Bayesian network methodology and machine learning approach: an application on the impact of digital technologies on logistics service quality

Behzad Maleki Vishkaei
Technology and Management Department, Bocconi University, Milano, Italy, and
Pietro De Giovanni
Strategy and Operations Management Knowledge Area,
SDA Bocconi School of Management and DIR—Claudio Dematté Research Division,
Sustainable Operations and Supply Chain Monitor, Milan, Italy

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Abstract

Purpose – This paper aims to use Bayesian network (BN) methodology complemented by machine learning (ML) and what-if analysis to investigate the impact of digital technologies (DT) on logistics service quality (LSQ), employing the service quality (SERVQUAL) framework.

Design/methodology/approach – Using a sample of 244 Italian firms, this study estimates the probability distributions associated with both DT and SERVQUAL logistics, as well as their interrelationships. Additionally, BN technique enables the application of ML techniques to uncover hidden relationships, as well as a series of what-if analyses to extract more knowledge.

Findings – The results show that the average probability of firms investing in DT for analytics (DTA) is higher than that of investing inDT for immersive experiences (DTIE). Furthermore, adopting both offers only a moderate likelihood of successfully implementing SERVQUAL logistics. Additionally, certain technologies may not directly influence some SERVQUAL dimensions. The application of ML reveals hidden relationships

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among technologies, enhancing the predictions of SERVQUAL logistics. Finally, what-if analyses provide further insights to guide decision-making processes aimed at enhancing SERVQUAL logistics dimensions through DTA and DTIE.

Originality/value – This research delves into the influence of DTIE and DTA on SERVQUAL logistics, thereby filling a gap in the existing literature in which no study has explored the intricate relationships between these technologies and SERVQUAL dimensions. Methodologically, we pioneer the integration of BN with ML techniques and what-if analysis, thus exploring innovative techniques to be used in logistics and supply-chain studies.

Keywords SERVQUAL logistics, Immersive experience, Digital technologies, Bayesian network, Machine learning

Paper type Research paper

1. Introduction

Logistic service quality (LSQ) refers to the extent to which a logistics service provider meets or exceeds the expectations of its customers in terms of delivering products or services. Therefore, LSQ is recognized as an effective driver of consumer satisfaction leading to a higher purchase (Kaswengi and Lambey-Checchin, 2020). Indeed, LSQ requires the strong support of digital tools to guarantee benefits such as accuracy, real-time communication, transparency and visibility. Under these circumstances, LSQ can be effective, meet the sophisticated expectations of customers and address the complexities of modern supply chains (Attaran, 2020).

Although the literature has highlighted the importance of digital tools in various domains (Stank *et al.*, 2019), studies have paid scant attention to which specific digital solutions should be adopted to optimize LSQ. On the one hand, firms are highly challenged to find the appropriate DT to achieve their desired outcomes in logistics and supply chain management (Yang *et al.*, 2021). In fact, it is well documented that recognizing and adopting DT, integrating them within systems and managing them properly requires resources, new skills and ad hoc competencies (Volpentesta *et al.*, 2023). Currently, no research identifies the various DT as well as their synergies that can support logistics services in achieving high levels of quality. Furthermore, in this era of digital proliferation, firms face the uncertainty of emerging and futurist technologies linked to virtual environments and immersive experiences like metaverse, which can substantially disrupt their logistics services and other business functions (Tan, 2023). For example, virtual commerce in the metaverse can lead to new business models and distribution channels that require logistics services to adapt to new forms of delivery (De Giovanni, 2023). The present literature does not show how immersive DT can interact with more traditional DT to offer high levels of LSQ.

This research fills the aforementioned gap by investigating the extent to which the adoption of DT helps optimize the quality of firms' logistics services. To address the rapid technological evolution, this study differentiates DT into DT for analytics (DTA) and DT for immersive experiences (DTIE). DTA consist of DT that collect, process and analyze data to improve decision-making processes (Cichosz *et al.*, 2020); therefore, by directly supporting logistics strategies through, for example, accurate forecasts, optimal routing planning and efficient inventory management, these technologies guarantee a high level of quality in logistics services (Attaran, 2020). Similarly, DTIE consist of DT that help create and manage a virtual environment through which firms can provide immersive experiences, interactive relationships and a high level of engagement (De Giovanni, 2023). These technologies will become very challenging for logistics services since customers will be able to visualize related logistics deliveries, interact with logistics operators over the whole delivery period, explore and verify goods in a virtual environment and enhance the quality of their purchasing experiences (Popescu *et al.*, 2022). To investigate the impact of DTA and DTIE on the quality of logistics services, we use the service quality (SERVQUAL) framework. The SERVQUAL model, which originates from the seminal work of Parasuraman *et al.* (1985), has been used extensively in previous studies and rigorously validated by empirical testing. Its five dimensions – tangibility, responsiveness, reliability, assurance and empathy – offer a valid and comprehensive taxonomy to measure the quality of logistics services and investigate how firms can achieve high levels of LSQ when adopting DTA and DTIE.

To adequately address the research objectives, this study employs the Bayesian networks (BNs) methodology along with machine learning (ML) algorithms and what-if analyses. BN has rarely been used in logistics and supply chain research. For example, Sutrisnowati *et al.* (2015) employ BN to analyze port logistics, specifically by examining various factors influencing container handling. Zhang *et al.* (2020) use BN to scrutinize reliability determinants in fresh food e-commerce logistics, encompassing elements such as information technology, facilities, equipment, personnel operations and the external environment. Similarly, Sakib *et al.* (2021) introduce a robust BN model tailored to predict vulnerabilities and disruptions, facilitating the analyses of ripple effects. To evaluate the use of drones in logistics, Hossain *et al.* (2022) devise a BN methodology that considers such factors as physical specifications, technical responses and economic costs. Within these research papers, BNs account for uncertainties, interactions and probabilistic influences within logistics and supply chain research, fostering a deeper and more complete understanding of underlying complexities and interdependencies. In this paper, besides using BN, we also employ some ML algorithms and what-if analyses to inform scholars on how to extract additional knowledge in logistics and supply chains starting from BN. Hence, by applying BN along with ML and what-if analysis, we seek to answer the following research questions (RQs):

RQ1. What is the likelihood of achieving high SERVQUAL logistics conditioned to the adoption of DTA and DTIE?

RQ2. Inside the complex network of relationships between DTA, DTIE and SERVQUAL logistics, which latent links can be discovered to provide further insights?

