

## Link between Industry 4.0 and green supply chain management: Evidence from the automotive industry

Abhijeet Ghadge<sup>a,\*</sup>, D.G. Mogale<sup>b</sup>, Michael Bourlakis<sup>a</sup>, Lohithaksha M. Maiyar<sup>c</sup>,  
Hamid Moradlou<sup>d</sup>

<sup>a</sup> Centre for Logistics and Supply Chain Management, School of Management, Cranfield University, UK

<sup>b</sup> Cardiff Business School, Cardiff University, UK

<sup>c</sup> Department of Entrepreneurship and Management, Indian Institute of Technology, Hyderabad, India

<sup>d</sup> Warwick Manufacturing Group, Warwick University, Coventry, UK

### ARTICLE INFO

#### Keywords:

Industry 4.0  
Internet of Things  
Blockchain  
Cyber-Physical Systems  
Green supply chain management  
Green practices  
Sustainability  
Automotive industry

### ABSTRACT

The paper evidence the link between two paradigms - Industry 4.0 and Green Supply Chain Management (GSCM) following an empirical study conducted in the automotive industry. 243 responses from the automotive supply chain professionals from Europe (including the UK) are used to test the developed hypotheses. An integrated, two-stage approach combining interpretive structural modelling and structural equation modelling develops a multi-level hierarchical structure for establishing the link between Industry 4.0 technologies, Green Supply Chain (GSC) practices and GSC performance. The study evidenced an indirect effect of Industry 4.0 technologies through GSC practices on GSC performance; and this link is found to be stronger than the direct effect of Industry 4.0 and GSC practices in the automotive supply chains. Future supply chains should focus on driving and linking technologies such as the Internet of Things (IoT), Cyber-Physical Systems (CPS) and Blockchain for effective implementation of GSC practices. GSC practices, mainly reverse logistics and green purchasing, are highly influenced by disruptive technologies and are critical for leading improvement in GSC performance. Identifying and linking key Industry 4.0 technologies with GSC practices will benefit organizations in making evidence-informed decisions for improved sustainability performance.

### 1. Introduction

The main aim of Industry 4.0 is to make manufacturing operations/systems efficient, autonomous, and sustainable (Koh et al., 2019). Industry 4.0 is the latest industry transformation, attempting to build smart systems by integrating physical objects with digital technologies (Dalenogare et al., 2018; Fatorachian and Kazemi, 2021). Internet of Things (IoT), Cyber-Physical Systems (CPS), Big Data Analytics (BDA), Additive Manufacturing (AM) and Cloud Computing (CC) are some of the technologies of Industry 4.0. These Industry 4.0 capabilities provide higher productivity and flexibility, but they also help drive the organisations' sustainability goals (Schroeder et al., 2019; Felsberger et al., 2020; Kamble et al., 2020).

Regarding the economic dimension of sustainability, Industry 4.0 technologies can reduce set-up times, lead times, labour and material cost, increase production and design flexibility, and enhance

productivity and customization (Wang et al., 2017). In case of the environmental dimension, the reduced energy and resource consumption leads to reduction of waste or Co2 emission across production and supply chain processes (Sarkis and Zhu, 2018). In case of the social dimension, smart factories and manufacturing support employee health and safety by improving working conditions, which results in higher employee satisfaction and motivation (Müller et al., 2018). These benefits highlight growing relationships between Industry 4.0 technologies and sustainability (Liu et al., 2020). However, except a few sporadic studies (such as Li et al., 2020; Bai et al., 2020), this relationship is not well investigated due to the lack of robust evidence (Kamble et al., 2018; de Sousa Jabbour et al., 2018).

Few scholars have looked at connected elements of sustainability, such as circular economy with Industry 4.0 in their studies (e.g., Tseng et al., 2018; Massaro et al., 2021). However, industry data-driven investigation is needed to establish the link between Industry 4.0 and

\* Corresponding author.

E-mail addresses: [Abhijeet.Ghadge@cranfield.ac.uk](mailto:Abhijeet.Ghadge@cranfield.ac.uk), [ghadge.abhijit@gmail.com](mailto:ghadge.abhijit@gmail.com), [Abhijeet.Ghadge@Cranfield.ac.uk](mailto:Abhijeet.Ghadge@Cranfield.ac.uk) (A. Ghadge), [MogaleD@cardiff.ac.uk](mailto:MogaleD@cardiff.ac.uk) (D.G. Mogale), [m.bourlakis@cranfield.ac.uk](mailto:m.bourlakis@cranfield.ac.uk) (M. Bourlakis), [l.maiyar@em.iith.ac.in](mailto:l.maiyar@em.iith.ac.in) (L. M. Maiyar), [Hamid.Moradlou@warwick.ac.uk](mailto:Hamid.Moradlou@warwick.ac.uk) (H. Moradlou).

<https://doi.org/10.1016/j.cie.2022.108303>

sustainability performance (Liu et al., 2020; Machado et al., 2020; Beltrami et al., 2021). Thus, this study attempts to close this research gap by empirically assessing the link between two paradigms.

The automotive industry is arguably the largest and most dominant manufacturing sector worldwide (Zailani et al., 2015). This industry faces numerous environmental challenges including ineffective management of the end of life of vehicles, growing air pollution, adverse impact of climate change, and meeting strict government rules and regulations (Orsato and Wells, 2007). Moreover, consumer expectations are continuously changing due to rapid advancements in digital technology. In recent times, major automotive giants have introduced driverless cars, where several digital technologies like the Internet of Things (IoT), artificial intelligence and Cyber-Physical Systems (CPS) have been deployed. Furthermore, global automotive organizations and their supply chains are under constant pressure to maintain stringent environmental regulations (Russo-Spena et al., 2018) without compromising innovation and technological advancements (Farahani et al., 2017). Several Industry 4.0 technologies like 3D printing, robotics and artificial intelligence can improve product design, production and supply chain efficiency, respectively (Ghadge et al., 2020). Such technologies are bound to influence new paradigms, principles, and models in supply chain management (Ivanov et al., 2019).

It may be well-argued that Industry 4.0 technologies can influence the implementation of Green supply chain (GSC) practices within automotive industry, with a likely indirect influence on the supply chain performance. However, to the best of the authors' knowledge, such empirical study linking Industry 4.0, GSC and supply chain performance is missing in the extant literature. In line with the identified research gap, this paper investigates the following research question: **What is the link between Industry 4.0 technologies, GSC practices and GSC performance?** An integrated, two-stage approach combining Interpretive Structural Modelling (ISM) and Structural Equation Modelling (SEM) is utilized to develop a multi-level hierarchical structure for investigating the link between Industry 4.0 technologies, Green Supply Chain (GSC) practices and GSC performance. 243 questionnaire survey responses from European automotive supply chain managers were used to test the developed hypotheses. This research study is expected to provide empirical evidence for the growing link between these two important paradigms-Industry 4.0 and Green Supply Chain Management (GSCM).

The rest of the paper is organized as follows. Section 2 provides literature on Industry 4.0, GSC practices and GSC performance metrics. The research methodology, adopting an integrated ISM and SEM approach, is described in Section 3. Section 4 is devoted to conducting analysis and presenting the results. Section 5 provides critical insights into key findings. In the concluding section, contribution to research and practice and the recommendations for future research are provided.

## 2. Literature review

### 2.1. Industry 4.0

Industry 4.0 is characterized by the combination of smart products, smart factories, smart logistics and IoT to enable real-time information on multiple activities through the entirety of the supply chain (de Sousa Jabbour et al., 2017). Recently, scholars have attempted to identify Industry 4.0 readiness and their impact on supply chains (e.g., Stentoft et al., 2020; Fatorachian and Kazemi, 2021) on developing maturity models (Wagire et al., 2020) and on evaluating adoption patterns and critical factors for successful implementation (e.g., Frank et al., 2019; Calabrese et al., 2020; Sony and Naik, 2020; Queiroz et al., 2019). Furthermore, a few studies focus on implementing digital technologies in the supply chain (e.g., Ivanov et al., 2019; Hennelly et al., 2020). Interested readers can refer to the review articles on Industry 4.0 technologies provided by Liao et al. (2017), Oztemel and Gursev (2020), Pereira and Romero (2017), Sony and Naik (2018) and Zheng et al. (2020) for additional details.

Within the automotive industry, Xu et al. (2018) believe organizations are incorporating Industry 4.0 technologies as part of their corporate strategy and vision. IoT devices capture a massive amount of data, which is later used for efficient and effective decision making (Ben-Daya et al., 2017). The use of big data analytics (BDA) may significantly improve forecast accuracy and demand planning in automotive supply chains (Farahani et al., 2017). Organizations will be enabled to enhance their capability and improve their business decisions through the continuous practice of business intelligence. The IoT, CPS, automation & robotics and AM are believed to bring significant benefits to manufacturing organizations. Table 1 illustrates key Industry 4.0 technologies identified from the literature that are likely to influence future supply chains.

The IoT allows for interconnectivity between various electronic devices, sensors, and machines through several identification codes, automatic identification, data collection and wireless sensor networks (Zhou et al., 2015; Farahani et al., 2017). With the assistance of cloud computing, this information may become available to all supply chain partners in real-time.

A CPS may be considered an integrated system that aims to integrate the physical and virtual world together and enable the synchronization of information between the physical and a virtual environment (Akanmu and Anumba, 2015; Berger et al., 2016). Recently CPS are also called 'Digital Twins' (Jones et al., 2020). Furthermore, as market demand is becoming more volatile, practitioners have paid increasing attention to

**Table 1**  
Emerging technologies within Industry 4.0.

Construct Code	Industry 4.0 Technology	Definition	Sources
T1	Cyber-Physical Systems (CPS)	Systems that integrate the physical world with virtual computational space	Akanmu and Anumba (2015)
T2	Internet of Things (IoT)	Interconnecting of small computing devices embedded in products and objects to the internet, enabling the ability to receive and send data	Feldmann et al. (2010) and Zhou et al. (2015)
T3	Automation and Robotics (A & RT)	Automated technology able to design, construct and operate without human intervention during the process	Tjahjono et al. (2017)
T4	Additive Manufacturing/3D-Printing (AM/3DP)	The official industry standard of utilizing 3D-printing to create components in production	Tjahjono et al. (2017); Ghadge et al. (2018).
T5	Cloud Computing (CC)	Practice consisting of a network of remote servers that enable the storage, process and managing of data compared to a local server	Hofmann and Rüschi (2017)
T6	Big Data Analytics (BDA)	Process of investigating large, varied data sets to discover useful information and patterns that may help the decision-making of organizations	Farahani et al. (2017) and Zhong et al. (2016)
T7	Miniaturization of Electronics (ME)	Process of manufacturing ever smaller electrical, optical, and mechanical devices	Feldmann et al. (2010)
T8	Blockchain (BC)	A distributed digital technology that ensures transparency, traceability and security	Saberi et al. (2019)

implementing robotics and AM and enabling machine-to-machine (M2M) communication (Tjajhono et al., 2017).

