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Industry 4.0 technologies assessment: A sustainability perspective

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ABSTRACT

The fourth industrial revolution, also labelled Industry 4.0, was beget with emergent and disruptive intelligence and information technologies. These new technologies are enabling ever-higher levels of production efficiencies. They also have the potential to dramatically influence social and environmental sustainable development. Organizations need to consider Industry 4.0 technologies contribution to sustainability. Sufficient guidance, in this respect, is lacking in the scholarly or practitioner literature. In this study, we further examine Industry 4.0 technologies in terms of application and sustainability implications. We introduce a measures framework for sustainability based on the United Nations Sustainable Development Goals; incorporating various economic, environmental and social attributes. We also develop a hybrid multi-situation decision method integrating hesitant fuzzy set, cumulative prospect theory and VIKOR. This method can effectively evaluate Industry 4.0 technologies based on their sustainable performance and application. We apply the method using secondary case information from a report of the World Economic Forum. The results show that mobile technology has the greatest impact on sustainability in all industries, and nanotechnology, mobile technology, simulation and drones have the highest impact on sustainability in the automotive, electronics, food and beverage, and textile, apparel and footwear industries, respectively. Our recommendation is to take advantage of Industry 4.0 technology adoption to improve sustainability impact but each technology needs to be carefully evaluated as specific technology will variably influence industry and sustainability dimensions. Investment in such technologies should consider appropriate priority investment and championing.

1. Introduction

Industry 4.0 is transforming manufacturing firm business models. These technologies can support production flexibility, efficiency, and productivity through various emergent communication, information and intelligence technologies (Ibarra et al., 2018; Rüßmann et al., 2015). Industry 4.0 technologies include, but are not limited to, additive manufacturing, artificial intelligence, big data and analytics, blockchain, cloud, industrial internet of things, and simulation (Dalenogare et al., 2018; Bai et al., 2017). These Industry 4.0 technologies can potentially provide tremendous innovation and competitiveness growth; they may also improve current industrial system sustainability (Müller et al., 2018; Stock and Seliger, 2016).

Industry 4.0 technologies adoption in companies and industries has taken on greater importance and visibility (Luthra and Mangla, 2018; de Sousa Jabbour et al., 2018; Kiel et al., 2017). Yet these technologies implications on society's sustainability objectives require more attention and evaluation (Bai and Sarkis, 2020). Traditional production systems are notorious in their poor ecological imbalances. The litany of higher resources consumption, global warming, general environmental degradation, and higher environmental pollution are traceable to traditional manufacturing systems and technologies (Tseng et al., 2018). We also face various social problems and challenges, including poverty, inequality, prosperity, and peace and justice concerns (Griggs et al., 2013).

Legitimacy theory argues that meeting key stakeholder sustainability requirements – such as carbon emissions reductions – contributes to superior performance (Lanis and Richardson, 2012). The fourth Industrial revolution can potentially address many of the ecological and social limitations of traditional industrial practices and technologies; to

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provide a more sustainable future (Morrar et al., 2017). Ultimately, these actions may translate into long-term organizational competitiveness. According to McKinsey's survey of 130 firm representatives from various industries in China, Chinese manufacturing firms have great enthusiasm and expectation for Industry 4.0, but only 57% of Chinese enterprises are fully prepared for Industry 4.0 technologies. This global study showed that it is far lower than the United States (71%) and Germany (68%) (mckinsey.com, 2016). A major reason is many manufacturing firms may not understand the value of these technologies. Industry 4.0 technologies are complex and integrated architecture manufacturing-information technology integration (Frank et al., 2019). Evaluating the impact of these technologies based on standard evaluation may be difficult; but additional evaluation for sustainability benefits can increase their strategic adoption, but makes the process even more complex. Thus, it is still an important and open subject of research in Industry 4.0 evaluation (Dalenogare et al., 2018). Overall, effective and robust evaluation methods and decision support tools can help manufacturing firms effectively implement and understand those Industry 4.0 technologies; especially considering broader economic implications. These broader implications, in addition to environmental and social concerns, include building competitiveness of firms and their nations.

This study argues that the principles and aims of Industry 4.0 technologies are not limited to conventional organizational business and economic performance, but will contribute to a more sustainable society. Further understanding of Industry 4.0 technologies and philosophical relationships to sustainability of society is important for practitioners; especially when capital investment decisions are to be made (Bai and Sarkis, 2013, 2017). Policymakers, seeking to make policies on Industry 4.0, could also benefit from further elicitation of this relationship (Lin et al., 2017). Yet, building and understanding the relationships between Industry 4.0 technologies and sustainability is not trivial. There is also significant lack of knowledge and uncertainty in this relationship between sustainability and Industry 4.0 technologies (Kamble et al., 2018a). This research seeks to answer three questions that address this knowledge gap and uncertainty:

Q1: What value can these Industry 4.0 technologies create for economic, environmental and social sustainability, and how can they help to achieve SDGs?
Q2: What are the differences in the value created by these Industry 4.0 technologies in different industries?
Q3: How can the value of these Industry 4.0 technologies be effectively evaluated?

This study identifies key challenges of Industry 4.0 technologies to contribute to sustainable society enhancement. This research makes three major contributions. First, we further refine Industry 4.0 technologies understanding in terms of society's sustainability. The application scope of these technologies is evaluated using a measurement framework based on a triple-bottom-line conceptualization (Elkington, 1998). Second, a novel multi-contextual decision-making method is introduced. This methodology integrates hesitant fuzzy set (HFS), cumulative prospect theory (CPT) and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) to evaluate Industry 4.0 technologies based on their application scope. Third, the method and sustainability attributes are applied to an empirical case, using secondary published data. The methodology provides insight to managers and researchers to comprehensively evaluate Industry 4.0 technologies for adoption. The secondary data derives from the World Economic Forum White Paper "Driving the Sustainability of Production Systems with Fourth Industrial Revolution Innovation" (World Economic Forum, 2018). The overall results show that the framework, methodology, and case application can prove valuable to both practitioners and researchers. It also sets the foundation for further application and research on the relationship between Industry 4.0 and sustainability.

