utilized to verify the results.

Existing studies on smart manufacturing typically focus on technical aspects. However, our findings indicated that social aspects should not be overlooked. Consequently, research must investigate the effects of employee deployment, establishing a clear link between the employees and the benefits of using technology. As our findings demonstrated that successfully implementing digital technologies in production is contingent on the recognition of interrelationships, it is crucial to analyze the relative importance of individual potentials and substantiate this through further studies, such as additional interviews. Finally, the advantages of digital technologies extend beyond economic considerations. In this study, we orientated ourselves toward a classification in accordance with the TBL. Further classifications according to sustainability definitions other than the TBL could provide an even more comprehensive overall picture to supplement the literature.

(The Appendix follows overleaf)

Appendices

Table A1. Overview of interviews

Interview no.	Management position	Industry	Number of employees (in 2023)	Sales in billion EUR (in 2023)
1	Project Manager Digital Production	Automotive industry	]50.000–100.000]	]50–100]
2	CEO	Electronics industry	]50–250]	]1–10]
3	CEO	Glass industry	]50–250]	>1
4	CEO	Synthetics industry	]50–250]	n/a
5	Expert Smart Factory and Digitalization	Automotive industry	]10.000–50.000]	]1–10]
6	Digitalization Manufacturing Powertrain	Automotive industry	]10.000–50.000]	]10–50]
7	Manager	Medical engineering	]50.000–100.000]	]10–50]
8	Head of Technology Planning	Conglomerate	<100.000	]50–100]
9	Function Owner Vehicle Connectivity	Automotive industry	<100.000	>100
10	Project Manager Smart Factory	Metal industry	]1.000–10.000]	>1
11	Development Engineer Digitalization	Mechanical engineering	]50–250]	n/a
12	Head of Logistics	Automotive industry	<100.000	]50–100]
13	IT Specialist	Automotive industry	<100.000	]10–50]
14	Head of Digital Office	Electronics industry	<100.000	]50–100
15	Head of Brake Systems Production	Automotive industry	<100.000	]50–100]
16	Head of Department	Conglomerate	]10.000–50.000]	]1–10]
17	Senior Data Scientist	Electronics industry	<100.000	]50–100]
18	Managing Director	Building industry	]250–1.000]	<1
19	Plant Manager	Mechanical engineering	]50.000–100.000]	]10–50]
20	Project Manager Smart Manufacturing	Synthetics industry	]1.000–10.000]	<1
21	Plant Manager	Automotive industry	]10.000–50.000]	]1–10]
22	Head of Department	Electronics industry	<100.000	]50–100]
23	Engineer for Digitalization and Automation	Automotive industry	<100.000	>100
24	Head of Production Development	Consumer goods	<100.000	]10–50]
25	Agile Coach Digital Industries Software	Electronics industry	<100.000	]50–100]
26	CEO	Mechanical engineering	]1.000–10.000]	]1–10]
27	Plant Manager	Automotive industry	<100.000	>100
28	Engineer for Automated Driving	Automotive industry	<100.000	>100
29	CEO	Automotive industry	]10.000–50.000]	<1
30	CTO	Electronics industry	n/a	<1
31	Plant Manager	Mechanical engineering	]10.000–50.000]	]1–10]
32	Vice President Information Technology	Automotive industry	<100.000	>100
33	CEO	Metal industry	[0–50]	<1

(*continued*)

Table A1. Continued

Interview no.	Management position	Industry	Number of employees (in 2023)	Sales in billion EUR (in 2023)
34	CEO	Synthetics industry	[0–50]	<1
35	Lead Digitalization	Mechanical engineering	]50–250]	<1
36	CEO	Metal industry	]50–250]	<1
37	CEO	Consumer goods	]50–250]	<1
38	CFO	Medical engineering	]50–250]	<1
39	CEO	Synthetics industry	]50–250]	n/a
40	CEO	Medical engineering	[0–50]	<1
41	CEO	Medical engineering	[0–50]	n/a
42	CEO	Synthetics industry	[50–250]	<1
43	Production Manager	Synthetics industry	]50–250]	n/a
44	Head of Controlling	Medical engineering	]50–250]	n/a

Source(s): Authors' own work

Table A2. Interview guideline

Interview section	Interview questions
Block 1 - digital technologies and sustainability	Which three digital technologies do you already use in your production *(e.g. virtual reality, CPS)*? What potential is associated with this • Economic • Environmental • social What obstacles exist to the (planned) introduction of further digital technologies?
Block 2 - Application in Smart Manufacturing	Please rate the three digital technologies mentioned according to the following criteria (Scale 1–10; 1 = low; 10 = high) • Own competencies *(IT, skilled workers, etc.)* • Market maturity • Degree of implementation *(in the company)* • Unutilized potential *(in the company)* • Environmental sustainability
Block 3 - Person	What is your name, and which company do you currently work for? What is your current position and function in the company?

Source(s): Authors' own work

Table A3.

How much influence has ….. Ax on Ay? **0** No influence **1** Weak influence **2** Moderate influence **3** Strong influence **4** Very strong influence		*Energy conservation*	*Material saving*	*Emission reduction*	*Data efficiency*	*Process optimization*	*Cost reduction*	*Employee motivation*	*Employee qualification*	*Employee support*
		F1	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*	*F8*	*F9*
Energy conservation	*F1*									
Material saving	*F2*									
Emission reduction	*F3*									
Data efficiency	*F4*									
Process optimization	*F5*									
Cost reduction	*F6*									
Employee motivation	*F7*									
Employee qualification	*F8*									
Employee support	*F9*									

Source(s): Authors' own work

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