AM utilizes 3D-printing technology to produce on-demand components under flexible geographic locations near to customer locations and circumstances that offers customized and low volume products (Rogers et al., 2016; Delic and Eyers, 2020). Blockchain (BC) supports vast amounts of product and supply chain information through data collection, storage and management (Kayikci et al., 2020). It helps to improve the economic (reduction of transaction cost and time), environmental (reduction of rework and recall due to accurate tracking) and social (fair and safe work practices) supply chain sustainability (Saber et al., 2019, Wamba and Queiroz, 2020).

## 2.2. Interface between Industry 4.0 and sustainability in SCs

Liu et al. (2020) predict that the new era of intelligence manufacturing will be driven by sustainability principles. Industry 4.0 is a new business mindset along with its technologies to assist organizations in transitioning towards sustainable development. Industry 4.0 capability driven smart systems contain several sustainability implications, such as optimized use of resources and technology (Quezada et al., 2017; Felsberger et al., 2020). According to a UK Automotive Sustainability report (2019), extensive efforts have been placed on digitalizing the automotive industry, where the next step in digitalizing automotive production resides in connecting manufacturers with wider supply chain operations. Though not explicitly stated, this emphasizes the importance of levitating the use of Industry 4.0 technologies to further improve the efficiency and effectiveness of automotive supply chains.

Centobelli et al. (2020) discuss the misalignment problem between the industry 4.0 technologies and supply chain green practices implemented. Yadav et al. (2020) identified 29 key Industry 4.0 technologies' enablers to achieve sustainability. Few other researchers (e.g., Yang et al., 2013; Chin et al., 2015; Vanalle et al., 2017) have evaluated the broad impact of GSC practices on GSC performance; however, Industry 4.0 dimension is missing in their studies. Thus, this study attempts to establish empirical evidence for establishing the link between Industry 4.0 and GSCM in the automotive industry.

## 2.3. GSC practices and performance

A coordinated and proactive approach among supply chain managers is essential to curb the environmental impact in manufacturing and supply chains (Tseng et al., 2019). Taking the case of the automotive industry of developing countries, Diabat et al. (2013) identified the most vital enablers such as eco-design, cooperation with customers and reverse logistics for improving sustainable performance. Similarly, Drohomerecki et al. (2014) and Khairani et al. (2017) considered the Brazilian and Malaysian automotive industries for analyzing the different green practices, respectively. Table 2 illustrates the most common green practices and performance indicators identified from the extant literature.

Supplier-customer environmental cooperation (SCEC) may be understood as the collaborative efforts made between partners to enhance understanding and support towards improving environmental performance through greener products and innovations (Diabat et al., 2013; Vanalle et al., 2017; Sauer and Seuring, 2018). Green manufacturing (GM) relates to sustaining waste, energy and resource management, optimal equipment utilization, eco-design and green packaging (Mathivathanan et al., 2018). Reverse logistics (RL) has been given significant attention in GSC practices in recent decades (Senthil et al., 2018; Sharma et al., 2017). Within the automotive industry, the practice of Internal Environmental Management (IEM) is argued by Vanalle et al. (2017) to be the result of ISO 14001 being of possible mandatory practice. In addition to the aforementioned GSC practices, multiple factors such as industry characteristics, regulations, cultural orientations, and dynamic capabilities have seldom appeared in the research

**Table 2**  
Common green practices and performance indicators.

	Construct Code	Green Practice	Source
	GP	Green purchasing	Khairani et al. (2017); de Sousa Jabbour et al. (2017); Vanalle et al. (2017) and Zhu et al. (2013)
	SCEC	Supplier/customer environmental cooperation	Sharma et al. (2017); Vanalle et al. (2017); Diabat et al. (2013) and Agyemang et al. (2018)
Green practices	GM	Green manufacturing	Scur and Barbosa et al. (2018) and Khairani et al. (2017)
	RL	Reverse logistics	Sharma et al. (2017); Khairani et al. (2017); Drohomerecki (2014) and Mathivathanan et al. (2018)
	IEM	Internal environmental management	Wu et al. (2015); Scur and Barbosa (2017); Vanalle et al. (2017) and Diabat et al. (2013)
	EconP	Economic performance	Wu et al. (2015) and Vanalle et al. (2017)
Performance indicators	EnvP	Environmental performance	Sharma et al. (2017), Wu et al. (2015) and Vanalle et al. (2017)
	OP	Operational performance	Sharma et al. (2017), Vanalle et al. (2017) and Zhu et al. (2013)

articles (e.g., Vijayvargy et al., 2017; Hong et al., 2018). However, these studies have overlooked the integration of Industry 4.0 with GSC practices and supply chain performance.

Green supply chain performance may be characterized into two main performance metrics: economic and environmental (Lin, 2013). However, Sharma et al. (2017) and Vanalle et al. (2017) acknowledge the importance of operational aspects as these may obtain useful insights towards competitive priorities related to the organization's operations. Performance may be measured using various indicators; therefore, this study has consolidated a total of three key performance indicators namely economic, environmental, and operational performance (Table 2).

## 3. Research methodology

The study followed an integrated, two-stage approach for data collection and analysis. In the first stage, following a critical literature review, key technologies were identified for Industry 4.0 along with practices for GSC, which were structured into different hierarchical levels following the ISM approach. Later A cross-impact matrix multiplication analysis (MICMAC) analysis was carried out to determine the independent and dependent variables. In the second stage, the hypotheses were framed for investigating the link between two paradigms and data were collected through the questionnaire survey. Finally, the proposed hypotheses were tested using the SEM method. The SEM approach helps to investigate causal relationships and correlations between variables. It ignores the information about the hierarchical structure as well as dependent and independent variables involved in the analysis (Sindhu and Arif, 2016; Nandal et al., 2019); and thus, is found to be suitable for this study.

Multiple techniques such as Analytic Hierarchy Process (AHP), Graph theory, Decision Making Trial and Evaluation Laboratory (DEMATEL) and Analytic Network Process (ANP) exist in the literature

to analyze the interdependencies among the variables and develop their structural hierarchy (Luthra et al., 2020). The advantage of the ISM-MICMAC approach over the other aforementioned methods is evident in the supply chain literature (Lahane et al., 2020). The ISM allows the experts to clarify the interpretative logic behind each paired relationship through the interpretative matrix and structural model (Shukla and Shankar, 2022). The commonly used Analytic Hierarchy Process (AHP) prioritizes different factors, whereas ISM evaluates the interrelations among these factors. The ISM provides a multi-level hierarchal structure comprising of all factors; however, it does not produce any insights into the importance of each factor. Thus, MICMAC analysis is employed to identify the key dependent and independent factors (Khaba and Bhar, 2018; Swarnakar et al., 2020). This overall research methodology, consisting of two stages, is described in flowchart form in Fig. 1.

3.1. Stage I

**Interpretive structural modelling (ISM)**

Several scholars in the literature have delineated clear and straightforward procedures for developing a model using an ISM method (e.g., Diabat and Govindan, 2011; Mathiyazhagan et al., 2013; Rajput and Singh, 2018; Kamble et al., 2018). Therefore, the generalized explanation about the ISM method is not incorporated in this study. In brief, the different steps of ISM modelling include identification of variables from extant literature, establishment of contextual relationships among identified variables, formation of a Structural self-interaction matrix (SSIM), initial reachability matrix, final reachability matrix (SSIM), initial reachability matrix, final reachability matrix

matrix, level partitioning, creation of a diagraph and final ISM model.

The ISM model depicts the influential level of all factors which help to achieve the main objective (here to improve GSC performance) in the form of a structural hierarchy. However, the classification of several variables and indirect relationship among them is not realized from the ISM model (Thirupathi and Vinodh, 2016; Khaba and Bhar, 2018). To gain some practical insights from the relational links, the study performed MICMAC analysis.

**MICMAC analysis**

MICMAC analysis is utilized to identify key Industry 4.0 technologies and GSC practices that affect GSC performance based on their driving and dependence power. The variables are classified into four categories (Kannan and Haq, 2007): (1) autonomous variable (Cluster I, low driving and dependence power), (2) dependent variables (Cluster II, strong dependence and weak driving power), (3) linkage variable (Cluster III, strong driving and dependence power) and (4) independent variables (Cluster IV, strong driving and weak dependence power).

3.2. Stage II

**Development of hypotheses**

Different hypotheses were created to empirically establish the link between two paradigms after identifying key variables for Industry 4.0 and GSC practices from the literature, translating into a multi-level hierarchical structure and classifying them into driving and dependent variables (following ISM and MICMAC approach respectively). To test the hypothesized link between Industry 4.0 and GSC practices, data was