Industry 4.0 technologies practically exhibit significant uncertainty and varying performance results across different applications or contexts. HFS can retain possible performance across multiple applications or varying opinions of all decision makers. However, the fuzzy set – alone as a basic technique – can only summarize these opinions and possible performance into a fuzzy value, and not effectively integrating diversity of the different applications and voices. This conversion of multiple opinions into a fuzzy value will result in information loss and may not accurately reflect performance within each context. Hence, HFS is an effective approach to represent and address uncertainty originating from diverse contexts and multiple decision maker involvement (Torra and Narukawa, 2009). It extends fuzzy sets and can represent the spectrum of Industry 4.0 technology possibilities across these diverse contexts. In our empirical evaluation we have completed a performance evaluation of each technology across different applications.

The remainder of this paper has the following organization. Section 2 provides literature background on Industry 4.0 technologies and sustainability to help set the foundation for this research and exemplify its contribution. In section 3, the HFS, CPT and VIKOR concepts are introduced. A multi-contextual decision-making model is advanced in section 4. A comparative analysis in section 5 verifies the feasibility and capabilities of the proposed method and allows us to discuss the initial findings in light of previous Industry 4.0 research. Finally, section 6 includes conclusions, contributions, limitations and future research directions.

2. Background and literature

2.1. Industry 4.0 technologies

Industry 4.0 is purported to be a new paradigm of smart and autonomous manufacturing. It more profoundly integrates manufacturing operations systems with communication, information and intelligence technologies (Wang et al., 2017; Jeschke et al., 2017). Among the litany of benefits, Industry 4.0 can provide manufacturing firms with profitable business models, higher efficiency, quality, and improved workplace conditions (Hofmann and Rüsch, 2017). It has gained considerable attention among researchers and practitioners given these potential benefits (Liao et al., 2017). But disadvantages including lack of understanding, costs, legacy system alterations, and potential energy disadvantages have made the decision for adoption and evaluation difficult (e.g. Saberi et al., 2019, which discusses barriers to blockchain technology as an example).

Industry 4.0 technologies may be grouped into physical and digital technologies. Physical technologies mainly refer to manufacturing technologies such as additive manufacturing (Gibson et al., 2014), or sensors and drones (Morrar et al., 2017). Digital technologies mainly refer to modern information and communication technologies, such as cloud computing, blockchain, big data analytics, and simulation (Liao et al., 2017). Table 1 summarizes various Industry 4.0 technologies (Dalenogare et al., 2018; Lu, 2017; Wan et al., 2015; Posada et al., 2015).

These Industry 4.0 technologies are relatively novel in developing countries, and in small and medium firms. Broader acceptance requires further in-depth understanding and developments especially for underrepresented populations; including Industry 4.0 impact on sustainability (Müller et al., 2018).

Table 1
List and definition of various Industry 4.0 technologies.

Technologies	Definition
Additive manufacturing (3D printing)	is a manufacturing technology that creates three-dimensional (3D) solid objects using a series of additive or layered development frameworks.
Artificial intelligence	is an area of computer science that emphasizes the creation of intelligent machines that work and react like humans.
Augmented reality	is a type of interactive, reality-based display environment that takes the capabilities of computer generated display, sound and other effects to enhance the real-world experience.
Autonomous robots (Robotics)	are used to replicate human actions in manufacturing.
Big data and analytics	refer to the strategy of analyzing large volumes of data that are used when traditional data mining and handling techniques cannot uncover the insights and meaning of the underlying data.
Blockchain	is a distributed database that maintains a completely, distributed and non-tampering continuously growing list of records using new encryption and authentication technology and network-wide consensus mechanism.
Cloud	refers to any IT services that are provisioned and accessed from a cloud computing provider.
Cobotic systems	is a robot intended to physically interact with humans in a shared workspace.
Cybersecurity	refers to preventative methods used to protect information from being stolen, compromised or attacked.
Unmanned aerial vehicle (Drones)	is aircraft without a human pilot onboard, and commonly known as a drone.
Global Positioning System (GPS)	is a technical marvel made possible by a group of satellites in Earth's orbit that transmit precise signals, allowing GPS receivers to calculate and display accurate location, speed and time information to the user.
Industrial Internet of Things	is the various sets of hardware pieces that work together through internet of things connectivity to help enhance manufacturing and industrial processes.
Mobile Technology	is the wireless communication technology integration based on the wireless devices.
Nanotechnology	also now referred to as molecular nanotechnology, is the particular technology to control individual atoms and molecules for fabrication of macroscale products.
RFID	refers to technologies that use wireless communication between an object (or tag) and interrogating device (or reader) to automatically track and identify such objects.
Sensors and actuators	is a device that responds to a physical stimulus (such as heat, light, sound, pressure, magnetism, or a particular motion) and transmits a resulting impulse (as for measurement or operating a control).
Simulation	refers to technologies that use the computer for the imitation of a real-world process or system.

2.2. Industry 4.0 technologies and sustainability

Industry 4.0 and sustainability[1] are relatively recent emerging technological and organizational trends that are influenced by or influence improving productivity and sustainable production (Luthra and Mangla, 2018). Industry 4.0 technologies seek to overcome contemporary challenges – global competition, volatile markets and demand, increased customization through communication, information and intelligence, and decreasing innovation and product life cycles (Kiel et al., 2017).

Industry 4.0 technologies potentials include substantial contributions or limitations to organizational and social sustainable development (Stock and Seliger, 2016). Considering the economic dimension, reduced set-up times, shorter lead times, reduced labor and material costs, increased production flexibility, higher productivity and enhanced customization exist (Dalenogare et al., 2018; Witkowski, 2017; Rüßmann et al., 2015).

From the ecological point of view, Industry 4.0 technologies can reduce energy and resource consumption through detection and data analysis across production and supply chain processes (Shrouf et al., 2014). They can lead to reduction in waste or CO_2-emissions through data-centered and traceable carbon footprint analyses (Gabriel and Pessl, 2016; Sarkis and Zhu, 2018). Products can be disassembled into their component elements for reuse, recycling, or remanufacturing.

For social sustainability dimensions, smart and autonomous production systems can support employee health and safety, by taking over monotonous and repetitive tasks; resulting in higher employee satisfaction and motivation (Müller et al., 2018). However, Industry 4.0 technologies also bring many challenges and limitations to society. For example, reduced employment, information security issues, data complexity, electronic wastes, and poor quality can prevail (Rojko, 2017).

