Received: 1 September 2022 | Revised: 5 March 2023 | Accepted: 8 March 2023

DOI: 10.1002/sres.2947

RESEARCH PAPER

SYSTEMS and BEHAVIORAL RESEARCH SCIENCE

WILEY

Exploring the relationships between Industry 4.0 implementation factors through systems thinking and network analysis

Christian Hoyer[1] | Indra Gunawan[1] | Carmen Haule Reaiche[2]

[1]Business School, University of Adelaide, Adelaide, South Australia, Australia

[2]College of Business, Law and Governance, JCU, Douglas, Queensland, Australia

Correspondence
Christian Hoyer, Adelaide Business School, University of Adelaide, 10 Pulteney Street, Adelaide, South Australia 5000, Australia.
Email: christian.hoyer@adelaide.edu.au

Abstract

Industry 4.0 provides companies with the technological and theoretical means to enhance data-driven decision-making procedures. To facilitate the transformation process, several studies have identified factors that need to be considered when implementing Industry 4.0 on a broader level. However, the dynamic relationship between these factors has yet to be understood to provide companies with the in-depth knowledge needed to effectively manage the transition. The principal aim of our research is therefore to map out the complex relationships between the identified factors, by adapting a novel approach that combines network analysis and causal loop diagrams. Results show that the roles of implementation factors are not static, and what role they play depends on their position in the network, complementing the findings of previous investigations about the drivers of change. Furthermore, our findings indicate that multiple intervention points exist, shedding more light on how to develop effective implementation strategies.

KEYWORDS

causal loop diagram, complexity, Industry 4.0, network analysis, systems thinking

1 | INTRODUCTION

In early 2000, Mendelson (2000) discussed the increasing importance of corporations being able to process data collected from internal and external environments, allowing them to improve their decision-making and their reaction time with respect to internal and external changes. Eleven years later, Industry 4.0 was born—a worldwide recognised concept that builds on that very principle (Kagermann et al., 2013; Lasi et al., 2014). Industry 4.0 is often associated with a number of key technologies such as artificial intelligence (AI), cyber-physical systems (CPS) and big data (Dalenogare et al., 2018; Raj et al., 2019). However, at its core, Industry 4.0 is a concept that promises to transform entire business models and the way goods are developed, produced and distributed. The aforementioned technologies are therefore not what constitutes Industry 4.0, but what allows the essential concept of Industry 4.0 to be put into practice (Calabrese et al., 2021; Castelo-Branco et al., 2019; Da Silva et al., 2020). This concept is about connecting as many entities as possible, such as machines and sensors, within and beyond an organisation to process and channel the resulting stream of information to augment the decision-making capabilities of workers and entire factories, including their customers and suppliers. Consequently, Industry 4.0-related technologies are needed to connect devices, to process information and to increase the pace and the accuracy of companies' decision-making processes both on micro and macro levels (Bai et al., 2020; Kagermann et al., 2013; Vaidya et al., 2018). Given this upcoming paradigm shift, it is no surprise that governments and corporations around the world have started to invest in the concept in order to cement and even further extend their competitive advantage (Lee et al., 2018; Lin et al., 2018). However, previous research has established that the transition towards Industry 4.0 is complex and that companies are still struggling with implementation (Hirsch-Kreinsen, 2016; Raj et al., 2019; Staufen AG, 2019). As a result, there is a growing body of literature that tries to identify potential implementation barriers and ways to overcome them instead of solely focusing on the potential of Industry 4.0 technologies (Müller et al., 2018; Stentoft et al., 2021).

In the beginning, Industry 4.0 research was predominantly geared towards the special characteristics of the manufacturing sector, but then more and more studies started discussing its usefulness in other areas. This research trend can also be observed for other manufacturing philosophies, such as lean manufacturing (Buer et al., 2018; Distelhorst et al., 2017; Santos et al., 2015). Therefore, since its inception in 2011, the scientific field of Industry 4.0 has been in constant motion. Besides becoming more diverse with respect to its usability beyond the manufacturing sector, the field has also moved away from a purely technological approach to solve Industry 4.0 implementation-related issues, towards an approach that considers other factors as equally important. Thus, instead of simply assessing which Industry 4.0 technologies can help companies to become more efficient and flexible, a number of studies have brought forward the idea that a successful implementation of the Industry 4.0 concept and technologies depends on a number of factors, such as how companies train their workforce and in which ways they perceive Industry 4.0 as beneficial (Cimini et al., 2017; Cugno et al., 2021; Raj et al., 2019). Initially, most of these implementation factors were discussed in isolation, without considering how their causal relationship to other factors might influence the overall implementation process. However, the field has recently started to shift again, with more studies indicating that certain implementation factors exert influence on other factors (Bakhtari et al., 2021). For example, the findings of Cimini et al. (2021) demonstrated that the introduction of new Industry 4.0 technologies can have an impact on how companies organise and train their workforce. In a similar vein, Büchi et al. (2020) showed how more openness, with respect to how companies use their IT infrastructure, improves the way companies seize opportunities.

Findings like these illustrate the risks involved in not recognising the underlying dynamic relationship between Industry 4.0 implementation factors. Recommending corporations to focus on a given set of factors without providing them with a deeper grasp of how these factors interact with others may lead to false expectations and ineffective or incomplete implementation strategies (Bakhtari et al., 2021; Calabrese et al., 2021). Although previous investigations have acknowledged this issue, research has yet to systemically study the complexity that arises from the interdisciplinary nature of the industry research field, 4.0, as well as the multicausality of the implementation factors (Hoyer et al., 2020). Hence, this study sets out to obtain a more comprehensive understanding of the multicausal relationship between previously identified and well-studied Industry 4.0 implementation factors. Furthermore, we seek to explore how the roles and the individual importance of factors change when considered as part of a larger network of implementation factors instead of examined individually. This systemic approach allows us to further explore the dynamics that take place within the complex system Industry 4.0 (Da Xu, 2020; Lin, 2012; Medoh & Telukdarie, 2022).

To account for the interdisciplinary DNA of Industry 4.0 and its implementation, we apply a novel approach of systems thinking by developing a causal loop diagram (CLD) based on the findings of our previously published systematic literature review and semi-structured interviews that we conducted with Industry 4.0 experts to learn more about the relationship between the factors which emerged as critical for Industry 4.0. We then analyse the characteristics of the CLD with the help of network theory to learn more about the characteristics of the network and the roles of the implementation factors within that network. This study stands out with its unique combination of systematic review, expert interviews, practitioner surveys, system dynamics and network theory to gain a deeper understanding of Industry 4.0 implementation complexities. The innovative utilisation of these methods and data sources offers a comprehensive and multifaceted perspective on the topic.

The remaining part of this study is organised as follows: Section 2 further discusses the application of systems thinking in the field of Industry 4.0. Our research approach, including the acquisition of data, is outlined in Section 3. Along with the numerical results from our network analysis, we present the final CLD, including identified feedback loops, in Section 4. We then continue discussing the key findings of the study in Section 5, before we conclude the study and outline suggestions for future research in Section 6.

2 | SYSTEMS THINKING AND THE IMPLEMENTATION OF INDUSTRY 4.0

The existing body of knowledge on Industry 4.0 suggests that the reasons for its complexity are manifold. From a technological perspective, the concept of Industry 4.0 requires organisations to make decisions based on an increasing amount of data shared and processed by a growing number of smart devices (Hoyer et al., 2020; Kagermann et al., 2013; Sjödin et al., 2018). However, as advocated by Whysall et al. (2019) and Freixanet et al. (2020), this continuing technological evolution creates a gap between what technologies can achieve and the competencies required by employees to work effectively in such an evolving environment, adding another layer of complexity to the implementation of Industry 4.0. What is more, Oliveira et al. (2020) argued that this internal perspective of complexity with respect to adapting Industry 4.0 must be extended, as the implementation process interacts with external factors such as economic growth and human capital. Hou et al. (2020) argued that these different elements of complexity inherent to Industry 4.0 must interact seamlessly to achieve a successful implementation process. In a similar vein, Da Xu (2020) views Industry 4.0 through the systems of systems lens, showing that there are multiple layer of complexity interacting within the system of Industry 4.0. One of the complexities presented in his study refers to the integration of Industry 4.0, which includes the relationship between the internal structures of an organisation and the external environment (Da Xu, 2020; Hirsch et al., 2007). This particular perspective has been further analysed by Hoyer et al. (2020), who explored the different factors that constitute the integration complexity. The results of their analysis show that the complex relationship between the identified internal and external factors needs to be explored further by using the tools of systems dynamics (Hoyer et al., 2020).

Although numerous approaches exist to address, evaluate and comprehend complexity, all of the authors mentioned above regard systems thinking as the most promising among them in the context of Industry 4.0. Due to its flexibility, systems thinking has also been employed in other scientific disciplines such as neurosciences, education and management (Azar, 2012; Jonker & Karapetrovic, 2004; Mahaffy et al., 2019; Uleman et al., 2021). As pointed out by McGlashan et al. (2016), systems science offers a wide range of qualitative techniques to capture the shared understanding of a given topic and a variety of quantitative methods to generate simulations (Berry et al., 2018). Similarly, Kenzie et al. (2018) referred to systems thinking as an appropriate tool for the synthesis of information gathered from different stakeholders and disciplines with the goal to develop a model that reflects their shared understanding of a complex system. This model can also help to identify gaps in theoretical and empirical knowledge that need to be addressed in future research (Cabrera et al., 2008; Ghaffarzadegan et al., 2011; Jones et al., 2011).

One specific and validated systems thinking tool that helps to visualise the synthesis of the shared understanding of a complex phenomenon is the CLD (Roberts, 1978; Saurin et al., 2013; Spector et al., 2001). In the present study, we use this tool to map out the causal relationship between Industry 4.0 implementation factors based on the shared understanding of Industry 4.0 experts with various backgrounds. More specifically, we aim to develop a visual grounded model that illustrates the dynamic relationship between Industry 4.0 implementation factors, by showing the direction of each relationship and whether a given factor either exerts a positive or negative influence on another factor. Both polarity and the direction of a causal relationship are based on the statements of our interview participants. This approach, to our knowledge, has never been taken before to explain the dynamic process of implementing Industry 4.0 with the goal to help managers and practitioners to understand and manage the complex nature of implementing Industry 4.0.