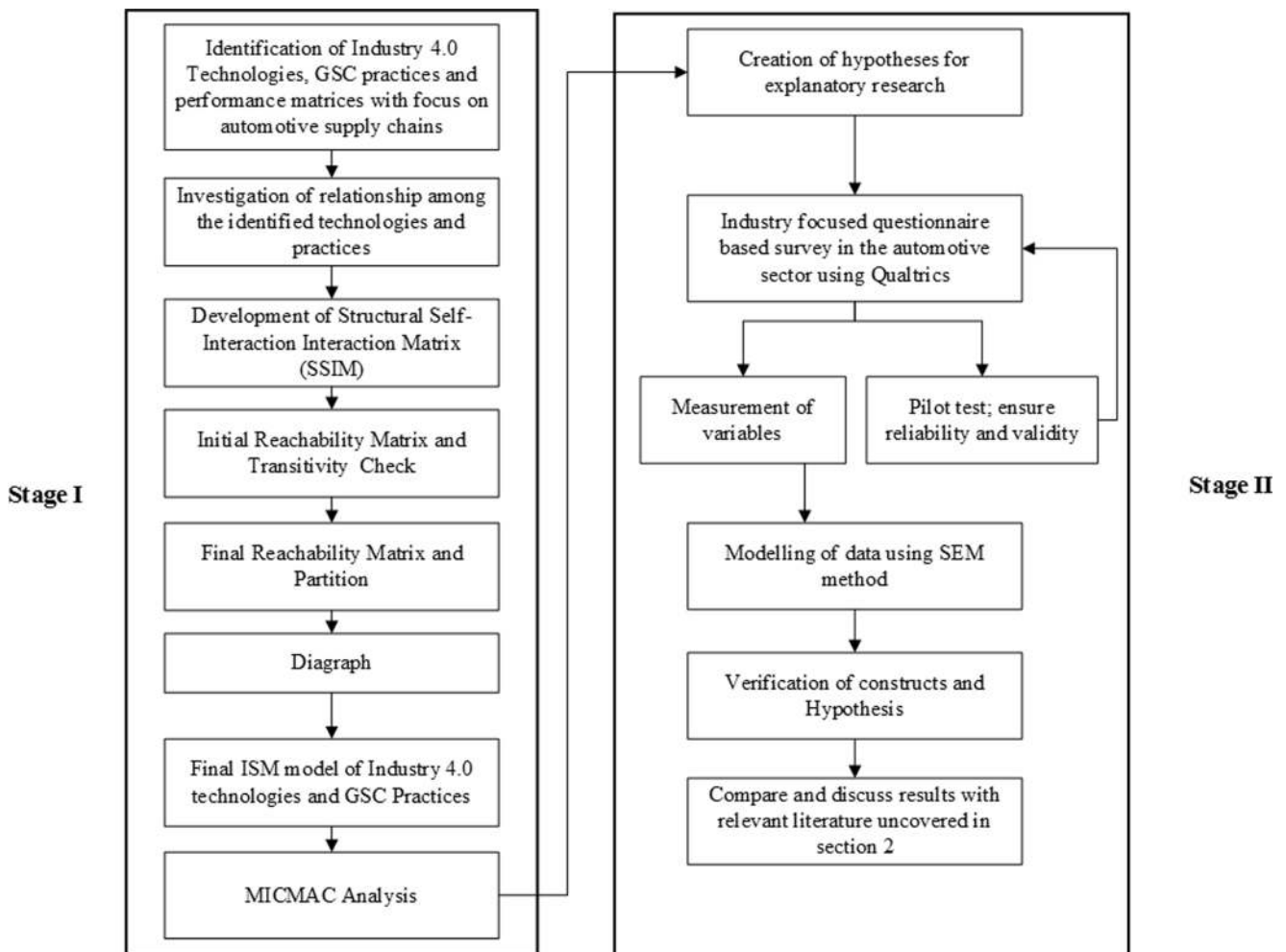


Fig. 1. Research methodology.

collected through a questionnaire survey.

*Industry 4.0 will provide positive support for implementing GSC practices and will collectively help in improving GSC performance in automotive supply chains.*

Following this primary hypothesis, we break this into three hypotheses for testing.

*H1: Industry 4.0 technologies will positively correlate with GSC practices.*

*H2: Industry 4.0 technologies will positively correlate with GSC performance.*

*H3: GSC practices will, as a result of Industry 4.0, positively impact GSC performance.*

Fig. 2 provides a conceptual framework, where these three hypotheses have been developed to answer the research question.

**Questionnaire survey data**

Boyer and Swink (2008) discuss the advantages of surveys, such as having a highly economical and non-invasive approach, and that standardized data are obtained that directly reflect an individual related to the area of interest. Hence, data was collected from automotive supply chain managers across Europe (including the UK) following a questionnaire survey. The Qualtrics-built questionnaire was distributed through personal email and professional social networks (like LinkedIn and Twitter) to collect structured data over nine months (from May 2019 to January 2020). The executives from the industry, who employed Industry 4.0 technologies and experts from the academia who work in the sustainability and Industry 4.0 domain verified and validated the initial draft of the questionnaire by rephrasing several questions, question sequencing and wordings to make the questionnaire clearer and more suitable for respondents to understand. In the next stage, doubts/queries from several respondents were clarified by providing suitable responses. In this way, each respondent participated in the survey following the complete delineation of the questionnaire.

To further ensure a reliable and effective response rate, the

questionnaire was simplistically and efficiently designed using mainly closed-ended questions. Structured questions exploiting the Likert scale (0–5) method determine the extent to which each respondent agrees or values the variables (Saunders et al., 2015). The Likert scale was adopted from Dubey et al. (2018). This approach helps to limit the choice of answers and minimize the time required to complete the survey, thus increasing the chance of reliable and valid responses. The survey was sent to over 900 contacts; however, only 288 respondents responded to multiple reminders and requests. After removing biased and incomplete surveys, 243 responses were deemed useful for subsequent analysis. Appendix A shows a developed questionnaire survey. The overall response rate was 27%.

Structural equation modelling (SEM).

SEM is a method to portray, stipulate, estimate and analyze models with linear relationships among the several observed (measured) variables in the form of a usually smaller number of unobserved (latent) variables (Shah and Goldstein, 2006). The measurement model depicts the relationship between the latent or hypothetical construct and indicators (observed variables). It delineates the measurement properties encompassing reliabilities and validities of the indicators. The conceptual ISM model is verified using PLS-SEM path modelling to achieve useful results.

**4. Results and analysis**

*4.1. ISM model for GSCM performance variables*

The use of experts' opinions, including academia and industry, is recommended while developing the contextual relationship among the variables in the ISM model. Expert opinions regarding Industry 4.0 and GSC practices were collected between the years 2017–19. The respondents were automotive supply chain professionals along with

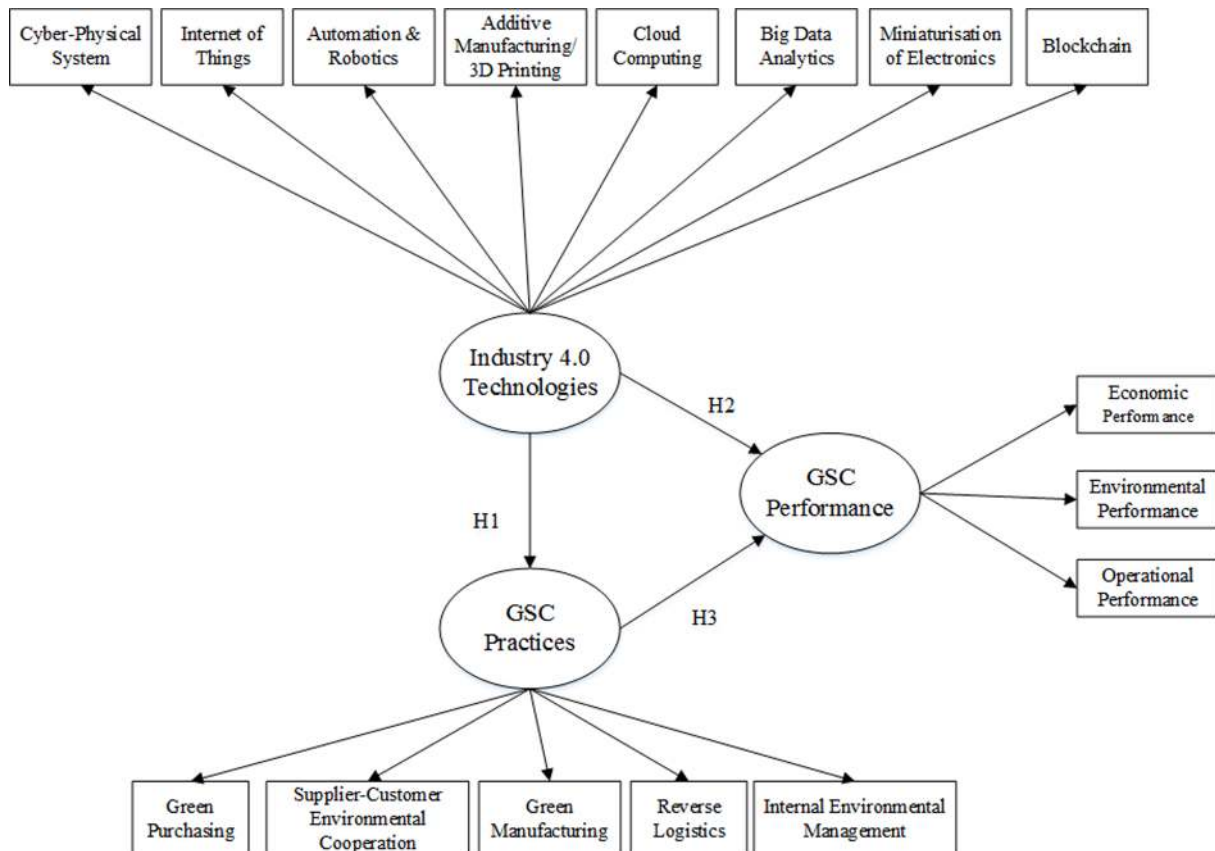


Fig. 2. Conceptual framework/hypothesis model.

several senior professors from renowned institutions with a strong research background in GSCM and Industry 4.0 technologies. The SSIM was developed following expert views about two eminent fields (Table 3). While evaluating the contextual link between two factors, each expert was asked the following three questions: (1) will factor 1 help factor 2; (2) will factor 2 help factor 1; (3) will both factors help each other or not? Later, the specific relationship between each of the two factors, based on the maximum number of respondents' answers to each question was established.

The following four symbols are used to indicate the direction of the relationship between two factors.

- V - If factor 'i' will support/help to achieve 'j'.
- A - If factor 'j' will support/help to achieve 'i'.
- X - If factor 'i' and 'j' will support/help each other.
- O - If factor 'i' and 'j' are not related.

The initial reachability matrix (binary matrix) is formed from SSIM by replacing the V, A, X and O with binary variables as illustrated in Table 4. The following rules are used for the transformation of SSIM to RM.

- If the (i, j) entry of the cell in SSIM is V, then replace it with 1 and (j, i) entry to 0 in initial RM.
- If the (i, j) entry of the cell in SSIM is A, then replace it with 0 and (j, i) entry to 1 in initial RM.
- If the (i, j) entry of the cell in SSIM is X, then replace both (i, j) and (j, i) by 1 in initial RM.
- If the (i, j) entry of the cell in SSIM is O, then replace both (i, j) and (j, i) with 0 in initial RM.

The final reachability matrix was obtained by incorporating the transitivity rule in the RM as shown in Table 4. This table also illustrates the driving and dependence power of factors which are obtained by summing up the rows and column entries.

The reachability, antecedent and intersection set are determined corresponding to each factor from the final RM for level partitioning. Following ten iterations (until each factor obtains its level) levels are established as shown in Table 5.

The ISM-based model for Industry 4.0 technologies and GSC practices that improve the GSC performance is constructed from the final RM and partitions level as shown in Fig. 3. The developed ISM model evaluates the ten-level structural relationship among the key Industry 4.0 technologies and GSC practices to improve GSC performance. This model reveals that the IoT is the most significant factor, followed by CPS, compared with other factors of Industry 4.0. The IoT and CPS directly or indirectly drive GSC practices. Additionally, CPS is the second most significant factor which confirms the Zhou et al. (2015) outcome that the IoT is closely linked to CPS, as it provides interconnectivity between various sensors, machines and electronic devices.