Few studies provide insight into the interface between Industry 4.0 technologies and sustainability. Some of them have focused conceptually on specific sustainability related industrial concerns such as the circular economy (de Sousa Jabbour et al., 2018; Tseng et al., 2018). For a systematic review of these studies, see Beltrami and Orzes, 2019.

Proponents of legitimacy theory have suggested that firms are incorporating sustainability to meet the concerns and demands of stakeholders (Park et al., 2010). As a result, manufacturing firms need to go beyond pure profit maximization, and address broader societal expectations; increasing social and environmental responsibility. Transforming industrial production through industry 4.0 to meet these sustainability needs has become a legitimacy goal (Kamble et al., 2018b).

Although imperfect (Spaiser et al., 2017), the United Nations Sustainable Development Goals (SDGs) provide a common framework and set of goals for firms, industries and countries to achieve sustainable development (Robert et al., 2005). Industry 4.0 technologies have potential to benefit all 17 SDGs. Potential relationships between SDGs and Industry 4.0 technologies appear in Table 2.

SDGs may be generally assigned, given there may be some overlap, to TBL dimensions. Ending poverty, providing decent work and economic growth, industry, innovation and infrastructure and reduced inequalities, partnerships for the goals are well aligned with economic sustainability attributes. Ending hunger, good health and well-being, quality education, gender equality, peace, justice and strong institutions are well aligned with social sustainability attributes. Clean water and sanitation, affordable and clean energy, sustainable cities and communities, responsible consumption and production, climate action, life below water and life on land are well aligned with environmental impact attributes. TBL, for organizational decisions, can be utilized to unfold benefits (Bai and Sarkis, 2019).

This framework grounds our study for understanding Industry 4.0 technologies relationships to society's sustainability. For example, lower emission level – climate action goal – technologies support manufacturing firm urban development efforts; and zero sewage discharge – life below water goal – technologies can aid manufacturing firms from polluting freshwater lakes.

2.3. Corporate industry 4.0 technologies evaluation and appraisal

Evaluation methods can aid organizations to further understand and adopt Industry 4.0 technologies. They can support managerial decision

[1] Sustainability has had many definitions over the years from a broad variety of disciplines. We utilize the intergenerational philosophy based on meeting the needs of current generations without compromising the ability of future generations to meet theirs (WCED, 1987). We also rely on the multidimensional concept of the 'triple-bottom-line' (TBL) (Elkington, 1998). The three main pillars of TBL are economic, environmental, and social dimensions. We also link sustainability to the United Nations Sustainable Development Goals (SDGs).

Table 2
The United Nations Sustainable Development Goals and Industry 4.0 technologies.

Attribute	Explanation	Relationship with Industry 4.0 technologies
End poverty (EP)	End poverty in all its forms everywhere.	Industry 4.0 technologies can bring access to information, education, health care and greater economic opportunity that provide more basic resources and services to the poor people and bring them out of poverty. Industry 4.0 technologies also can alleviate the unexpected economic losses during disasters.
End hunger (EH)	End hunger, achieve food security and improved nutrition and promote sustainable agriculture.	Industry 4.0 technologies can promote sustainable agriculture and fair distribution systems to make sure that nobody will ever suffer from hunger again. Industry 4.0 technologies also help to achieve food security and improved nutrition.
Good health and well-being (GHW)	Ensure healthy lives and promote well-being for all at all ages.	Industry 4.0 technologies are enabling the digitalization of healthcare, it promotes healthy lifestyles, preventive measures and modern, efficient healthcare services for everyone.
Quality education (QE)	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.	Industry 4.0 technologies can help enjoy affordable, equitable and quality primary and secondary education.
Gender equality (GE)	Achieve gender equality and empower all women and girls.	Industry 4.0 technologies will provide the equal opportunity to succeed in every function and at every level for both men and women.
Clean water and sanitation (CWS)	Ensure availability and sustainable management of water and sanitation for all.	Industry 4.0 technologies can help provide affordable equipment and education in hygiene practices that access to clean drinking water and sanitation.
Affordable and clean energy (ACE)	Ensure access to affordable, reliable, sustainable and modern energy for all.	Industry 4.0 technologies will bring sustainable energy efficiency to enable both increased quality and cost savings to users.
Decent work and economic growth (DWEG)	Promote inclusive and sustainable economic growth, employment and decent work.	Industry 4.0 technologies have significant direct and indirect economic impact while not harming the environment. Economic growth will create decent and fulfilling jobs.
Industry, innovation and infrastructure (III)	Build resilient infrastructure, promote sustainable industrialization and foster innovation.	Industry 4.0 technologies, be as new industries and information and communication technologies, are the important ways to promoting sustainable industries, investing in scientific research and innovation, upgrading infrastructure.
Reduced inequalities (RI)	Reduce inequality within and among countries.	Industry 4.0 technologies can help to connect the unconnected and helps to bridge the digital divide to reduce inequality within and among countries or people.
Sustainable cities and communities (SCC)	Make cities inclusive, safe, resilient and sustainable.	Industry 4.0 technologies can help build modern, sustainable, intelligent, public order, safety and security cities with green and culturally inspiring living conditions.
Responsible consumption and production (RCP)	Ensure sustainable consumption and production patterns.	Industry 4.0 technologies are already being used to bring greater efficiency across industries, greater transparency in supply chains, and improved production and consumption patterns.
Climate action (CA)	Take urgent actions to combat climate change and its impacts.	Industry 4.0 technologies can lead to a reduction of CO2-emissions by data-centered and traceable carbon footprint.
Life Below Water (LBW)	Conserve and sustainably use the oceans, seas and marine resource.	Industry 4.0 technologies can contribute to more sustainable use of the oceans resources.
Life on land (LL)	Sustainably manage forests, combat desertification, halt and reverse land degradation, halt biodiversity loss.	Industry 4.0 technologies are key to management of forests and biodiversity.
Peace, justice and strong institutions (PJSI)	Promote just, peaceful and inclusive societies.	Industry 4.0 technologies can ensure and promote a responsible firm or supply chain, human rights and freedom of expression.
Partnerships for the goals (PG)	Revitalize the global partnership for sustainable development.	Industry 4.0 technologies can help collaborate with a broad range of stakeholders in order to drive sustainable development forward.

