A mixed-method analysis of Industry 4.0 technologies in value generation for collaborative consumption companies

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Abstract

Purpose. This research aims to extract Industry 4.0 technological building blocks (TBBs) capable of value generation in collaborative consumption (CC) and the sharing economy (SE). Furthermore, by employing a mixed methodology, this research strives to analyse the relationship among TBBs and classify them based on their impact on CC.

Method. Due to the importance of technology for the survival of collaborative consumption in the future, this study suggests a classification of the auxiliary and fundamental industry 4.0 technologies and their current upgrades, such as the metaverse or non-fungible tokens (NFT). First, by applying a systematic literature review and thematic analysis (SLR-TA), we extracted the TBBs that impact collaborative consumption and SE. Then, using the Bayesian best-worst method (BBWM), TBBs are weighted and classified using experts opinions. Eventually, a score function is proposed to measure organisations readiness level to adopt Industry 4.0 technologies.

Originality. With an in-depth investigation, this research identifies TBBs of Industry 4.0 with the capability of value generation in CC and SE. To the authors knowledge, this is the first research that identifies and examines the TBBs of Industry 4.0 in the CC and SE sectors and examines them. Furthermore, a novel mixed method has identified, weighted, and classified pertinent technologies. The score function that measures the readiness level of each company to adopt TBBs in CC and SE is a unique contribution.

Results. The findings illustrated that virtual reality (VR) plays a vital role in CC and SE. Of the 11 TBBs identified in the CC and SE, VR was selected as the most determinant TBB and metaverse was recognised as the least important. Furthermore, digital twins, big data, and VR were labelled as “fundamental”, and metaverse, augmented reality (AR), and additive manufacturing were stamped as “discretional”. Moreover, cyber-physical systems (CPSs) and artificial intelligence (AI) were classified as “auxiliary” technologies.

Keywords. Bayesian best-worst method, Industry 4 technologies, collaborative consumption, sharing economies

1. Introduction

The Fourth Industrial Revolution (Industry 4.0), driven by digital technology integration, has changed the business landscape over the last few years. The integration of digital technologies such as Blockchain, the Internet of Things (IoT), Artificial Intelligence (AI), Virtual Reality (VR), and Augmented Reality (AR) into various products are aimed at enhancing their value through the establishment of an interconnected system for the collection, analysis, and dissemination of data (Marrucci et al., 2023). Industries across various levels of organisations utilise these technologies, as their added value has transcended the sale of products over the last few years. Accordingly, Antony et al. (2023) research shows that integrating disruptive technologies within organisations significantly transforms their business models, enabling them to support various operational aspects and enhance customer satisfaction effectively. In light of the recent inflationary trends observed in developed nations, the phenomenon of asset sharing has been attributed, as elucidated by Gebeyehu and Twinomurinzi (2022). The sharing economy, a widely recognised concept, operates on the fundamental principle of offering resources at a reasonable cost, with the added potential for environmental and societal advantages (Lin and Zhai, 2023).

The business model has experienced widespread global adoption since its establishment, proliferating its consumer base due to sharing economies financial and economic benefits (Cabral and Gohr, 2023). A wide range of evidence underscores the influence of disruptive technologies in enhancing the value of sharing economy platforms: The wide use of social media and smartphones has proven to be influential disruptive technologies that have facilitated the expansion of the sharing economy business model (Stickle, 2023). According to Tan and Salo (2023), the blockchain is a technological tool that has enhanced the value of collaborative consumption platforms by providing seamless peer-to-peer payment solutions. Furthermore, personalisation and improving user experiences have augmented the sharing economy's capabilities through disruptive technologies such as AI and digital twins (Chen et al., 2022).

In addition to the potential of disruptive technologies to significantly enhance the performance of the sharing economy and ultimately bolster company resilience (Ranjitha and Jeesha, 2023), we firmly believe that additional research is necessary to ensure the effective implementation of these technologies in sharing economies. Indeed, There exists an extensive array of disruptive technologies, each possessing distinct capabilities that have the potential to augment sharing economies. Research needs to be published examining the utilisation of Industry 4.0 technologies in these platforms and their potential to generate value collaboratively or independently. Furthermore, implementing technological resources is subject to multiple factors, such as the financial resources available to the platform and its unique market position (Liu et al., 2023). The prudent utilisation of these resources should be considered, as it enhances consumer satisfaction and fosters trust (Oliveira et al., 2020). Hence, it is imperative to thoroughly evaluate industry readiness and the efficacy of new technology integration before its implementation, as indicated by the research conducted by Akbar and Hoffmann (2023). Identifying the capabilities of these technologies assists proprietors of sharing economy businesses in gaining a deeper comprehension of the role of digital technology within their operational framework, thereby providing them with a competitive advantage over their competitors (Hsu, 2023).

The primary objective of this study is to identify the Technological Building Blocks (TBBs) of the sharing economy to enhance financial and operational processes. This contributes to businesses success and promotes environmental sustainability (Delcie and Diemer, 2021). Therefore, to determine the TBBs that have received the most significant contributions from academics and to address the initial gap in research, it is necessary to conduct a systematic literature review (SLR) as a preliminary step. The Bayesian best-worst (BBWM) method is employed to assign weights to these technologies to address the second gap. Mohammadi and Rezaei (2020) asserted that the BBWM method, a contemporary Multiple-Criteria Decision-Making (MCDM) approach, demonstrates advantages over other methods by employing fewer paired comparisons and yielding outcomes of higher consistency. The utilisation of BBWM in this research is used to enhance the dependability of findings, thereby leading to more advantageous decision-making within organisations. Therefore, the objectives of this study are to (i) categorise TBBs, (ii) determine TBBs that are essential to the sharing economy business model, and (iii) create a scoring mechanism to assess an organisations preparedness for implementing TBBs.

In the subsequent phase of this study, an initial literature review is undertaken, encompassing the implementation of disruptive technologies within sharing economy and collaborative consumption platforms. Section 3 of this study provides a comprehensive explanation of the methodology employed, focusing on the extraction of TBBs and further descriptions of BBWM. It also delves into the uses and advantages of the sharing economy, along with related concepts such as collaborative consumption platforms. Next, section 4 presents the score functions analysis, classification, and formulation. Finally, the last section encompasses the conclusion, implications, research limitations, and future recommendations.

2. Literature review

The advent of changes in the business landscape has prompted the evolution of traditional business models into novel paradigms to adapt to the shifting environmental conditions. One such concept is referred to as "collaborative consumption" (CC), which has been defined as a collection of resource circulation systems that facilitate consumers in acquiring resources or services through direct engagement with other consumers or with the assistance of an intermediary, either on a temporary or permanent basis (Amat-Lefort et al., 2020). According to the model, consumers can temporarily utilise a product without formally transferring ownership or obtain medium- to long-term access through legal means. According to Nadeem et al. (2023), this allows consumers to evaluate the advantages of non-proprietary products. One of the concepts emphasised in contemporary discourse is the "Sharing Economy" (SE). Within this emerging economic paradigm, peer-to-peer services facilitate individuals access to services conveniently and cost-effectively. The sharing economy has gained significant traction recently as a lucrative approach for various industries and researchers (De las Heras et al., 2021). The utilisation of the business model has been widely observed in multiple domains, such as crowdfunding (Chandna, 2022), house renting (Liying et al., 2020), ridesharing (Cheng et al., 2020), and knowledge sharing (Pang et al., 2020), on a global scale. This paradigm presents a mutually beneficial solution for business owners by leveraging online services and digital platforms. It enables consumers to access services or products at reduced rates while benefiting from shared experiences and discussions within the online community (Madhi & Alhammah, 2021). The rapid increase in value of the ridesharing company "Uber" to approximately 68 billion USD by 2015, as demonstrated in a case study, highlights the significant susceptibility of this business model to rapid maturation (Ritter and Schanz, 2019). Moreover, the inherent characteristic of sharing economies also safeguards the environment by sharing assets among individuals, resulting in decreased production (Sadiq et al., 2023).

Accordingly, it can be argued that Industry 4.0 has benefited various industries in recent years, as noted by Yu et al. (2020). The phenomenon, which was first presented at the Hanover Trade Fair in Germany in 2011 (Elnadi and Abdallah, 2023; Ijaz Baig and Yadegaridehkordi, 2023), enables the automation, production, analysis, and dissemination of knowledge within organisations (Antony et al., 2023). Disruptive technologies have garnered significant adoption in both industrial and academic domains owing to their capacity to provide additive value. According to Gebeyehu and Twinomurinzi (2022), the sharing economies and collaborative consumption platforms were not exempted.

Given the exponential advancement of Industry 4.0 technologies and the inherent characteristics of the subject matter, scholars and professionals commonly adopt diverse viewpoints to compile a comprehensive inventory of these foundational components. To date, a thorough evaluation that contributes to understanding the significance of digital assets within the context of sharing economies still needs to be present. As a result of analysing numerous relevant literature evaluations on similar topics like (Beheshti et al., 2023), these technologies, including (i) digital twins (e.g. Mu et al., 2023; Bisht et al., 2022); (ii) the Metaverse (e.g., Tlili et al., 2023; Yao et al., 2022); (iii) Internet of Things (IoT); (iv) cyber-physical systems (CPSs); (v) big data; (vi) cloud computing (e.g., Antony et al., 2023; Ammar et al., 2022; Amoozad Mahdiraji et al., 2022; Sharifpour et al., 2020); (vii) additive manufacturing (e.g., Jamwal et al., 2021; Zheng et al., 2021; Bai et al., 2020); (viii) Artificial Intelligence (AI) (e.g., Kumar et al., 2022; Silvestri et al., 2020); (ix) Blockchain (e.g., Sharifpour et al., 2020; Dalmarco et al., 2019); (x) Augmented Reality (AR) (e.g., Silvestri et al., 2020; Dalmarco et al., 2019); (xi) Virtual Reality (VR) (e.g., Ammar et al., 2022; Jamwal et al., 2021); (xii) simulation (e.g., Elnadi and Abdallah, 2023; Sharifpour et al., 2020); (xiii) smart robotics (e.g., Elnadi and Abdallah, 2023; Ammar et al., 2022); and (xiv) radio-frequency identification (RFID) (e.g., Amoozad Mahdiraji et al., 2022; Dalenogare et al., 2018) were listed as the building blocks for this research. The TBBs are presented in a summary in Table 1.