**Table 3**  
Structural self-interaction matrix (SSIM).

Factors	IEM	RL	GM	SCEC	GP	BC	ME	BDA	CC	AM/3DP	A&RT	IOT
CPS	V	V	V	V	V	V	V	A	A	V	V	A
IOT	V	V	V	V	V	X	A	V	V	V	V	
A&RT	V	O	V	V	O	O	V	A	X	V		
AM/3DP	V	O	V	X	A	A	V	O	A			
CC	V	O	O	X	O	X	V	V				
BDA	V	X	V	V	V	V	A					
ME	X	V	X	V	O	O						
BC	V	V	O	V	V							
GP	X	X	V	X								
SCEC	X	A	V									
GM	V	A										
RL	V											

#### 4.2. Classification of factors using MICMAC analysis

A cross-impact matrix multiplication analysis (MICMAC) is mainly used for evaluating the driving and dependence power of factors (Shukla and Shankar, 2022). Three groups of factors are found after the implementation of the MICMAC method and insights about these factors are described considering their driving and dependence power as shown in Fig. 4. Autonomous factors are not present in the analysis, which denotes that all the considered Industry 4.0 and GSC practices are significant. Industry 4.0 technologies like IoT, CPS and A&RT come under the category of independent factors on which the performance of GSCM depends, as they are root causes behind the dependent factors. Among the various driving/independent factors, IoT is a key factor, which has the highest driving power of 13 and dependence power of 4 (Table 6). Therefore, it is placed in the cluster IV with a given dependence and driving power. Blockchain (BC), cloud computing (CC) and ME are found as linkage variables, which can affect other factors in the system as well as receiving the reaction effect. These factors consist of strong driving and dependence power. Blockchain has the highest driving power of 13 and dependence power of 10 and is positioned in cluster III. ME is interlinked with most independent and dependent factors, since it consists of smaller mechanical, optical and electronic devices that are manufactured through Industry 4.0 technologies (Feldmann et al., 2010).

The BC is highly applicable in the optimization of logistics due to the ability to track products in real-time, enabling the ability to collect vast amounts of data (Saber et al., 2019; Kamble et al., 2021). With the help of BDA, ME and CC, this may then be utilized to optimize vehicle routing and reduce emissions. Dependent variables observed include, Reverse Logistics (RL), Supplier and Customer Environmental Collaboration (SCEC), Green Purchasing and Manufacturing, and Internal Environmental Management (IEM). All these dependent variables are the practices of GSCM. Thus, it can be interpreted from this analysis that to implement GSC practices within automotive supply chains, Industry 4.0 technologies are essential. The variables classified in dependent and independent categories required extensive research due to their strategic significance for improvement in the GSC performance.

#### 4.3. Model analysis by SEM

SEM comprises multiple regression and factor analysis and is mainly used to test/verify several relationships simultaneously among the different variables in a single model (Bamgbade et al., 2018). There are several applications of SEM, which include path analysis, regression models, confirmatory factor analysis, covariance, and correlation structure models. The structural model shown in Fig. 2 is evaluated using Smart-PLS software to capture the impact of the observed variables and their latent constructs on GSC performance.

Reliability tests are required in order to safeguard that variance of responses across periods remain at a minimum in order that a measurement recorded at any point in time is reliable (Sardana et al., 2016).

**Table 4**  
Final reachability matrix with driving and dependence power.

		1	2	3	4	5	6	7	8	9	10	11	12	13	Driving Power
	Factors	CPS	IOT	A&RT	AM/3DP	CC	BDA	ME	BC	GP	SCEC	GM	RL	IEM	
1	CPS	1	0	1	1	1	1	1	1	1	1	1	1	1	12
2	IOT	1	1	1	1	1	1	1	1	1	1	1	1	1	13
3	A&RT	0	0	1	1	1	0	1	1	1	1	1	1	1	10
4	AM/3DP	0	0	0	1	1	0	1	1	1	0	1	1	1	8
5	CC	1	0	1	1	1	1	1	1	1	1	1	1	1	12
6	BDA	1	0	1	0	1	1	1	1	0	1	1	1	1	10
7	ME	0	1	0	0	1	1	1	1	1	1	1	1	1	10
8	BC	1	1	1	1	1	1	1	1	1	1	1	1	1	13
9	GP	0	0	0	0	1	0	0	0	1	1	1	1	1	6
10	SCEC	0	0	0	1	1	0	0	1	1	1	0	0	1	6
11	GM	0	0	0	0	0	0	1	0	0	0	1	0	1	3
12	RL	0	1	0	0	0	1	0	0	1	1	1	1	1	7
13	IEM	0	0	0	0	0	0	1	1	1	1	1	0	1	6
	Dep. Power	5	4	6	7	10	7	10	10	11	11	12	10	13	

**Table 5**  
Level partition iterations.

F. n	Factors	Reachability set	Antecedent set	Intersection set	Level
13	IEM	7,9,10,13	1,2,3,4,5,6,7,8,9,10,11,12,13	7,9,10,13	I
11	GM	7,11,13	1,2,3,4,5,6,7,8,9,10,11,12	7,11	II
9	GP	4,9,10,11,12,13	1,2,3,4,5,6,7,8,9,10,12,13	4,9,10,12,13	III
10	SCEC	4,5,9,10,11,13	1,2,3,4,5,6,7,8,9,10,12,13	4,5,9,10,13	III
12	RL	6,9,10,11,12,13	1,2,3,4,5,6,7,8,9,12	6,9,12	IV
5	CC	1,3,4,5,6,7,8,9,10,11,12,13	1,2,3,4,5,6,7,8,10	1,3,4,5,6,7,8,10	V
7	ME	2,5,6,7,9,10,11,12,13	1,2,3,4,5,6,7,11,13	2,5,6,7,11,13	V
8	BC	2,4,5,8,9,10,11,12,13	1,2,3,4,5,6,8	2,4,5,8	V
6	BDA	1,3,5,6,7,8,9,10,11,12,13	1,2,3,4,5,6,7,12	1,3,5,6,7,12	VI
4	AM/3DP	4,5,6,7,8,9,10,11,12,13	1,2,3,4,5,8,9,10	4,5,8,9,10	VII
3	A&RT	3,4,5,6,7,8,9,10,11,12,13	1,2,3,5,6	3,5,6	VIII
1	CPS	1,3,4,5,6,7,8,9,10,11,12,13	1,2,5,6	1,5,6	IX
2	IOT	1,2,3,4,5,6,7,8,9,10,11,12,13	2,7,8	2,7,8	X

A single observed reliability test evaluates the standardized outer loadings of the indicators to delineate the variance of an individual indicator against the unobserved variables (Zhao et al., 2019). Indicators with a loading value of 0.4 or greater are highly acceptable, and indicators with loadings below 0.4 are removed from the model (Hair et al., 2012). All indicators considered in the current study obtained a loading of more than 0.4, which confirms the single observed reliability test (Table 6).

The structural validity of the factor analysis was examined by following four major tests, i.e., Cronbach Alpha, Kaiser-Meyer-Olkin (KMO), Bartlett’s test of Sphericity and Composite Reliability. The Cronbach’s Alpha scores were all above 0.752, where the recommended threshold is 0.7 (Draper and Smith, 1998). The KMO measure of sampling adequacy achieved scores above 0.656, which is well above the 0.6 level considered as a requirement for conducting factor analysis (Guimarães et al., 2016). In addition, Bartlett’s test of sphericity was also utilized to assess the feasibility of EFA and found to be significant as the Sig. value from Table 6 demonstrates statistical significance.

Finally, the composite reliability tests had the lowest recorded value of 0.807 for GSC performance variable which is, again, above the recommended threshold of 0.6 for conducting a factor analysis. The results of the test mentioned above are reported in Table 6. The approach suggested by Armstrong and Overton (1977) was used to verify the non-response bias. The study found no statistically significant differences in the responses that indicate the absence of non-response bias. Further, the common method bias was verified after the successful scrutiny of Harmon’s single factor test. As per this test, a single factor should not show the most variance (50%) when all items were loaded into one common factor (Podsakoff et al., 2003). The current model shows 34% total variance, which is lower than the threshold (Queiroz et al., 2020).

Furthermore, all the tests imply that the constructs within each concentrated variable remain consistent in measuring the latent

variable. Despite the GSC performance variable achieving a relatively low Cronbach’s Alpha score, the variable was still deemed reliable. All other concentrated variables were both very reliable and highly reliable (see Table 6) and are, therefore, valid latent variables for CFA. The average variance extracted (AVE) of each latent construct was determined to confirm the convergent validity of the variables. The latent construct takes 50% of the variance from indicators; thus, the AVE of all constructs remains above 0.5. Following above tests, internal consistency and convergent validity were confirmed for the study. Fornell and Larcker (1981) suggest that the comparison between the AVE and corresponding inter-construct squared correlation approximations improves the discriminant validity. As the AVE values for Industry 4.0 technologies, GSC practices and GSC performance are greater than the squared inter-construct correlations, they prove the discriminant validity criteria of the constructs.

After confirmation of the measurement model, we must measure the outcome of the inner structural model by investigating the model’s predictive relevancy and the relationship between the constructs. The inner path model illustrates 0.784 as a coefficient of determination for the GSC performance-dependent latent construct which means that Industry 4.0 technologies and GSC practices are responsible for the 78.4% improvement of GSC performance. According to Hair et al. (2013), a coefficient of determination value of 0.26 is considered as weak, 0.5 as moderate and 0.75 as significant. Therefore, the obtained coefficient of determination value in this study is substantial. Furthermore, the study used Stone-Geisser’s Q<sup>2</sup> test for endogenous constructs to evaluate the predictive power of the model (Stone, 1974; Hair et al., 2017; Sreedevi and Saranga, 2017). The Q<sup>2</sup> value above 0 is sufficient to depict the power of the predictive model (Hair et al., 2013; Wamba et al., 2020). This study obtained the Q<sup>2</sup> values (GSC practices = 0.273 and GSC performance = 0.432) higher than 0, showing the acceptable predictive power of the model.