Therefore, to construct the CLD, we conduct semi-structured interviews with Industry 4.0 experts with various Industry 4.0 backgrounds. In that context, we focus on interview participants who are also engaged with Industry 4.0-related activities such as working on Industry 4.0 initiatives. In a similar vein, our previously conducted systematic review drew from a wide spectrum of different Industry 4.0 studies, reflecting what is known about the implementation factors according to the existing body of Industry 4.0 literature. Combined with the findings of Da Xu (2020), these factors both account for the internal environment of corporations that want to implement Industry 40 and the external environment that has an impact on the transitional process. Consequently, within the complex system Industry 4.0, this study focuses on the implementation process that is defined by the complex dynamic between the previously identified implementation factors.

3 | METHODS

To gain a better understanding of the relationships between the previously investigated implementation factors, we developed a three-stage research approach. First, based on the results of our systematic literature review and the findings of our Industry 4.0 survey of practitioners, we conducted interviews with Industry 4.0

experts to learn more about the factors themselves and the relationship between them. Second, based on their explanations, we used the program Vensim PLE 8.2.1 to visualise the connections between the factors. Finally, we identified causal loops and used NetworkX for Python and Gephi 0.9.2 to analyse the overall structure of the CLD, which was interpreted as a directed network based on the studies of Uleman et al. (2021) and McGlashan et al. (2016).

3.1 | Expert interviews

In our semi-structured interviews, we asked participants to discuss the Industry 4.0 implementation factors that they consider crucial. After asking them why they think these factors are important, we asked them if there were any other factors they would like to discuss before we proceeded with asking them about the relationship between the factors they mentioned (Adams, 2015). Following the recommendation of McIntosh and Morse (2015), every question was asked in the same way and in the depicted order to ensure replicability between interviews.

Due to the multifaceted nature of Industry 4.0, our goal was to interview experts with a wide spectrum of Industry 4.0 knowledge and experience (Bartodziej, 2017; Bogner et al., 2009; Lee et al., 2018). Consequently, the study was not limited to participants with an industry background (Luthra & Mangla, 2018; Raman & Rathakrishnan, 2019; Sung, 2018). Furthermore, we specifically looked for participants with more than 5 years of experience with Industry 4.0 projects in a leading position with the assumption that they would have solved problems that were not only limited to technological issues. Third, we prioritised participants engaged with Industry 4.0 beyond their profession. This includes being part of Industry 4.0 committees, initiatives and associations.

We used the database of the Hanover Industrial Fair to find suitable candidates, due to its significance in the field of Industry 4.0, as well as other databases that provided publicly accessible information, such as the webpage 'Plattform Industrie 4.0'. We selected and contacted 30 candidates after cross-checking their profiles with the help of additional publicly available information; 16 agreed to an interview. Following the recommendations of Symon and Cassell (2012), we considered this number sufficient, taking into account that we had two additional sources of data with which we could compare the results. At the time of the interviews, nine participants worked for a corporation, four worked for an Industry 4.0-related initiative and three worked as university researchers. All of our participants fulfilled all of our criteria.

Finally, we employed the findings of our systematic literature review to classify the implementation factors in our thematic analysis and added new factors to the list when a factor that was discussed by one or more participants did not match the description of our systematic synthesis.

3.2 | CLD

To draw the causal connection between the identified implementation factors, we used the software tool Vensim. These connections are represented by directed arrows, whereby solid lines show positive causal relationships and dotted lines show negative causal relationships. A positive causal connection indicates that if a causal factor, 'A', moves in one direction, the factor it is connected to, 'B', moves in the same direction. In contrast, if a connection is negative, an increase of A results in a decrease of B (Kiani et al., 2009; Roxas et al., 2019; Sahin et al., 2020; Uleman et al., 2021).

After drawing the connections, we continued with the identification of feedback loops. These feedback loops are indicators for a sequence of change that can further amplify the original momentum (reinforcing feedback loops) or push back against it (balancing feedback loops). Reinforcing and balancing sequences are initiated by introducing change to one factor whereby the sequences of change can go through an unlimited number of factors (Kiani et al., 2009).

We distinguished between internal and external implementation factors to account for the fact that some of the identified implementation factors are under the direct control of corporations that want to implement Industry 4.0, whereas other factors such as 'Political Support' cannot be directly influenced by corporations (Hoyer et al., 2020).

3.3 | Network analysis

In 2016, McGlashan et al. (2016) demonstrated how quantitative network analysis can be used to examine the structure of a CLD to learn more about its properties and the underlying dynamics between the variables in the system. This approach was then adopted and further refined by Uleman et al. (2021), who added additional steps to the analysis to study the robustness of their CLD. For the present study, we build on both approaches to analyse the relationship between the previously identified and examined Industry 4.0 implementation factors. In the following section, we describe the measures and techniques used to analyse the CLD and test its robustness.

3.3.1 | Structural metrics

Structural metrics are used to describe the overall topology of the network and can help to better understand how change in one factor might cause change in other factors (Hansen et al., 2011; McGlashan et al., 2016).

'Network Density' (ND) is a measure that shows the fractions of connection between the 'Actual Number of Implementation Factors' in the CLD (AC) relative to the 'Maximum Possible Number of Connections Between the Factors' (PC), where n represents the number of factors. The higher the density, in other words, the closer the actual number of connections between factors gets to the theoretical maximum number of possible connections, the higher the chance that introducing change to one factor will cause change in other parts of the network (McGlashan et al., 2016; Metcalf & Casey, 2016).

$$PC = n\frac{n-1}{2}; ND = \frac{AC}{DC}. \tag{1}$$

The 'Degree Distributions' simply refers to the number of directed causal connections leading to or exiting a given factor. The degree distribution is, therefore, divided into in-degree distribution and out-degree distribution and shows the level of involvement of a given factor in the network. As argued by McGlashan et al. (2016), this means that factors with a high in-degree and/or out-degree can serve as important hubs in the network from which change can be initiated due to their interconnectedness.

The 'Average Path Length' (L) depicts the smallest number of connections between any given implementation factors in the network. The distance d_{ij} between two chosen factors i and j includes all directed connection on the shortest path in the network between these two factors. If there is no connection between a pair of factors, then $d_{ij} = N$ (Xiong, 2012). The average path length is a strong indicator of how efficiently change spreads from one factor to the other (McGlashan et al., 2016).

$$L = \frac{1}{N(N-1)} \sum\nolimits_{ij=1,\ i \neq j}^{N} {}^{d_{ij}}. \tag{2}$$

'Network Modularity' is a measure that helps to identify clusters in the network and shows their level of segregation. Therefore, if a given network exhibits a high level of modularity, clusters should be targeted individually to introduce change, and factors with high betweenness centrality (BC) should be targeted to spill over change from one cluster to another (McGlashan et al., 2016). To calculate the modularity of the CLD, we used the algorithm proposed by Blondel et al. (2008), which is based on the approach developed by Leicht and Newman (2008). In a partition of a directed network, the modularity Q_d is defined as follows:

$$Q_d = \frac{1}{m} \sum_{i,j} \left[A_{ij} - \frac{d_i^{in} d_j^{out}}{m} \right] \delta(c_i, c_j). \tag{3}$$

A_{ij} stands for the existing connection between two chosen factors i and j, whereas d_i^{in} and d_j^{out} stand for the in- and out-degree of i and j, respectively. The variable m represents the number of connections within the network, and c_i is defined as the cluster the factor i belongs to (Blondel et al., 2008; Leicht & Newman, 2008).

3.3.2 | Network centrality measures

Centrality measures can reveal the importance of each factor in the network. However, depending on the centrality measure applied, importance has a different meaning. Following the approaches of McGlashan et al. (2016) and Uleman et al. (2021), we focused on BC and 'closeness centrality' (CC) to identify factors that either lie on and/or have the shortest paths in the network.

The importance of high BC factors arises from their potential to act as a bridge between other factors and clusters in the network (Ahmed, 2017; Uleman et al., 2021). It shows how many times a factor can be found on the shortest path between other factor in the network (Kolli & Khajeheian, 2020; McGlashan et al., 2016). The BC for a chosen factor v is calculated as followed:

$$BC_v = \frac{1}{(N-1)(N-2)} \sum_{s,t} \frac{\sigma(s,t|v)}{\sigma(s,t)}. \tag{4}$$

N represents the total number implementation factors within the network, whereas $\sigma(s,t)$ is defined as the total number of shortest paths between two chosen factors s and t. The expression $\sigma(s,t|v)$ stands for the number of shortest paths going through factor v (Kolli & Khajeheian, 2020; Uleman et al., 2021).

CC measures how close each factor is to other factors in the network. It can therefore help to identify factors that influence the entire network at the highest speed. In that context, Uleman et al. (2021) and McGlashan et al. (2016) recommended using this measure to identify efficient spreaders of information that can be used to initiate potential interventions (Ahmed, 2017; Kolli & Khajeheian, 2020). The CC of a chosen variable v is calculaqted as follows:

$$CC_v = (n-1)\frac{1}{\sum_{u=1}^{n-1} d(v,u)}. \quad (5)$$

The number of reachable factors in the network is represented by $(n-1)$, whereas $d(v,u)$ is defined as the distance of the shortest path from a chosen factor v to u. After calculating the shortest paths between all the factors in the network, a score is assigned to each implementation factor with respect to the number of its shortest paths (Kolli & Khajeheian, 2020).