Table 1. An Overview of Industry 4.0 TBBs (source: created by the authors)

Industry 4.0 TBBs	Brief Definition
Digital Twin	The digital twin is the engine of future innovation and one of the foundations of Industry 4.0. It is a virtual representation of a person, object, city, or even society with real-time data. It changes to position immediately. Using reality simulations, digital twins can solve complex problems and help with decision-making (Bisht et al., 2022).
Metaverse	Metaverse, similar to AR and VR, creates virtual worlds for a multiuser environment and digitally integrates them with the physical world. User communication in the Metaverse visualises the real world; however, in the virtual space, it is based on sensory interactions in reality. Large companies have included the Metaverse in their organisational strategy and are building the infrastructure and drivers to attract users (Mystakidis, 2022).
IoT	IoT connects things, products, and people to each other, optimising sales and production lines and providing solutions for after-sales services (Dalenogare et al., 2018). IoT connects objects, products, and people and can automate production. A network of sensors from the Internet of Things can be updated in real-time and react to demands (Ammar et al., 2022).
CPSs	CPSs connect all levels and elements of an organisation, its processes, and networks (Elnadi and Abdallah, 2023). In a cyber-physical environment, all networks can collect and share information through other TBBs of Industry 4.0, such as the IoT and big data (Kumar et al., 2020). CPSs make a system flexible and dynamic, properly monitoring privacy (Ammar et al., 2022).
Big Data	Big data is a huge amount obtained from various sources and can be structured and semi-structured. Volume, variety, velocity, and veracity are the characteristics of big data, and it plays an essential role in the decisions of organisations and stakeholders (Elnadi and Abdallah, 2023).
Cloud Computing	Cloud computing has high computing power to analyse data and share in all organisations processes and between different people and stakeholders (Jamwal et al., 2021). This technology makes storing and retrieving data easy and gives an organisation constant access to information, transparency, and accountability (Kumar et al., 2020).
Additive manufacturing	Additive manufacturing, also called 3D printing, creates 3D objects in Industry 4.0. This technology can speed up the design process of new products that meet consumers wishes and needs. This technology is very important due to the speed of changing consumer demands (Elnadi and Abdallah, 2023). Today, additive manufacturing supports large-scale production (Dalmarco et al., 2019), is very flexible, and can easily produce complex designs while being very accurate and cost-effective (Kumar et al., 2020).
AI	AI consists of several technologies, and it is connected to production processes through planning and self-learning from human activities. It helps devices and machines learn and understand the processes, making them more efficient and sustainable (Jamwal et al., 2021). AI creates self-control for processes, responds to unforeseen situations, and facilitates decision-making processes for users, stakeholders, and managers (Sharifpour et al., 2022).
Blockchain	Blockchain is a digital network that permanently records and maintains transactions (Elnadi and Abdallah, 2023), providing security, transparency, and trust in the organisational network (Jamwal et al., 2021). Blockchain ensures reliable information sharing between business partners and enables automatic negotiation between organisations (Zheng et al., 2021). Blockchain removes concerns about the security of transactions and offers a solution to strengthen trust between stakeholders to increase the efficiency and quality of communication (Bisht et al., 2022).
AR	AR, a developing TBB in Industry 4.0, fills the gap between reality and digital. AR expands information about the real environment into the digital world and allows users to physically coexist and interact with the digital world (Elnadi and Abdallah, 2023).

VR	VR lets users control the virtual space in real-time (Zheng et al., 2021) and provides innovative solutions to develop production processes. It improves organisational processes and helps to make the process more dynamic to meet the needs of consumers (Jamwal et al., 2021).
Simulation	Simulation is an imitation of an operation of a process or system, product design, and layout using computer tools, which is tested virtually. When a simulated performance is deemed positive, it can be developed in the real world (Dalmarco et al., 2019). Simulation optimises production and minimises production time and waste (Elnadi and Abdallah, 2023).
Smart robots	Smart robots are enablers of TBBs in Industry 4.0. They automatically participate in physical processes and have common learning behaviours in dealing with human activities (Zheng et al., 2021). Smart robots help humans in complex activities, and with their digital sensors, if they sense danger or get too close to humans, they immediately turn off to prevent harm (Ammar et al., 2022). Organisations use smart robots for mass customisation and to increase efficiency and effectiveness by reducing waste, cycle time, and workload (Elnadi and Abdallah, 2023).
RFID	RFID obtains pre-embedded information through a barcode or a label on an object (Sharifpour et al., 2022). It tracks and identifies objects automatically (Bai et al., 2020).

This study utilised a Systematic Literature Review (SLR) methodology to identify the corresponding TBBs of Industry 4.0 concerning CC and SE. Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) three-step protocol is employed in conducting SLR. The protocol was developed and presented by Paul et al. (2021). The SPAR-4-SLR protocol distinguishes itself from other protocols by addressing several limitations commonly associated with them. These limitations include the inability to anticipate potential issues, the lack of comprehensiveness, and the lack of integrity in the research path. By mitigating these limitations, SPAR-4-SLR enhances the SLR process by reducing arbitrariness and promoting accountability. This protocol facilitates detailed planning and transparency, thereby improving the overall quality of the SLR. The protocol encompasses three distinct stages: (i) Assembly, which involves the identification and acquisition of relevant components; (ii) Arrangement, which entails organising and purifying the gathered materials; and (iii) Assessment, which involves evaluating and reporting the outcomes.

The initial stage of the SPAR-4-SLR protocol involves the assessment of the survey scope, source type, and source quality (identification). Subsequently, an examination is conducted on searching and acquiring materials, including the duration of the search period and the specific keywords used for the search (acquisition). During the identification phase, the examination of Industry 4.0 TBBs and their utilisation in the context of the CC and SE is deliberated as the focal point of investigation. In this study, the analysis is focused on articles indexed in Scopus and Google Scholar, considered two reputable databases with substantial data (Paul et al., 2021). The search period encompassed the duration of the last decade, commencing in 2012 and concluding at the end of February 2023. The search was conducted using the websites dorks search protocol. To ensure the attainment of the most precise outcomes, the search query employed in the Scopus database was formulated as follows: "TITLE-ABS-KEY(("sharing economies" OR "collaborative consumption") AND "industry 4") AND (DOCTYPE(ar) AND NOT DOCTYPE(bk) AND NOT DOCTYPE(cp) AND NOT DOCTYPE(ed)) AND (LANG(English)) AND (PUBYEAR AFT 2012 AND PUBYEAR BEF 2024)".

Similarly, the process above was replicated for Google Scholar using the search query "("sharing economies" OR "collaborative consumption") AND "industry 4" after:2012 before:2023". The analysis employed a methodology that involved excluding non-academic sources, such as book chapters, editorials, and conference papers, to obtain the most favourable outcomes. The potential impact of excluding non-English articles on the scope of interpretation was considered. The comprehensive dataset was constructed by gathering relevant publications on disruptive technologies by querying the titles, abstracts, and keywords of papers indexed in Scopus and Google Scholar.

In the second phase, the SPAR-4-SLR was organised and refined. At this stage, the publications underwent a review process that considered their title, keywords, and the study's scope, specifically focusing on the subjects of SE and CC. In the third phase of the SPAR-4-SLR methodology, 39 articles were chosen and subjected to scrutiny, utilising the specified filters. Thematic Analysis (TA) was employed in the conclusive phase of the SPAR-4-SLR methodology to analyse 39 articles. TA, in conjunction with the SLR, is effectively elucidated in the study conducted by Chaudhary et al. (2021). The analytical results were presented using Excel and MAXQDA software and were visually represented through figures and tables. The SLR conducted in this study revealed that 11 TBBs were identified and utilised in the domains of CC and SE. Figure 1 displays the neural network-based theme map generated using MAXQDA software, which showcases the interconnectedness of Industry 4.0 TBBs in the fields of CC and SE.

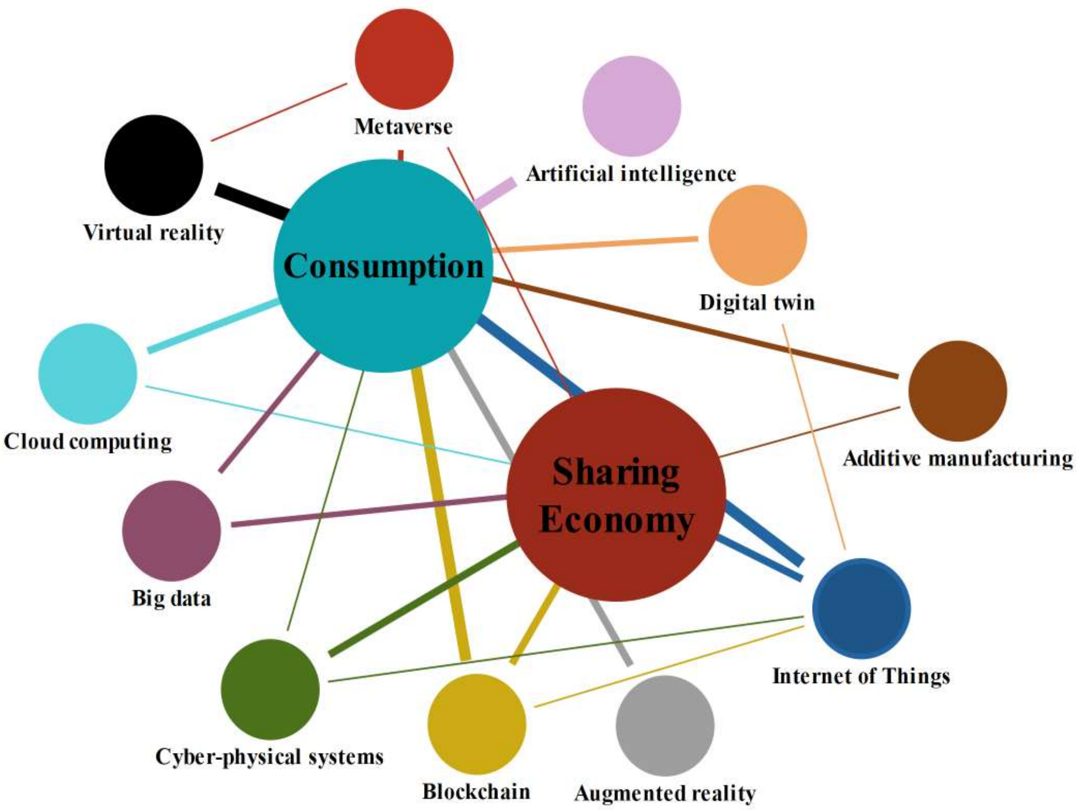

Figure 1. Neural network model of Industry 4.0 TBBs in consumption and SE (source: created by the authors)

Researchers investigated TBBs of Industry 4.0 in different ways. For instance, Pamucar et al. (2023) examined the applications of the metaverse in SE. Furthermore, Shen et al. (2021) measured the impact of the metaverse on consumer perceptions of virtual commerce, and Fathy et al. (2021) studied digital twins and IoT in-home consumption. The main contribution of each research, area of study, type of research (i.e., quantitative or qualitative), and type of article are briefly specified in Table 2.

Table 2. Relevant researches overview (source: created by the authors)

Scholar (s)	Year	Contribution	Area of Study		Methodology		Type of article		
			SE	C	Qualitative	Quantitative	RH	RE	CL
El-Shamandi Ahmed et al.	2023	AR mirror application for consumer makeup		*	Case study	Statistical analysis	*		
Chandra and Verma	2023	The role of big data in sustainable consumption		*	SLR-TA			*	
Pamucar et al.	2023	Application of Metaverse in SE	*			fuzzy Schweizer-Sklar	*		
Jokhan et al.	2022	The role of AI in education decisions		*	Case study	Random forest	*		
Kim and Lee	2022	Using VR in sustainable consumption of art		*	LR		*		
Filimonau et al.	2022	Metaverse's role in changing tourism consumption patterns		*	LR				*
Cheng et al.	2022	Energy consumption based on IoT		*	SLR		*		
Yang et al.	2021	The role of additive manufacturing in SE	*			MILP	*		
Fathy et al.	2021	The role of digital twins and the IoT in-home consumption		*		Simulation	*		
Shen et al.	2021	The role of Metaverse on consumer perception in virtual commerce		*	SLR			*	
Smit et al.	2021	Simulation of food consumption using AR		*	Case study	Simulation	*		
Himeur et al.	2021	Energy consumption based on AI and presenting a solution to reduce it		*	SLR		*		
Lee	2021	Examining the opportunities and challenges of big data in the SE	*		LR		*		

Scholar (s)	Year	Contribution	Area of Study		Methodology		Type of article		
			SE	C	Qualitative	Quantitative	RH	RE	CL
Sedlmeir et al.	2021	The state of blockchain in energy consumption		*	LR		*		
Liu et al.	2020	Examining the privacy challenges of the IoT in the SE	*		LR		*		
Lavoie and King	2020	The role of VR in consumption		*	LR			*	
Bolandnazar et al.	2020	The role of AI in the energy consumption of the agricultural sector		*	Case study	CD, MLR, MLP		*	
Sedlmeir et al.	2020	Blockchain and energy consumption		*	LR			*	
L. Wei and Yang	2019	Big data review in SE	*			Duplication dynamic evolution game theory	*		
Ding and Wu	2019	Scheduling energy consumption in the IoT		*		Multi-objective fuzzy algorithm	*		
Nwogugu	2019	Investigation of CPSs in portfolio management related to SE organisations	*		LR		*		
Hang and Kim	2019	Investigating the trust of business partners in the blockchain-based SE	*		Case study		*		
N. Wei et al.	2019	Using AI in energy consumption		*	LR	Mean absolute percentage error	*		
Wang et al.	2019	The role of Big data in consumption		*	SLR		*		
Peng et al.	2019	Investigating cloud computing in energy consumption		*	LR			*	
Tumasjan and Beutel	2019	Conditions for using blockchain in the SE	*			Agent-based modelling	*		
Rynarzewska	2018	Investigating the influencing factors of VR in sports and consumer expectations		*		Questionnaires		*	
Jia and Wu	2018	Use of CPSs in the coordination of supply and demand	*			Markov decision process		*	
Zhan et al.	2018	The role of CPSs in consumption		*		simulation		*	