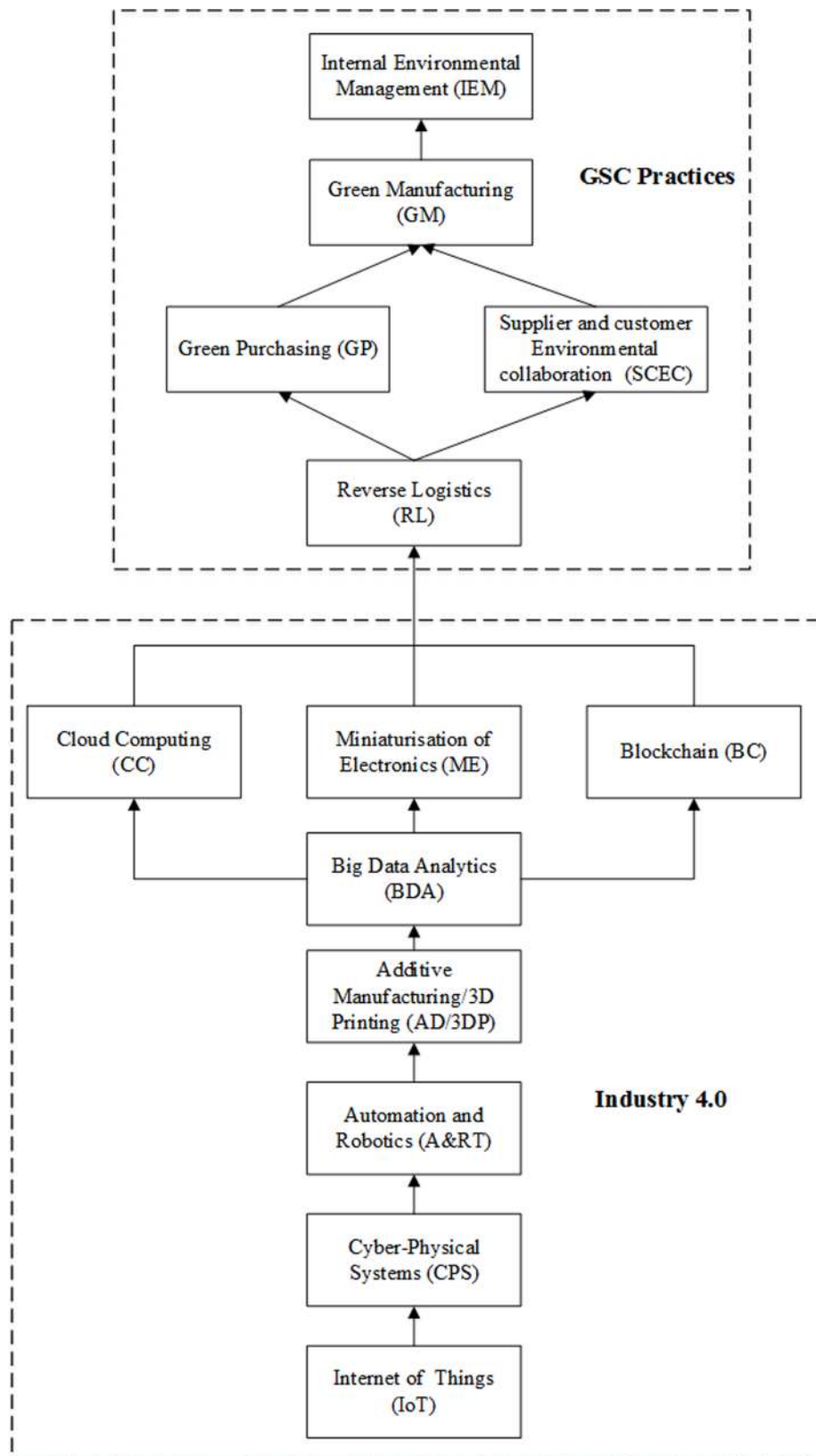


Fig. 3. ISM depicting the levels of Industry 4.0 technologies and GSC practices for the improvement of GSC performance.

The path coefficient in the PLS is similar to the standardized  $\beta$  coefficient in the regression analysis. The  $\beta$  value for each path in the hypothesized model was determined, and its impact on the endogenous latent construct was also evaluated. A T-statistics test is used to verify

the significance level of  $\beta$  value. The significance of the hypothesis is evaluated by means of bootstrapping procedure in PLS. The path coefficient and T-statistics are tested through the bootstrapping procedure using 5000 subsamples with non-sign changes.



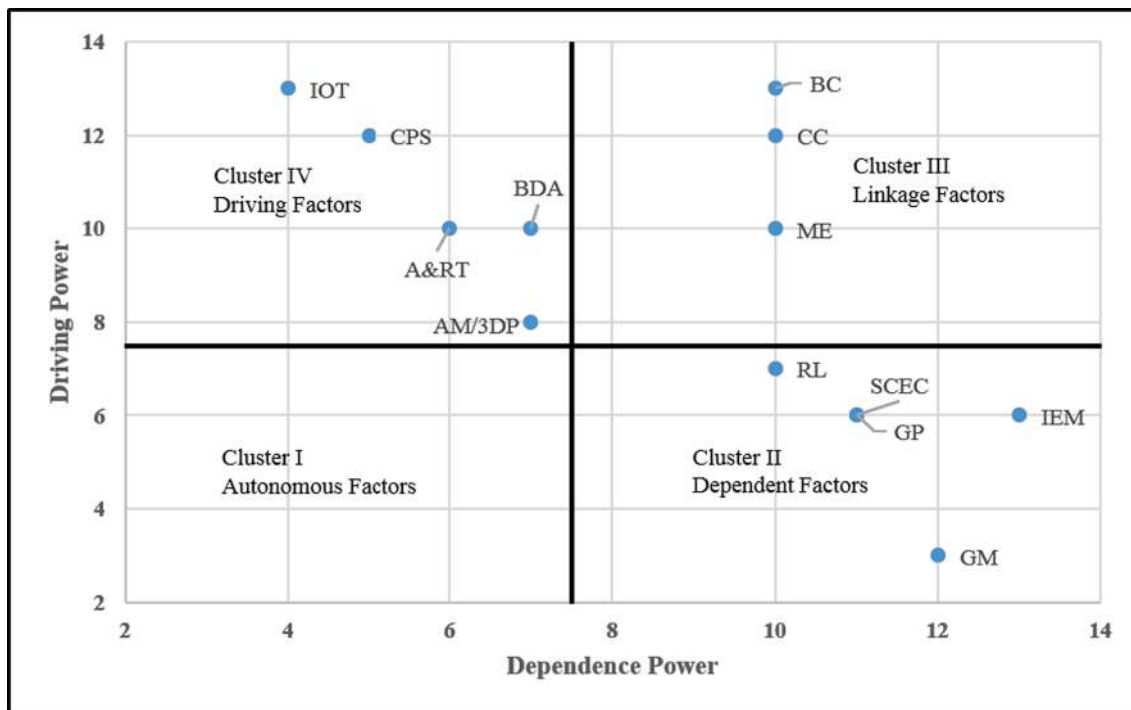


Fig. 4. Results of MICMAC analysis.

Table 6  
Reliability tests of construct groupings to variables.

Variable	Indicators	Loadings	Cronbach's Alpha	KMO Measure of Sampling	Bartlett's Test of Sphericity Approx. Chi-Square	Sig.	Composite Reliability	AVE	Evaluation
Industry 4.0 Technologies	CPS	0.676	0.818	0.683	123.623	0.000	0.823	0.58	Very Reliable
	IoT	0.728							
	A&RT	0.680							
	AM/3DP	0.686							
	CC	0.732							
	BDA	0.725							
	ME	0.555							
GSC Practices	BC	0.550	0.898	0.779	151.024	0.000	0.912	0.72	Highly Reliable
	GP	0.727							
	SCEC	0.930							
	GM	0.917							
	RL	0.809							
GSC Performance	IEM	0.844	0.752	0.677	28.107	0.000	0.807	0.67	Reliable
	EconP	0.802							
	EnvP	0.857							
	OprP	0.797							

5. Findings

Following the analysis above, this section presents key findings. In H1, we anticipated that Industry 4.0 technologies would positively correlate with GSC practices in automotive supply chains. Table 7 confirmed empirically that the Industry 4.0 technologies are significantly correlated with GSC practices. Thus, H1 is fully satisfied, which confirms the significant positive relationship between the extent of Industry 4.0 implementation and the perceived impact on the implementation of GSC practices. It is evident that, as the organizations within the automotive sector increase their implementation of Industry 4.0 technologies, there is a higher perceived impact these technologies have on implementing GSC practices. This result confirms the multi-level hierarchy obtained through the ISM method, indicating that Industry 4.0 technologies drive GSC practices. This provides the first empirical evidence and supports the notion that Industry 4.0 technologies will

Table 7  
Path co-efficient and T-statistics.

H. No.	Hypothesis	Stand Beta	T-statistics	p values	Evaluation
H1	Industry 4.0 → GSC Practices	0.351	2.912	0.006 (Sig. 0.01 level)	Satisfied
H2	Industry 4.0 → GSC Performance	0.254	2.056	0.046 (Sig. at 0.05 level)	Satisfied
H3	GSC Practices → GSC Performance	0.720	6.937	0.000 (Sig. 0.01 level)	Satisfied

improve the implementation of GSC initiatives leading to a more

efficient and competitive supply chain.

Similarly, findings from Table 7 illustrate a slight positive correlation between Industry 4.0 implementation and the perceived impact it will impose on GSC performance. Thus, as the implementation of Industry 4.0 increases, the expected/perceived impact on GSC performance metrics will increase. The results support the argument that the ability of smart products, factories and logistics in collaboration with the IoT and CC will enable monitoring of real-time information on production, machines and flow of components throughout the supply chain resulting in improved managerial decision-making and monitoring of performance.

There is a powerful positive relationship between the perceived impacts the GSC practices will impose on GSC performance because of Industry 4.0 technologies. The mediating variable in the model (i.e., GSC practices) helps to establish the link between independent (i.e., Industry 4.0) and dependent (i.e., GSC performance) variables. This strong relationship can be interpreted from Table 7. Therefore, it is evident that GSC performance will be highly impacted as a result of increased implementation of GSC practices due to Industry 4.0 technologies. The extent of the relationship may be seen from the strong linear relationship between the two concentrated variables. However, the extent of this relationship was expected to be highly positive as GSC practices are initiatives conducted by organizations to improve their GSC performance (Diabat et al., 2013). Nevertheless, these results yield empirical evidence that the influence of enhancing GSC practices as a result of Industry 4.0 will improve the green performance of automotive SCs. Finally, all three hypotheses are presented in Fig. 5.