* the relationships were built from the following websites: https://www.globalgoals.org/17-partnerships-for-the-goals, https://www.nokia.com/about-us/sustainability/our-approach/nokia-and-the-united-nations-sustainable-development-goals/, https://www.undp.org/content/undp/en/home/sustainable-development-goals.html.

making. Initial efforts have utilized various tools in disparate Industry 4.0 evaluation and appraisal approaches. The analytical hierarchy process (AHP) has been used to evaluate challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies (Luthra and Mangla, 2018). AHP-VIKOR methodologies were utilized to support Industry 4.0 application strategies evaluation (Erdogan et al., 2018). But, overall, the literature, thus far, has been quiet on the evaluation of Industry 4.0 technologies on sustainable performance and integrating them with by multiple attribute decision making (MADM) methods.

Many MADM methods for technology evaluation exist (for example see Bai et al., 2017); but they are difficult to apply for the evaluation of Industry 4.0 technologies. First, Industry 4.0 technologies are relatively new and there is a lack of knowledge about the real impact and contribution of the Industry 4.0 technologies in general. Second, Industry 4.0 technologies need to be integrated with traditional production systems, making the fitness and compatibility issues even more important. Third, the Industry 4.0 technologies performance is associated with high uncertainties because they are applied in different contexts and industries.

There is still considerable uncertainty and confusion since applications may result in contradictory performance on Industry 4.0 applications; especially in trying to balance sustainability contributions. For example, greater digitization may improve equality and economic business factors, but require additional energy requirements resulting in resource depletion or environmentally damaging emissions.

These challenges in the evaluation of Industry 4.0 technologies contribute to lack of clarity in sustainability contribution from Industry 4.0 implementation. Specifically, the current academic journal published research does not provide a comprehensive decision support tool with regard to the assessment and analysis of the complex Industry 4.0 and sustainability relationships. This paper introduces a hybrid multi-context decision method that incorporates hesitant fuzzy sets, cumulative prospect theory, and VIKOR to evaluate the Industry 4.0 technologies resulting in a ranking of sustainability attributes.

HFSs have been used to handle imprecise data and vague linguistic expressions of decision makers (Xu and Xia, 2011). We use HFSs to represent the uncertainty and diverse performance of Industry 4.0 technologies across different applications. CPT considers decision maker psychological characteristics under risk and uncertain environments; it also evaluates the probability of meeting sustainability performance. Most CPT related methods assume that the reference points are exogenously fixed, but it might not be true in Industry 4.0 decisions; there are shared reference points. Decision makers may update their perceptions and adjust their reference points in response to changes in different decision-making situations (Munro and Sugden, 2003). We integrate this characteristic with CPT; a new perspective not previously applied in CPT related studies.

This study considers every technology as an endogenous reference point to characterize decision maker behaviors under risk or uncertainty. We also convert it into possible reference points – each Industry 4.0 technology – based on the prevalence of each technology in a decision context. In decision-making, there is a tendency to apply too much weight to low probability outcomes and too little weight to high probability outcomes (Bai and Sarkis, 2017). CPT can help alleviate this issue.

Third, the VIKOR method evaluates the degree Industry 4.0 technologies relate to sustainability attributes. The valuation is based on a value between 0 and 1 [0, 1] that better represents the degree of the technology and sustainability linkage (Bai and Sarkis, 2019).

Given the various limitations in methodologies and unique Industry 4.0 and sustainability relationship, we integrate HFS, CPT, and VIKOR in a multistage methodology. We now introduce some general foundation for each technique.

3. HFS, CPT and VIKOR definitions and functions

In this section, we present general definitions, notation, and functions of HFS, CPT, and VIKOR. Throughout this paper, $X = \{x_1, x_2, \ldots, x_n\}$ is used to denote the reference set.

3.1. Hesitant fuzzy set (HFS)

HFS (Torra and Narukawa, 2009) – an extension of fuzzy sets – is used to represent and address uncertainty originating from decision maker hesitancy (doubt) in providing their alternative preferences in decision making. In our study, it represents uncertainty and performance of Industry 4.0 technologies in diverse contexts; further delineation of these contexts appears in the case application.

Definition 1. A hesitant fuzzy set A on X is defined in terms of a function $h_A(x)$, when applied to X returns a finite subset of values in [0, 1],

$$A = \{ < x, h_A(x) > | x \in X \}. \tag{1}$$

where $h_A(x) = \{\gamma | \gamma \in h_A(x)\}$, is called a hesitant fuzzy element (HFE), and represents the possible membership degrees of the element $x \in X$ to A.

Definition 2. Let $h_A(x)$ and $h_B(x)$be two HFEs, the number of values in HFEs $h_A(x)$ and $h_B(x)$ are defined as $l(h_A(x))$ and $l(h_B(x))$.

The number of values in different HFEs may be different. In order to be computable, we make the following assumptions (Wei, 2012). First, all the elements are arranged in decreasing order in each HFE $h_A(x)$. Hence, $h_A^{(o)}$ is referred to as the oth smallest value in HFE $h_A(x)$. Second, for two HFEs $h_A(x)$ and $h_B(x)$, $l(h_A(x)) \neq l(h_B(x))$, then let $l = \max\{l(h_A(x)), l(h_B(x))\}$. Two HFEs $h_A(x)$ and $h_B(x)$calculated from each other must be of the same length l. Hence, the smaller set is extended until it has the same number of elements as the longer set. For optimistic situations, if $l(h_A(x)) < l(h_B(x))$, then $h_A(x)$ should repeat the maximum valued set element until it has the same length as $h_B(x)$. Alternatively, for a pessimistic situation, $h_A(x)$ should repeat its minimum valued element until it has the same set length as $h_B(x)$.