RQ3. Are there any additional and relevant ad hoc scenarios investigating the impact of DTA and DTIE on SERVQUAL logistics that can be studied to provide further insights?

Our results reveal that firms are more likely to invest in DTA than in DTIE, with both offering various influences on the likelihood of achieving successful SERVQUAL logistics. Specifically, by adopting artificial intelligence (AI), cloud computing and virtual reality (VR), firms can ensure a certain tangibility; these DT, along with the IoT, also offer a high probability of achieving a reliable and satisfactory performance. Moreover, the simultaneous adoption of these four technologies is not required when seeking to provide assurance and responsiveness, for which pairs of DT are sufficient: assurance only requires the adoption of cloud computing and IoT, while responsiveness is driven primarily by AI and VR. Regarding empathy, triple cloud computing, augmented reality (AR), and VR have great potential for achieving excellent performance. Furthermore, ML reveals that while cloud computing indirectly supports empathy, digital avatars do not directly influence assurance. However, there is interplay between investments in digital avatars and AR, with VR supporting AI, IoT, and the control tower. Additionally, cloud computing boosts the control tower, AI and IoT for data management. Finally, what-if analyses show that certain DT, especially AI, control tower and IoT, can improve the chances of achieving SERVQUAL logistics, but focusing solely on IoT affects some dimensions negatively. Instead, investing in DTA can enhance responsiveness, although the advantages of the DTIE remain unclear.

The remainder of the paper is structured as follows. Section 2 introduces the literature review on DT and SERVQUAL logistics. Section 3 explains the methodology, including BN, ML and what-if analysis, while Section 4 discusses the results and provides contributions and methodological observations. Finally, Section 5 concludes and proposes future research avenues. Furthermore, in this study, we use several acronyms related to logistics SERVQUAL and the methodology. So, to summarize them, we provide Table 1 which displays the list of acronyms used in the manuscript, along with their definitions.

Table 1. Acronyms and definitions

Acronym	Definition
LSCM	Logistics and Supply Chain Management
BN	Bayesian Network
ML	Machine Learning
LSQ	Logistics Service Quality
SERVQUAL	Service Quality
DT	Digital Technologies
DTA	Digital Technologies for Analytics
DTIE	Digital Technologies for Immersive Experiences
AI	Artificial Intelligence
IoT	Internet of Things
AR	Augmented Reality
VR	Virtual Reality
MDL	Minimum Description Length

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2. Literature review

2.1 The links between DTA, DTIE and SERVQUAL logistics

The definition of logistic service quality (LSQ) implies that part of the value of a product is created by logistics services (Mentzer *et al.*, 1999), which indicates the importance of this concept in providing customer satisfaction and achieving high performance (Rafiq and Jaafar, 2007). Accordingly, an analysis of LSQ is crucial for managers aiming to enhance customer satisfaction and improve the performance of processes that address customers' requirements (Gaudenzi *et al.*, 2020).

The SERVQUAL model, delineated by Parasuraman *et al.* (1985), provides a rigorous framework for examining LSQ through five distinct dimensions: tangibility, responsiveness, reliability, assurance and empathy. Applying this framework to the logistics field turns into the concept of SERVQUAL logistics. In this sense, the tangibility dimension applied to logistics encompasses the physical elements of logistics services, ranging from the appearance of facilities and personnel to communication materials. Gupta *et al.* (2022) and De Giovanni and Zaccour (2022) support this view, according to which the tangibility aspect has a direct bearing on customers' perceptions and evaluations. A tangible commitment – manifested through well-maintained facilities, professional personnel and pristine transportation modes – sends a potent signal of a company's dedication to customer satisfaction. In the same vein, reliability emphasizes the consistent and precise execution of a logistics service. As Vishkaei and De Giovanni (2023) note, customers gravitate towards logistics providers that uphold their commitments. A consistent track record in delivering reliable services not only bolsters trust but also fosters customer relationships. According to Papert *et al.* (2016), responsiveness revolves around the agility and eagerness of logistics providers to cater to customers' needs. Whether such responsiveness lies in addressing queries, providing swift assistance or adapting services, a heightened level of responsiveness enhances a company's reputation and underscores its customer-centric ethos. Similarly, assurance relies on the personnel's expertise, participation, and ability to instill trust (García-Arca *et al.*, 2018). This dimension in a logistics provider signals the competence and professionalism of employees to customers, which supports differentiation in a competitive market. Finally, empathy, combined with well-trained employees, underscores a tailored, caring approach that allows logistics firms not only to fulfill customer expectations but also to surpass them in aligning their strategies with their specific customers' needs (Gaudenzi *et al.*, 2020).

While each dimension of the SERVQUAL model contributes distinctly to LSQ, only their collective application shapes a truly comprehensive, customer-centric approach to the provision of logistics services. However, achieving this holistic excellence hinges on the strategic adoption of the right digital solutions. DTA play a crucial role in enhancing LSQ by automating processes and increasing efficiency, which results in faster, more accurate service delivery (Ivanov *et al.*, 2021). Technological advancements, particularly in inventory management, for instance, help provide additional information that facilitates operational management and improves decision-making (Williams and Tokar, 2008). Increasing the digitalization of operations makes new information more accessible and facilitates the seamless integration of supply chain scheduling (Öhman *et al.*, 2021). Real-time visibility provided by tracking systems and data analytics enables logistics service providers to monitor shipments and inventory levels and promptly address issues, enhancing transparency and customer satisfaction (Papert *et al.*, 2016). DTA facilitates data-driven decision making and allows for better demand forecasting, resource optimization, and proactive risk identification, ultimately improving operational planning and SERVQUAL (Vishkaei and De Giovanni, 2023). Moreover, DTA enable seamless, continuous communication and collaboration among stakeholders, leading to faster response times and better coordination; in fact, DTA empower logistics service providers to offer customer-centric services by ensuring personalized experiences, real-time updates and self-service options (Bhattacharjya *et al.*, 2016).