3.3.3 | Robustness test

To test the structural robustness of the centrality measures, we adopted the approach that was recently proposed by Uleman et al. (2021). In their study, they created mutated CLDs by introducing five random mutations to the connections between the variables in the network. These mutations were equiprobably implemented by rewiring the connection between a random set of factors and by randomly adding new connections to the adjacency matrix of the CLD. Similarly, existing connections can be randomly removed from the CLD. For example, instead of A having a directed connection to B, the connection can be either removed entirely from the CLD or changed to a new connection where A directly connects to C. Furthermore, a not already existing connection between two factors can be added to the CLD.

Following this method, we created 300 mutated CLDs by introducing five random changes to the final adjacency matrix of the CLD, as described above, in order to test the robustness of the centrality measures to random perturbations. This test was done by calculating the centrality measures of each of the mutated CLDs. These measures were then used to calculate the interquartile ranges of each factor's CC and BC to construct error bars (Uleman et al., 2021).

4 | RESULTS

Table 1 portrays the factor relationships that emerged from the analysis of the qualitative data obtained from a set of 16 interviews. Out of the 13 initial factors that have been mentioned as part of a relationship with other factors, 10 factors have been further divided into subthemes to illustrate which specific facet of a given factor was addressed by the interviewees.

Overall, we consider the inclusion of 25 factors into the CLD appropriate, highlighting the 65 existing connections between them (Figure 1). As discussed in the previous section, we divided the CLD into two clusters based on the findings from the systematic literature review by Hoyer et al. (2020).

4.1 | CLD structure

The density of the final network is 0.1, meaning that the network contains 10% of all the possible edges if all the nodes in the network were completely interconnected. As pointed out by Uleman et al. (2021), this sparse network topology demands a more strategic approach when it comes to identifying and using potential leverage-critical points in the system. This notion is supported by McGlashan et al. (2016) who argued that compared to dense networks, sparse networks are more likely to require multiple points of intervention in order to introduce change in the overall system. Sparse networks are more vulnerable to this problem, as with decreasing density, the number of alternative routes from one node to another decreases accordingly. With respect to the implementation of Industry 4.0, this could mean that not taking into consideration certain key factors can lead to a more challenging and less efficient transition towards Industry 4.0.

The observed average path length in the CLD is 3.518, meaning that the average causal distance between two factors is 3.518 connections. Consequently, almost all implementation factors are interconnected within a short number of edges, indicating a smooth flow of information despite the low density.

We calculated a modularity of 0.332, indicating that different clusters within the network exist. Upon further analysis, we identified three clusters, which are shown in Figure 2. Interestingly, while there are two main clusters that reflect the exact division between internal and external implementation factors, a third cluster was identified. This cluster builds a subcluster within the internal cluster and seems to comprise implementation factors that are more relevant for the operational aspects of Industry 4.0 such as 'Lean Performance' and 'Improving Productivity and Efficiency'.

The degree distributions and the individual in- and out-degree values are shown in Figure 3. In both cases, the degrees range from 0 to 9 with most factors having a degree of 2. Similarly, in both cases, only a few larger hubs can be observed, leading to a heavy-tailed degree distribution (Kolli & Khajeheian, 2020; Metcalf & Casey, 2016). Moreover, only one factor was found to not have an impact on at least one other factor. As stated by McGlashan et al. (2016), factors with an out-degree of 0 are less likely to occur than factors with an in-degree of 0, as shown in the presented CLD.

TABLE 1 Implementation factors integrated into the CLD.

Subthemes	*n*	Subthemes	*n*
1. Political Support	42	**7. Perceived Implementation Benefits**	60
		7.1. New Business Models	
2.1. IT Standardisation	32	7.2. Need for New Technologies	
2.2. Data Ownership and Privacy Rules		7.3. Improving Productivity and Efficiency	
2.3. Broad Band and 5G Expansion			
		8. Strategic Consideration	27
3. Corporate and Institutional Cooperation	57		
3.1. Availability of Cooperation Platforms		**9. IT-Infrastructure Maturity**	19
3.2. Inter-Institutional Cooperation			
		10. Internal Knowledge and Skills Development	17
4. Cost Assessment and Available Funding Options	21	10.1. Industry 4.0-Related Skill Promotion	
4.1. Cost of Transition		10.2. Internal HR Capacity	
4.2. Financial Support and Initiatives			
4.3. Financial Support for I.4.0. Initiatives		**11. Lean Manufacturing Experience**	6
		11.1. Lean Performance	
5. Available Knowledge and Education	39	11.2. Lean Experience	
5.1. Availability of Skilled Workers			
5.2. Education System		**12. Occupational Health and Safety**	4
5.3. Availability of Industry 4.0 Knowledge		12.1. Safety and Job Loss Anxiety	
6. Pressure to Adapt	19	**13. Attitude and Mindset**	15
6.1. Market Pressure to Adapt Industry 4.0		13.1. Openness to Change and Cooperation	
6.2. Customer Demand for Current		13.2. Scepticism Towards Change	

4.2 | Variable centrality

The network analysis returned the highest BC for the factor 'IT-Infrastructure Maturity' (Figure 4). Therefore, it lies directly on the shortest path that connects various factors with each other (Hansen et al., 2011; Kolli & Khajeheian, 2020; Layton & Watters, 2015). A closer look reveals that the factor seems to act as a bridge between the inner workings of corporations and the factors that have a more strategic component, such as the creation of new business models. Therefore, despite its comparatively low individual reference score (Table 1) in combination with other factors, the analysis shows that its importance changes when the implementation of Industry 4.0 is considered as a complex system. In fact, the connection between 'IT-Infrastructure Maturity' and 'Perceived Implementation Benefits' was found to be the connection that Industry 4.0 experts most referred to, indicating that the execution of implementation plans is connected to the capabilities of the local infrastructure.

In the same vein, 'Inter-Institutional Cooperation' may have a similar role, acting as a junction between internal and external implementation factors. Its high BC indicates that in order to have a strong impact on corporations from the outside and vice versa, 'Inter-Institutional Cooperation' may offer the most efficient paths to achieve these goals. The fact that this factor also has the highest CC is one of the most striking results found, as it strengthens the idea that cooperation represents a crucial platform through which both corporations and outside parties can address key issues related to Industry 4.0 across internal and external boundaries. Consequently, the factor not only sits on a number of shortest paths between external and internal factors, but it also shows that 'Inter-Institutional Cooperation' is very close to all other factors in the network, making it crucial for implementation strategies. According to network theory, this, on average, short distance to other factors in the network gives cooperation a position from which information spreads quickly (McKnight, 2014).

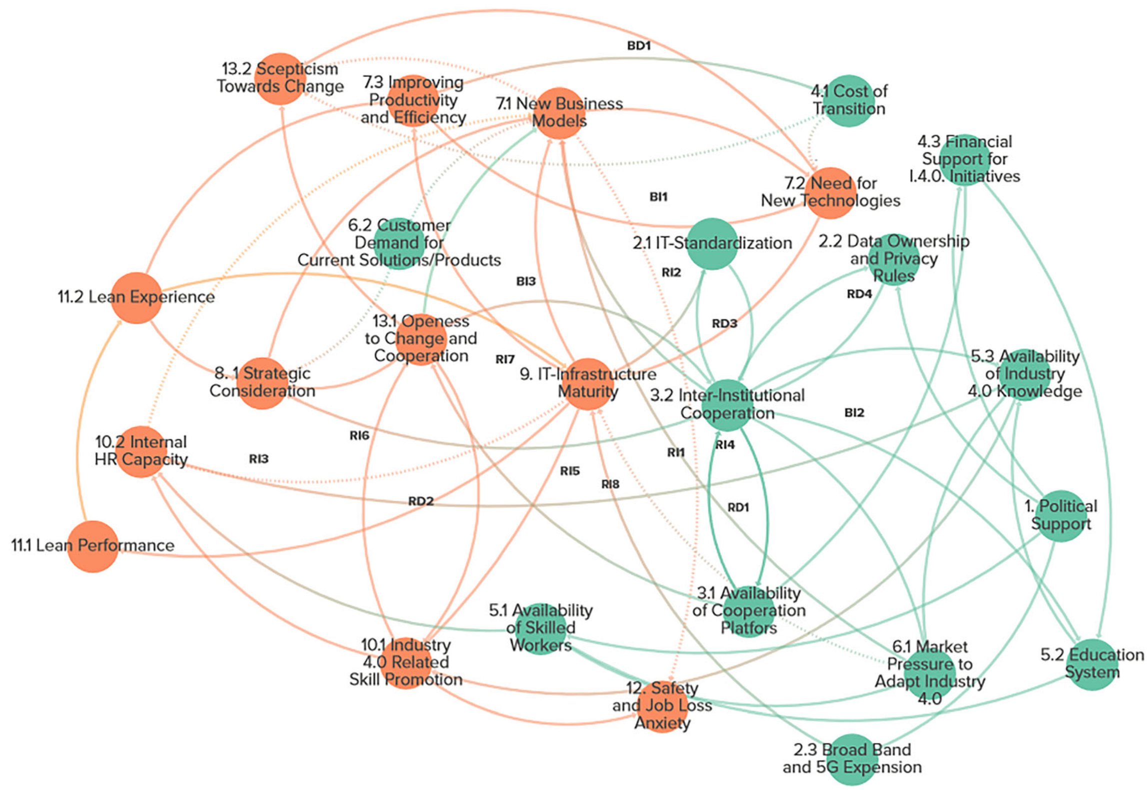

FIGURE 1 Industry 4.0 implementation factors CLD: internal factors are in green, and external factors are in orange. [Colour figure can be viewed at wileyonlinelibrary.com]