Scholar (s)	Year	Contribution	Area of Study		Methodology		Type of article		
			SE	C	Qualitative	Quantitative	RH	RE	CL
Yadav et al.	2018	Providing an algorithm to reduce cloud computing energy consumption		*		Gdr, MCP	*		
Al Qadami	2018	Using the concept of SE in restaurants and using cloud computing to share information in the restaurant	*		Case study		*		
Angrisani et al.	2018	Using the IoT and augmented reality to monitor energy consumption		*		Mathematical Programming	*		
Bekaroo et al.	2018	The role of AR in green consumption		*	LR	Mathematical Programming	*		
Hawlitschek et al.	2018	Investigating blockchain-based trust in the SE	*		LR		*		
Watson and Taminger	2018	Investigating energy consumption in additive manufacturing		*	LR		*		
Truby	2018	Reducing energy consumption in blockchain		*	LR		*		
Zhang et al.	2018	Energy consumption analysis based on IoT		*	LR		*		
Abd et al.	2017	Reducing energy consumption when using cloud computing		*		DNA-based Fuzzy Genetic Algorithm	*		
Seo et al.	2017	Analysis of factors affecting CPSs in SE	*		LR		*		
Our study	*2023*	*Analysis of Industry 4.0 TBBs in CC and SE*	*	*	*SLR*	*BBWM*	*		

(C) consumption, (LR) Literature review, (RH) Empirical Research, (RE) Review research, (CL) Conceptual, (MILP) Mixed-integer linear program, (CD) Cobb–Douglas, (MLR) Multiple linear regressions, (MLP) Multilayer perceptron, (Gdr) Radient descent-based regression, (MCP) Maximise correlation percentage

Despite the researchers examination of TBBs in both CC and SE sectors, no existing study identified, classified, and assigned weights to TBBs in either business model. Table 3 illustrates the TBBs employed in the fields of CC and SE, serving as the foundational elements for the subsequent analyses presented in the following sections. While technologies such as smart robots, simulation, and RFID are recognised as significant components of Industry 4.0, their utilisation in CC and SE has not been thoroughly explored in existing scholarly works.

Table 3. List of TBBs applied in CC and SE (source: created by the authors)

TBBs	Brief Definition	Sample Reference(s)
Metaverse (TBB_1)	Metaverse is a non-fungible token whose emergence causes the development of CC and SE	Pamucar et al. (2023), Filimonau et al. (2022) and Belk et al. (2022)
Digital twin (TBB_2)	Digital twins in stores help manage consumption and improve productivity, and it causes the growth of CC and SE.	Fathy et al., 2021)
Cyber-physical systems (TBB_3)	CPSs can be used to monitor consumption in SE	Yang et al. (2021), Nwogugu (2019), Jia and Wu (2018), Zhan et al. (2018) and Seo et al. (2017)
Internet of Things (TBB_4)	IoT helps to create a suitable optimisation and scheduling model in CC and SE	Cheng et al. (2022), Halim and Hutagalung (2022), Y. Liu et al. (2020), Ding and Wu (2019) and Hang and Kim (2019)
Blockchain (TBB_5)	Blockchain plays the role of trust and transparency in CC and SE information transactions	Tan and Salo (2023), Sedlmeir et al. (2021), Sedlmeir et al. (2020), Tumasjan and Beutel (2019), Hawlitschek et al. (2018) and Truby (2018)
Big Data (TBB_6)	CC and SE, with the characteristic of big data, can be a competitive advantage	Chandra and Verma, (2023), Kumar et al. (2022), Lee (2021), Wei and Yang (2019) and Wang et al. (2019)
Cloud computing (TBB_7)	Cloud computing features such as data analysis and information sharing create digital platforms with important roles in SE and CC	Feng et al. (2020), Peng et al. (2019), Yadav et al. (2018) and Abd et al. (2017)
Artificial intelligence (TBB_8)	AI brings stability and efficiency to SE and CC	Wu et al. (2023), Chen et al. (2022), Jokhan et al. (2022), Himeur et al. (2021), Bolandnazar et al. (2020) and Wei et al. (2019)
Augmented reality (TBB_9)	AR can be used to design SE models and optimal consumption patterns	El-Shamandi Ahmed et al. (2023), Angrisani et al. (2018) and Bekaroo et al. (2018)
Virtual reality (TBB_{10})	VR can influence SE and consumer behaviour in the real world	Kim and Lee (2022), Smit et al. (2021), Lavoie and King (2020) and Rynarzewska (2018)
Additive manufacturing (TBB_{11})	Additive manufacturing optimises energy consumption and improves SE	Yang et al. (2021) and Watson and Taminger (2018)

3. Methodology

The research objectives include (i) identifying TBBs that are important in value generation in CC and SE, (ii) analysing their relationship and classifying them, and (iii) providing a score function to measure the readiness level of organisations to employ TBBs. A mixed method, including SLR-TA (qualitative research) and multi-criteria decision-making (MCDM) (quantitative analysis), was designed and applied to achieve these goals. The general framework of this research is presented in Figure 2 and described after.

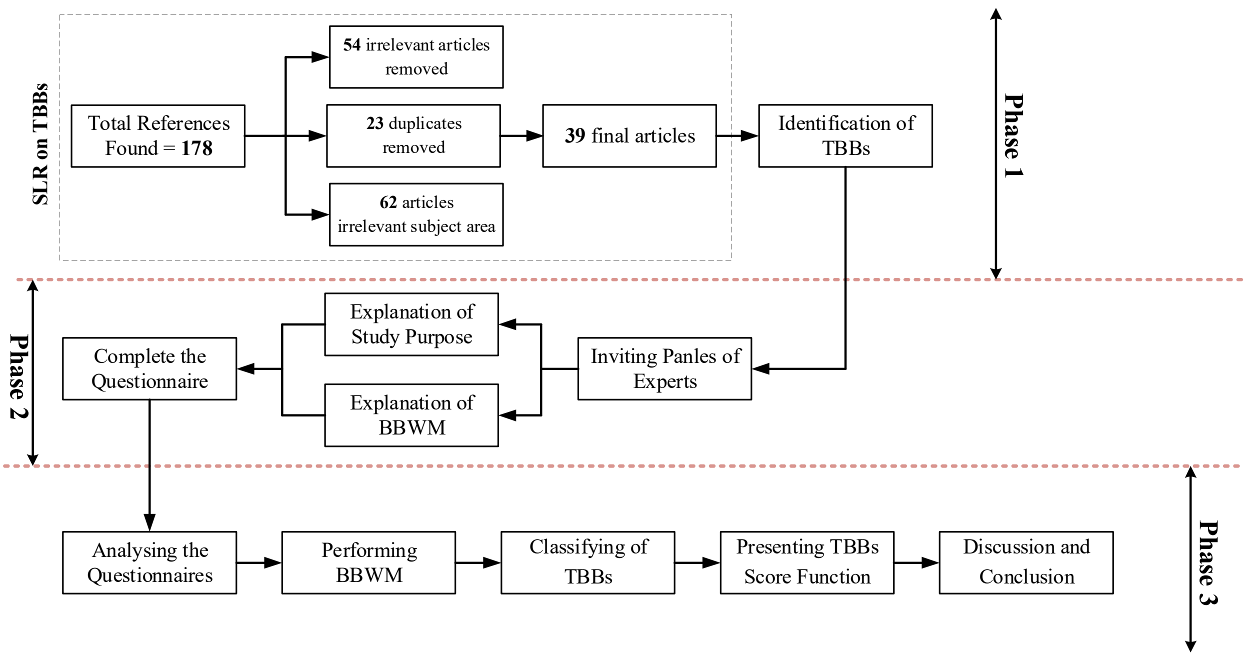

Figure 2. Research framework (source: created by the authors)

In the first phase, we employed an SLR method based on PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), using Excel and MAXQDA software. We utilised the systematic literature review to enhance our understanding within the specific domain of study, providing a dependable foundation for informed decision-making by experts (Tranfield et al., 2003). Moreover, Applying TA provides a clear insight into the research literature (Chaudhary et al., 2021). Hence, this study employed SLR to extract TBBs accurately, and TA was applied with the SLR for a more classified analysis of the current literature. Indeed, Expert opinions were gathered to measure the importance and analyse and classify TBBs. After extracting relevant TBBs, experts with the following qualifications were selected via a judgemental snowball sampling.

(i) Age. At least 30 years old;
(ii) Education. At least a bachelor's degree in engineering or management science;
(iii) Familiar with Industry 4.0 technologies. Read at least three relevant articles in 2022-2023;
(iv) Familiar with collaborative consumption and sharing economies. Read at least three relevant articles in 2022-2023;
(v) Experience. At least five years;
(vi) Managerial role. At least the head of a department in a CC/SE organisation;
(vii) Accessibility and willingness. Eager to participate in the research and available to complete the BBWM questionnaire.

Then, a briefing session was held for the experts, and the research objectives were explained to them. Accordingly, three panels, with five experts in each, were invited to complete the questionnaires related to the BBWM. Moreover, the qualifications of an academic member for each panel were considered as having at least a lecturer position at a university and having published at least five journal articles in the field of Industry 4.0, CC, or SE. These academics participated in each panel to explain the research objectives and methodology and how to complete the questionnaire. The specifications of the experts are listed in Table 4.

Table 4. Experts profile (source: created by the authors)

Panel	Expert ID	Gender		Age	Education				Experience	Area	
		F	M		PhD	MBA	MA	BA		A	I
	E_1		✓	35-44			✓		15^+		✓
	E_2		✓	25-34				✓	5^+		✓
P_1	E_3		✓	45-54	✓				20^+	✓	
	E_4	✓		25-34		✓			5^+		✓
	E_5	✓		55-64	✓				15^+	✓	
	E_6		✓	25-34		✓			5^+		✓
	E_7		✓	35-44	✓				10^+	✓	
P_2	E_8	✓		45-54		✓			15^+		✓
	E_9		✓	55-64	✓				20^+	✓	
	E_{10}		✓	55-64				✓	20^+		✓
	E_{11}		✓	45-54				✓	20^+		✓
	E_{12}	✓		35-44	✓				10^+	✓	
P_3	E_{13}		✓	55-64	✓				20^+	✓	
	E_{14}		✓	35-44	✓				10^+		✓
	E_{15}	✓		25-34			✓		5^+		✓

(F) Female, (M) Male, (MA) MA/MSc/MEng etc., (BA) BA/BSc/BEng etc., (A) Academic, (I) Industry

In the third phase of this study, BBWM was used to measure the importance of adopting TBBs and to classify and present a readiness score function for them. Scholars have developed several weighting methods. The BBWM provides a confidence level of decision-makers group preferences in the Bayesian form. This leads to more reliable and accurate decision-making. Therefore, BBWM is used in this research to pave the way for organisational decision-making (Mohammadi and Rezaei, 2020). Several researchers have used BBWM. Debnath et al. (2023) applied this method to evaluate the critical success factors of lean production. Before, Khan et al. (2022) used BBWM to evaluate resiliency. At the same time, Kelly et al. (2022) employed BBWM to examine the obstacles of closed-loop supply chains. Previously, scholars measured the impact of blockchain in the oil and gas industry and ranked the challenges of creating a sustainable supply chain with this method. (Munim et al., 2022; Liu et al., 2021). The first four steps of BBWM are similar to the BWM, described as follows (Rezaei, 2015).