Along with DTA, new solutions linked to DTIE have significant potential for supporting and enhancing SERVQUAL logistics. These technologies offer virtual collaboration and communication, allowing logistics professionals to interact and collaborate, regardless of location (Vishkaei, 2022). Simulations and virtual training for logistics operators improve skills and competency (Upadhyay and Khandelwal, 2022), while advanced visualization and analytics tools enable proactive decision-making and logistics optimization (Popescu *et al.*, 2022). DTIE also enhance customer engagement through immersive experiences and remote monitoring and control using IoT devices that ensure compliance and minimize errors (Park and Kim, 2022). Overall, DTIE contribute to improved coordination among actors over a supply chain and offer optimized processes by giving visibility and synchronization of flows. Avatars in the metaverse can control physical objects in logistics, solving problems in real-time with logistics operators (De Giovanni, 2023); furthermore, DTIE connects machines and processes virtually to logistics services to verify the correct alignment between planning and deliveries (Popescu *et al.*, 2022).

Most previous research has concentrated on DTA rather than DTIE, revealing several difficulties when it comes to improving logistics services through metaverse technologies. As an example, Kern (2021) in his review of the state of digitalization across logistics infrastructure, logistics execution and logistics and advisory services, shows that just half of customers are satisfied with their third-party logistics (3PL) providers' Information Technology (IT) capabilities. This may be related to the different complexities involved and barriers encountered in adopting new technologies. Cichosz *et al.*'s (2020) study identifies the main obstacles encountered in the logistics network and the lack of resources. They also identify leadership and creating a supportive organizational culture as the main success factors for adopting new technologies. Similarly, Ooi *et al.* (2023) provide insights from a multidisciplinary viewpoint on the opportunities and challenges of metaverse adoption. They discuss the endless opportunities that implementing the metaverse and its related technologies can bring to logistics and manufacturing. However, concerns about data privacy, security, governance, ethics and the psychological impact of metaverse of immersive technology usage still present challenges to be overcome.

For readers who are interested in investigating more about DT, we invite them to read some literature review articles related to this topic for more information (Núñez-Merino *et al.*, 2020; Parola *et al.*, 2021; Oliveira-Dias *et al.*, 2022). All of the proposed papers insist on the need for further exploration into the emerging DT in logistics and the supply chain. For instance, Núñez-Merino *et al.* (2020) discuss the relationship between DT and lean supply chain management, and Oliveira-Dias *et al.* (2022) study the role and implications of DT for an agile Supply Chain (SC) strategy through a systematic literature review. Similarly, Parola *et al.* (2021) use a systematic literature review to provide insights into the importance of adopting emerging technologies in logistics centers in maritime supply chains to increase business opportunities.

Within this framework, our research also seeks to investigate whether investments in DTA and DTIE contribute to superior SERVQUAL logistics outcomes. It is well documented that the implementation of DTA empowers logistics service providers to enhance operational efficiency (Cichosz *et al.*, 2020). Notably, the literature highlights the transformative role of AI, the Internet of things (IoT), cloud computing and control towers in increasing the performance of the supply chain and logistics (Attaran, 2020; Oliveira-Dias *et al.*, 2022). Although the existing literature has investigated the effects of DTA comprehensively, there is still a need to explore the influence of DTIE on SERVQUAL logistics as well as how DTA and DTIE interact to facilitate the performance of SERVQUAL. Therefore, we seek to fill this gap by addressing the RQ1 mentioned in the introduction. Figure 1 illustrates the intricate web of interactions between DTA, DTIE and the SERVQUAL logistics explored in this study.

2.2 The latent links between DTA, DTIE and SERVQUAL logistics

Besides focusing on studying the network of relationships emerging rather than only proposing BN, we also apply some machine learning (ML) approaches to extract more knowledge from the networks of relationships involving DTA, DTIE and SERVQUAL. Although ML is a new and unexplored field, some studies use ML algorithms in Bayesian networks. For instance, Cui *et al.* (2006) develop an innovative ML method (BNs learned by evolutionary programming) and show its potential for providing more accurate prediction, transparent procedures and interpretable results compared to neural networks, classification, regression tree (CART) and latent class regression. Similarly, Boutselis and McNaught (2019) construct a model for forecasting spare parts, and used a BN approach to compare results with expert-adjusted forecasts and other techniques. With the BN framework, De Giovanni

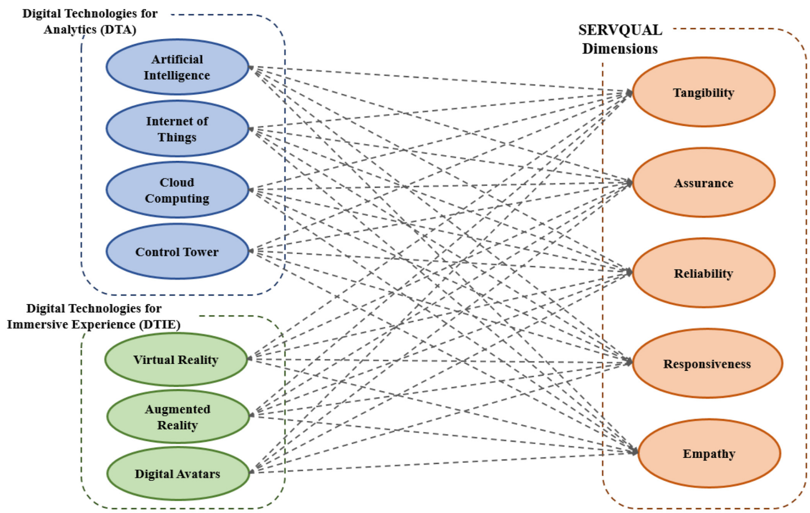

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Figure 1.
Conceptual model and network

et al. (2022) employ several ML algorithms to study firms' investments in I4.0 technologies that aim to bolster operational and logistics performance. Interestingly, the aforementioned studies use BN to exploit its capacity to identify and discover hidden factors and relationships to extract more knowledge and further insight from a model. Therefore, we seek to follow the same path in our research and then answer RQ2 to discover significant and hidden relationships between DTA, DTIE and SERVQUAL Logistics that can be used to improve the selection of DTA and DTIE and optimize SERVQUAL logistics.