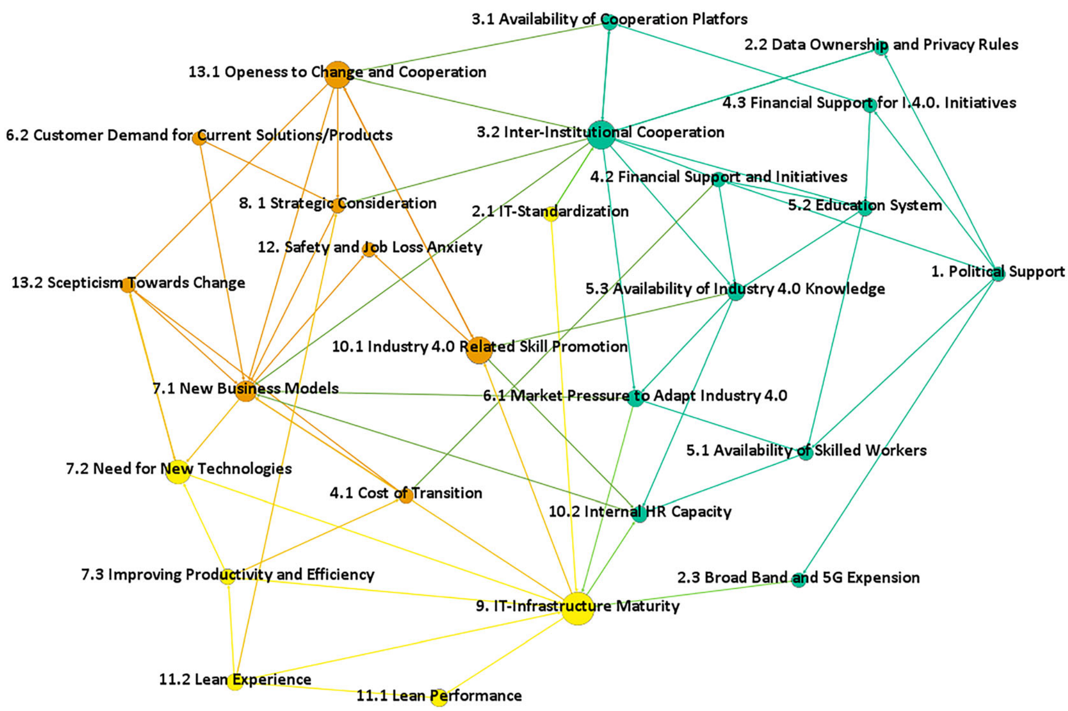

FIGURE 2 Network Modularity and Centrality Analysis (each cluster is shown in a different colour). [Colour figure can be viewed at wileyonlinelibrary.com]

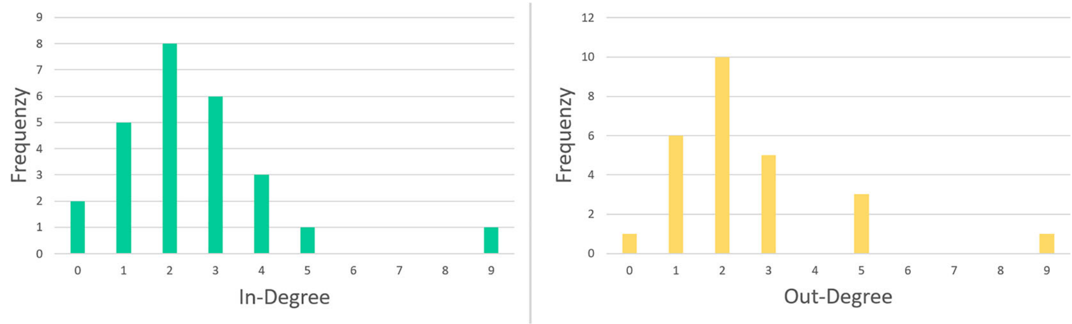

FIGURE 3 Distribution of factor in- and out-degree. [Colour figure can be viewed at wileyonlinelibrary.com]

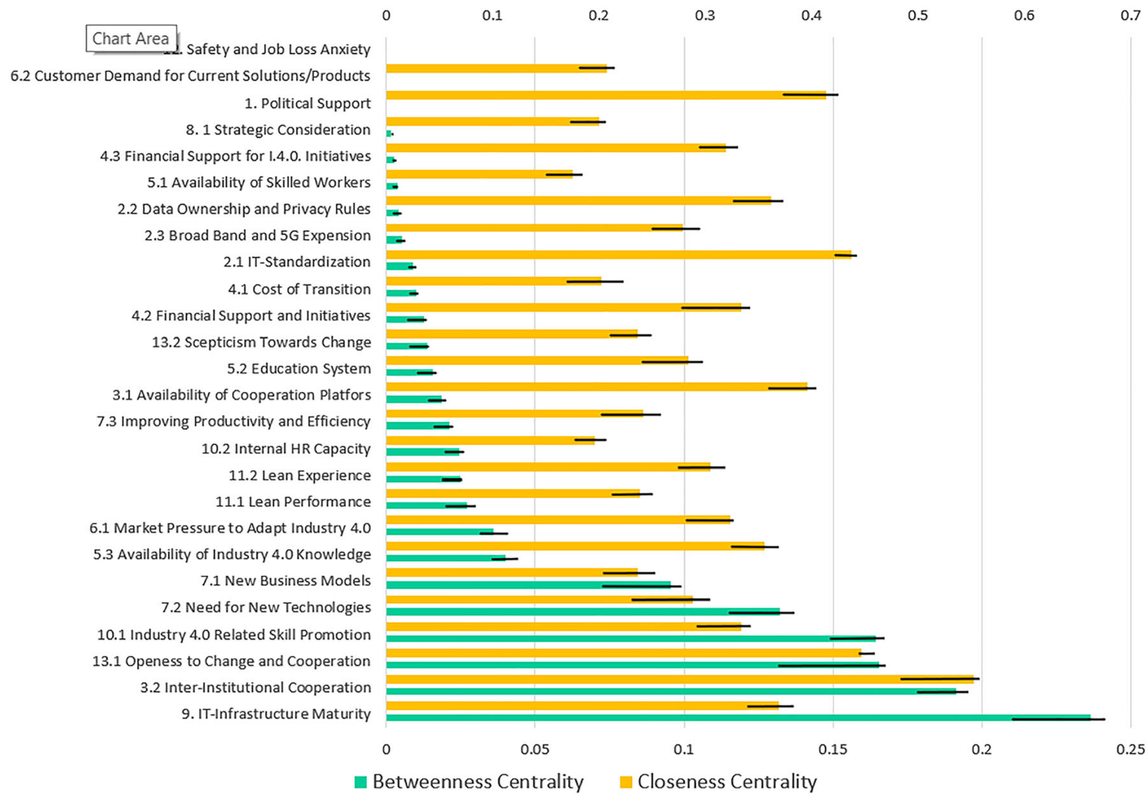

FIGURE 4 Factor variability including interquartile range of the mutated CLDs (represented by black error bars). [Colour figure can be viewed at wileyonlinelibrary.com]

Besides cooperation, the factors 'Openness to Change', 'Political Support' and 'IT Standardisation' emerged from the analysis as key factors with high CC, indicating on the one hand that from a corporation's perspective, incorporating measures that encourage an open mindset towards Industry 4.0 may be the strongest leverage point in terms of having an impact on as many implementation factors as possible.

Elaborating now on the factor 'Political Support', the results show that despite its high CC, it has a BC of 0, indicating that the factor can have a significant impact on the system, while changes in the system do not impact the factor itself. Although it is a widely held view that political institutions play an important role when it comes to Industry 4.0, our findings may offer an additional explanation as to why the support of political institutions is crucial. Its exogenous nature combined with a high CC suggests that the factor has many and short connections to other influential factors in the network (Metcalf & Casey, 2016; Uleman et al., 2021).

To test the robustness of the centrality measures, we included the interquartile range of the mutated CLDs for each factor in Figure 4, showing that the error bars only rarely overlap, suggesting that small errors in connecting the implementation factors will not lead to different qualitative interpretations (Uleman et al., 2021).

TABLE 2 Implementation factors integrated into the CLD.

Loop	1st variable	2nd variable	3rd variable	4th variable
RD1	3.1. Availability of Cooperation Platforms	3.2. Inter-Institutional Cooperation	-	-
RD2	13.1. Openness to Change and Cooperation	10.1. Industry 4.0-Related Skill Promotion	-	-
RD3	3.2. Inter-Institutional Cooperation	2.1. IT Standardisation	-	-
RD4	3.2. Inter-Institutional Cooperation	2.2. Data Ownership and Privacy Rules	-	-
RI1	3.2. Inter-Institutional Cooperation	3.1. Availability of Cooperation Platforms	13.1. Openness to Change and Cooperation	-
RI2	7.1. New Business Models	7.2. Need for New Technologies	9. IT-Infrastructure Maturity	-
RI3	9. IT-Infrastructure Maturity	11.1. Lean Performance	11.2. Lean Experience	-
RI4	9. IT-Infrastructure Maturity	7.2. Need for New Technologies	7.3. Improving Productivity and Efficiency	-
RI5	3.2. Inter-Institutional Cooperation	5.3. Availability of Industry 4.0 Knowledge	10.1. Industry 4.0-Related Skill Promotion	13.1. Openness to Change and Cooperation
RI6	7.3. Improving Productivity and Efficiency	7.2. Need for New Technologies	9. IT-Infrastructure Maturity	11.1. Lean Performance
RI7	7.1. New Business Models	7.2. Need for New Technologies	9. IT-Infrastructure Maturity	10.1. Industry 4.0-Related Skill Promotion
RI8	6.1. Market Pressure to Adapt Industry 4.0	9. IT-Infrastructure Maturity	10.1. Industry 4.0-Related Skill Promotion	13.1. Openness to Change and Cooperation
BI1	13.2. Scepticism Towards Change	7.2. Need for New Technologies	7.1. New Business Models	-
BI2	4.1. Cost of Transition	7.2. Need for New Technologies	9. IT-Infrastructure Maturity	7.3. Improving Productivity and Efficiency
BI3	7.1. New Business Models	7.2. Need for New Technologies	9. IT-Infrastructure Maturity	10.2. Internal HR Capacity

4.3 | Feedback loops

As shown in Table 2, both direct and indirect balancing (BD and BID) as well as reinforcing (RD and RID) feedback loops are present in the CLD (see Figure 1). Direct feedback loops are defined as feedback loops between two variables whereas indirect feedback loops include more than two variables (Uleman et al., 2021). Before we extend our discussion on the overall findings, the following part of the paper describes different feedback loops considered important across feedback loops and intersections identified in the CLD.