1. Extracting TBBs based on SLR-TA;
2. Identifying the best and worst TBB based on experts opinions in each panel separately;
3. Comparing the best TBB (the most important) with other TBBs on a scale of 1 to 9;
4. Comparing other TBBs with the worst TBB (least significant) on a scale of 1 to 9.

In BBWM, group decision probability distribution is used to find the optimal values of TBB weights. In this regard, if $A_B^{1:K}$presents the comparison of the best against the first TBB from the perspective of the k[th] expert, indicates the comparison of the first TBB against the worst based on the k[th] expert opinion, and W^{agg} denote the optimal group weight, the following probability distribution was used for group decision-making (Mohammadi and Rezaei, 2020).

$$P(W^{agg}, W^{1:K} | A_B^{1:K}, A_W^{1:K}) \tag{1}$$

According to $(X) = \sum_y P(x, y)$, the criterion probability of each expert is obtained, where x and y present random variables. Respectively, Eq. 2 indicates the optimal group weight W^{agg}, which depends on the optimal weight of each expert (W^K).

$$P(A_W^K | W^{agg}, W^K) = P(A_W^K, | W^K) \tag{2}$$

The following equation was used to calculate the joint probability distribution (considering all the different independent variables and Bayes theorem) (Liu et al., 2021).

$$P(W^{agg}, W^{1:K} | A_B^{1:K}, A_W^{1:K}) \propto P(A_B^{1:K}, A_W^{1:K} | W^{agg}, W^{1:K}) P(W^{agg}, W^{1:K}) = P(W^{agg}) \prod_{k=1}^{k} P\,(A_W^K | W^K) P(A_B^K | W^K) P(W^K | W^{agg}) \tag{3}$$

A chain between different parameters is created in Eq. 3, called a hierarchical model. Nonetheless, the distribution of each element has not been determined. Thus, it is modelled as follows (Munim et al., 2022).

$$PA_B^K | W^K \sim multinomial(1/W^K), \qquad \forall k = 1, \ldots, K, \tag{4}$$

$$A_W^K | W^K \sim multinomial(W^K), \qquad \forall k = 1, \ldots, K$$

As the value of W^K is in the vicinity of W^{agg}, the Dirichlet distribution was modelled through the optimal group weight W^{agg} depending on the optimal weight of each expert W^K according to the following equation. Note that W^{agg} has a distribution with a mean of γ, a non-negative parameter (Mohammadi and Rezaei, 2020).

$$W^K | W^{agg} \sim Dir(\gamma \times W^{agg}), \qquad \forall k = 1, \ldots, K \tag{5}$$

Based on Eq. 5, when (γ) is under control, W^K is close to W^{agg}. In this case, the gamma distribution is as $\gamma \sim gamma(a, b)$. Where a and b are the shape and scale parameters of the distribution (Mohammadi and Rezaei, 2020). To obtain W^{agg} distribution parameter, the ignorance of the Dirichlet distribution with *alpha equal to one* should be used, which is $W^{agg} \sim Dir(a)$. The presented model is not a closed-form solution; therefore, Markov-chain Monte Carlo was used to measure the posterior distribution. The Markov-Chain Monte Carlo samples were obtained from Eq. 3. Credal ranking was applied to calibrate the degree of superiority of one criterion over another to develop the Bayesian model. The difference between credal ranking and other ranking schemes is that confidence in credal ranking is based on the Dirichlet distribution of W^{agg}. On the other hand, other rating methods usually take two numbers/intervals and try to find their limit. Credal ordering was conceptualised through the following equation, in which O denotes the credal ranking for C_i and C_j criteria. Morevoer, $d \in [0,1]$ indicates the reliability of relationships.

$$O = (C_i, C_j, R, d) \quad where \quad R <=> C_i, C_j \quad , \quad \mathrm{d} \in [0,1] \tag{6}$$

Credal ranking for all criteria $C=(C_1, C_2, ..., C_n)$ is a set of credal orderings that includes conjugate criteria C_i, C_j for all $C_i, C_j \in C$. W^{agg} posterior distribution was used for credit ranking confidence level. The probability of C_i being better than C_j is as follows.

$$P(c_i > c_j) = \int I_{(W_i^{agg} > W_j^{agg})} P(W^{agg}) \tag{7}$$

In Eq. (7), W^{agg} is the group weight of the factor, $P(W^{agg})$ the posterior distribution of W^{agg}, and I the condition parameter. To calculate the I parameter, the $W_i^{aggq} > W_j^{aggq}$ and $W_j^{aggq} > W_i^{aggq}$ conditions must be met, otherwise, the value of I is zero. The confidence level is obtained by measuring (Q) in the posterior distribution from Eq. 8 (Mohammadi and Rezaei, 2020).

$$P(c_j > c_i) = \frac{1}{Q} \sum_{Q=1}^{Q} I\left(W_j^{aggq} > W_i^{aggq}\right) \tag{8}$$

$$P(c_i > c_j) = \frac{1}{Q} Q = 1QI(W_i^{aggq} > W_j^{aggq})$$

W^{aggq} is equal to the q^{th} sample of W^{agg} from the Markov-Chain Monte Carlo in Eq. 8. Under these conditions, it is possible to calculate the superiority of one over the other for each pair of criteria. In this case, $P(c_i > c_j) + P(c_j > c_i) = 1$. It can be concluded that when $P(c_i > c_j) > 0.5$, C_i is more important than the C_j factor. Hence, by applying a threshold of 0.5, a common credal ranking was achieved for each criteria. This phase was coded in MATLAB software. After, the weights of TBBs were obtained, and classification was performed. The classification is based on the weights resulting from BBWM. The following logic is used to classify the technologies.

1. If W_j is more than the third quartile (Q_3), then the technology is placed in the first cluster and labelled fundamental;
2. If W_j is less than the third quartile (Q_3) but more than the second (Q_2), then the technology is placed in the second cluster and labelled important;
3. If W_j is more than the first quartile (Q_1) but less than the second (Q_2), then the technology is placed in the third cluster and labelled auxiliary;
4. If W_j is less than the first quartile (Q_1), the technology is placed in the fourth cluster and labelled discretional.

Finally, a score function of $\sum_{j=1}^{n} W_j \times T_j$ was presented and employed to measure an organisation's readiness for adopting Industry 4.0 technologies.

4. Results and Discussion

After identifying TBBs through the SLR, the TBBs were analysed by the BBWM. The relevant questionnaire was shared with the panel of experts mentioned in Table 3, and then completed and collected. Consequently, the completed questionnaires were entered into the MATLAB software and analysed. Table 5 presents the initial pairwise comparisons by the experts.

Table 5. Pairwise comparison input (source: created by the authors)

Best vs other TBBS				others vs the worst			
Panel	**P_1**	**P_2**	**P_3**	**Panel**	**P_1**	**P_2**	**P_3**
Best TBB	**Blockchain**	**AI**	**Digital twin**	**Worst TBB**	**Additive manufacturing**	**Additive manufacturing**	**CPSs**
TBB_1	8	7	8	TBB_1	3	4	6
TBB_2	5	3	2	TBB_2	4	5	9
TBB_3	5	3	2	TBB_3	4	3	1
TBB_4	3	1	5	TBB_4	5	5	3
TBB_5	4	4	3	TBB_5	8	4	4
TBB_6	2	2	3	TBB_6	7	5	6
TBB_7	1	3	5	TBB_7	5	5	6
TBB_8	5	4	6	TBB_8	6	7	4
TBB_9	6	4	9	TBB_9	4	6	7
TBB_{10}	3	2	1	TBB_{10}	4	6	7
TBB_{11}	6	4	4	TBB_{11}	1	1	2

Using the BBWM method, as explained previously, and coding the process in the same software, the weights of each TBB were measured and presented in Table 6.

Table 6. The final weights of TBBs based on BBWM (source: created by the authors)

Technology	ID	Weight
Metaverse	TBB_1	0.056
Digital twin	TBB_2	0.108
CPSs	TBB_3	0.076
IoT	TBB_4	0.094
Blockchain	TBB_5	0.098
Big Data	TBB_6	0.122
Cloud computing	TBB_7	0.106
AI	TBB_8	0.087
AR	TBB_9	0.076
VR	TBB_{10}	0.122
Additive manufacturing	TBB_{11}	0.056

After calculating the final weights, the credal ranking of the TBBs was measured (Eqs. 6 and 7). Figure 3 illustrates the credal ranking, which results from the final weights of TBBs from implementing the BBWM model. This figure displays Industry 4.0 TBBs in CC and SE from top to bottom (most to least important). As shown, VR (TBB_{10}) has the highest weight/importance. The values on the lines indicate the degree of certainty of the superiority of the source TBB over the destination. For instance, VR (TBB_{10}) over metaverse (TBB_1) has a credal ranking of 99%, which indicates that 99% of experts agree on the superiority of VR (TBB_{10}) over metaverse (TBB_1).

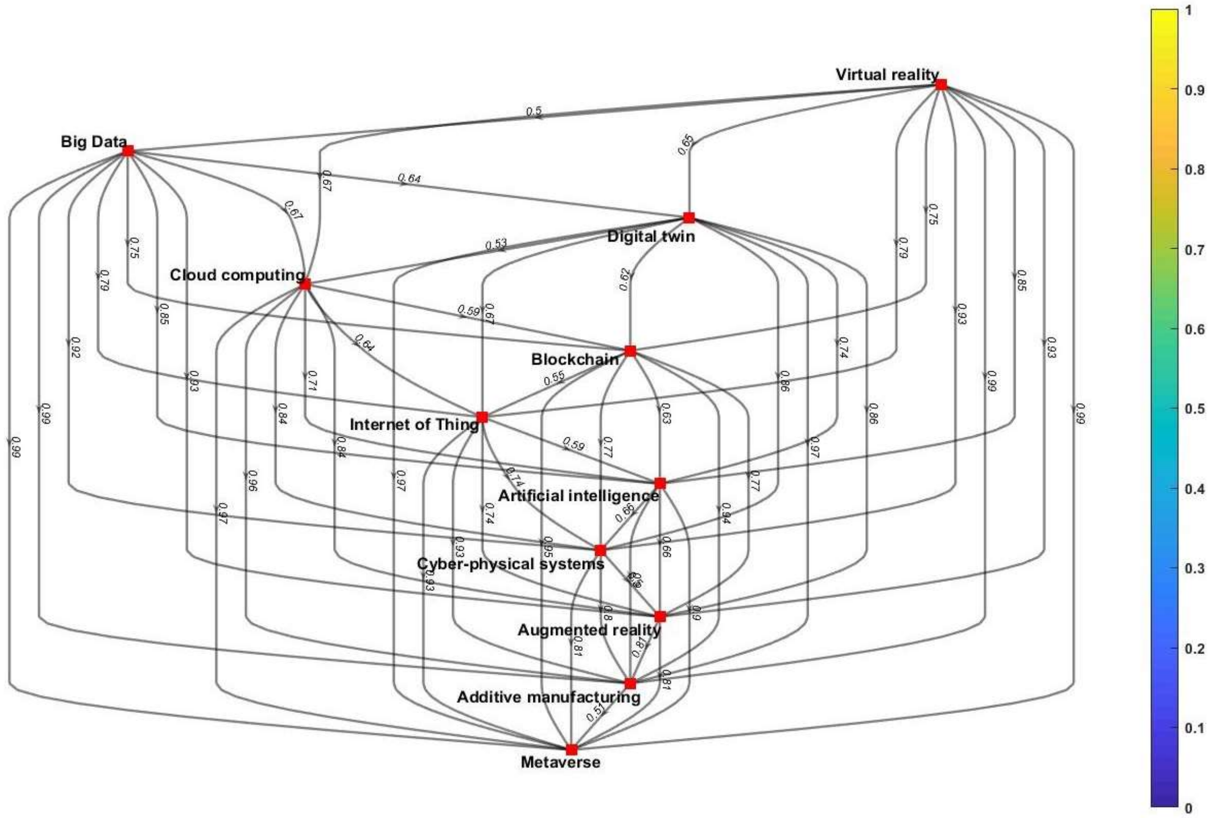

Figure 3. The visualisation of the credal ranking for Industry 4.0 TBBs in CC and SE (source: created by the authors)

The authors ran the model with different threshold values to extract the more critical relations between the technologies. As a result, considering the threshold of 0.8 (80%), the adjusted visualised credal ranking of TBBs in CC and SE emanated as Figure 4. As is evident, each technology has several outgoing edges. These links can be used to deduce technology's influence and power. As a result, the bottom TBBs with the most incoming links have lower weights and are heavily influenced by those at the top. Considering the number of outgoing edges, VR, digital twin, and big data are the most influential technologies, influencing the other two levels of technologies. The technologies remaining at the top of the graph are the second-most influential. Lower-level technologies rarely create value on their own. Consequently, despite finding several records of the use of metaverse and additive manufacturing in sharing economies, these technologies are suggested to be highly influenced by other technologies.