2.3 Ad hoc scenarios on DTA, DTIE and SERVQUAL logistics

Along with ML, an additional way to extract information from a BN consists of the creation of ad hoc scenarios, generated through what-if analyses. The latter plays a crucial role in logistics research by providing a systematic framework for exploring and evaluating potential scenarios and their implications, enabling a comprehensive understanding of the complexities and dynamics within logistics systems. By conducting what-if analyses, researchers can simulate and assess the consequences of changes in different variables, such as demand patterns, transportation routes, inventory levels or resource allocations to identify potential risks, bottlenecks and opportunities in logistics operations besides analyzing the resilience, robustness and efficiency of logistics systems and evaluating strategic decisions (de Waal and Joubert, 2022). For example, De Giovanni *et al.* (2022) use a what-if analysis with BNs to discover the best portfolios of DT firms can adopt to excel in operations management. Similarly, de Waal and Joubert (2022) use BN and what-if analysis to predict people's daily travel behavior. Interestingly, they focus on the travelers' vulnerability by analyzing a set of demographic variables, activity and trip variables, and the temporal variables associated with activity and trip durations. Along the same lines, this study investigates the impact of DTA and DTIE on SERVQUAL logistics using what-if analysis through BNs. Accordingly, we developed a what-if analysis to answer RQ3, aiming to generate additional knowledge and deeper insights into the relationships between DTA, DTIE and SERVQUAL Logistics by proposing some ad hoc scenarios among the constellation of scenarios that could be potentially created.

3. Methodology

To properly pursue the research directions exemplified in RQs 1–3, we combine BNs along with ML and what-if analyses. Hereby, we describe the motivations for using this combination of methodological approaches:

(1) Considering that DT and SERVQUAL involve multiple variables within a network of relationships, we employ BN methodology to calculate conditional dependencies and examine the interdependencies among nodes, as well as their causal relationships (Zhang *et al.*, 2020). Researchers should employ BNs when they estimate the desired relationships among variables and nodes in terms of conditional probabilities and dependencies (Sutrisnowati *et al.*, 2015). In fact, BNs provide a framework for analyzing probabilistic reasoning, adeptly managing uncertainty and offering predictive insights (Hossain *et al.*, 2022). Therefore, BNs are not substitutes for traditional empirical approaches (see Appendix E) rather; they offer complementary research opportunities by modeling uncertainty and probabilistic dependencies among variables (Boutselis and McNaught, 2019). Researchers can then understand the likelihood of various outcomes, how different variables influence each other within a network, and make them well-suited for scenarios in which uncertainty and conditional relationships are significant (Bayesia, 2024).

(2) BN can be enriched by ML analysis with the purpose of uncovering latent relationships, hypotheses and models that are not initially considered in the research

design (Bayesia, 2024). Especially when there is a huge amount of data and many variables, searching for new and significant latent connections can be a challenging task, which can be handled more easily when ML techniques provide predictive insights (De Giovanni *et al.*, 2022). Discovering new and significant patterns is very important in logistics and supply chains due to the multidimensional aspects of these phenomena that make their interrelationships extremely complex and their dependencies very articulated (Cui *et al.*, 2006).

(3) BN can be supported by what-if analyses any time researchers seek to model specific scenarios (Bayesia, 2024). Interestingly, one key advantage of BNs is that they provide the opportunity to update beliefs as new data becomes available or when researchers have specific scenarios or situations to test (De Giovanni *et al.*, 2022). Therefore, the application of BN is suitable in all cases in which the data are continuously collected or when researchers have new information available; the BN can then be updated to make real-time decisions, which is particularly important in logistics and supply chain management (de Waal and Joubert, 2022).

Since the primary focus of this paper is not on detailing the fundamentals of BN, we have provided an explanation of BN techniques with a numerical example (Figure 3) in the online Appendix A. This is intended for scholars and researchers in the fields of logistics and supply chain management who may not be familiar with this technique. Instead, Figure 2 presents a methodological flowchart designed for use in future research. This flowchart clearly presents the research steps we follow in our study and allows researchers to replicate the steps that we have undertaken.

Below is a brief description of the various steps that appear in the flowchart:

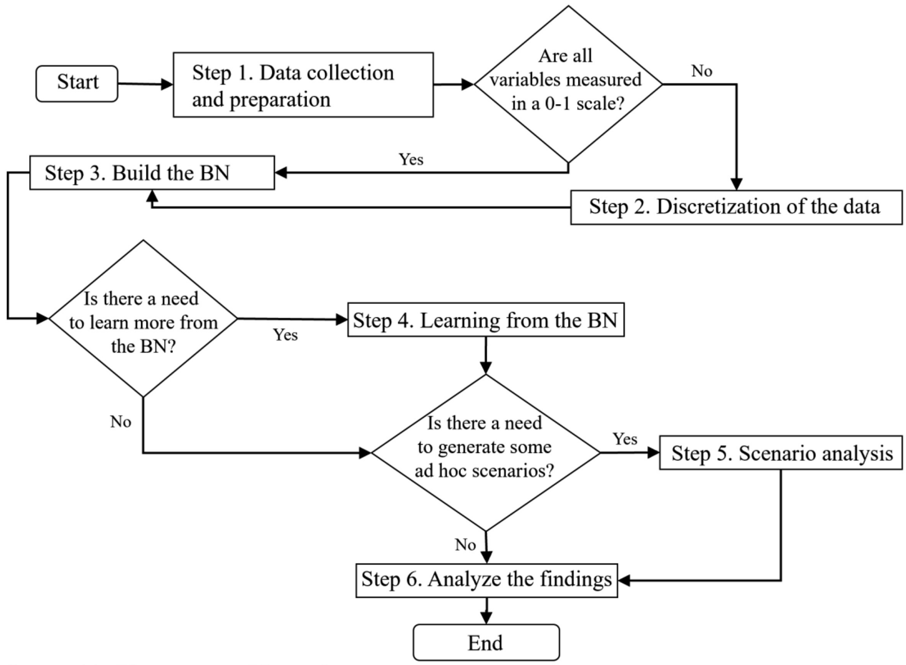

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Figure 2.
Methodological flowchart

Step 1. Data preparation. After the data are collected and prepared for analysis, the researcher should verify whether the data are all measured in terms of probability. If this is so, the researcher can move to Step 3, otherwise Step 2 can follow for discretizing the data.

Step 2. Discretization of the data. When the data are not measured on a scale of 0–1, which expresses a probability distribution, the researcher should apply some discretization algorithms. For example, a 7-point Likert scale should be transformed into a scale of 0–1. When all the data are discretized, the researcher can move to Step 3.

Step 3. Build the BN. According to the research design, the researcher fixes the arcs connecting the various nodes and builds the BN, through which the conditional probabilities are estimated using the data along with the relationships among nodes. The researcher retains only the significant relationship between nodes.