Definition 3. The score function of a HFE $h_A(x)$is defined in (2) (Xu and Xia, 2011):

$$s(h_A(x)) = \frac{1}{l(h_A(x))} \sum_{\gamma \in h_A(x)} \gamma \tag{2}$$

Definition 4. The distance function between $h_A(x)$ and $h_B(x)$ is defined by (3):

$$d(h_A(x), h_B(x)) = \frac{1}{l} \sum_{o=1}^{l} \left(\left| h_A^{(o)}(x) - h_B^{(o)}(x) \right| \right) \tag{3}$$

3.2. Cumulative prospect theory

CPT, utilizing behavioral decision theory (Tversky and Kahneman, 1992), is a descriptive paradigm for human decision behavior under uncertainty or risk. It has been widely used to solve various decision-making problems using bounded rationality theory and subjective decision maker preferences (Bai and Sarkis, 2017).

In cumulative prospect theory, the prospect value of the object is determined using a value function $\phi(x_i)$. This function represents the subjective value of outcome x_i and the weighting function π_i of a cumulative probability p, calculated by expression (4).

$$\phi\left(x, p\right) = \sum_{i=1}^{k} \phi\left(x_i\right) \pi(p_i)^{+} + \sum_{i=k+1}^{n} \phi\left(x_i\right) \pi(p_i)^{-} \tag{4}$$

The value function $\phi(x_i)$represents the risk preference and is determined by expression (5).

$$\phi(x_i) = \{ (x_i - x_0)^{\alpha}, x_i \geq x_0 - \lambda(- (x_i - x_0))^{\beta}, x_0 < x_i \tag{5}$$

where x_i is the subjective value of an outcome and x_0 is a reference point of an outcome; $(x_i - x_0)^{\alpha}$ represents gains and$-\lambda(-(x_i - x_0))^{\beta}$ represents the losses. $0 < \alpha < 1$ and $0 < \beta < 1$ are parameters related to the exponential parameters for gains and losses, respectively. If the parameter $\lambda > 1$, then it is a loss aversion parameter; decision makers are more sensitive to losses than gains. In this study, we adopt the values of $\alpha = \beta = 0.88$, $\lambda = 2.25$, which are determined by Tversky and Kahneman (1992) as reasonable initial values.

The weighting function $\pi(p_i)^{+}$ is the potential cumulative gain by expression (6), and the weighting function $\pi(p_i)^{-}$ is the potential cumulative loss by expression (7). The cumulative probability weight function decision weights are determined by expressions (6) and (7).

These functions increase the influence of rare events and shrink the influence of "average" events.

$$\pi_i^+(p_i) = w^+(p_i + \cdots + p_n) - w^+(p_{i+1} + \cdots + p_n) \tag{6}$$

$$\pi_i^-(p_i) = w^-(p_1 + \cdots + p_i) - w^-(p_1 + \cdots + p_{i-1}) \tag{7}$$

where $w^+(p_i)$ and $w^-(p_i)$ denote the weighting functions (subjective probability) for gains and losses, respectively, and defined by (8) and (9).

$$w^+(p_i) = \exp(-\gamma(-\ln(p_i)^{\phi})) \tag{8}$$

$$w^-(p_i) = \exp(-(\delta(-\ln(p_i)^{\phi})) \tag{9}$$

where p_i is the objective probability, γ and δ are model parameters. $w^+(p_i)$ and $w^-(p_i)$ are monotonic and exhibit inverse S-shapes for $0<\gamma$, $\delta < 1$. Similarly, $\gamma = \delta = 0.8$, and $\phi = 1$ are determined through experiments as most realistic (Prelec, 2000).

3.3. The VIKOR method

The *VlseKriterijumska Optimizacija I Kompromisno Resenje* (VIKOR), is a MADM method for ranking and selecting alternatives (Opricovic and Tzeng, 2004). It has some advantages over other MADM methods; it can integrate conflicting criteria, provides a simple calculation process, easily scalable, and generates compromise solutions based on proximity to an ideal solution (Awasthi and Kannan, 2016).

The multi-criteria measure for compromise ranking is developed with the following Lp-metric:

$$L_{p,i} = \left\{ \sum_{j=1}^{m} \left[w_j \left(\left| f_j^+ - f_{ij} \right| \right) / \left(\left| f_j^+ - f_j^- \right| \right) \right]^p \right\}^{1/p}, 1 \le p \le \infty; i = 1, \ldots, n \tag{10}$$

where f_j^+ is the best performance value for the jth attribute among all objects. Likewise, f_j^- is the worst performance value for the jth attribute. f_{ij} is the performance value for an objectx_i with respect to the jth attribute. Within the VIKOR method $p = 1$ (as S_i) and $p = \infty$ (as Q_i) are used to formulate the ranking measure.

$$S_i = L_{p=1,i} = \sum_{j=1}^{m} \left[w_j \left(\left| f_j^+ - f_{ij} \right| \right) / \left(\left| f_j^+ - f_j^- \right| \right) \right] \tag{11}$$

$$Q_i = L_{p=\infty,i} = \max_j \left[w_j \left(\left| f_j^+ - f_{ij} \right| \right) / \left(\left| f_j^+ - f_j^- \right| \right) \right] \tag{12}$$

VIKOR ranks the alternatives by sorting the values of R_i (see expression (13)), for $i = 1, 2, \ldots, n$, in increasing order.

$$R_i = v(S^- - S_i)/(S^- - S^+) + (1 - v)(Q^- - Q_i)/(Q^- - Q^+) \tag{13}$$

where $S^+ = \min_i S_i$, $S^- = \max_i S_i$, $Q^+ = \min_i Q_i$, $Q^- = \max_i Q_i$ and v is the weight on the strategy with maximum group utility and 1-v is the weight of the individual regret.

4. Case study application

In this section, we develop a multi-contextual – including industry, SDG category, sustainability dimension, and technology type – method that integrates hesitant fuzzy set, cumulative prospect theory, and VIKOR for evaluating the degree of Industry 4.0 technologies. We utilize secondary data from a World Economic Forum White Paper (World Economic Forum (WEF)Accenture, 2018) to provide foundational insight on how Industry 4.0 technologies relate to sustainability.

4.1. Case background

As Industry 4.0 diffuses, many regions in the world have sought to develop Industry 4.0 technologies. A World Economic Forum (WEF) project and white paper (World Economic Forum - Accenture, 2018) asked the question: "What changes will the Fourth Industrial Revolution bring to systems of production, and how will they affect sustainability?"