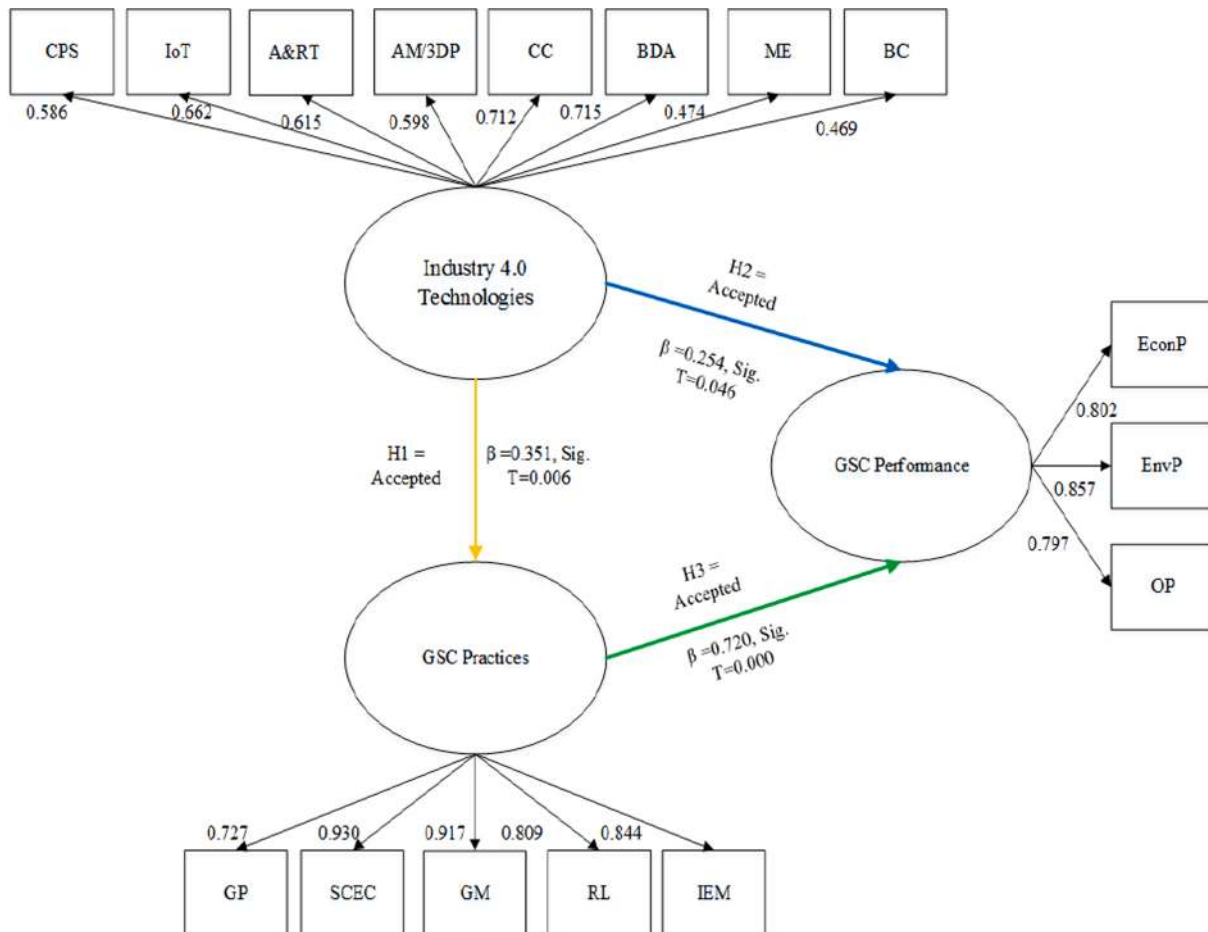
The conceptual model presented in Fig. 5 is based on tested hypotheses. The arrows interlinking the concentrated variables have been coloured to demonstrate the strength of the relationship. Green signifies

a strong, statistically significant positive relationship. Orange reflects a moderate positive relationship, which is statistically significant. The effect of exogenous construct on the endogenous construct depends on the  $\beta$  coefficient, which implies that the greater the  $\beta$  coefficient, the stronger the effect. It can be noticed that GSC practices, as a result of Industry 4.0 technologies, has the highest path coefficient  $\beta = 0.720$  compared with the remaining  $\beta$  values in the model. This indicates a larger variance and significant effect of GSC practices through Industry 4.0 technologies on the improvement of GSC performance. On the other hand, Industry 4.0 technologies have the least direct impact on GSC performance with  $\beta = 0.254$ . This means that the indirect effect of Industry 4.0 technologies through GSC practices on GSC performance is higher than the direct effect of Industry 4.0 and GSC practices. Here, Industry 4.0 technologies play a moderating variable role between GSC practices and GSC performance.

The correlation coefficient of the latent variable is provided in Table 8. The strong correlation between the latent exogenous constructs and latent endogenous construct is observed from this table. The measurement and structural models are confirmed through the comprehensive analysis. The three hypotheses are statistically significant and accepted, thus, yielding empirical insight into the relationships of

**Table 8**  
Latent variable correlation.

	Industry 4.0	GSC practices	GSC performance
Industry 4.0	1		
GSC practices	0.414	1	
GSC performance	0.306	0.735	1



**Fig. 5.** Conceptual framework and model tested.

Industry 4.0 and GSCM implementation.

## 6. Conclusion and implications

### 6.1. Discussion

The paper aimed to assess and evidence the link between Industry 4.0 and GSC practices and how they influence GSC performance in the automotive supply chain following an empirical study. The scarce literature surrounding the relationship between two paradigms - Industry 4.0 and GSCM was the motivation for study. While attempting to address the defined research question, the study found that the implementation of Industry 4.0 technologies will positively impact the implementation of GSC practices in automotive supply chains. Furthermore, Industry 4.0 technologies will also positively improve GSC performance metrics and, therefore, provide evidence that the technologies of Industry 4.0 will assist organizations in transitioning towards sustainable development (Bonilla et al., 2018; Stock et al., 2018). Moreover, it is also apparent that the impact of Industry 4.0 on GSC practices will indirectly lead to an improvement in the green performance of automotive supply chains, which supports the findings made by Kamble et al. (2020).

The study employed an integrated, two-stage approach by combining ISM and SEM methods to provide multiple findings. First, following the ISM method, a multi-level structural relationship among the key Industry 4.0 technologies and GSC practices for improving GSC performance was built. The ten-level hierarchical structure revealed that IoT and CPS are the most significant factors compared to other Industry 4.0 technologies influencing GSC practices. Later, MICMAC analysis supported in developing a driving and dependence power matrix. Within GSC practices, it was found that RL carried the highest driving power, strongly influencing GP and SCEC (Cluster II in Fig. 4). In linking factors, although CC, ME and BC carry the same level of dependence power on other high-level Industry 4.0 technologies, BC carries the highest driving power for linking Industry 4.0 technologies with GSC practices and other SC processes (Cluster III in Fig. 4).

Building on these insights, the SEM method was employed to test/verify the developed hypothesis models simultaneously. Following multiple reliability and statistical tests, the measurement and structural models were evaluated. All hypotheses (H1, H2, H3) were satisfied and accepted, reflecting the strong influential relationship between Industry 4.0 technologies, GSC practices and GSC performance. The  $\beta$  coefficient, representing the strength of the effect, was found to be strongest between GSC practices and GSC performance. This was a predictable result as GSC practices will invariably help in driving GSC performance (Chin et al., 2015; Vanalle et al., 2017). However, similar, strong (but with lower strength) relationships between Industry 4.0 & GSC practices and Industry 4.0 & GSC performance were observed. More importantly, the indirect effect of Industry 4.0 technologies through GSC practices on SC performance was found to be higher compared to the direct effect of Industry 4.0 and GSC practices. The establishment of this relationship overcomes the limitation identified by Centobelli et al. (2020) concerning the two paradigms.

### 6.2. Theoretical implications

The research conducted in this study presents multiple theoretical contributions to the paradigms between Industry 4.0 and GSCM. Firstly, this research provides robust empirical evidence into how the integration of Industry 4.0 technologies in automotive supply chains will corroborate the initiation of GSC practices and their impact on improving GSC performance concerning economic, environmental, and operational dimensions (Liu et al., 2020; Kamble et al., 2020). Past studies mainly discuss the implications and benefits of Industry 4.0 in the manufacturing, automotive and service sectors (e.g., Quezada et al., 2017; Fatorachian and Kazemi, 2018; Rahman et al., 2020) and identify

the drivers and barriers for GSCM implementation (e.g. de Sousa Jabbour et al., 2018; Kaur et al., 2018). Furthermore, there are limited theoretical approaches in the literature that focus on the integration of Industry 4.0 technologies and their significance towards greening supply chains (Beier et al., 2020; Centobelli et al., 2020). This first empirical study in the automotive supply chains, sheds light on the unique relationships between Industry 4.0 and GSCM.

Secondly, the power matrix provides novel insights into key driving and linking disruptive technologies from Industry 4.0 and how they influence measuring and implementing core aspects of GSCM. Dependent factors from GSC practices will play critical roles in improving the overall environmental performance of supply chains, provided they are aptly linked to Industry 4.0 technologies. Thirdly, from the methodological perspective, the application of an integrated ISM and SEM approach for modelling the causal relationship between Industry 4.0 and GSCM in the automotive supply chains is distinctive. Fourthly, while exploring the role played by mediating and moderating variables of the model, the study established that there is an indirect effect of Industry 4.0 technologies through GSC practices on GSC performance, and this link is stronger than the direct effect of Industry 4.0 and GSC practices. Overall, this research contributes to the growing literature on sustainability and Industry 4.0 in the broad domain of supply chain management.

### 6.3. Practical implications

From a managerial perspective, the study provides evidence to organizations that although the implementation of GSCM and Industry 4.0 varies depending on the organization's size and SC area of operation, there are quantifiable benefits of implementing both within their supply chains. Wagire et al. (2020) call for developing Industry 4.0 maturity models, which are empirically grounded, and technology focussed. Empirically establishing the link between Industry 4.0 and GSCM can help practitioners with improved confidence in implementing GSC practices along with Industry 4.0 technologies for improved firm performance. Furthermore, this study provides a detailed analysis into the extent to which the technologies of Industry 4.0 will influence the implementation of GSC practices and their indirect impact on GSC performance. These insights will help early adopting practitioners with a better understanding of the interplay of smart production systems (driven by integrated Industry 4.0 technologies) for overcoming safety, control and other operational issues faced by organizations (Queiroz et al., 2020). Furthermore, the structural relationship among the key Industry 4.0 technologies and GSC practices (Fig. 3) will guide supply chain managers in making hard decisions regarding the choice of technologies/practices to implement first for enhanced supply chain performance. This data-driven study will encourage managers to further explore the implications of Industry 4.0 on wider sustainability aspects within their supply chains.

### 6.4. Limitations and future research

Like any other research, the study has several limitations. The following research could benefit from a larger sample size, where a geographical area is a key focus of the research. The data were mostly collected in developed countries (Europe and UK), where some level of advancement is found in technology acceptance and adherence to sustainability principles. It would be interesting to expand the scope of this study worldwide to capture the perspective of automotive sectors in developing and under-developed countries. Due to the vastness of Industry 4.0 applications, in future, similar studies in other sectors (such as aerospace and locomotive) can be conducted to support the generalization of the established link as noted in this paper. Furthermore, the current research did not consider variables such as firm experience, size, and other moderating variables with Industry 4.0 technology and GSCM, and whether this may influence the relationships of the coexisting

paradigms is an interesting research question to explore in the future. Several technologies fall under the remit of Industry 4.0, and the study selected only relevant technologies based on the authors' perceptions (Ivanov et al., 2020). From the research methodology perspective, the application of Fuzzy ISM-MICMAC to the problem may have provided better results and should be further explored. In the near future, macro and micro-level analysis can be conducted by investigating the impact of the individual as well as the combined Industry 4.0 technologies on GSCM.

### CRedit authorship contribution statement

**Abhijeet Ghadge:** Conceptualization, Methodology, Writing - original draft. **D.G. Mogale:** Data curation, Formal analysis. **Michael Bourlakis:** Supervision. **Lohithaksha M. Maiyar:** Validation. **Hamid Moradlou:** Writing - review & editing.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Acknowledgement

The authors are grateful to three anonymous reviewers and the Guest Editor for their constructive comments and suggestions to improve the contents of this paper.