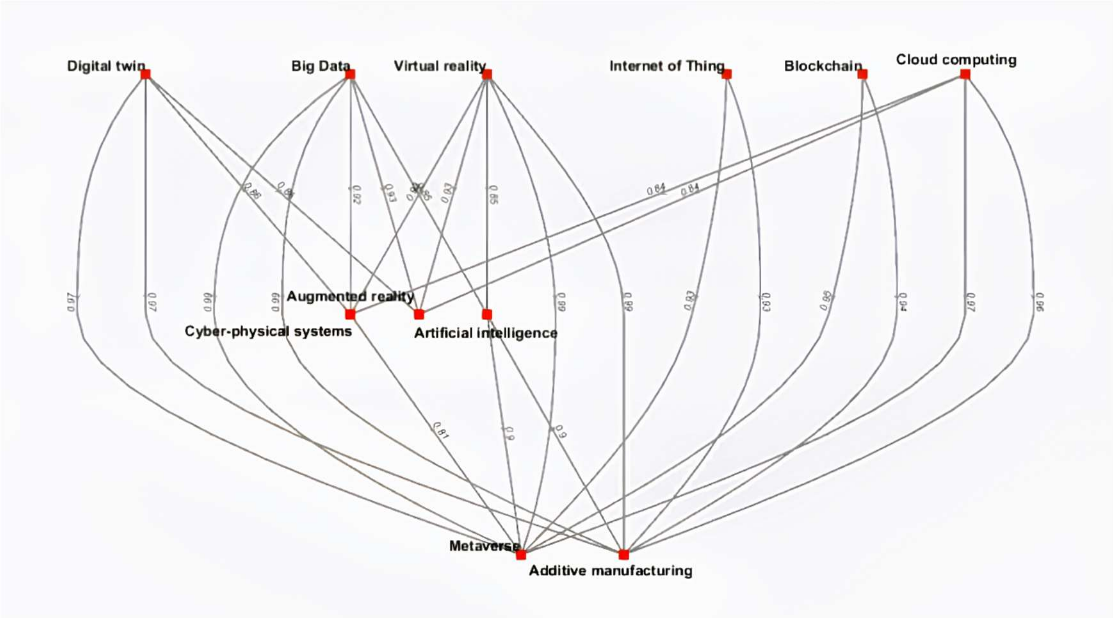

Figure 4. The modified visualised credal ranking (source: created by the authors)

For a better understanding and further discussion, TBBs were clustered into four distinct categories based on the weight of each technology, which indicates their influencing power. Cluster 1 includes weights over the third quartile, labelled as "fundamental" and highlighted blue. Cluster 2 encompasses technologies with weights between the second and third quartile, labelled "important" and highlighted green. Cluster 3 embraces TBBs with weights between the first and second quartile, labelled "auxiliary" and highlighted yellow. Then, cluster 4 covers technologies with weights less than the first quartile, labelled "discretional" and coloured red. Figure 5 presents the clustering results. The following is obtained by combining the weights of the technologies from the DM panels, considering $\sum w_j = 1$.

This categorisation facilitates a comprehensive comprehension of the credal ranking since it delineates the relative influence of each technology on sharing economies, utilising four unique criteria. According to our analysis conducted using the BBWM, technologies exhibiting higher percentages (blue and green) should be given priority by the SEs, as they possess a greater likelihood of generating value. Nevertheless, organisations must employ multiple TBBs to optimise their profitability. Therefore, the collective impact of technologies has been assessed in this section.

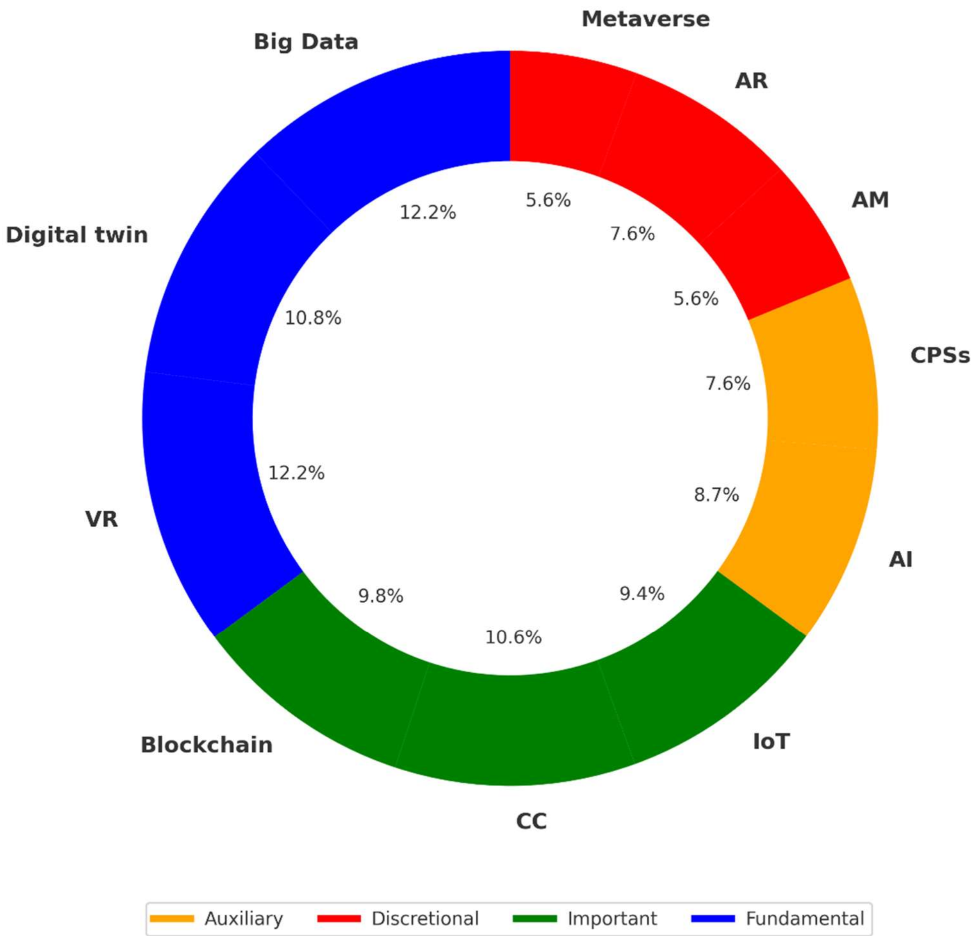

Figure 5. The clustering results (Auxiliary (yellow); Discretional (red); important (green); Fundamental (blue)) (source: created by the authors)

The impact of disruptive technologies on collaborative consumption platforms is evident, as our research findings demonstrate an interconnectedness among the TBBs. A Cartesian matrix is employed to comprehend the significance of the between technologies intersection. A total of 121 potential cross-combinations among technologies were identified. Figure 6 illustrates the specified items of digital technologies obtained from the systematic literature review conducted in this research, with the X-axis representing the corresponding categories. The utilisation of the BBWM approach led to the expert's proposal of TBB weights (Z-axis), thereby highlighting the significance of disruptive technologies. The Y-axis represents the technologies that have been influenced. The intersection depicted on the three-dimensional scatter plot indicates the importance and capacity of the technology to enhance value in sharing economies. When considering the sharing economy industry, it is essential to prioritise the technologies that generate more excellent synergetic added value when combined with their corresponding technologies on the Y-axis. This prioritisation should be implemented in both practical applications and future research endeavours. The subsequent section will delve into a comprehensive examination of TBBs, encompassing both practical and theoretical aspects. This analysis aims to foster a more nuanced comprehension of how recent discoveries contribute to existing research and inform future actions required to fully leverage the potential of disruptive technologies in the realm of sharing economies.

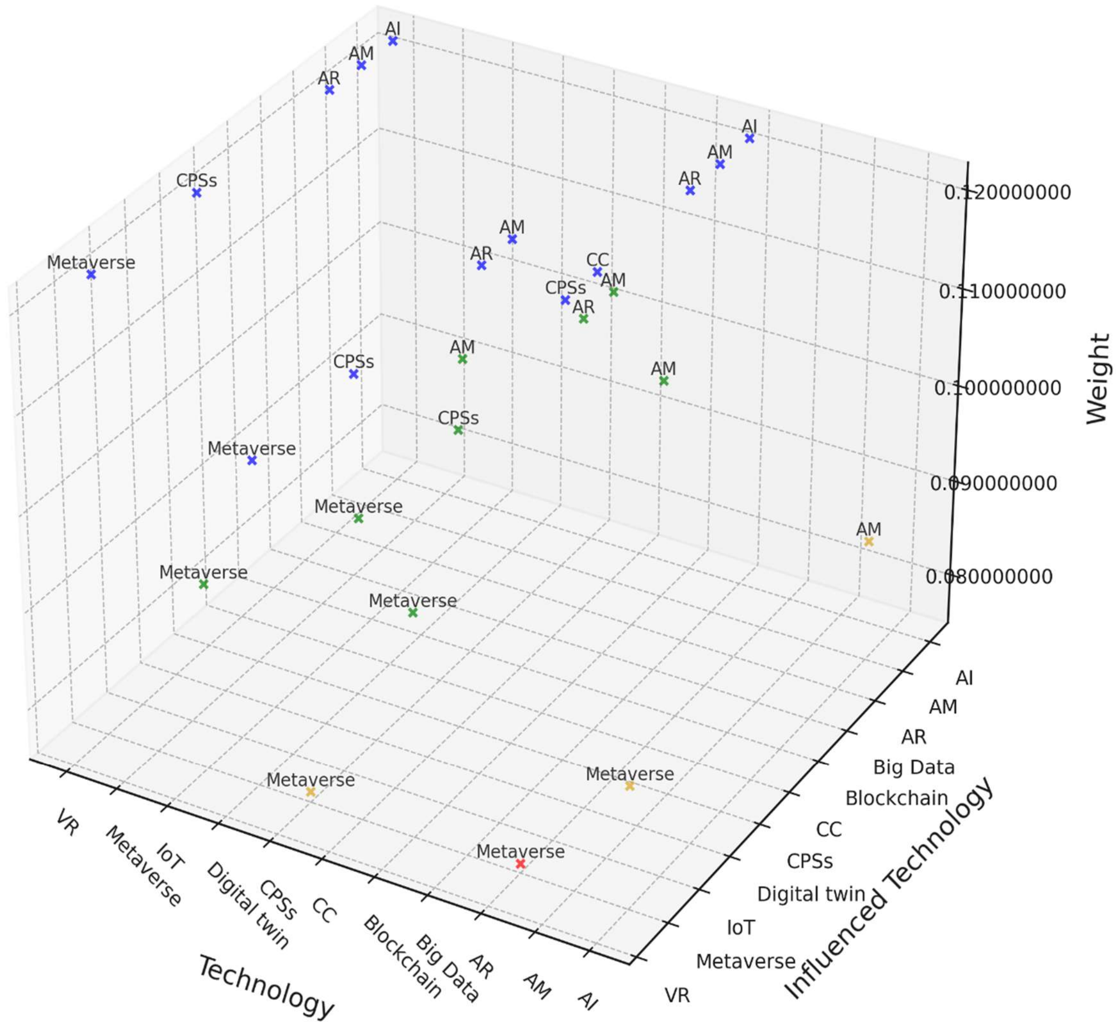

Figure 6. TBBs in different clusters (Auxiliary (yellow); Discretional (red); important (green); Fundamental (blue)) (source: created by the authors)