The WEF project utilized community outreach meetings in Berlin, Germany, Dalian, China and New York to help address its question. Automotive, electronics, food and beverage, and textiles, apparel and footwear were identified as key influenced industries. Together the industries represented low and high-tech product manufacturing industries with high environmental implication relationships, end-consumer visibility and good potential for further transformation. Europe (Poland), Africa (Kenya, Ethiopia), Asia Pacific (India, Thailand, Vietnam) and Latin America (Argentina, Mexico) were examined to keep the analysis specific yet globally representative and contextual. Forty disruptive applications were identified across four industries to accelerate sustainable production practice.

This evaluation framework utilized United Nation SDGs and indicators. Fourteen of the 17 SDGs were selected; these SDGs were grouped into the three areas for evaluating sustainability (economic, social and environmental). The 40 disruptive applications are based on desk research and interviews, noting upside potential and downside risks. This WEF White Paper is the fruit of an intense collaboration between 70 stakeholders from four sectors covering low-and high-tech product manufacturing industries with high environmental productivity, end-consumer visibility and good potential for further transformation (for the full list of expert, please see World Economic Forum - Accenture, 2018, pp. 47–49). We aggregated and utilized the acquired data from this study (Figures 3, 5, 7 and 9 in the White Paper) as foundational data for this study.

It should be noted that the WEF report evaluates the 40 disruptive applications. This paper only focused on Industry 4.0 technologies. Their 40 applications include various Industry 4.0 technologies, biotechnology and traditional manufacturing system elements. Their corresponding relationships appear in the report. For example, Semiconductor fab 4.0 is a disruptive application in the electronics industry. It refers to the application of advanced manufacturing techniques to the production of electronic components such as silicon wafer fabrication, semiconductors and microchips – and energy and resource intensive set of processes. It contains key Industry 4.0 technologies – Cloud computing, Big data and analytics, Cobotic systems and Artificial intelligence, according to the McKinsey White Paper. The value of sustainability for Semiconductor fab 4.0 is very plausible for those four Industry 4.0 technologies. HFS is used to represent and address this uncertainty of Industry 4.0 technologies business and sustainability performance originating from the diverse and complementary disruptive applications.

4.2. Proposed methodology

The proposed multi-stage methodology utilizing HFS, CPT, and VIKOR, is composed of 10 steps. These steps are detailed with exemplary calculations explicitly identified.

Step 1: Construct an Industry 4.0 technologies evaluation system.

An evaluation system $T = (U, P, C, H)$ for Industry 4.0 technologies based on various sustainability attributes is identified in this step. $U = \{x_1, x_2, \ldots, x_n\}$ is a set of n evaluated Industry 4.0 technologies – we will use *I4.0T* from now. $P^t = \{p_1^t, p_2^t, \ldots, p_n^t\}$ is a set of probabilities of using n I4.0T in industry t, where $\sum_{i=1}^{n} p_i^t = 1$. $C = \{c_1, c_2, \ldots, c_m\}$ is a set of m sustainability attributes which are used to evaluate the I4.0T. $H = \{h_{i,k}^t, i = 1, \ldots, n, k = 1, \ldots, m$ and $t = 1, \ldots, T\}$ is the HFE value of I4.0T i for sustainability attribute c_k in industry t.

For this empirical case, a total of $n = 17$ potential I4.0T will be in the evaluation: additive manufacturing, artificial intelligence, augmented reality, autonomous robots, big data and analytics, blockchain, cloud, cobotic systems, cybersecurity, drones, GPS, Industrial Internet of Things, mobile technology, nanotechnology, RFID, sensors and actuators and simulation (see Table 2). Each I4.0T is evaluated on $m = 14$ sustainability attributes (SDGs). These attributes and values are from the WEF White Paper. There are four economic impact attributes: End Poverty (EP), Decent Work and Economic Growth (DWEG), Industry, Innovation and Infrastructure (III), Reduced Inequalities (RI). There are four social impact attributes: End Hunger (EH), Gender Equality (GE), Good Health and Well-being (GHW), Quality Education (QE). There are six environmental impact attributes: Clean Water and Sanitation (CWS), Affordable and Clean Energy (ACE), Sustainable Cities and Communities (SCC), Responsible Consumption and Production (RCP), Life Below Water (LBW), Life on Land (LL).

Step 2: Convert application performance values into I4.0T hesitant fuzzy elements.

I4.0T are not necessarily applied individually and separately. Often multiple I4.0T are applied to various disruptive industry applications each having a different performance outcome. For example, short-loop recycling in the automotive industry may utilize sensors, clouds, and big data analytics.

In this multi-context decision-making environment, it is difficult for experts to evaluate each technology's sustainability performance. There are many disruptive applications in different industries. For example, artificial intelligence (an I4.0T) can be used in various disruptive applications in the automotive industry, such as Short Loop Recycling for Manufacturing, Cobotics 2.0, Smart Digital Twins, Robotic disassembly for remanufacturing, and Smart Warehouse Robotics. The performance of those five disruptive applications can be used as a reference for the performance of artificial intelligence.

A specific I4.0T may appear multiple times in different applications of one industry. In this uncertain and diverse environment, all performance values of an I4.0T for different applications can be converted into a HFE of an industry I4.0T. In this case, a value repeated more times has no more importance than other values repeated fewer times (Xu and Xia, 2011). Hence, deleting repeated values and arranging those values in decreasing order, the results evaluated in the different applications of one industry are contained in a hesitant fuzzy decision matrix, as shown in Table 3, where $h_{i,k}^t$ are in the form of HFEs for I4.0T x_i, attribute c_k, and industry t.

In the empirical case, artificial intelligence x_2 has been applied to five different disruptive applications (Short Loop Recycling for Manufacturing, Cobotics 2.0, Smart Digital Twins, Robotic disassembly for remanufacturing, and Smart Warehouse Robotics) in the automobile industry, which yields five performance results 2, 3, 2, 2 and 2 for SDG attribute c_1 (EP – ending poverty SDG). Each value uses a 0–4 scale to indicate no impact, low impact, medium impact, medium high impact, and high impact, respectively. After deleting repeated values and arranging those values in decreasing order, performance values in different applications can be converted into an HFE $h_{2,1}^1 = (3, 2)$; appearing in the Artificial Intelligence row and EP column of Table 3. Due to space constraints, the hesitant fuzzy decision matrices of other three industries are not shown.