4.3.1 | Within scale feedback loops

We define within scale feedback loops as loops that take place within the cluster of internal or external implementation factors (Uleman et al., 2021). For example, as Figure 5 shows, the development of new business models not only increases the need for new technologies but also the capabilities of a corporation's IT infrastructure resulting from introducing these new technologies—a process that exclusively happens within the boundaries of an organisation. Meanwhile, the feedback loop also proposes that an improved infrastructure gives organisations more opportunities to develop new business models. Similar to several implementation studies, the particular importance of new business models and optimisation opportunities was a recurrent theme among the interviewed group of Industry 4.0 experts.

4.3.2 | Cross-scale feedback loops

RI5 shows a causal chain between internal and external implementation factors (see Figure 6). More specifically, the internal promotion of skills of an organisation could

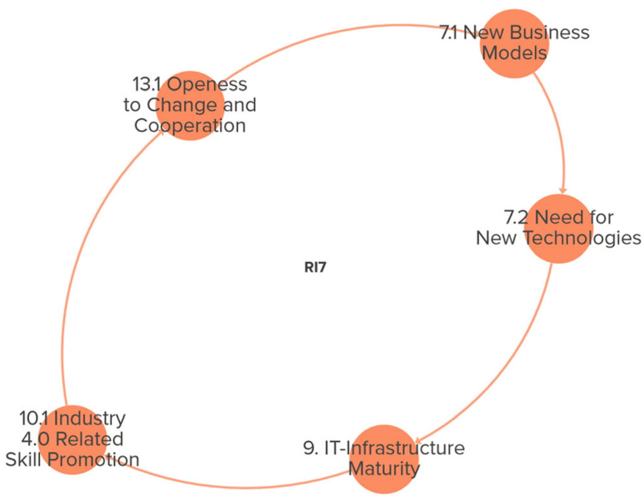

FIGURE 5 Example of a within scale loop (RI7). [Colour figure can be viewed at wileyonlinelibrary.com]

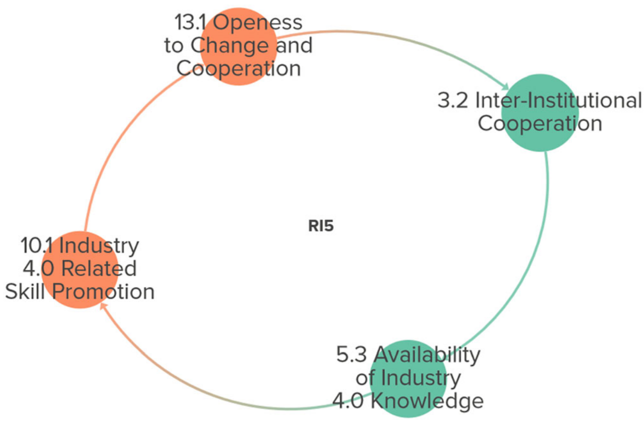

FIGURE 6 Example of a cross-scale loop (RI5). [Colour figure can be viewed at wileyonlinelibrary.com]

benefit from the availability of accessible Industry 4.0 knowledge. While this is an expected and well-documented relationship, a surprising finding is that organisations seem to have an impact on the availability of skilled workers that goes beyond a simple supply and demand logic—cooperation and collaboration also seem to play a crucial role.

4.3.3 | Loop intersections

Starting with Inter-Institutional Cooperation, Figure 7 summarises all the factors and feedback loops that are connected it. What stands out is that cooperation seems to take a key role when it comes to the standardisation of IT solutions and communication (RD3 and RD4). The interviewed experts argued that the lack of existing IT standards forces companies to invest more time and resources into identifying IT solutions that are compatible with the infrastructures of their customers and suppliers. They further argued that cooperation, even with direct competitors, seems inevitable as the most optimal solution always involves players outside of an organisation.

In contrast to 'Inter-Institutional Cooperation', 'IT-Infrastructure Maturity' (Figure 8) mainly exerts its influence on the internal part of the system and is only connected to a small number of cross-scale loops such as RI8. Nonetheless, as illustrated earlier, its overall impact on the network is strong, indicating that internal implementation processes and endeavours in particular are directly connected to the maturity and capability of the company's infrastructure.

5 | DISCUSSION

Recent studies have come to the conclusion that a systematic approach to Industry 4.0 is inevitable (Freixanet et al., 2020; Hou et al., 2020; Oliveira et al., 2020). For example, Neumann et al. (2021) argued that because companies tend to enter unsafe states when they are engaged with process innovation, unanticipated system risks are even more likely to occur when approaching Industry 4.0 through isolated steps. This accords with our findings that shed new light on how the implementation factors influence each other within the system. For instance, in Figure 9, it can be seen that developing business models (Factor 7.1) may also lead to job loss anxiety among employees (Factor 12). A sole focus on developing new business model, without considering the impact on other factors such as 'Internal Promotion of Industry 4.0 Skills', could therefore lead to a stronger resistance against change and to lower productivity, as suggested by our interviews and the findings of Saniuk et al. (2021).

The density of the presented CLD is low, indicating that the implementation of Industry 4.0 through one factor will likely not affect as many other factors as in dense networks. Therefore, to introduce change in the system effectively, multiple leverage points must be identified (Hansen et al., 2011; Kolli & Khajeheian, 2020). This further strengthens the idea that comprehensive approaches should be chosen over single projects, despite seeming more practical on the surface, as illustrated by the most recent German Industry 4.0 Index (Staufen AG, 2019).

Our modularity test showed that the network is divided, not only confirming our initial separation between external and internal implementation factors but also suggesting that a third cluster may exist. This third cluster is consistent with the growing body of

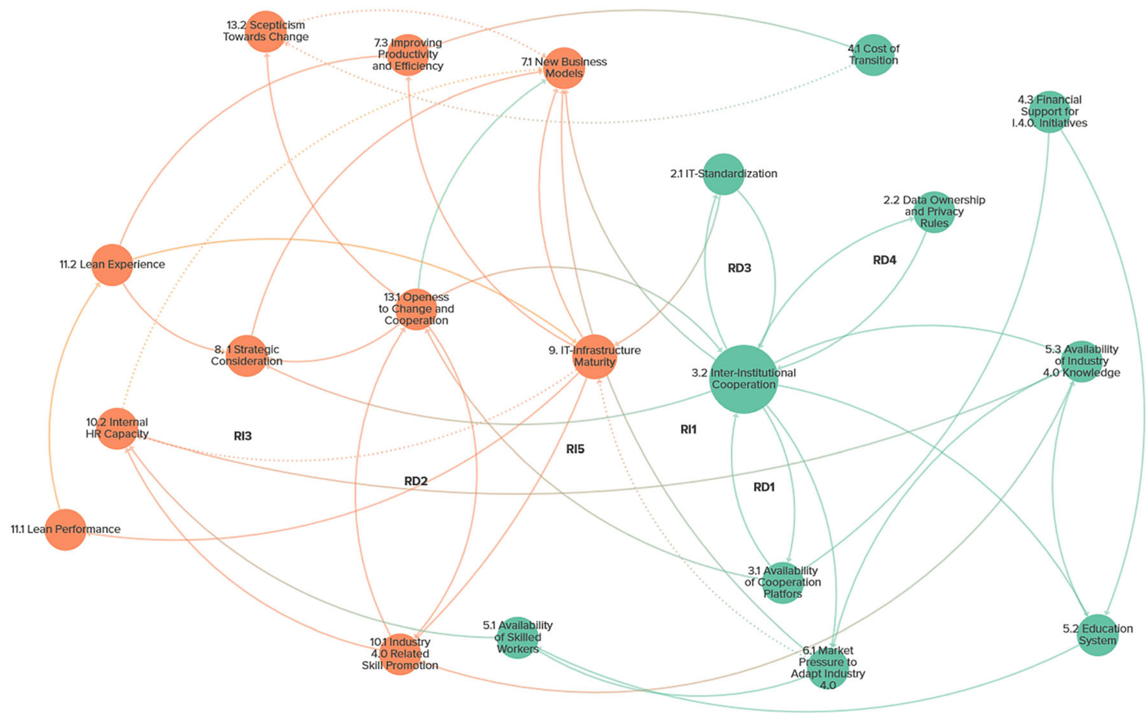

FIGURE 7 Loops connected to Inter-Institutional Cooperation. [Colour figure can be viewed at wileyonlinelibrary.com]