Step 4. Learning from the BN. If the researcher wants to learn more information from the BN, a set of ML algorithms can be applied, which are generally implemented inside the software the researcher uses to run the analysis. The new set of relationships discovered through the ML algorithms enriches the BN found in Step 3. If the researcher does not wish to discover latent relationships inside the network through ML, she/he can move directly to Step 5.

Step 5. Scenario analysis. If the researcher wants to answer specific RQs within ad hoc scenarios, a what-if analysis can be run using positive and negative hard evidence. The former allows the researcher to fix a certain probability to 1 (an event surely occurs), while the latter allows the researcher to fix a certain probability to 0 (an event surely does not occur). If the researcher does not wish to create any specific scenario analysis, she/he can directly move directly to Step 6.

Step 6. Analyze the findings. The researcher draws the findings from the empirical analyses resulting from Steps 3–5.

Below and later in Sections 4 and 5, we apply the methodological flowchart displayed in Figure 2 to our research.

3.1 Data collection and preparation (step 1)

To establish the connections depicted in Figure 1, we conducted a data collection process involving 1,200 Italian companies that are affiliates of our university. To gather the necessary data, we designed a questionnaire, which is displayed in the online Appendix B and which was specifically tailored for industrial and service companies directly engaged in managing logistics-related activities and investing in DT. The companies were contacted via email and invited to respond following a Qualtrics link. We asked the companies to complete the questionnaire only if they were directly managing a logistics service. Although we received a decent number of responses within two weeks, we solicited responses via phone for six additional weeks, and obtained a total of 244 useable observations, excluding those removed as invalid. This number represents about 20.33% of the entire population of companies we targeted.

The sample comprises professionals occupying diverse positions and roles within organizations. The majority of professionals in this sample are directors, who account for 42.12% of the total. Chief Executive Officers (CEOs) make up 24.69% of the sample, while managers represent 30.40%, and junior managers 14.34%. A small percentage of professionals (13.14%) falls under the "Other" category. In terms of sales figures, the majority of companies (49.69% of the sample) record sales (in euros) ranging from 0 to 9.9

million, while 22.40% of companies have sales between 10 and 24.9 million, followed by companies in the 25 to 249.9 million range (18.1%) and (12.6%) of companies in the 250 to 999.9 million range. Almost one-tenth of companies (9.81%) report sales of more than 250 million. Companies with less than 50 employees constitute the largest portion of the sample (40.08%). There is an almost equal distribution of companies with 50–99 (10.91%) employees and companies with 100–200 employees (10.91%). The remaining companies, however, have more than 200 employees, making up 38.18% of the sample. The sample includes a variety of sectors, of which the largest is the logistics sector (31.01%). This is followed by the fashion make up sector (18.36% of the sample), followed by process industries such as chemical, oil and gas, and food (14.92%), electronics (16.35%) and agriculture (23.69%). The category "other sectors" accounts for 14.03% of the sample. Since the data were collected using a Likert scale ranging from 1 (Strongly disagree) to 7 (Strongly agree), we proceed with data discretization in Step 2.

3.2 Discretization of data (step 2)

The discretization consists of transforming variables from continuous to discrete values that mimic the continuous variables as closely as possible. The various discretization techniques that can be used depend on the software employed for the analysis. In this research, we use BayesiaLab 11.0 and apply the minimum description length (MDL) to detect the best discretization approach to be used. The MDL is a well-known approach that allows for the automatic selection of the best model for representing data without having *a priori* information about them (Bruni *et al.*, 2022). Among the discretization algorithms available in BayesiaLab and given by OptRandom, K-means, density approximation, normalized equal distance and equal frequency, the OptRandom* algorithm performed the best MDL. The last mentioned allows us to determine the optimal number of intervals (or bins) to which continuous attributes should be discretized, with the primary objective of reducing the amount of information (or description length) required to describe the discretized data and the discretization model itself. In the online Appendix C, we describe all the discretization techniques available in BayesiaLab and explain how the MDL was used to select the best discretization solution.

4. Results

In this section, we present the results linked to the BN and related to Step 3, the ML procedure related to Step 4, and the scenario analysis related to Step 5.

4.1 Build the BN (step 3)

Using the discretized data, the BN is made and then analyzed. The constellation of nodes is composed of SERVQUAL logistics given by *X*{*Empathy, Assurance, Reliability, Responsiveness and Tangibility*} as well as the nodes corresponding to DT given by *Y* {*Cloud computing, Control tower, AI, IoT, Digital Avatars, AR and VR*}. The nodes Y and X are linked according to the research design displayed in Figure 1, to estimate the conditional probabilities along with their relationships and answer RQ1.

The joint probability distributions result to be: *P(Control tower = adopted) = 61.48%, P(AI = adopted) = 65.16%, P(Cloud computing = adopted) = 77.05%, P(IoT = adopted) = 69.67%, P(Digital avatars = adopted) = 32.79%, P(AR = adopted) = 52.05%,* and *P(Virtual reality = adopted) = 52.87%; in sum, Σ = P(Y = adopted)* indicates the probability that all the explored DT are adopted. Then, the probability that firms are able to achieve the SERVQUAL dimensions given the fact that DT are adopted results: *P(Tangibility = achieved |Σ) = 63.48%,* *P(Assurance = achieved |Σ) = 55.62%, P(Reliability = achieved |Σ) = 60.47%, P(Responsiveness = achieved |Σ) = 56.14% and P(Empathy = achieved |Σ) = 51.72%.*

Using these conditional probability distributions, the estimation of the links among the Y-nodes and the X-nodes is displayed in Table 2.

4.2 Learning from the BN (step 4)

In Step 4, we employed various unsupervised ML techniques to search the BN with the lowest MDL (De Giovanni *et al.*, 2022). In general, *supervised* learning is run when the researcher fixes a node as a target. *Unsupervised* learning is used when the researcher does not fix a target node. In BayesiaLab, there are three unsupervised ML techniques to be used for learning without altering the connections linked to the RQs. Specifically: equivalence (EQ), Taboo and TabooEQ search for optimal network structures with equivalent classes of BN; that is, networks with the same conditional independence and, consequently, the best fit with the data. Taboo searching is a general interactive optimization technique that moves from one solution to another according to the best neighborhood, which is given by the network structure. Finally, TabooEQ is a combination of EQ classes and Taboo searching algorithms. In our research, the best ML technique was TabooEQ; accordingly, after retaining only the significant relationships, the final BN is displayed in Figure 4 (online Appendix D), while the new and hidden relationships emerging from ML are displayed in Table 3.