Step 3: Calculate the HFE value function for each I4.0T SDG attribute

Since SDG attribute values are HFE, the CPT value function (expression (5)) needs to be altered to calculate the HFE attribute value function. This study considers every I4.0T as a reference point for the risk aversion attitudes of decision makers. Using CPT and HFEs, the value function $\phi(h_{i,k}^t)_j$ of I4.0T x_i and I4.0T x_j (the reference point) for SDG attribute k in industry t is determined by expression (14):

$$
\begin{aligned}
z_{ij,k}^t = \phi\left(h_{i,k}^t\right)_j = \left\{ sh_{i,k}^t\right) - s\left(h_{j,k}^t\right)\Big)^{\alpha}, \\
s\left(h_{i,k}^t\right) > s\left(h_{j,k}^t\right) - \lambda - sh_{j,k}^t\right) - s\left(h_{i,k}^t\right)\Big)\Big)^{\beta}, \quad s\left(h_{i,k}^t\right) \le s\left(h_{j,k}^t\right)
\end{aligned}
\tag{14}
$$

For this case, the HFE of I4.0T x_1 and I4.0T x_2 are (3) and (3, 2) for attribute c_1 (EP) in the automobile industry $t = 1$. We find $s(h_{1,1}^1) = \frac{1}{1}*3 = 3$and $s(h_{2,1}^1) = \frac{1}{2}(3 + 2) = 2.5$, and the value function $z_{12,1}^1 = (3 - 2.5)^{\alpha} = (0.5)^{\alpha=0.88} = 0.543$.

The value function calculation results are used to construct the value function matrix among I4.0T for attribute c_1 (EP) in automobile industry $t = 1$. The value function matrix is shown in Table 4. Due to space constraints, the value function of other attributes and other industries are not shown.

Step 4: Calculate value function decision weights

Using the value function z_{ij}^t, k and technology probabilities $P^t = \{p_1^t, p_2^t, \ldots, p_n^t\}$, the value function cumulative decision weights $\pi(p)$can be calculated. This step is divided into three sub-steps.

Sub-step 4.1 Calculate the probabilities of each I4.0T.

The probability of each I4.0T needs to be calculated, and in this case represents the percentage of appearances across industry applications. The probability$p_i^t = \frac{N_i^t}{\sum_{i=1}^{n} N_i^t}$ refers to the probability of the I4.0T x_i appearing in an industry. N_i^t refers to the number of times I4.0T x_i appears in all industry t applications.

Table 3
HFEs of I4.0T on sustainability attributes in the automobile industry and influence on SDG.

I4.0T	EP*	EH	GHW	QE	GE	CWS	ACE	DWEG	III	RI	SCC	RCP	LBW	LL
Additive manufacturing	(3)	(2)	(3)	(2)	(2)	(3)	(2)	(3)	(4)	(2)	(2)	(3)	(2)	(3)
Artificial intelligence	(3,2)	(2)	(3,2)	(3,2)	(3,2)	(3,2)	(2)	(4,3)	(4,3)	(3,2)	(4,3,2)	(4)	(3,2)	(4,2)
Augmented reality	(2)	(2)	(3)	(2)	(2)	(3)	(2)	(4)	(4)	(2)	(3)	(4)	(2)	(2)
Autonomous robots	(3,2)	(2)	(3,2)	(3,2)	(3,2)	(3)	(2)	(4,3)	(4,3)	(3,2)	(4,3,2)	(4)	(3,2)	(4,2)
Big data and analytics	(3,2)	(3,2)	(3,2)	(3,2)	(3,2)	(3,2)	(2)	(4,3)	(4,3)	(3,2)	(4,3,2)	(4)	(3,2)	(4,3,2)
Blockchain	(2)	(2)	(3)	(3)	(2)	(2)	(2)	(4)	(4)	(2)	(3)	(4)	(2)	(2)
Cloud	(3,2)	(3,2)	(3,2)	(3,2)	(3,2)	(3,2)	(2)	(4,3)	(4,3)	(3,2)	(4,3,2)	(4)	(3,2)	(4,3,2)
Cybersecurity	(3)	(2)	(3)	(2)	(2)	(3)	(2)	(3)	(4)	(2)	(2)	(3)	(2)	(3)
Industrial Internet of Things	(3,2)	(2)	(3,2)	(3,2)	(3,2)	(3)	(2)	(4)	(4,3)	(3,2)	(3,2)	(4)	(3,2)	(4,2)
Mobile Technology	(2)	(2)	(3)	(2)	(2)	(3)	(2)	(4)	(4)	(2)	(3)	(4)	(2)	(2)
Nanotechnology	(3)	(3)	(3)	(2)	(2)	(2)	(2)	(4)	(4)	(3)	(3)	(4)	(3)	(3)
RFID	(2)	(2)	(3)	(3,2)	(2)	(3,2)	(2)	(4,3)	(4)	(2)	(4,3)	(4)	(2)	(4,2)
Sensors and actuators	(3,2)	(2)	(3,2)	(3,2)	(3,2)	(3,2)	(2)	(4)	(4,3)	(3,2)	(3,2)	(4)	(3,2)	(4,2)
Simulation	(2)	(2)	(2)	(2)	(2)	(3)	(2)	(4)	(4)	(2)	(2)	(4)	(2)	(2)

*Note: See Table 2 for abbreviations of sustainable development goals (SDGs).

Table 4
The value function matrix among I4.0T for attribute c_1 (EP) in automobile industry.