Our research and literature discovered that certain technological combinations have no relationship. As a result, they were eliminated to highlight those with the potential to add value. Inspired by the same colour scheme in Figure 5, VR, big data, and digital twins technologies have a high degree of influence on other technologies, which is consistent with prior research findings by (Kim & Han, 2022), who emphasised the power of disruptive technologies in creating added value in the sharing economy. However, this study delves deeper into this case and demonstrates which digital technology combinations should be used in sharing economies to maximise value while minimising risk. As such, this research, when combined with (Ashtari Talkhestani et al., 2019; Ionescu & Andronie, 2021; Sahlab et al., 2022) findings that highlight the financial benefits of big data, cloud computing, and cyber-physical production systems used in similar business models, shows that the chances are high that big data and VR combined with AI, AR, and AM can create value with lower risks. Future research should consider combining VR and big data with other technologies, such as the "ARinVR" approach proposed by Zhang et al. (2021) or Jaszcz et al. (2023) suggestion for combining VR with human-controlled AI platforms to increase customer interaction in sharing economies, as it can assess the SE's service level enhancement. According to (Rohani et al., 2022; Serrano et al., 2021), the high value of extensive CRM records in ridesharing and rental-sharing economies should be highlighted and investigated when combined with VR for the potential creation of consumer personalisation value. This study also demonstrates the importance of real-time analysis and anomaly detection in SE operation systems that use big data with cyber-physical systems. As a result, future research is encouraged to investigate further the policies required for SEs using a framework proposed by (Bagozi et al., 2022).

Our findings further contribute to the critical role of newly emerged digital assets like metaverse and their potential in adding values to CCs based on Huynh-The et al. (2023) and Mozumder et al. (2022) studies. However, based on Figure 6, unlike the (Tan & Salo, 2023) findings that encourage marketing managers to deploy the blockchain and metaverse in the sharing economies, our BBWM analysis shows that investments for these TBBs should be adopted cautiously. In addition, unlike (Gattullo et al., 2022) findings, the metaverse combination with AR is discretion and highly risky in adding value to sharing economies based on the BBWM evaluation. As a result, future studies are encouraged to investigate metaverse combinations with digital twins and IoT as they provide a higher chance for adding value to sharing economies.

Since implementing the DM adoption suggestion is difficult, we must evaluate the platform's resources, market position, and readiness to integrate innovations as suggested by Mihai et al.'s (2022) research. To assess innovation adoption readiness, various perspectives can be used. The manufacturing readiness level (MRL) projects manufacturing processes, whereas the integration readiness level (IRL) highlights process integration maturity. Another critical and practical approach is the technology readiness level (TRL). It differs from similar approaches in that each level represents a different stage in the lifecycle of a technology, beginning with observed fundamental principles (TRL1) and progressing to absolute operational readiness (TRL9) (EARTO, 2014). This levelling is proposed for determining the maturity of TBBs.

TRL.1 *Observe and evaluate the TBB*
TRL.2 *Formulate the TBB*
TRL.3 *Make a mock experiment on the proof of the TBB*
TRL.4 *Verify the TBB in a lab*
TRL.5 *Put the TBB to the blind test for industrial use*
TRL.6 *Expand the investigation scope*
TRL.7 *Showcase the operative mode in industrial use*
TRL.8 *Adoption of the system has a positive response*
TRL.9 *The actual system is in operational mode*

After documenting evidence of technology adoption through these TRL scales, based on the weights of the TBBs in Table 5, the following weighted technology readiness score (WTRS) equation is $WTRS = \sum_{j=1}^{n}(W * T_j)$. To understand better how the weights generated from this research might be implemented, we will look at a case study by van Nuenen and Scarles (2021). Their research stressed the importance of virtual reality in tourist and sharing economies while exploring other industry 4.0 technologies such as augmented reality and artificial intelligence. While this study highlighted the potential of research in this subject, the actual ramifications of these technologies in real-world circumstances remain unknown. It must also be evident how the combination of these assets might add value. Following our research findings and the TRL technique, the maturity level of TBBs for employing VR in an industry is measured as follows.

The BBWM weights: *VR: 0.1217* *AI: 0.087*

TRL.1	Evaluate the VR applicability in a shared economy tourism company: $WTRS = (0.127 * 1)$
TRL.2	Assessment of the requirements (design, price, marketing): $WTRS = (0.127 * 2)$
TRL.3	By the end of the second phase, the company may realise that AI can be used with VR to provide better customer service. Then, the mock test should be conducted for the combination of these technologies as below: $WTRS = (0.127 + 0.087) * 3$
…	This process continues for all TRL steps.

Through the implementation of this methodology, a comprehensive aggregate score for the WTRS is acquired. The maturity level of an organisation's utilisation of VR technology is assessed by calculating a score, which is determined by an overarching threshold. Due to variations in the financial, structural, and market characteristics of industries across different socioeconomic contexts, the optimal range of values differs globally. The assessment of TRLs is contingent upon numerous aspects and typically necessitates meticulous investigation and thoughtful deliberation. The purpose of this case study is to enhance comprehension of the technological aspects of TRL based on the weights obtained from BBWM.

In general, the utilisation of this strategy is deemed pragmatic for several reasons. Managers can assess the present condition of their organisation and conduct trials on technological advancements. This methodology depends on examining the environmental factors and market conditions, so assuring the adoption of the technology is contingent upon consumer perceptions and market demand. Ultimately, this aids policymakers in discerning the relationship between their strategic plan and fostering innovation in the context of experimentation.

5. Conclusion

This paper advances the study of Industry 4.0 TBBs that affect CC and SE. This paper has been enriched by engaging industry and academic experts with the literature review on Industry 4.0

TBBs. To accomplish the research aim, Industry 4.0 TBBs, which include the metaverse, digital twins, CPSs, IoT, blockchain, big data, cloud computing, AI, AR, VR, and additive manufacturing, used in CC and SE, were initially extracted through SLR-TA. Then the importance of each was determined through the BBWM, and finally, they were classified. Accordingly, VR was selected as the most important TBB and the Metaverse as the least important TBB. Based on the classification, (i) VR, big data, and digital twins were among the fundamental; (ii) IoT, cloud computing, and blockchain were among the important; (iii) AI and CPSs were considered auxiliary; and (iv) AR, additive manufacturing, and the metaverse were identified as discretional TBBs. This paper presented a score function for organisations to measure readiness to employ these TBBs in sharing economies.

The authors used the SLR-BBWM method to understand better how digital technologies can add value to sharing economies. However, using SLR had limitations in finding research direction due to the number of articles and text mining capabilities. To improve accuracy, future research can employ advanced techniques such as Random Projection (RP), Latent Semantic Analysis (LSA), Term Frequency-Inverse Document Frequency (TF-IDF), Hierarchical Dirichlet Processes (HDPs) and Latent Semantic Indexing (LSI) based on machine and deep learning. Furthermore, current research used an alternative definition for sharing economy business model, i.e., collaborative consumption. Future research should explore other definitions like peer economy, access economy, crowd economy, or platform economies and include a larger corpus of articles using industry 4.0 technologies and sharing economies.

This research considers the opinions of experts from BBWM; nonetheless, it is important to note that these opinions may differ in the context of an alternative expert panel. To better understand the challenges and infrastructures of Industry 4.0 TBBs in CC and SEs, further studies should consider using uncertainty approaches that involve subjective judgments, doubt, and intuition. For example, methods like Pythagorean fuzzy, Fermatean fuzzy, Hesitant Fuzzy, and Intuitionistic Fuzzy can provide more realistic results. Alternatively, weighting techniques like the fuzzy best-worst method (F-BWM) can be used.

References

Abd, S. K., Al-Haddad, S. A. R., Hashim, F., Abdullah, A. B. H. J., and Yussof, S. (2017), “An effective approach for managing power consumption in cloud computing infrastructure”, *Journal of Computational Science*, Vol. 21, 349–360. https://doi.org/10.1016/j.jocs.2016.11.007

Akbar, P., and Hoffmann, S. (2023), “Collaborative space : framework for collaborative consumption and the sharing economy”, *Journal of Services Marketing*, Vol. 37 No. 4, pp. 496–509. https://doi.org/10.1108/JSM-03-2021-0078

Al Qadami, S. F. H. (2018), “Research and development of shared restaurant platform based on cloud computing”, *American Journal of Industrial and Business Management*, Vol. 8 No. 12, pp. 2321–2333.

Amat-Lefort, N., Marimon, F., and Mas-Machuca, M. (2020), “Towards a new model to understand quality in collaborative consumption services”, *Journal of Cleaner Production*, Vol. 266, Article 121855. https://doi.org/10.1016/j.jclepro.2020.121855

Ammar, M., Haleem, A., Javaid, M., Bahl, S., and Verma, A. S. (2022), “Implementing Industry 4.0 technologies in self-healing materials and digitally managing the quality of manufacturing”, *Materials Today: Proceedings*, Vol. 52 No. 4, pp. 2285–2294. https://doi.org/10.1016/j.matpr.2021.09.248

Amoozad Mahdiraji, H., Yaftiyan, F., Abbasi Kamardi, A. A., Garza-Reyes, J. A., and Razavi Hajiagha, S. H. (2022), “The role of Industry 4.0 technologies on performance measurement systems of supply chains during global pandemics: an interval-valued intuitionistic hesitant fuzzy approach”, *International Journal of Quality and Reliability Management*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/IJQRM-03-2022-0094

Angrisani, L., Bonavolontà, F., Liccardo, A., Lo Moriello, R. S., and Serino, F. (2018), “Smart power meters in augmented reality environment for electricity consumption awareness”, *Energies*, Vol. 11 No. 9, pp. 1–17.

Antony, J., Sony, M., and McDermott, O. (2023), “Conceptualizing Industry 4.0 readiness model dimensions: an exploratory sequential mixed-method study”, *TQM Journal*, Vol. 35 No. 2, pp. 577–596.

Ashtari Talkhestani, B., Jung, T., Lindemann, B., Sahlab, N., Jazdi, N., Schloegl, W., & Weyrich, M. (2019, September 1). An architecture of an Intelligent Digital Twin in a Cyber-Physical Production System. At - Automatisierungstechnik, 67(9), 762–782. https://doi.org/10.1515/auto-2019-0039

Bagozi, A., Bianchini, D., & Rula, A. (2022, August 20). Multi-perspective Data Modelling in Cyber Physical Production Networks: Data, Services and Actors. Data Science and Engineering, 7(3), 193–212. https://doi.org/10.1007/s41019-022-00194-4

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

Beheshti, M., ZareRavasan, A., Mahdiraji, H. A., Jafari-Sadeghi, V., & Sakka, G. An overview of the consumer-centric disruptive technology research: Insights from topic modelling and literature review. *Journal of Consumer Behaviour*. https://doi.org/10.1002/cb.2204

Bekaroo, G., Sungkur, R., Ramsamy, P., Okolo, A., and Moedeen, W. (2018), “Enhancing awareness on green consumption of electronic devices: the application of augmented reality”, *Sustainable Energy Technologies and Assessments*, Vol. 30, 279–291.

Belk, R., Humayun, M., and Brouard, M. (2022), “Money, possessions, and ownership in the metaverse: NFTs, cryptocurrencies, Web3 and wild markets”, *Journal of Business Research*, Vol. 153, 198–205.