### References

- Armstrong, J. Scott, & Overton, Terry S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, 14(3), 396–402.
- Agyemang, M., Zhu, Q., Adzanyo, M., Antarciuc, E., & Zhao, S. (2018). Evaluating barriers to green supply chain redesign and implementation of related practices in the West Africa cashew industry. *Resources, Conservation and Recycling*, 136 (April).
- Akanmu, A., & Anumba, C. J. (2015). Cyber-physical systems integration of building information models and the physical construction. *Engineering, Construction and Architectural Management*, 22(5), 516–535.
- Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, 229, Article 107776.
- Bamgbade, J. A., Kamaruddeen, A. M., Nawi, M. N. M., Yusoff, R. Z., & Bin, R. A. (2018). Does government support matter? Influence of organizational culture on sustainable construction among Malaysian contractors. *International Journal of Construction Management*, 18(2), 93–107.
- Ben-Daya, M., Hassini, E., & Bahroun, Z. (2017). Internet of things and supply chain management: a literature review. *International Journal of Production Research*, 7543, 1–24.
- Berger, C., Hees, A., Braunreuther, S., & Reinhart, G. (2016). "Characterization of Cyber-Physical Sensor Systems." *Procedia CIRP* 41. Elsevier B.V.: 638–643.
- Beier, G., Ullrich, A., Niehoff, S., Reißig, M., & Habich, M. (2020). Industry 4.0: How it is defined from a sociotechnical perspective and how much sustainability it includes—A literature review. *Journal of Cleaner Production*, 259, Article 120856.
- Beltrami, M., Orzes, G., Sarkis, J., & Sartor, M. (2021). Industry 4.0 and sustainability: Towards conceptualization and theory. *Journal of Cleaner Production*, 312, Article 127733.
- Bonilla, S. H., Silva, Helton R. O., da Silva, M. T., Gonçalves, R. F., & Sacomano, J. B. (2018). Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges. *Sustainability* 10, no. 10 (2018): 3740.
- Boyer, K. K., & Swink, M. L. (2008). Empirical elephants—why multiple methods are essential to quality research in operations and supply chain management. *Journal of Operations Management*, 26(3), 338–344.
- Calabrese, A., Levialdi Ghiron, N., & Tiburzi, L. (2020). Evolutions' and 'revolutions' in manufacturers' implementation of industry 4.0: A literature review, a multiple case study, and a conceptual framework. *Production Planning & Control*, 1–15.
- Centobelli, P., Cerchione, R., Chironi, D., Del Vecchio, P., & Urbinati, A. (2020). Designing business models in circular economy: A systematic literature review and research agenda. *Business Strategy and the Environment*, 29(4), 1734–1749.
- Chin, T. A., Tat, H. H., & Sulaiman, Z. (2015). Green supply chain management, environmental collaboration and sustainability performance. *Procedia CIRP*, 26, 695–699.
- 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 (August). Elsevier B.V.: 383–394.
- Jabbour, D. S., Lopes, A. B., Jabbour, C. J. C., Foropon, C., & Filho, M. G. (2018). When titans meet – can industry 4.0 revolutionize the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technological Forecasting and Social Change*, 132, 18–25.
- Diabat, A., & Govindan, K. (2011). An analysis of the drivers affecting the implementation of green supply chain management. *Resources, Conservation and Recycling*, 55(6), 659–667.
- Diabat, A., Khodaverdi, R., & Olfat, L. (2013). An exploration of green supply chain practices and performances in an automotive industry. *International Journal of Advanced Manufacturing Technology*, 68(1–4), 949–961.
- Delic, M., & Eyers, D. R. (2020). The effect of additive manufacturing adoption on supply chain flexibility and performance: An empirical analysis from the automotive industry. *International Journal of Production Economics*, 228, 107689.
- Draper, N. R., & Smith, H. (1998). Fitting a straight line by least squares. *Applied Regression Analysis*, 15–46.
- Drohomeretski, E., Costa, S. G. D., & Lima, E. P. D. (2014). Green supply chain management: drivers, barriers and practices within the Brazilian automotive industry. *Journal of Manufacturing Technology Management*, 25(8), 1105–1134.
- Dubey, R., Gunasekaran, A., Childe, S. J., Luo, Z., Wamba, S. F., Roubaud, D., & Foropon, C. (2018). Examining the role of big data and predictive analytics on collaborative performance in context to sustainable consumption and production behaviour. *Journal of Cleaner Production*, 196, 1508–1521.
- Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics*, 210, 15–26.
- Farahani, P., Meier, C., & Wilke, J. (2017). Digital supply chain management agenda for the automotive supplier industry. *In Shaping the digital enterprise* (pp. 157–172). Springer, Cham.
- Fatorachian, H., & Kazemi, H. (2018). A critical investigation of Industry 4.0 in manufacturing: Theoretical operationalization framework. *Production Planning & Control*, 29(8), 633–644.
- Fatorachian, H., & Kazemi, H. (2021). Impact of Industry 4.0 on supply chain performance. *Production Planning & Control*, 32(1), 63–81.
- Felsberger, A., Qaiser, F. H., Choudhary, A., & Reiner, G. (2020). The impact of Industry 4.0 on the reconciliation of dynamic capabilities: Evidence from the European manufacturing industries. *Production Planning & Control*, 1–24.
- Feldmann, K., Franke, J., & Schüßler, F. (2010). Development of micro assembly processes for further miniaturization in electronics production. *CIRP Annals - Manufacturing Technology*, 59(1), 1–4.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50.
- Ghadge, A., Karantoni, G., Chaudhuri, A., & Srinivasan, A. (2018). Impact of additive manufacturing on aircraft supply chain performance: A system dynamics approach. *Journal of Manufacturing Technology Management*, 29(5), 846–865.
- Ghadge, A., Kara, M. E., Moradlou, H., & Goswami, M. (2020). The impact of Industry 4.0 implementation on supply chains. *Journal of Manufacturing Technology Management*, 31(4), 669–686.
- Guimarães, J. C. F. de, Severo, E. A., Dorion, E. C. H., Coallier, F., & Olea, P. M. (2016). The use of organisational resources for product innovation and organizational performance: a survey of the Brazilian furniture industry. *International Journal of Production Economics* 180: 135–147.
- Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, 40(3), 414–433.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: rigorous applications, better results and higher acceptance. *Long Range Planning*, 46(1–2), 1–12.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed). Thousand Oaks, CA: Sage Publications.
- Hennelly, P. A., Srari, J. S., Graham, G., & Wamba, S. F. (2020). Rethinking supply chains in the age of digitalization. *Production Planning and Control*, 2(3), 93–95.
- Hofmann, E., & Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry*, 89, 23–34.
- Hong, J., Zhang, Y., & Ding, M. (2018). Sustainable supply chain management practices, supply chain dynamic capabilities, and enterprise performance. *Journal of Cleaner Production*, 172, 3508–3519.
- Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829–846.
- Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterizing the digital twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology*, 29, 36–52.
- Kamble, S. S., Gunasekaran, A., Ghadge, A., & Raut, R. (2020). A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMES-A review and empirical investigation. *International journal of production economics*, 229, 107853.
- Kamble, S. S., Gunasekaran, A., & Sharma, R. (2018). Analysis of the driving and dependence power of barriers to adopt industry 4.0 in Indian manufacturing industry. *Computers in Industry*, 101(May), 107–119.
- kamble, S. S., Gunasekaran, A., Subramanian, N., Ghadge, A., Belhadi, A., & Venkatesh, M. (2021). Blockchain technology's impact on supply chain integration and sustainable supply chain performance: Evidence from the automotive industry. *Annals of Operations Research*, 1–26. In press.
- Kamble, S., Gunasekaran, A., & Dhone, N. C. (2020). Industry 4.0 and lean manufacturing practices for sustainable organizational performance in Indian