4.3 Analysis of scenarios (step 5)

In this section, we derive additional insights and information through a what-if analysis (to answer RQ3). To do so, we run a set of inferences using positive and negative hard evidence. The positive hard evidence on the DT can be obtained by imposing the condition that all technologies are implemented, e.g. Σ^+ = *P (Control tower = adopted) = 1, P(AI = adopted) = 1, P(Cloud computing = adopted) = 1, P(IoT = adopted) = 1, P(Digital avatars = adopted) = 1, P(AR = adopted) = 1, P (VR = adopted) = 1*. Therefore, we can ask the following question:

> What-if all the DT are implemented?

The probabilities resulting from the BN are: *P(Empathy = achieved* | Σ^+*) = 70.8%, P(Responsiveness = achieved* | Σ^+*) = 83.33%, P(Reliability = achieved* | Σ^+*) = 83.02%, P(Assurance = achieved* | Σ^+*) = 75.25% and P(Tangibility = achieved* | Σ^+*) = 89.89%.*

Similarly, we can set negative hard evidence on the DT; that is, imposing the condition that all technologies are not implemented, e.g. Σ^- = *P (Control tower = adopted) = 0, P(AI = adopted) = 0, P(Cloud computing = adopted) = 0, P(IoT = adopted) = 0, P(Digital avatars = adopted) = 0, P(AR = adopted) = 0, P (VR = adopted) = 0*. Therefore, we can ask the following question:

	Assurance	Empathy	Reliability	Responsiveness	Tangibility
Control tower	*−0.0736*	*−0.0485*	*0.0346*	*−0.0154*	*0.0401*
AI	*0.0268*	*0.0763*	0.1344**	0.0857*	0.0861*
Cloud computing	0.0853*	0.1894*	0.1822**	*0.0587*	0.1137**
IoT	0.319***	*−0.007*	0.0887*	*−0.0586*	*0.0318*
Digital avatars	−0.0762*	*0.0632*	*0.0459*	*−0.0076*	*−0.0106*
Augmented reality	*−0.0694*	0.169**	*0.0399*	*0.00289*	*−0.037*
Virtual reality	*0.036*	0.0994*	0.0995*	0.124**	0.101*

Note(s): *p-value<0.1, **p-value<0.05, ***p-value<0.01, italic values are nonsignificant
Source(s): Table created by authors

Table 2. The empirical results of BN

Parent	Child	Coefficient	New results obtained through ML
Augmented reality	Virtual reality	0.7865***	Learned results
Artificial intelligence	Cloud computing	0.6646***	Learned results
Digital avatars	Augmented reality	0.583***	Learned results
Virtual reality	Artificial intelligence	0.5331***	Learned results
Virtual reality	Control tower	0.4978***	Learned results
Cloud computing	Internet of things	0.5067***	Learned results
Virtual reality	Internet of things	0.4629***	Learned results
Cloud computing	Control tower	0.4468***	Learned results
Cloud computing	Reliability	0.1673***	Updated results
Artificial intelligence	Tangibility	0.2117***	Updated results
Control tower	Tangibility	0.2616***	Learned results
Cloud computing	Tangibility	0.2128***	Updated results
Virtual reality	Tangibility	0.1795***	Updated results
Artificial intelligence	Reliability	0.1699***	Updated results
Internet of things	Tangibility	0.1775***	Learned results
Cloud computing	Responsiveness	0.1397***	Learned results
Artificial intelligence	Responsiveness	0.2202***	Updated results
Internet of things	Reliability	0.1553***	Updated results
Virtual reality	Responsiveness	0.1324***	Updated results
Virtual reality	Reliability	0.1697***	Updated results
Cloud computing	Assurance	0.0989**	Updated results
Virtual reality	Empathy	0.0975**	Updated results
Digital avatars	Responsiveness	0.0974**	Learned results
Augmented reality	Tangibility	0.1022**	Learned results
Augmented reality	Empathy	0.1063**	Updated results
Augmented reality	Responsiveness	0.1143**	Learned results
Internet of things	Assurance	0.0524*	Updated results
Cloud computing	Empathy	*0.0564*	Nonsignificant/Reversed results with respect to Part A
Digital avatars	Assurance	*0.0322*	Nonsignificant/Reversed results with respect to Part A

Note(s): *p-value<0.1, **p-value<0.05, ***p-value<0.01, italic values are nonsignificant
Source(s): Table created by authors

Table 3. Results from the machine learning analysis

What-if all the DT are not implemented?

Then, the probabilities resulting from the BN are: *P(Empathy = achieved* | Σ^-*) = 49.12%, P(Responsiveness = achieved* | Σ^-*) = 55%, P(Reliability = achieved* | Σ^-*) = 51.43%, P(Assurance = achieved* | Σ^-*) = 55.02% and P(Tangibility = achieved* | Σ^-*) = 56.67%.*

We can also apply both positive and negative hard evidence by creating, for example, the following probability distribution for DT: $\Sigma^{\#}$ = *P (Control tower = adopted) = 0, P(AI = adopted) = 0, P(Cloud computing = adopted) = 0, P(IoT = adopted) = 1, P(Digital avatars = adopted) = 0, P(AR = adopted) = 0, P (VR = adopted) = 0,* which can be used to ask the following question:

What-if only IoT is implemented?

Then, the probabilities resulting from the BN are: *P(Empathy = achieved | Σ#) = 49.12%, P(Responsiveness = achieved | Σ#) = 55%, P(Reliability = achieved | Σ#) = 50%, P(Assurance = achieved | Σ#) = 66.67% and P(Tangibility = achieved | Σ#) = 79.11%.*

Finally, positive and negative hard evidence can also be applied to SERVQUAL Logistics, for example, *P(Responsiveness = achieved) = 1* captures the case in which the firms perform responsiveness and serve to ask the following question:

> What-if Responsiveness is surely achieved?

The probability distribution of technologies will be as follows: *P(Control tower = adopted) = 65.24%, P(AI = adopted) = 71.20%, P(Cloud computing = adopted) = 81.78%, P(IoT = adopted) = 73.23%, P(Digital avatars = adopted) = 35.40%, P(AR = adopted) = 55.74%, P (VR = adopted) = 57.70%.*

Note: While we run only for what-if analysis, other (and potentially countless) analyses can be devised, depending on the researchers' interests. BNs are very flexible and easily create multiple scenarios through what-if analyses by updating beliefs through new or ad hoc information.