Bisht, D., Singh, R., Gehlot, A., Akram, S. V., Singh, A., Montero, E. C., Priyadarshi, N., and Twala, B. (2022), “Imperative role of integrating digitalization in the firms finance: a technological perspective”, *Electronics (Switzerland)*, Vol. 11 No. 19. https://doi.org/10.3390/electronics11193252

Bolandnazar, E., Rohani, A., and Taki, M. (2020), “Energy consumption forecasting in agriculture by artificial intelligence and mathematical models”, *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*, Vol. 42 No. 13, pp. 1618–1632.

Cabral, N. G. C., and Gohr, C. F. (2023), “Sustainable value creation in sharing economy: Conceptual framework proposition and application in Brazilian offline communities”, *Technological Forecasting and Social Change*, Vol. 186 Part A. Article 122124. https://doi.org/10.1016/j.techfore.2022.122124

Chandna, V. (2022, January). Social entrepreneurship and digital platforms: Crowdfunding in the sharing-economy era. Business Horizons, 65(1), 21–31. https://doi.org/10.1016/j.bushor.2021.09.005

Chandra, S., and Verma, S. (2023), "Big data and sustainable consumption: a review and research agenda", *Vision*, Vol. 27 No. 1, pp. 11–23.

Cheng, X., Su, L., & Yang, B. (2020, March). An investigation into sharing economy enabled ridesharing drivers' trust: A qualitative study. Electronic Commerce Research and Applications, 40, 100956. https://doi.org/10.1016/j.elerap.2020.100956

Chaudhary, S., Dhir, A., Ferraris, A., and Bertoldi, B. (2021), "Trust and reputation in family businesses: a systematic literature review of past achievements and future promises", *Journal of Business Research*, Vol. 137, pp. 143–161. https://doi.org/10.1016/j.jbusres.2021.07.052

Chen, Y., Prentice, C., Weaven, S., and Hsiao, A. (2022), "A systematic literature review of AI in the sharing economy", *Journal of Global Scholars of Marketing Science: Bridging Asia and the World*, Vol. 32 No. 3, pp. 434–451.

Cheng, Y. L., Lim, M. H., and Hui, K. H. (2022), "Impact of internet of things paradigm towards energy consumption prediction: a systematic literature review", *Sustainable Cities and Society*, Vol. 78 No. 52, Article 103624.

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

Dalmarco, G., Ramalho, F. R., Barros, A. C., and Soares, A. L. (2019), "Providing industry 4.0 technologies: the case of a production technology cluster", *Journal of High Technology Management Research*, Vol. 30 No. 2, Article 100355.

De las Heras, A., Relinque-Medina, F., Zamora-Polo, F., and Luque-Sendra, A. (2021), "Analysis of the evolution of the sharing economy towards sustainability. trends and transformations of the concept", *Journal of Cleaner Production*, Vol. 291, Article 125227. https://doi.org/10.1016/j.jclepro.2020.125227

Debnath, B., Shakur, M. S., Bari, A. B. M. M., and Karmaker, C. L. (2023), "A Bayesian Best–Worst approach for assessing the critical success factors in sustainable lean manufacturing", *Decision Analytics Journal*, Vol. 6, Article 100157.

Ding, X., and Wu, J. (2019), "Study on energy consumption optimization scheduling for Internet of Things", *IEEE Access*, Vol. 7, pp. 70574–70583.

Elnadi, M., and Abdallah, Y. O. (2023), "Industry 4.0: critical investigations and synthesis of key findings", *Management Review Quarterly*, Vol. ahead-of-print https://doi.org/10.1007/s11301-022-00314-4.

El-Shamandi Ahmed, K., Ambika, A., and Belk, R. (2023), "Augmented reality magic mirror in the service sector: experiential consumption and the self", *Journal of Service Management*, Vol. 34 No. 1, pp. 56–77.

EARTO. (2014). *The TRL Scale as a Research & Innovation Policy Tool.* Tech. rep

Fathy, Y., Jaber, M., and Nadeem, Z. (2021), "Digital twin-driven decision making and planning for energy consumption", *Journal of Sensor and Actuator Networks*, Vol. 10 No. 2. https://doi.org/10.3390/jsan10020037

Feng, L., Xu, S., Zhang, L., Wu, J., Zhang, J., Chu, C., Wang, Z., and Shi, H. (2020), "Anomaly detection for electricity consumption in cloud computing: framework, methods, applications, and challenges", *EURASIP Journal on Wireless Communications and Networking*, Vol. 2020, Article 194. https://doi.org/10.1186/s13638-020-01807-0

Filimonau, V., Ashton, M., and Stankov, U. (2022), "Virtual spaces as the future of consumption in tourism, hospitality and events", *Journal of Tourism Futures*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/JTF-07-2022-0174

Gattullo, M., Laviola, E., Evangelista, A., Fiorentino, M., & Uva, A. E. (2022, December 8). Towards the Evaluation of Augmented Reality in the Metaverse: Information Presentation Modes. Applied Sciences, 12(24), 12600. https://doi.org/10.3390/app122412600

Gebeyehu, S., and Twinomurinzi, H. (2022), "A collaborative consumption digital platform for government organizations using design science", *Digital Government: Research and Practice*, Vol. 3 No. 1. https://doi.org/10.1145/3510615

Halim, D. K., and Hutagalung, S. (2022), “Towards data sharing economy on Internet of Things: a semantic for telemetry data”, *Journal of Big Data*, Vol. 9 No. 1, pp. 1–24.

Hang, L., and Kim, D. H. (2019), “SLA-based sharing economy service with smart contract for resource integrity in the internet of things”, *Applied Sciences*, Vol. 9 No. 17, Article 3602. https://doi.org/10.3390/app9173602

Hawlitschek, F., Notheisen, B., and Teubner, T. (2018), “The limits of trust-free systems: a literature review on blockchain technology and trust in the sharing economy”, *Electronic Commerce Research and Applications*, Vol. 29, pp. 50–63. https://doi.org/10.1016/j.elerap.2018.03.005

Himeur, Y., Ghanem, K., Alsalemi, A., Bensaali, F., and Amira, A. (2021), “Artificial intelligence based anomaly detection of energy consumption in buildings: a review, current trends and new perspectives”, *Applied Energy*, Vol. 287, Article 116601.https://doi.org/10.1016/j.apenergy.2021.116601

Hsu, C. C. (2023, January). The role of the core competence and core resource features of a sharing economy on the achievement of SDGs 2030. Journal of Innovation & Knowledge, 8(1), 100283. https://doi.org/10.1016/j.jik.2022.100283

Huynh-The, T., Gadekallu, T. R., Wang, W., Yenduri, G., Ranaweera, P., Pham, Q. V., . . . Liyanage, M. (2023). Blockchain for the metaverse: A Review. *Future Generation Computer Systems*.

Ijaz Baig, M., and Yadegaridehkordi, E. (2023), “Exploring moderating effects of industry 4.0 adoption on sustainable performance of Malaysian manufacturing organizations”, *Journal of Industrial and Production Engineering*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1080/21681015.2023.2190766

Ionescu, L., & Andronie, M. (2021). Big Data Management and Cloud Computing: Financial Implications in the Digital World. SHS Web of Conferences, 92, 05010. https://doi.org/10.1051/shsconf/20219205010

Jamwal, A., Agrawal, R., Sharma, M., and Giallanza, A. (2021), “Industry 4.0 technologies for manufacturing sustainability: A systematic review and future research directions”, *Applied Sciences*, Vol. 11 No. 12, Article 5725. https://doi.org/10.3390/app11125725

Jaszcz, A., Prokop, K., Połap, D., Srivastava, G., & Lin, J. C. (2023). Human-AI Collaboration to Increase the Perception of VR. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).*

Jia, Q. S., and Wu, J. (2018). On distributed event-based optimization for shared economy in cyber-physical energy systems. *Science China Information Sciences*, Vol. 61 No. 11, 110203–110205.

Jokhan, A., Chand, A. A., and Singh, V. (2022), “Increased digital resource consumption in higher educational institutions and the artificial intelligence role in informing decisions related to student performance”, *Sustainability,* Vol. 14 No. 4, Article 2377. https://doi.org/10.3390/su14042377

Kelly, R., Ghadimi, P., and Wang, C. (2022). “Barriers to closed-loop supply chains implementation in Irish medical device manufacturers: Bayesian best–worst method analysis”, Ghadimi, P., Gilchrist, M.D, Xu, M. (Eds.) *Role of Circular Economy in Resource Sustainability*, Springer, Cham, pp. 43–61.

Khan, M. S. A., Etonyeaku, L. C., Kabir, G., Billah, M., and Dutta, S. (2022), “Bridge infrastructure resilience assessment against seismic hazard using bayesian best worst method”, *Canadian Journal of Civil Engineering*, Vol. 49 No. 11, pp. 1669–1685.

Kim, Y., and Lee, H. (2022), “Falling in love with virtual reality art: a new perspective on 3D immersive virtual reality for future sustaining art consumption”, *International Journal of Human-Computer Interaction*, Vol. 38 No. 4, pp. 371–382.

Kim, G., & Han, I. (2022, November 30). Applications and Prospects of Fourth Industrial Revolution Technology in Environmental Areas - Focusing on Environmental Policy based Public Technology Development Projects -. Journal of Korean Society of Environmental Engineers, 44(11), 515–524. https://doi.org/10.4491/ksee.2022.44.11.515

Kumar, A., Alghamdi, S. A., Mehbodniya, A., Webber, J. L., and Shavkatovich, S. N. (2022), “Smart power consumption management and alert system using IoT on big data”, *Sustainable Energy Technologies and Assessments*, Vol. 53 Part C, Article 102555. https://doi.org/10.1016/j.seta.2022.102555

Lavoie, R., and King, C. (2020), “The virtual takeover: the influence of virtual reality on consumption”, *Canadian Journal of Administrative Sciences*, Vol. 37 No. 1, pp. 9–12.

Lee, J. W. (2021), “The data sharing economy and open governance of big data as public good”, *Journal of Asian Finance, Economics and Business*, Vol. 8 No. 11, pp. 87–96.

Li, K., Cui, Y., Li, W., Lv, T., Yuan, X., Li, S., Ni, W., Simsek, M., & Dressler, F. (2023, March 1). When Internet of Things Meets Metaverse: Convergence of Physical and Cyber Worlds. IEEE Internet of Things Journal, 10(5), 4148–4173. https://doi.org/10.1109/jiot.2022.3232845

Lin, H., and Zhai, X. (2023), "Energy efficiency through user adoption of the sharing economy leading to environmentally sustainable development", *Journal of Innovation and Knowledge*, Vol. 8 No. 1, Article 100315. https://doi.org/10.1016/j.jik.2023.100315

Liu, L., Song, W., and Liu, Y. (2023), "Leveraging digital capabilities toward a circular economy: reinforcing sustainable supply chain management with Industry 4.0 technologies", *Computers and Industrial Engineering*, Vol. 178, Article 109113. https://doi.org/10.1016/j.cie.2023.109113

Liu, P., Hendalianpour, A., Hamzehlou, M., Feylizadeh, M. R., and Razmi, J. (2021), "Identify and rank the challenges of implementing sustainable supply chain blockchain technology using the Bayesian best worst method", *Technological and Economic Development of Economy*, Vol. 27 No. 3, pp. 656–680.

Liu, Y., Xue, K., He, P., Wei, D. S. L., and Guizani, M. (2020), "An efficient, accountable, and privacy-preserving access control scheme for Internet of Things in a sharing economy environment. *IEEE Internet of Things Journal*, Vol. 7 No. 7, pp. 6634–6646.