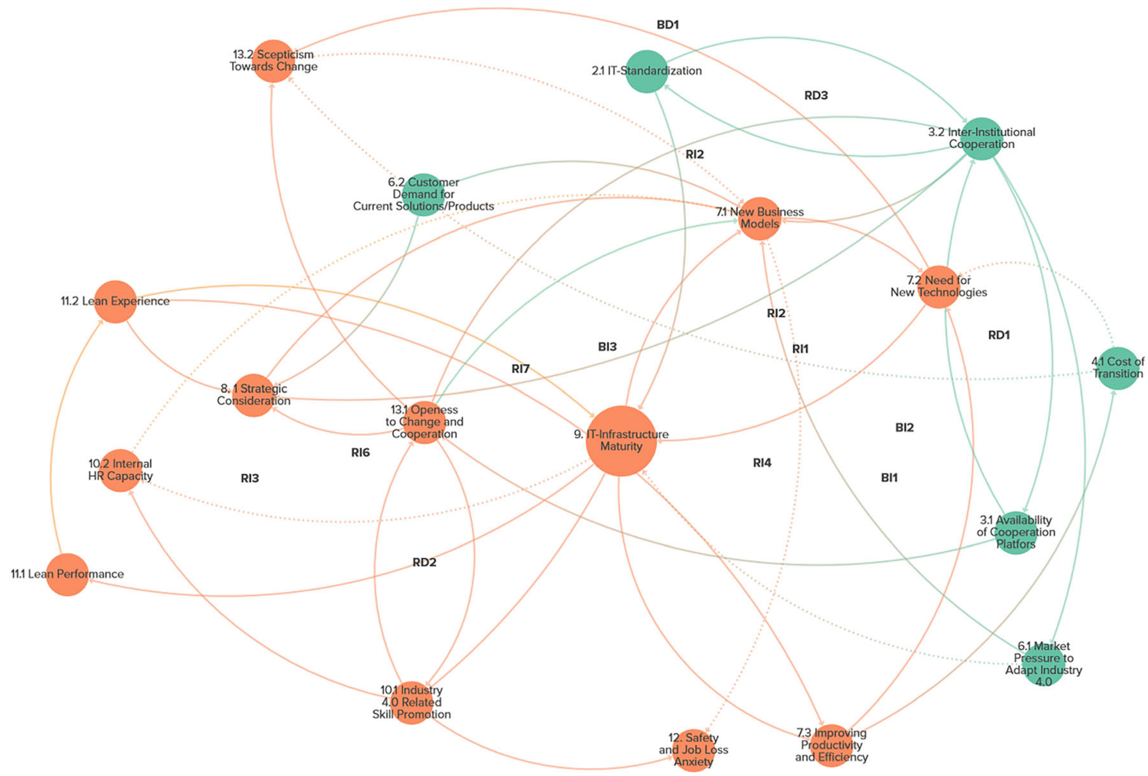

FIGURE 8 Loops connected to IT-Infrastructure Maturity. [Colour figure can be viewed at wileyonlinelibrary.com]

Operations Management literature that is mainly focused on increasing the overall flexibility and efficiency of operations with the help of Industry 4.0, as illustrated by the findings of Zhang et al. (2020) and Hastig and Sodhi (2020). A possible explanation that complements those observations might lie in the nature of the factor 'Perceived Implementation Benefits'. The factor was divided into subclusters to account for the fact that our interview

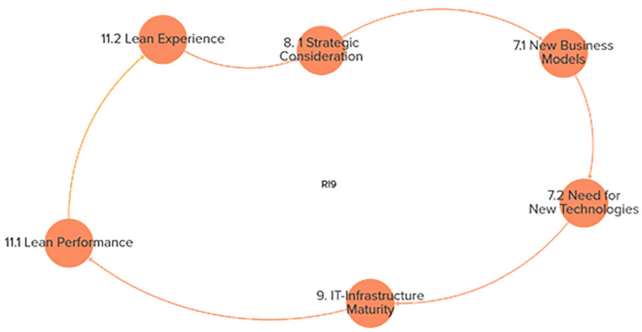

FIGURE 9 Feedback loop illustrating the connection between strategy and Lean Experience. [Colour figure can be viewed at wileyonlinelibrary.com]

partners treated the desire to build new business models differently from the desire to increase the overall efficiency of processes, which is consequently also reflected by their respective connections to other factors in the CLD. This could mean that the differentiation between operational and business model-oriented goals is more important with respect to Industry 4.0 strategy development than previously assumed (Masood & Sonntag, 2020).

The fact that all, except one, interviewed Industry 4.0 experts advocated for a more systematic approach to Industry 4.0 that involves multidisciplinary cooperation across institutions, offers a sound explanation for the high BC value of 'Inter-Institutional Cooperation' and its central position in the network. Moreover, combined with its high out-degree, it is no surprise that 'Inter-Institutional Cooperation' is the main hub in the network that connects the external implementation cluster with the internal one. Recent studies have presented evidence that cooperation plays a major role when it comes to overcoming certain implementation barriers, such as the lack of know-how and experience with smart technologies and new IT standards (Masood & Sonntag, 2020; Saniuk et al., 2021; Stentoft et al., 2021). Moreover, the findings of Cugno et al. (2021) have shown that incentives such as Industry 4.0 support and awareness programmes are not effectively targeting the barriers companies need to overcome while moving towards Industry 4.0, indicating a lack of coordination between key players such as the corporate sector and government institutions. In that context, our CLD offers new insights as to which implementation processes would directly benefit from cooperation, which could be used to tailor support programmes around the needs of corporations. Furthermore, the discussed network structure of the CLD puts forward the idea that even when support programmes are aimed at a specific barrier, such as the lack of skilled workers, they need to consider multiple factors in order to effectively target this Industry 4.0-related barrier. In that regard, our developed CLD can facilitate the identification of implementation factors that need to be acknowledged in order to develop more effective approaches.

We also demonstrated that every internal implementation factor is either directly dependant on the IT infrastructure of the organisation or indirectly connected to it through a short causal loop. It is probable therefore that every organisation's attempt to move towards Industry 4.0 stands and falls with their ability to efficiently manage and scale their IT infrastructure, which may further help to explain why a great deal of Industry 4.0 literature is still focused on Industry 4.0 technologies (Ghobakhloo, 2020; Jiang et al., 2022; Nara et al., 2021). However, our findings also show that 'IT Infrastructure' has the second highest in-degree, which is unusual for high out-degree variables in a network and indicative of a dynamic and complex relationship to other factors. Our findings, therefore, broadly support the notion that the maturity of an IT infrastructure should not only be assessed based on its technological capabilities but also based on their relationship to other implementation factors and drivers, as proposed by other recent investigations (Jiang et al., 2020; Pozzi et al., 2021; Stentoft et al., 2021; Wagire et al., 2021).

The results of this study assert that more factors causally influence the creation of Industry 4.0-related business models, rather than the other way around. As a result, the degree to which other implementation factors influence the creation of new business models becomes more important than we previously assumed (Lin et al., 2018; Müller et al., 2018). However, what remains unchanged is the overall importance of the factor. As pointed out by McGlashan et al. (2016), factors with high in-degree centrality can serve as a central hub for change in a network and therefore be viewed as an important factor to consider when implementing Industry 4.0.

6 | LIMITATIONS AND FUTURE WORK

The construction of our CLD was based on interviews with Industry 4.0 experts. Although we adapted the methods and recommendations from McGlashan et al. (2016) and Uleman et al. (2021) to increase the overall robustness of our approach and compared the results against the findings of our systematic literature review, a certain level of subjectivity cannot be avoided with respect to how the presented implementation factors are connected. Furthermore, a major challenge of CLDs is to find the right level of detail to avoid either difficult to comprehend or overly simplified representations of reality (Richards et al., 2021). The introduction of mutated CLDs to test how changing existing and adding new connections to the network influences the centrality measures of the presented CLD, however, has shown a strong resilience against random permutations, making alternative qualitative conclusions less likely (Uleman et al., 2021). As proposed by Uleman et al. (2021), conducting systematic reviews on every connection identified in the network might further strengthen the model.

Another important limitation of CLDs is their static nature when it comes to emergent behaviour, nonintuitive quantitative results and time delays (Richards et al., 2021; Richardson, 1986; Sterman, 2002). These factors can alter the properties of a given network by, for instance, changing the calculated centrality measures of variables within the network and thereby affecting the overall dynamic of the system. In future research, we will therefore aim to quantitively define the connections between Industry 4.0 implementation factors by collecting empirical data on implementation processes, to simulate different implementation scenarios, making it more suitable for practical application.

Finally, although we integrated different perspectives by interviewing experts with various Industry 4.0-related backgrounds, we want to use the findings of this study to conduct future research that revolves around more specific implementation scenarios. Together with various stakeholders, we will perform participatory systems mapping which not only involves stakeholders in the process of defining the system boundaries but also in the analysis process (Barbrook-Johnson & Penn, 2022). With this approach, we hope to develop distinct implementation strategies that can be tailored to the specific needs of a given organisation.

7 | CONCLUSION

The aim of the present research was to examine and map out the complexity inherent in the implementation of Industry 4.0 through the application of network analysis to a CLD developed based on in-depth interviews with Industry 4.0 experts. Our study has shown that a comprehensive grasp of the importance of Industry 4.0 implementation factors cannot be obtained without considering the role of each factor in a multicausal network. Through the application of network analysis, we determined the specific properties of the CLD to derive potential intervention points in the network to introduce and spread change more efficiently. These insights not only help to explain why focusing on one implementation factor can cause negative side effects but also which factors are crucial to achieve a more effective implementation of Industry 4.0. Therefore, the flexible combination of systems thinking, and network theory has allowed us to shed more light on the specific functions of previously investigated implementation factors. At the same time, through the identification of feedback loops, our findings demonstrated that the role of a given factor is not static, as it changes depending on which other factors it is connected to. In order to illustrate and study this effect, the flexible use of system dynamics combined with other methods was crucial to explore the complex dynamics between the previously studied implementation factors. Without this flexible application of system dynamics, the knowledge about the implementation factors would still be limited to the static function of each isolated factor.

Our modularity test further supports the notion that the internal transformation process interacts with external implementation factors. The presented CLD can therefore be used to further expand our understanding of how external implementation factors exert influence on internal implementation processes and vice versa, thereby providing external key players, such as government institutions, with a more comprehensive understanding of how specific measures influence the transition process of corporations. Taken together, our findings therefore highlight the importance of approaching the implementation of Industry 4.0 in a systemic manner that accounts for its complexity. Scientific investigations should, therefore, favour the application of holistic and interdisciplinary approaches to further improve our understanding of the underlying dynamics of implementing Industry 4.0. Similarly, we recommend that corporations and governments need to change their perspectives on Industry 4.0. Isolated use cases and pilot projects may be beneficial to assess the potential of certain technologies, but they fail to make allowances for the various factors that need to be considered to have a sustainable impact. Our findings suggest that strategic approaches that acknowledge the dynamic behaviour of complex adaptive systems are more likely to have a strong enough effect on the overall system to introduce lasting change.

Due to the static nature of CLDs, emergent behaviour within the network cannot be entirely captured, which is why we will focus our future research on the simulation of the dynamics between the identified networks by collecting more empirical data. At the same time, this will also help us to further decrease the level of subjectivity that comes with interviewing experts.