5. Analysis and discussion (step 6)

In this section, we discuss the findings and managerial implications of our research resulting from Steps 3–5. Furthermore, we make some methodological observations to highlight the additional knowledge and complementary information of BN, ML and what-if analysis to analyze logistics and supply chain problems.

5.1 Analysis and discussion based on step 3

> *Contribution 1.* The average probability that firms invest in DTA is higher than the average probability of investing in DTIE.

A descriptive analysis of the probability distributions reveals a certain level of maturity reached by DTA, which has been around for many years. In contrast, DTIE are still in the infancy stage; firms are investing in proof of concepts to understand how business models can be modified in the future, while the scale-up will require a few more years.

> *Methodological observation 1.* Unlike other empirical methods, BNs calculate the conditional dependencies between phenomena, e.g. the probability that firms perform SERVQUAL dimensions given the probability that they adopt DTA and DTIE.

> *Contribution 2.* When assessing the impacts of DT on SERVQUAL logistics, the results of which are displayed in section 3.3, we find that:

> 2a. The probability of achieving tangibility is influenced by the probability of adopting AI, cloud computing and VR.

> 2b. Achieving high reliability links to contributions from the probability of adopting AI, IoT, cloud computing and VR is likely.

> 2c. The probability of attaining high levels of assurance is enhanced by the probability of adopting cloud computing and the IoT.

> 2d. The likelihood of achieving responsiveness is driven primarily by the probability of adopting AI and VR.

> 2e. The probability of achieving empathy is influenced by the probability of adopting cloud computing, AR and VR.

In principle, the probability of achieving tangibility depends on all the prior probability distribution of technologies given by Σ and resulting in *P(Tangibility = achieved* $|\Sigma) = 63.48\%$. However, as stated in 2a, the probability of adopting AI, cloud computing and VR contributes the most to achieving tangibility by enhancing the appearance of physical facilities, equipment, personnel and communication materials.

Similarly, although *P(Reliability = achieved* $|\Sigma) = 60.47\%$, AI, IoT, cloud computing and VR contribute the most to achieving reliability in logistics by enhancing adaptability, real-time monitoring, collaboration and risk mitigation (2b). The probability of jointly adopting these technologies enhances rapid adaptation, proactive risk management, effective real-time monitoring and efficient collaboration, ensuring high reliability.

Furthermore, the probability of achieving assurance (e.g. *P(Assurance = achieved* $|\Sigma) = 55.62\%$) depends most likely on cloud computing and IoT by providing connectivity, real-time data exchange and improved visibility across the supply chain (2c). In fact, cloud computing enables secure storage, analysis and sharing of logistics data, ensuring seamless collaboration and transparency among stakeholders. Furthermore, IoT devices enable continuous monitoring of assets, inventory and transportation conditions, reducing uncertainties and enabling proactive risk management.

Regarding responsiveness, the results show that *P(Responsiveness = achieved* $|\Sigma) = 56.14\%$, which depends on the probability of adopting AI and VR (2d). On the one hand, AI algorithms have the capacity to analyze vast amounts of data to optimize logistics processes, such as route planning, inventory management, and demand forecasting, resulting in quicker response times and improved efficiency. On the other hand, VR technology helps create immersive and simulated environments, enabling one to visualize and interact with logistics operations, quickly identify and address bottlenecks, improve coordination, and make informed decisions in dynamic and time-sensitive situations.

Finally, our results demonstrate that cloud computing, AR and VR contribute the most to achieving empathy with probability *P(Empathy = achieved* $|\Sigma) = 51.72\%$ (2e). These solutions enable virtual simulations, training and remote collaboration, fostering empathy by providing a realistic and engaging platform for effective communication and problem solving. Moreover, they facilitate a deeper connection between logistics service providers and customers, leading to improved empathy and customer satisfaction.

> *Methodological observation 2.* BN measures the relationships among variables in terms of conditional probabilities by answering the following general RQ: What would the impact of the probability of implementing DTIE and DTA be on the probability of performing SERVQUAL logistics conditioned to the fact that firms implement DTIE and DTA?

5.2 Analysis and discussion based on step 4

> *Contribution 3.* Using ML derived in section 3.4 to complement BN analyses shows latent relationships that, if included, can provide new information not included in the research design. Specifically, cloud computing supports empathy without exerting a direct effect upon it. At the same time, digital avatar technology does not manifest a direct influence on the dimensions of assurance. Interestingly, a symbiotic relationship exists between investments in digital avatars and those in AR. In contrast, VR emerges as an instrumental tool for AI, IoT and the control tower. In a separate vein, cloud computing fortifies the control tower, AI and IoT to properly manage vast data repositories.

Based on the results of ML, it emerges that while cloud computing can indirectly support empathy by facilitating timely access to customer information and enabling better communication and coordination among logistics operators, it does not directly impact the emotional aspect of empathy. The latter is driven primarily by human-to-human interactions, emotional intelligence and interpersonal skills and requires other types of support. Similarly, digital avatars may not directly influence the assurance aspects of logistics services, which are built through tangible actions and evidence, such as real-time tracking information, physical security measures and adherence to industry standards and regulations. Therefore, digital avatars alone cannot guarantee the assurance dimension of SERVQUAL logistics.

Moreover, Table 3 provides information about the relationships between different technologies. Accordingly, a positive relationship exists between investments in avatars and investments in AR due to the complementary nature of these technologies and their shared goal of enhancing efficiency and customer experience. Furthermore, using them jointly provides an efficient immersive experience as AR enhances the physical environment superimposing digital information onto real-world objects.

VR enables users to visualize and simulate logistics scenarios in a virtual environment. This allows logistics professionals to better understand and analyze complex data generated by AI and IoT systems and data managed by the control tower. They can explore and interact with virtual representations of AI algorithms, IoT devices and data streams, facilitating better decision-making and problem-solving.

Finally, cloud computing offers the ability to scale computing resources on demand, allowing the control tower, AI and IoT systems to handle large volumes of data and process complex algorithms efficiently. It provides the flexibility to accommodate varying workloads and enables seamless integration with different data sources and devices. Furthermore, AI feeds cloud computing by providing updated and timely information to improve logistics strategies.

> *Methodological observation 3.* Using ML can further contribute to the field of logistics by uncovering models, hypotheses, and relationships that were not initially considered in the research design, thereby expanding the scope of the investigation. In this sense, it can yield additional knowledge and lead to further outcomes.