Liying, C., Ziwei, Y., & Tingfang, T. (2020). Consumption Choice in Choosing Online Short-term House Rental Platform in Sharing Economy. Frontiers of Management, 2(2), 79–110. https://doi.org/10.35534/fm.0202010

Madhi, H. A. B., & Alhammah, M. M. (2021). What Drives Airbnb Customers' Satisfaction in Amsterdam? A Sentiment Analysis. International Journal of Advanced Computer Science and Applications, 12(6). https://doi.org/10.14569/ijacsa.2021.0120628

Marrucci, A., Rialti, R., and Balzano, M. (2023), "Exploring paths underlying Industry 4.0 implementation in manufacturing SMEs: a fuzzy-set qualitative comparative analysis", *Management Decision*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/MD-05-2022-0644

Mihai, S., Yaqoob, M., Hung, D. V., Davis, W., Towakel, P., Raza, M., . . . Nguyen, H. X. (2022). Digital Twins: A Survey on Enabling Technologies, Challenges, Trends and Future Prospects. *IEEE Communications Surveys and Tutorials*.

Mohammadi, M., and Rezaei, J. (2020), "Bayesian best-worst method: a probabilistic group decision making model", *Omega*, Vol. 96, Article 102075.https://doi.org/10.1016/j.omega.2019.06.001

Mozumder, M. A., Sheeraz, M. M., Athar, A., Aich, S., & Kim, H. C. (2022). Overview: Technology Roadmap of the Future Trend of Metaverse based on IoT, Blockchain, AI Technique, and Medical Domain Metaverse Activity. *International Conference on Advanced Communication Technology, ICACT.*

Mu, H., He, F., Yuan, L., Commins, P., Wang, H., and Pan, Z. (2023), "Toward a smart wire arc additive manufacturing system: a review on current developments and a framework of digital twin", *Journal of Manufacturing Systems*, Vol. 67, pp. 174–189.

Munim, Z. H., Balasubramaniyan, S., Kouhizadeh, M., and Hossain, N. U. I. (2022), "Assessing blockchain technology adoption in the Norwegian oil and gas industry using Bayesian best-worst method. *Journal of Industrial Information Integration*, Vol. 28, Article 100346. https://doi.org/10.1016/j.jii.2022.100346

Nadeem, W., Alimamy, S., & Ashraf, A. R. (2023, January). Navigating through difficult times with ethical marketing: Assessing consumers' willingness-to-pay in the sharing economy. Journal of Retailing and Consumer Services, 70, 103150. https://doi.org/10.1016/j.jretconser.2022.103150

Nwogugu, M. C. I. (2019), "Alternative-risk premia and value-drivers in the sharing economy (and digital currencies)", *SSRN Electronic Journal*, *November*. https://dx.doi.org/10.2139/ssrn.4282169

Oliveira, T., Tomar, S., and Tam, C. (2020), "Evaluating collaborative consumption platforms from a consumer perspective", *Journal of Cleaner Production*, Vol. 273, Article 123018. https://doi.org/10.1016/j.jclepro.2020.123018

Pamucar, D., Deveci, M., Gokasar, I., Delen, D., Köppen, M., and Pedrycz, W. (2023), "Evaluation of metaverse integration alternatives of sharing economy in transportation using fuzzy Schweizer-Sklar based ordinal priority approach", *Decision Support Systems*, Vol. ahead-of-print No. ahead-of-print, Article 113944. https://doi.org/10.1016/j.dss.2023.113944

Peng, H., Wen, W. S., Tseng, M. L., and Li, L. L. (2019), "Joint optimization method for task scheduling time and energy consumption in mobile cloud computing environment", *Applied Soft Computing Journal*, Vol. 80, pp. 534–545. https://doi.org/10.1016/j.asoc.2019.04.027

Pang, S., Bao, P., Hao, W., Kim, J., & Gu, W. (2020, March 17). Knowledge Sharing Platforms: An Empirical Study of the Factors Affecting Continued Use Intention. Sustainability, 12(6), 2341. https://doi.org/10.3390/su12062341

Ranjitha, G. P., and Jeesha, K. (2023), "Collaborative consumption: the future of sharing economy", Bhattacharyya, J. (Ed.), *Dealing with Socially Responsible Consumers: Studies in Marketing*, Palgrave Macmillan, Singapore, pp. 69–81.

Rezaei, J. (2015), "Best-worst multi-criteria decision-making method", *Omega*, Vol. 53, pp. 49–57. https://doi.org/10.1016/j.omega.2014.11.009

Ritter, M., and Schanz, H. (2019), "The sharing economy: a comprehensive business model framework", *Journal of Cleaner Production*, Vol. 213, pp. 320–331. https://doi.org/10.1016/j.jclepro.2018.12.154.

Rynarzewska, A. I. (2018), "Virtual reality: a new channel in sport consumption", *Journal of Research in Interactive Marketing*, Vol. 12 No. 4, pp. 472–488.

Sadiq, M., Moslehpour, M., Qiu, R., Hieu, V. M., Duong, K. D., & Ngo, T. Q. (2023, January). Sharing economy benefits and sustainable development goals: Empirical evidence from the transportation industry of Vietnam. Journal of Innovation & Knowledge, 8(1), 100290. https://doi.org/10.1016/j.jik.2022.100290

Sahlab, N., Braun, D., Köhler, C., Jazdi, N., & Weyrich, M. (2022). Extending the Intelligent Digital Twin with a context modeling service: A decision support use case. Procedia CIRP, 107, 463–468. https://doi.org/10.1016/j.procir.2022.05.009

Sedlmeir, J., Buhl, H. U., Fridgen, G., and Keller, R. (2020), "The energy consumption of blockchain technology: beyond myth", *Business and Information Systems Engineering*, Vol. 62 No. 6, pp. 599–608.

Sedlmeir, J., Buhl, H. U., Fridgen, G., and Keller, R. (2021), "Recent Developments in Blockchain Technology and their Impact on Energy Consumption", 1–11. https://doi.org/10.48550/arXiv.2102.07886

Seo, A., Jeong, J., and Kim, Y. (2017), "Cyber physical systems for user reliability measurements in a sharing economy environment", *Sensors*, Vol. 17 No. 8, Article 1868. https://doi.org/10.3390/s17081868

Sharifpour, Hojat, Aghajani, H., and Safaei Ghadikolaei, A. (2020), "Investigating the interactive relationships of fourth generation industry technologies in selected food industries with the revised DEMATEL approach", *Journal of Decisions and Operations Research*, Vol. 5 No. 2, pp. 151–166.

Sharifpour, H., Ghaseminezhad, Y., Hashemi-Tabatabaei, M., and Amiri, M. (2022), "Investigating cause-and-effect relationships between supply chain 4.0 technologies", *Engineering Management in Production and Services*, Vol. 14 No. 4, pp. 22–46.

Shen, B., Tan, W., Guo, J., Zhao, L., and Qin, P. (2021), "How to promote user purchase in metaverse? A systematic literature review on consumer behavior research and virtual commerce application design", *Applied Sciences*, Vol. 11 No. 23, Article 11087.

Silvestri, L., Forcina, A., Introna, V., Santolamazza, A., and Cesarotti, V. (2020), "Maintenance transformation through Industry 4.0 technologies: a systematic literature review", *Computers in Industry*, Vol. 123, Article 103335. https://doi.org/10.1016/j.compind.2020.103335

Smit, E. S., Meijers, M. H. C., and van der Laan, L. N. (2021), "Using virtual reality to stimulate healthy and environmentally friendly food consumption among children: an interview study", *International Journal of Environmental Research and Public Health*, Vol. 18 No. 3, pp. 1–13.

Stickle, B. (2023), "Crime sharing: how the sharing economy may impact crime victims", *Victims and Offenders*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1080/15564886.2022.2159905

Tan, T. M., and Salo, J. (2023), "Ethical marketing in the blockchain-based sharing economy: theoretical integration and guiding insights", *Journal of Business Ethics*, Vol. 183 No. 4, pp. 1113–1140.

Tlili, A., Huang, R., and Kinshuk. (2023), "Metaverse for climbing the ladder toward 'Industry 5.0'and 'Society 5.0'?", *The Service Industries Journal*, Vol. 43 No. 3–4, pp. 260–287. https://doi.org/10.1080/02642069.2023.2178644

Tranfield, D., Denyer, D., and Smart, P. (2003), "Towards a methodology for developing evidence-informed management knowledge by means of systematic review", *British Journal of Management*, Vol. 14 No. 3, pp. 207–222.

Truby, J. (2018), "Decarbonizing Bitcoin: law and policy choices for reducing the energy consumption of blockchain technologies and digital currencies", *Energy Research and Social Science*, Vol. 44, pp. 399–410. https://doi.org/10.1016/j.erss.2018.06.009

Tumasjan, A., and Beutel, T. (2019), "Blockchain-based decentralized business models in the sharing economy: a technology adoption perspective. Treiblmaier, H., and Beck, R. (Eds.), *Business Transformation through Blockchain*, Springer International Publishing, Chapter 3. https://doi.org/10.1007/978-3-319-98911-2_3

van Nuenen, T., & Scarles, C. (2021), Advancements in technology and digital media in tourism. *Tourist Studies*, *21*(1), 119–132. https://doi.org/10.1177/1468797621990410

Wang, Z., Xue, M., Wang, Y., Song, M., Li, S., and Zhang, B. (2019), "Big data: New tend to sustainable consumption research", *Journal of Cleaner Production*, Vol. 236, Article 117499. https://doi.org/10.1016/j.jclepro.2019.06.330

Watson, J. K., and Taminger, K. M. B. (2018), "A decision-support model for selecting additive manufacturing versus subtractive manufacturing based on energy consumption",e *Journal of Cleaner Production*, Vol. 176, pp. 1316–1322. https://doi.org/10.1016/j.jclepro.2015.12.009

Wei, N., Li, C., Peng, X., Zeng, F., and Lu, X. (2019), "Conventional models and artificial intelligence-based models for energy consumption forecasting: a review", *Journal of Petroleum Science and Engineering*, Vol. 181, Article 106187. https://doi.org/10.1016/j.petrol.2019.106187

Wu, Z., Zhou, W., and Yu, A. (2023), "Analysis of a legal regulation approach and strategy of a sharing economy based on technological change and sustainable development", *Sustainability*, Vol. e No. 2, Article 1056. https://doi.org/10.3390/su15021056

Yadav, R., Zhang, W., Kaiwartya, O., Singh, P. R., Elgendy, I. A., and Tian, Y. C. (2018), "Adaptive energy-aware algorithms for minimizing energy consumption and SLA violation in cloud computing", *IEEE Access*, Vol. 6, pp. 55923–55936. https://doi.org/10.1109/ACCESS.2018.2872750

Yang, H., Chen, R., and Kumara, S. (2021), "Stable matching of customers and manufacturers for sharing economy of additive manufacturing", *Journal of Manufacturing Systems*, Vol. 61, pp. 288–299. https://doi.org/10.1016/j.jmsy.2021.09.013

Yao, X., Ma, N., Zhang, J., Wang, K., Yang, E., and Faccio, M. (2022), "Enhancing wisdom manufacturing as industrial metaverse for industry and society 5.0", *Journal of Intelligent Manufacturing*, 1–21. https://doi.org/10.1007/s10845-022-02027-7

Yu, C., Xu, X., Yu, S., Sang, Z., Yang, C., and Jiang, X. (2020), "Shared manufacturing in the sharing economy: concept, definition and service operations", *Computers and Industrial Engineering*, Vol. 146, Article 106602. https://doi.org/10.1016/j.cie.2020.106602

Zhan, M., Wu, J., Wen, H., and Zhang, P. (2018), "A novel error correction mechanism for energy-efficient cyber-physical systems in smart building. *IEEE Access*, Vol. 6, pp. 39037–39045. https://doi.org/10.1109/ACCESS.2018.2854794

Zhang, M., Zuo, Y., and Tao, F. (2018), "Equipment energy consumption management in applications", *2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC)*, 27-29 March 2018, Zhuhai, China. https://doi.org/10.1109/ICNSC.2018.8361272

Zheng, T., Ardolino, M., Bacchetti, A., and Perona, M. (2021), "The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review", *International Journal of Production Research*, Vol. e No. 6, pp. 1922–1954.