ACKNOWLEDGEMENTS

Open access publishing facilitated by The University of Adelaide, as part of the Wiley - The University of Adelaide agreement via the Council of Australian University Librarians.

ORCID

Christian Hoyer https://orcid.org/0000-0002-3271-1857
Indra Gunawan https://orcid.org/0000-0001-7357-509X

REFERENCES

Adams, W. C. (2015). Conducting semi-structured interviews. In K. E. Newcomer, H. P. Hatry, & J. S. Wholey (Eds.), *Handbook of practical program evaluation* (pp. 492–505). John Wiley & Sons, Inc. https://doi.org/10.1002/9781119171386.ch19

Ahmed, S. E. (2017). Big and complex data analysis: Methodologies and applications. In S. Ejaz Ahmed (Ed.), *Contributions to statistics*. Springer.

Azar, A. T. (2012). System dynamics as a useful technique for complex systems. *International Journal of Industrial and Systems Engineering*, *10*, 377–410. https://doi.org/10.1504/IJISE.2012.046298

Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, *229*, 107776. https://doi.org/10.1016/j.ijpe.2020.107776

Bakhtari, A. R., Waris, M. M., Sanin, C., & Szczerbicki, E. (2021). Evaluating Industry 4.0 implementation challenges using interpretive structural modeling and fuzzy analytic hierarchy process. *Cybernetics and Systems*, *52*, 350–378. https://doi.org/10.1080/01969722.2020.1871226

Barbrook-Johnson, P., & Penn, A. S. (2022). *Systems mapping*. Springer International Publishing. https://doi.org/10.1007/978-3-031-01919-7

Bartodziej, C. J. (2017). *The concept Industry 4.0: An empirical analysis of technologies and applications in production logistics*. BestMasters. Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-16502-4

Berry, H. L., Waite, T. D., Dear, K. B. G., Capon, A. G., & Murray, V. (2018). The case for systems thinking about climate change and mental health. *Nature Climate Change*, *8*, 282–290. https://doi.org/10.1038/s41558-018-0102-4

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*, P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008

Bogner, A., Littig, B., & Menz, W. (Eds.). (2009). *Interviewing experts. Research methods series*. Palgrave Macmillan. https://doi.org/10.1057/9780230244276

Büchi, G., Cugno, M., & Castagnoli, R. (2020). Smart factory performance and Industry 4.0. *Technological Forecasting and Social Change*, *150*, 119790. https://doi.org/10.1016/j.techfore.2019.119790

Buer, S.-V., Strandhagen, J. O., & Chan, F. T. S. (2018). The link between Industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda. *International Journal of Production Research*, *3*, 1–17. https://doi.org/10.1080/00207543.2018.1442945

Cabrera, D., Colosi, L., & Lobdell, C. (2008). Systems thinking. *Evaluation and Program Planning*, *31*, 299–310. https://doi.org/10.1016/j.evalprogplan.2007.12.001

Calabrese, A., Levialdi Ghiron, N., & Tiburzi, L. (2021). 'Evolutions' and 'revolutions' in manufacturers' implementation of Industry 4.0: a literature review, a multiple case study, and a conceptual framework. *Production Planning and Control*, *32*, 213–227. https://doi.org/10.1080/09537287.2020.1719715

Castelo-Branco, I., Cruz-Jesus, F., & Oliveira, T. (2019). Assessing Industry 4.0 readiness in manufacturing: Evidence for the European Union. *Computers in Industry*, *107*, 22–32. https://doi.org/10.1016/j.compind.2019.01.007

Cimini, C., Boffelli, A., Lagorio, A., Kalchschmidt, M., & Pinto, R. (2021). How do Industry 4.0 technologies influence organisational change? An empirical analysis of Italian SMEs. *Journal of Manufacturing Technology Management*, *32*, 695–721. https://doi.org/10.1108/JMTM-04-2019-0135

Cimini, C., Pinto, R., & Cavalieri, S. (2017). The business transformation towards smart manufacturing: A literature overview about reference models and research agenda. *IFAC-PapersOnLine*, *50*(1), 14952–14957.

Cugno, M., Castagnoli, R., & Büchi, G. (2021). Openness to Industry 4.0 and performance: The impact of barriers and incentives. *Technological Forecasting and Social Change*, *168*, 120756. https://doi.org/10.1016/j.techfore.2021.120756

Da Silva, V. L., Kovaleski, J. L., Pagani, R. N., Silva, J. D. M., & Corsi, A. (2020). Implementation of Industry 4.0 concept in companies: empirical evidences. *International Journal of Computer Integrated Manufacturing*, *33*, 325–342. https://doi.org/10.1080/0951192X.2019.1699258

Da Xu, L. (2020). The contribution of systems science to Industry 4.0. *Systems Research and Behavioral Science*, *37*, 618–631. https://doi.org/10.1002/sres.2705

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, *204*, 383–394. https://doi.org/10.1016/j.ijpe.2018.08.019

Distelhorst, G., Hainmueller, J., & Locke, R. M. (2017). Does lean improve labor standards? Management and social performance in the Nike supply chain. *Management Science*, *63*, 707–728. https://doi.org/10.1287/mnsc.2015.2369

Freixanet, J., Rialp, A., & Churakova, I. (2020). How do innovation, internationalization, and organizational learning interact and co-evolve in small firms? A complex systems approach. *Journal of Small Business Management*, *7*, 1–34. https://doi.org/10.1111/jsbm.12510

Ghaffarzadegan, N., Lyneis, J., & Richardson, G. P. (2011). How small system dynamics models can help the public policy process. *System Dynamics Review*, *27*, 22–44. https://doi.org/10.1002/sdr.442

Ghobakhloo, M. (2020). Industry 4.0, digitization, and opportunities for sustainability. *Journal of Cleaner Production*, *252*, 119869. https://doi.org/10.1016/j.jclepro.2019.119869

Hansen, D. L., Shneiderman, B., & Smith, M. A. (2011). Calculating and visualizing network metrics. In *Analyzing social media networks with NodeXL* (pp. 69–78). Elsevier. https://doi.org/10.1016/B978-0-12-382229-1.00005-9

Hastig, G. M., & Sodhi, M. S. (2020). Blockchain for supply chain traceability: Business requirements and critical success factors. *Production and Operations Management*, *29*, 935–954. https://doi.org/10.1111/poms.13147

Hirsch, G. B., Levine, R., & Miller, R. L. (2007). Using system dynamics modeling to understand the impact of social change initiatives. *American Journal of Community Psychology*, *39*, 239–253. https://doi.org/10.1007/s10464-007-9114-3

Hirsch-Kreinsen, H. (2016). Digitization of industrial work: Development paths and prospects. *Journal for Labour Market Research*, *49*, 1–14. https://doi.org/10.1007/s12651-016-0200-6

Hou, T., Cheng, B., Wang, R., Xue, W., & Chaudhry, P. E. (2020). Developing Industry 4.0 with systems perspectives. *Systems Research and Behavioral Science*, *37*, 741–748. https://doi.org/10.1002/sres.2715

Hoyer, C., Gunawan, I., & Reaiche, C. H. (2020). The implementation of Industry 4.0—A systematic literature review of the key factors. *Systems Research and Behavioral Science*, *37*, 557–578. https://doi.org/10.1002/sres.2701

Jiang, H., Gai, J., Zhao, S., Chaudhry, P. E., & Chaudhry, S. S. (2022). Applications and development of artificial intelligence system from the perspective of system science: A bibliometric review. *Systems Research and Behavioral Science*, *39*, 361–378. https://doi.org/10.1002/sres.2865

Jiang, H., Sun, S., Xu, H., Zhao, S., & Chen, Y. (2020). Enterprises' network structure and their technology standardization capability in Industry 4.0. *Systems Research and Behavioral Science*, *37*, 749–765. https://doi.org/10.1002/sres.2716

Jones, N. A., Ross, H., Lynam, T., Perez, P., & Leitch, A. (2011). Mental models: An interdisciplinary synthesis of theory and methods. *Ecology and Society*, *16*, art46. https://doi.org/10.5751/ES-03802-160146

Jonker, J., & Karapetrovic, S. (2004). Systems thinking for the integration of management systems. *Business Process Management Journal*, *10*, 608–615. https://doi.org/10.1108/14637150410567839

Kagermann, H., Wahlster, W., & Helbig, J. (2013). Recommendations for implementing the strategic initiative INDUSTRIE 4.0. Final report of the Industrie 4.0 Working Group.

Kenzie, E. S., Parks, E. L., Bigler, E. D., Wright, D. W., Lim, M. M., Chesnutt, J. C., Hawryluk, G. W. J., Gordon, W., & Wakeland, W. (2018). The dynamics of concussion: Mapping pathophysiology, persistence, and recovery with causal-loop diagramming. *Frontiers in Neurology*, *9*, 203. https://doi.org/10.3389/fneur.2018.00203

Kiani, B., Gholamian, M., Hamzehei, A., & Hosseini, S. (2009). Using causal loop diagram to achieve a better understanding of e-business models. *International Journal of Electronic Business Management*, *7*, 159–167.

Kolli, S., & Khajeheian, D. (2020). How actors of social networks affect differently on the others? Addressing the critique of equal importance on actor-network theory by use of social network analysis. In I. Williams (Ed.), *Contemporary applications of actor network theory*. Palgrave Macmillan, Singapore. https://doi.org/10.1007/978-981-15-7066-7_12

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business and Information Systems Engineering*, *6*, 239–242. https://doi.org/10.1007/s12599-014-0334-4

Layton, R., & Watters, P. A. (2015). *Algorithms for automating open source intelligence (OSINT). Computer science reviews and trends*. Syngress.