5.3 Analysis and discussion based on step 5

> *Contribution 4.* Using the what-if analysis derived in Section 3.5 with positive and negative hard evidence, we find that:
>
> 4a. The probability of achieving SERVQUAL logistics increases when firms implement AI, the control tower, IoT, cloud computing, avatars, AR and VR.
>
> 4b. If firms implement only IoT technology, there will be an improvement in the probability of implementing assurance and tangibility dimensions but it affects the other dimensions negatively.
>
> 4c. Firms seeking to improve responsiveness should increase the probability of investing in DTA in the future, while the benefits of DTIE still need to be understood.

One can demonstrate the result of 4a by comparing the probabilities in the analyses of the positive and negative hard evidence. For example, the lowest difference is obtained for empathy (79.8–49.12% = 21.68%) and the highest difference is related to tangibility (89.89–56.67% = 33.22%). Regarding 4b, the adoption of IoT allows firms to increase the probability of performing tangibility by 22.44% and assurance by 11.65%. Instead, the sole adoption of IoT does not grant any improvement in terms of empathy and responsiveness, while the probability of achieving reliability deteriorates slightly (by 1.43%). Finally, 4c shows that firms can achieve responsiveness when increasing the probability of adopting DTA while disregarding the implementation of DTIE.

Methodological observation 4. The what-if analysis allows decision makers to customize the research design and understand the implications of the related modifications.

6. Conclusions

This research investigates how firms can enhance the quality of their logistics services by adopting two groups of DT: DTA and DTIE. Although the current literature has explored the impact of DTA in various business aspects, this study tests the impact of DTA on SERVQUAL logistics, whose framework comprehensively describes the quality dimensions in logistics services. Furthermore, the research also accounts for DTIE, which are currently underexplored by logistics and supply chain management. DTIE provide the basis for unique customer experiences and engagement, which translates into new logistics challenges. For example, transparency and visibility of the logistics status and deliveries, continuous interactions with logistics service providers, and verification of the quality and stock availability of goods, by directly connecting them to virtual environments. Therefore, this research investigates how the profound transformations brought about by DTIE can significantly modify interactions with traditional DTA, alter the synergies and interactions among DT, and allow firms to potentially achieve higher levels of SERVQUAL logistics.

To pursue our research objectives, we employed a combination of methodologies, including BNs, ML, and what-if analysis to create an adaptable framework for investigating and predicting the intricate relationships within DT and SERVQUAL logistics. We chose BN as the focal methodology of this research due to our interest in studying the probabilistic reasoning and conditional dependencies between DT and SERVQUAL logistics. While traditional methods excel at directly measuring associations or relationships between dependent and independent variables, we selected BNs because they complement these traditional techniques by modeling uncertainty and estimating the likelihood of various outcomes under uncertainty. This decision aligns with our investigated topic, where, for instance, DTIE are still in their infancy and their effectiveness is highly uncertain. Accordingly, we have also proposed the potential use of ML algorithms to extract more information from the network of nodes involving DT and SERVQUAL logistics. These applications enable researchers to uncover new and hidden relationships that were not apparent in the initial research design but have become significantly important for increasing the predictability of the model. Their application is particularly effective in logistics and supply chain management when handling large datasets with multiple variables, where manually exploring all possible connections would be impractical. Finally, we utilized what-if analysis in conjunction with BNs, as it allows researchers to shape scenarios according to their interests, analyze specific situations or update the BN with newly available information. This flexibility renders BNs highly informative, and their related models significantly predictive.

Using these methods, our findings show that the probability that firms invest in DTIE is lower on average than the probability of investing in other DT such as IoT, cloud computing, and AI. This could be due to the infancy of DTIE. Moreover, various technologies have different impacts in achieving each SERVQUAL dimension. For instance, AI, cloud computing and VR contribute the most to increasing the probability of performing tangibility while AI and VR significantly increase firms' probability of performing responsiveness. Furthermore, ML analysis corroborating the BN reveals hidden relationships between technologies that can better explain and predict firms' probability of performing SERVQUAL logistics dimensions. For example, cloud computing can scale computing resources on demand and allow control tower, AI and IoT systems to handle large volumes of data efficiently. Besides, what-if analysis demonstrates that firms can increase the probability of achieving SERVQUAL logistics by implementing AI, control tower, IoT, cloud computing, avatars, AR and VR. Moreover, we discover that the sole implementation of IoT does not increase the probability of performing SERVQUAL logistics. Finally, by focusing on the probability of offering great responsiveness, our results demonstrate the effectiveness of implementing DTA while highlighting doubt about the effects exerted by DTIE.

This research is not without limitations, which are mentioned here to stimulate more research in the field. First, in this study, we consider the five main SERVQUAL dimensions while, as mentioned in the research of De Giovanni and Zaccour (2023), new dimensions of quality have emerged that should be considered for future research. For example, DTIE and DTA can impact other quality aspects such as traceability, authenticity, customization, sustainability, connectivity, upgrading, pre-experience and desirability and are worth considering for future research. Second, other types of technologies are ignored in this study such as drones, blockchain, human enhancement (e.g. the use of robotic exoskeletons), autonomous vehicles and 3D printing, and future research could compare them with the results of our study. Third, this paper concentrates on the use of unsupervised ML techniques to explore all feasible connections between technologies and SERVQUAL dimensions. However, it is important to note that research can also employ supervised ML techniques by establishing a predetermined target variable whose probability influences the probabilities of all other variables encompassed within the model. Noteworthy examples of such supervised techniques include Naïve Bayes, Son&Spouses and Markov Blanket. Furthermore, BN approaches offer the opportunity for various other types of analysis that align with traditional empirical techniques. For instance, cluster analysis can be conducted within BN frameworks by employing diverse ML techniques to identify clusters via algorithm-based or data-based analyses. Future research can search for clusters linked to the sectors, the firm's size, the countries, etc., to complement the findings obtainable from traditional BN with additional insights and further knowledge. Finally, as suggested by Wang *et al.* (2023), BN can be integrated with other methodologies like, for instance, the partial least square structural equation modeling (PLS-SEM) method, to investigate complex phenomenon and generate new and different outcomes for both academia and practitioners.

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Appendix

The supplementary material for this article can be found online.

Corresponding author
Pietro De Giovanni can be contacted at: pietro.degiovanni@sdabocconi.it