- manufacturing companies. *International Journal of Production Research*, 58(5), 1319–1337.
- Kannan, G., & Noorul Haq, A. (2007). Analysis of interactions of criteria and sub-criteria for the selection of supplier in the built-in-order supply chain environment. *International Journal of Production Research*, 45(17), 3831–3852.
- Kaur, J., Sidhu, R., Awasthi, A., Chauhan, S., & Goyal, S. (2018). A DEMATEL based approach for investigating barriers in green supply chain management in Canadian manufacturing firms. *International Journal of Production Research*, 56(1–2), 312–332.
- Kayikci, Y., Subramanian, N., Dora, M., & Bhatia, M. S. (2020). *Food supply chain in the era of Industry 4.0: Blockchain technology implementation opportunities and impediments from the perspective of people, process, performance and technology*. Production Planning and Control.
- Khaba, S., & Bhar, C. (2018). Analyzing the barriers of lean in Indian coal mining industry using integrated ISM-MICMAC and SEM. *Benchmarking*, 25(7), 2145–2168.
- Khairani, N. S., Kasim, E. S., Rajamanoharan, I. D., & Misman, F. N. (2017). Green supply chain management in the Malaysian automotive industry: A systems thinking perspective. *International Journal of Supply Chain Management*, 6(2), 38–48.
- Koh, L., Orzes, G., & Jia, F. J. (2019). The fourth industrial revolution (Industry 4.0): Technologies disruption on operations and supply chain management. *International Journal of Operations & Production Management*, 39(6/7/8), 817–828.
- Lahane, S., Kant, R., & Shankar, R. (2020). Circular supply chain management: A state-of-art review and future opportunities. *Journal of Cleaner Production* 258: 120859.
- Li, Y., Dai, J., & Cui, L. (2020). The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model. *International Journal of Production Economics*, 229, Article 107777.
- Liao, Y., Deschamps, F., de Freitas, E., Loures, R., & Ramos, L. F. P. (2017). Past, present and future of industry 4.0 - a systematic literature review and research agenda proposal. *International Journal of Production Research*, 55(12), 3609–3629.
- Lin, R. J. (2013). "Using Fuzzy DEMATEL to Evaluate the Green Supply Chain Management Practices." *Journal of Cleaner Production* 40: 32–39.
- Liu, Y., Zhu, Q., & Seuring, S. (2020). New technologies in operations and supply chains: Implications for sustainability. *International Journal of Production Economics*, 229, Article 107889.
- de Sousa, J., Beatriz, A., Vazquez-Brust, D., Jabbour, C. J. C., & Latan, H. (2017). Green supply chain practices and environmental performance in Brazil: Survey, case studies, and implications for B2B. *Industrial Marketing Management* 66: 13–28.
- de Sousa, J., Beatriz, A., Jabbour, C. J. C., Filho, M. G., & Roubaud, D. (2018). Industry 4.0 and the circular economy: a proposed research agenda and original roadmap for sustainable operations. *Annals of Operations Research* 270 (1–2): 273–286.
- Luthra, S., Kumar, A., Zavadskas, E. K., Mangla, S. K., & Garza-Reyes, J. A. (2020). Industry 4.0 as an enabler of sustainability diffusion in supply chain: an analysis of influential strength of drivers in an emerging economy. *International Journal of Production Research*, 58(5), 1505–1521.
- Mathivathanan, D., Kannan, D., & Noorul Haq, A. (2018). Sustainable supply chain management practices in Indian automotive industry: a multi-stakeholder view. *Resources, Conservation and Recycling*, 128, 284–305.
- Mathiyazhagan, K., Kannan Govindan, A., NoorulHaq, and Geng, Y. (2013). "An ISM approach for the barrier analysis in implementing green supply chain management." *Journal of Cleaner Production* 47: 283–297.
- Massaro, M., Secinaro, S., Dal Mas, F., Brescia, V., & Calandra, D. (2021). Industry 4.0 and circular economy: An exploratory analysis of academic and practitioners' perspectives. *Business Strategy and the Environment*, 30(2), 1213–1231.
- 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(1), 247.
- Machado, C. G., Winroth, M. P., & Ribeiro da Silva, E. H. D. (2020). Sustainable manufacturing in Industry 4.0: An emerging research agenda. *International Journal of Production Research*, 58(5), 1462–1484.
- Nandal, V., Kumar, R., & Singh, S. K. (2019). Barriers identification and analysis of solar power implementation in Indian thermal power plants: An Interpretative Structural Modeling approach. *Renewable and Sustainable Energy Reviews*, 114, Article 109330.
- Orsato, R. J., & Wells, P. (2007). The automobile industry & sustainability. *Journal of Cleaner Production*.
- Queiroz, M. M., Pereira, S. C. F., Telles, R., & Machado, M. C. (2019). *Industry 4.0 and digital supply chain capabilities: A framework for understanding digitalization challenges and opportunities*. Benchmarking: An International Journal, online.
- Queiroz, M. M., Wamba, S. F., Machado, M. C., & Telles, R. (2020). Smart production systems drivers for business process management improvement. *Business Process Management Journal*, online.
- Oztemel, E., & Gursev, S. (2020). Literature Review of Industry 4.0 and Related Technologies. *Journal of Intelligent Manufacturing*. <https://doi.org/10.1007/s10845-018-1433-8>
- Quezada, L. E., Chiu, (A.) S. F., Gouvea da Costa, S. E., and Tan, K. H. (2017). Operational excellence towards sustainable development goals through industry 4.0. *International Journal of Production Economics* 190: 1–2.
- Pereira, A. C., & Romero, F. (2017). A review of the meanings and the implications of the Industry 4.0 concept. *Procedia Manufacturing*, 13, 1206–1214.
- Rahman, S. M., Perry, N., Müller, J. M., Kim, J., & Laratte, B. (2020). End-of-life in industry 4.0: Ignored as before? *Resources, Conservation and Recycling*, 154, Article 104539.
- Rajput, S., & Singh, S. P. (2018). Identifying industry 4.0 IoT enablers by integrated PCA-ISM-DEMATEL approach. *Management Decision*. <https://doi.org/10.1108/MD-04-2018-0378>
- Rogers, H., Baricz, N., & Pawar, K. S. (2016). 3D printing services: Classification, supply chain implications and research agenda. *International Journal of Physical Distribution & Logistics Management*.
- Russo-Spena, T., Tregua, M., & De Chiara, A. (2018). Trends and drivers in CSR disclosure: a focus on reporting practices in the automotive industry. *Journal of Business Ethics*, 151(2), 563–578.
- Sarkis, J., & Zhu, Q. (2018). Environmental sustainability and production: Taking the road less travelled. *International Journal of Production Research*, 56(1–2), 743–759.
- Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research*, 57(7), 2117–2135.
- Sardana, D., Terziowski, M., & Gupta, N. (2016). The impact of strategic alignment and responsiveness to market on manufacturing firm's performance. *International Journal of Production Economics*, 177.
- Sauer, P. C., & Seuring, S. (2018). A three-dimensional framework for multi-tier sustainable supply chain management. *Supply Chain Management*, 23(6), 560–572.
- Saunders, M., Lewis, P., & Thornhill, A. (2015). *Research methods. Business Students* (5th.). England: Pearson Education Limited.
- Schroeder, A., Ziaee Bigdeli, A., Galera Zarco, C., & Baines, T. (2019). Capturing the benefits of industry 4.0: A business network perspective. *Production Planning & Control*, 30(16), 1305–1321.
- Scur, G., & Barbosa, M. E. (2017). Green supply chain management practices: multiple case studies in the Brazilian home appliance industry. *Journal of Cleaner Production*, 141, 1293–1302.
- Senthil, S., Murugananthan, K., & Ramesh, A. (2018). Analysis and prioritization of risks in a reverse logistics network using hybrid multi-criteria decision-making methods. *Journal of Cleaner Production*, 179, 716–730.
- Shah, R., & Goldstein, S. M. (2006). Use of structural equation modeling in operations management research: looking back and forward. *Journal of Operations Management*, 24(2), 148–169.
- Sharma, V. K., Chandna, P., & Bhardwaj, A. (2017). Green supply chain management related performance indicators in agro industry: a review. *Journal of Cleaner Production*, 141, 1194–1208.
- Sony, M., & Naik, S. (2020). Critical factors for the successful implementation of Industry 4.0: A review and future research direction. *Production Planning & Control*, 31(10), 799–815.
- Sreedevi, R., & Saranga, H. (2017). Uncertainty and supply chain risk: The moderating role of supply chain flexibility in risk mitigation. *International Journal of Production Economics*, 193, 332–342.
- Stentoft, J., Adsboll Wickstrom, K., Philipsen, K., & Haug, A. (2020). Drivers and barriers for Industry 4.0 readiness and practice: Empirical evidence from small and medium-sized manufacturers. *Production Planning & Control*, 1–18.
- Stock, T., Obenaus, M., Kunz, S., & Kohl, H. (2018). Industry 4.0 as enabler for a sustainable development: A qualitative assessment of its ecological and social potential. *Process Safety and Environmental Protection*, 118, 254–267.
- Stone, M. (1974). Cross-validated choice and assessment of statistical predictions. *Journal of the Royal Statistical Society: Series B (Methodological)*, 36(2), 111–133.
- Shukla, M., & Shankar, R. (2022). An extended technology-organization-environment framework to investigate smart manufacturing system implementation in small and medium enterprises. *Computers & Industrial Engineering*, 163, Article 107865.
- Swarnakar, V., Singh, A. R., Antony, J., Tiwari, A. K., Cudney, E., & Furterer, S. (2020). A multiple integrated approach for modelling critical success factors in sustainable LSS implementation. *Computers & Industrial Engineering*, 150, Article 106865.
- Thirupathi, R. M., & Vinodh, S. (2016). Application of interpretive structural modelling and structural equation modelling for analysis of sustainable manufacturing factors in Indian automotive component sector. *International Journal of Production Research*, 54(22), 6661–6682.
- Tjahjono, B., Esplugues, C., Ares, E., & Pelaez, G. (2017). What does industry 4.0 mean to supply chain? *Procedia Manufacturing*, 13, 1175–1182.
- Tseng, M. L., Tan, R. R., Chiu, A. S., Chien, C. F., & Kuo, T. C. (2018). Circular economy meets industry 4.0: Can big data drive industrial symbiosis? *Resources, Conservation and Recycling*, 131, 146–147.
- Tseng, M. L., Islam, M. S., Karia, N., Fauzi, F. A., & Afrin, S. (2019). A literature review on green supply chain management: trends and future challenges. *Resources, Conservation and Recycling*, 14, 145–162.
- UK Automotive Sustainability Report, 2019, <https://www.smmmt.co.uk/wp-content/uploads/sites/2/SMMT-Sustainability-Report-2019.pdf>, Accessed on 20 March 2022.
- Vanalle, R. M., Ganga, G. M. D., Filho, M. G., & Lucato, W. C. (2017). Green supply chain management: an investigation of pressures, practices, and performance within the Brazilian automotive supply chain. *Journal of Cleaner Production*, 151, 250–259.
- Vijayvargy, L., Thakkar, J., & Agarwal, G. (2017). Green supply chain management practices and performance. *Journal of Manufacturing Technology Management*, 28(3), 299–323.
- Wamba, S. F., & Queiroz, M. M. (2020). Industry 4.0 and the supply chain digitalization: A blockchain diffusion perspective. *Production Planning & Control*, 1–18.
- Wamba, S. F., Queiroz, M. M., Wu, L., & Sivarajah, U. (2020). Big data analytics-enabled sensing capability and organizational outcomes: Assessing the mediating effects of business analytics culture. *Annals of Operations Research*, 1–20.
- Wagire, A. A., Joshi, R., Rathore, A. P. S., & Jain, R. (2020). Development of maturity model for assessing the implementation of Industry 4.0: Learning from theory and practice. *Production Planning & Control*, 1–20.
- Wang, Y., Ma, H. -S., Yang, J. -H., and Wang, K. -S. Industry 4.0, 2017: a way from mass customization to mass personalization production. *Advances in Manufacturing* 5 (4): 311–320.
- Wu, K. J., Liao, C. J., Tseng, M. L., & Chiu, A. S. F. (2015). Exploring decisive factors in green supply chain practices under uncertainty. *International Journal of Production Economics*, 159, 147–157.

- Yadav, G., Kumar, A., Luthra, S., Garza-Reyes, J. A., Kumar, V., & Batista, L. (2020). A framework to achieve sustainability in manufacturing organizations of developing economies using industry 4.0 technologies' enablers. *Computers in industry*, *122*, Article 103280.
- Yang, C. S., Chin Shan, L., Haider, J. J., & Marlow, P. B. (2013). The effect of green supply chain management on green performance and firm competitiveness in the context of container shipping in Taiwan. *Transportation Research Part E: Logistics and Transportation Review*, *55*, 55–73.
- Zailani, S., Govindan, K., Iranmanesh, M., Shaharudin, M. R., & Chong, Y. S. (2015). Green Innovation adoption in automotive supply chain: The Malaysian case. *Journal of Cleaner Production*, *108*, 1115–1122.
- Zhong, R. Y., Newman, S. T., Huang, G. Q., & Lan, S. (2016). Big data for supply chain management in the service and manufacturing sectors: challenges, opportunities, and future perspectives. *Computers and Industrial Engineering*, *101*, 572–591.
- Zhou, L. i., Chong, A. Y. L., & Ngai, E. W. T. (2015). Supply chain management in the era of the internet of things. *International Journal of Production Economics*, *159*, 1–3.
- Zhu, Q., Sarkis, J., & Lai, K. H. (2013). "Institutional-based antecedents and performance outcomes of internal and external green supply chain management practices." *Journal of Purchasing and Supply Management* *19* (2): 106–117.
- Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: State of the art and future trends. *International Journal of Production Research*, *56*(8), 2941–2962.
- Zhao, X., Wang, S., & Sun, L. (2019). Single and sequential sampling plans for multi-attribute products and multi-class lot in reliability test. *IEEE Access*, *7*, 81145–81155.