Lee, M., Yun, J., Pyka, A., Won, D., Kodama, F., Schiuma, G., Park, H., Jeon, J., Park, K., Jung, K., Yan, M.-R., Lee, S., & Zhao, X. (2018). How to respond to the fourth industrial revolution, or the second information technology revolution? Dynamic new combinations between technology, market, and society through open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *4*, 21. https://doi.org/10.3390/joitmc4030021

Leicht, E. A., & Newman, M. E. J. (2008). Community structure in directed networks. *Physical Review Letters*, *100*, 118703. https://doi.org/10.1103/PhysRevLett.100.118703

Lin, D., Lee, C., Lau, H., & Yang, Y. (2018). Strategic response to Industry 4.0: an empirical investigation on the Chinese automotive industry. *Industrial Management & Data Systems*, *118*(3), 589–605. https://doi.org/10.1108/IMDS-09-2017-0403

Lin, Y. (2012). *Systems science: Methodological approaches*. Advances in Systems Science and Engineering (ASSE). Chapman and Hall/CRC. https://doi.org/10.1201/b13095

Luthra, S., & Mangla, S. K. (2018). Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies. *Process Safety and Environmental Protection*, *117*, 168–179. https://doi.org/10.1016/j.psep.2018.04.018

Mahaffy, P. G., Matlin, S. A., Holme, T. A., & MacKellar, J. (2019). Systems thinking for education about the molecular basis of sustainability. *Nature Sustainability*, *2*, 362–370. https://doi.org/10.1038/s41893-019-0285-3

Masood, T., & Sonntag, P. (2020). Industry 4.0: Adoption challenges and benefits for SMEs. *Computers in Industry*, *121*, 103261. https://doi.org/10.1016/j.compind.2020.103261

McGlashan, J., Johnstone, M., Creighton, D., de La Haye, K., & Allender, S. (2016). Quantifying a systems map: Network analysis of a childhood obesity causal loop diagram. *PLoS ONE*, *11*, e0165459. https://doi.org/10.1371/journal.pone.0165459

McIntosh, M. J., & Morse, J. M. (2015). Situating and constructing diversity in semi-structured interviews. *Global Qualitative Nursing Research*, *2*, 2333393615597674. https://doi.org/10.1177/2333393615597674

McKnight, W. (2014). *Information management strategies for gaining a competitive advantage with data*. Elsevier.

Medoh, C., & Telukdarie, A. (2022). The future of cybersecurity: A system dynamics approach. *Procedia Computer Science*, *200*, 318–326. https://doi.org/10.1016/j.procs.2022.01.230

Mendelson, H. (2000). Organizational architecture and success in the information technology industry. *Management Science*, *46*, 513–529. https://doi.org/10.1287/mnsc.46.4.513.12060

Metcalf, L., & Casey, W. (2016). *Cybersecurity and applied mathematics*. Syngress.

Müller, J. M., Buliga, O., & Voigt, K.-I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technological Forecasting and Social Change*, *132*, 2–17. https://doi.org/10.1016/j.techfore.2017.12.019

Müller, J. M., Kiel, D., & Voigt, K.-I. (2018). What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability*, *10*, 247. https://doi.org/10.3390/su10010247

Nara, E. O. B., Da Costa, M. B., Baierle, I. C., Schaefer, J. L., Benitez, G. B., do Santos, L. M. A. L., & Benitez, L. B. (2021). Expected impact of Industry 4.0 technologies on sustainable development: A study in the context of Brazil's plastic industry. *Sustainable Production and Consumption*, *25*, 102–122. https://doi.org/10.1016/j.spc.2020.07.018

Neumann, W. P., Winkelhaus, S., Grosse, E. H., & Glock, C. H. (2021). Industry 4.0 and the human factor—A systems framework and analysis methodology for successful development. *International Journal of Production Economics*, *233*, 107992. https://doi.org/10.1016/j.ijpe.2020.107992

Oliveira, B. G., Liboni, L. B., Cezarino, L. O., Stefanelli, N. O., & Miura, I. K. (2020). Industry 4.0 in systems thinking: From a narrow to a broad spectrum. *Systems Research and Behavioral Science*, *37*, 593–606. https://doi.org/10.1002/sres.2703

Pozzi, R., Rossi, T., & Secchi, R. (2021). Industry 4.0 technologies: Critical success factors for implementation and improvements in manufacturing companies. *Production Planning and Control*, *34*(2), 139–158. https://doi.org/10.1080/09537287.2021.1891481

Raj, A., Dwivedi, G., Sharma, A., Lopes de Sousa Jabbour, A. B., & Rajak, S. (2019). Barriers to the adoption of Industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. *International Journal of Production Economics*, *224*, 107546. https://doi.org/10.1016/j.ijpe.2019.107546

Raman, A., & Rathakrishnan, M. (Eds.). (2019). *Redesigning higher education initiatives for Industry 4.0*. Information Science Reference. https://doi.org/10.4018/978-1-5225-7832-1

Richards, C. E., Lupton, R. C., & Allwood, J. M. (2021). Re-framing the threat of global warming: an empirical causal loop diagram of climate change, food insecurity and societal collapse. *Climatic Change*, *164*, 49. https://doi.org/10.1007/s10584-021-02957-w

Richardson, G. P. (1986). Problems with causal-loop diagrams. *System Dynamics Review*, *2*, 158–170. https://doi.org/10.1002/sdr.4260020207

Roberts, N. (1978). Teaching dynamic feedback systems thinking: An elementary view. *Management Science*, *24*, 836–843. https://doi.org/10.1287/mnsc.24.8.836

Roxas, F. M. Y., Rivera, J. P. R., & Gutierrez, E. L. M. (2019). Locating potential leverage points in a systems thinking causal loop diagram toward policy intervention. *World Futures*, *75*, 609–631. https://doi.org/10.1080/02604027.2019.1654784

Sahin, O., Salim, H., Suprun, E., Richards, R., MacAskill, S., Heilgeist, S., Rutherford, S., Stewart, R. A., & Beal, C. D. (2020). Developing a preliminary causal loop diagram for understanding the wicked complexity of the COVID-19 pandemic. *System*, *8*, 20. https://doi.org/10.3390/systems8020020

Saniuk, S., Caganova, D., & Saniuk, A. (2021). Knowledge and skills of industrial employees and managerial staff for the Industry 4.0 implementation. *Mobile Networks and Applications*. https://doi.org/10.1007/s11036-021-01788-4

Santos, Z. G., Vieira, L., & Balbinotti, G. (2015). Lean manufacturing and ergonomic working conditions in the automotive industry. *Procedia Manufacturing*, *3*, 5947–5954. https://doi.org/10.1016/j.promfg.2015.07.687

Saurin, T. A., Rooke, J., & Koskela, L. (2013). A complex systems theory perspective of lean production. *International Journal of Production Research*, *51*, 5824–5838. https://doi.org/10.1080/00207543.2013.796420

Sjödin, D. R., Parida, V., Leksell, M., & Petrovic, A. (2018). Smart factory implementation and process innovation. *Research-Technology Management*, *61*, 22–31. https://doi.org/10.1080/08956308.2018.1471277

Spector, J., Christensen, D. L., Sioutine, A. V., & McCormack, D. (2001). Models and simulations for learning in complex domains: Using causal loop diagrams for assessment and evaluation. *Computers in Human Behavior*, *17*, 517–545. https://doi.org/10.1016/S0747-5632(01)00025-5

Staufen AG. (2019). Studie: Industrie 4.0 Index 2019.

Stentoft, J., Adsbøll Wickstrøm, K., Philipsen, K., & Haug, A. (2021). Drivers and barriers for Industry 4.0 readiness and practice: Empirical evidence from small and medium-sized manufacturers. *Production Planning and Control*, *32*, 811–828. https://doi.org/10.1080/09537287.2020.1768318

Sterman, J. D. (2002). All models are wrong: Reflections on becoming a systems scientist. *System Dynamics Review*, *18*, 501–531. https://doi.org/10.1002/sdr.261

Sung, T. K. (2018). Industry 4.0: A Korea perspective. *Technological Forecasting and Social Change*, *132*, 40–45. https://doi.org/10.1016/j.techfore.2017.11.005

Symon, G., & Cassell, C. (2012). In G. Symon & C. Cassell (Eds.), *Qualitative organizational research: Core methods and current challenges*. SAGE. https://doi.org/10.4135/9781526435620

Uleman, J. F., Melis, R. J. F., Quax, R., van der Zee, E. A., Thijssen, D., Dresler, M., van de Rest, O., van der Velpen, I. F., Adams, H. H. H., Schmand, B., de Kok, I. M. C. M., de Bresser, J., Richard, E., Verbeek, M., Hoekstra, A. G., Rouwette, E. A. J. A., & Olde Rikkert, M. G. M. (2021). Mapping the multicausality of Alzheimer's disease through group model building. *Geroscience*, *43*, 829–843. https://doi.org/10.1007/s11357-020-00228-7

Vaidya, S., Ambad, P., & Bhosle, S. (2018). Industry 4.0—A glimpse. *Procedia Manufacturing*, *20*, 233–238. https://doi.org/10.1016/j.promfg.2018.02.034

Wagire, A. A., Joshi, R., Rathore, A. P. S., & Jain, R. (2021). Development of maturity model for assessing the implementation of Industry 4.0: Learning from theory and practice. *Production Planning and Control*, *32*, 603–622. https://doi.org/10.1080/09537287.2020.1744763

Whysall, Z., Owtram, M., & Brittain, S. (2019). The new talent management challenges of Industry 4.0. *Journal of Management Development*, *38*, 118–129. https://doi.org/10.1108/JMD-06-2018-0181

Xiong, G. (2012). *Service science, management, and engineering: Theory and applications. Intelligent systems series*. Elsevier/AP; Zhejiang University Press.

Zhang, F., Wu, X., Tang, C. S., Feng, T., & Dai, Y. (2020). Evolution of operations management research: From managing flows to building capabilities. *Production and Operations Management*, *29*, 2219–2229. https://doi.org/10.1111/poms.13231

How to cite this article: Hoyer, C., Gunawan, I., & Reaiche, C. H. (2023). Exploring the relationships between Industry 4.0 implementation factors through systems thinking and network analysis. *Systems Research and Behavioral Science*, 1–17. https://doi.org/10.1002/sres.2947