I4.0T	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
X1	0.000	0.543	1.000	0.543	0.543	1.000	0.543	0.000	0.543	1.000	0.000	1.000	0.543	1.000
X2	−1.223	0.000	0.543	0.000	0.000	0.543	0.000	−1.223	0.000	0.543	−1.223	0.543	0.000	0.543
X3	−2.250	−1.223	0.000	−1.223	−1.223	0.000	−1.223	−2.250	−1.223	0.000	−2.250	0.000	−1.223	0.000
X4	−1.223	0.000	0.543	0.000	0.000	0.543	0.000	−1.223	0.000	0.543	−1.223	0.543	0.000	0.543
X5	−1.223	0.000	0.543	0.000	0.000	0.543	0.000	−1.223	0.000	0.543	−1.223	0.543	0.000	0.543
X6	−2.250	−1.223	0.000	−1.223	−1.223	0.000	−1.223	−2.250	−1.223	0.000	−2.250	0.000	−1.223	0.000
X7	−1.223	0.000	0.543	0.000	0.000	0.543	0.000	−1.223	0.000	0.543	−1.223	0.543	0.000	0.543
X8	0.000	0.543	1.000	0.543	0.543	1.000	0.543	0.000	0.543	1.000	0.000	1.000	0.543	1.000
X9	−1.223	0.000	0.543	0.000	0.000	0.543	0.000	−1.223	0.000	0.543	−1.223	0.543	0.000	0.543
X10	−2.250	−1.223	0.000	−1.223	−1.223	0.000	−1.223	−2.250	−1.223	0.000	−2.250	0.000	−1.223	0.000
X11	0.000	0.543	1.000	0.543	0.543	1.000	0.543	0.000	0.543	1.000	0.000	1.000	0.543	1.000
X12	−2.250	−1.223	0.000	−1.223	−1.223	0.000	−1.223	−2.250	−1.223	0.000	−2.250	0.000	−1.223	0.000
X13	−1.223	0.000	0.543	0.000	0.000	0.543	0.000	−1.223	0.000	0.543	−1.223	0.543	0.000	0.543
X14	−2.250	−1.223	0.000	−1.223	−1.223	0.000	−1.223	−2.250	−1.223	0.000	−2.250	0.000	−1.223	0.000

Sub-step 4.2 Rank order of the value functions.

An increasing rank order of the value functions z_{ij}^t, k is determined by comparing z_{ij}^t, k of each I4.0T $x_i$over all other I4.0T for an attribute c_k in industry t. For example, the ranking result is noted as $z_{ij,k}^{t\ \ (1)} \leq z_{ij,k}^{t\ \ (2)} \leq \ldots \leq 0 \leq \ldots \leq z_{ij,k}^{t\ \ (n)}$, where $z_{ij,k}^{t\ \ (o)}$ is the oth smallest rank among z_{ij}^t, k. Correspondingly, according to $z_{ij,k}^{t\ \ (1)} \leq z_{ij,k}^{t\ \ (2)} \leq \ldots \leq 0 \leq \ldots \leq z_{ij,k}^{t\ \ (n)}$, the probability of each I4.0T is $p^{t(o)}$, $p^{t(o)} \in \{p_1^t, p_2^t, \ldots, p_n^t\}$.

Sub-step 4.3 Calculate the decision weights of the value function.

The decision weights $\pi^+(p^{t(o)})$ or $\pi^-(p^{t(o)})$can be determined for the possible values $\{p_1^t, p_2^t, \ \ldots \ , p_n^t\}$ using expressions (6) and (7).

In our case, the occurrences of the 14 I4.0T in the automobile industry are 1, 5, 1, 4, 5, 1, 5, 1, 4, 1, 1, 2, 4, and 1 respectively. Thus, the probabilities of these I4.0T x_i are 2.78%, 13.89%, 2.78%, 11.11%, 13.89%, 2.78%, 13.89%, 2.78%, 11.11%, 2.78%, 2.78%, 5.56%, 11.11%, and 2.78%. Second, an increasing rank order is determined by comparing the z_{ij}^t, k of each I4.0T x_i to other I4.0T. The ranking result is: $0 = z_{11,1}^{1\ \ (1)} = z_{18,1}^{1\ \ (2)} = z_{1\ \ 11,1}^{1\ \ (3)} < z_{12,1}^{1\ \ (4)} = z_{14,1}^{1\ \ (5)} = z_{15,1}^{1\ \ (6)} = z_{17,1}^{1\ \ (7)} = z_{19,1}^{1\ \ (8)} = z_{1\ \ 13,1}^{1\ \ (9)} < z_{13,1}^{1\ \ (10)} = z_{16,1}^{1\ \ (11)} = z_{1\ \ 10,1}^{1\ \ (12)} = z_{1\ \ 12,1}^{1\ \ (13)} = z_{1\ \ 14,1}^{1\ \ (14)}$. Correspondingly, according to the ranking results, the probability of I4.0T $p^{t(o)}$ are noted as $p^{1(1)}, p^{1(2)}, \cdots, p^{1(14)} =$ 2.78%, 2.78%, …, 2.78%. Using expressions (6) and (7), the cumulative decision weights for value $z_{1j}^1, 1$ are 0.023, 0.149, 0.057, 0.120, 0.149, 0.057, 0.149, 0.023, 0.120, 0.057, 0.023, 0.099, 0.120, and 0.057, respectively. The cumulative decision weights are shown in Table 5.

Step 5: Calculate the cumulative prospect value for each SDG attribute and each I4.0T

Using the value function $z_{ij,k}^{t\ \ (o)}$, decision weights $\pi_{(o)}^+$ and $\pi_{(o)}^-$, the cumulative prospect value $\phi_{i,k}^t$ of I4.0T x_i for SDG attribute c_k in industry t can be calculated by expression (15).

$$\phi_{i,k}^t = \sum_{o=1}^{O} z^{(d)} \pi_{(d)}^- + \sum_{o=O+1}^{n} z^{(d)} \pi_{(d)}^+ \tag{15}$$

For example, end poverty (EP) of I4.0T x_1 has 14 value functions for performance 0, 0.543, 1, 0.543, 0.543, 1, 0.543, 0, 0.543, 1, 0, 1, 0.543, 1 corresponding to all I4.0T and 14 decision weights: 0.023, 0.149, 0.057, 0.12, 0.149, 0.057, 0.149, 0.023, 0.12, 0.057, 0.023, 0.099, 0.12, 0.057.

According to expression (15), the prospect value $\phi_{1,1}^1$of I4.0T x_1 is:$\phi_{1,1}^1 = 0 * 0.023 + \ldots \ldots + (1*0.057)) = 0.756$. The cumulative prospect values of I4.0T on each automobile industry SDG are shown in Table 6.

Step 6: Determine the ideal I4.0T solution for each industry

The 'ideal' I4.0T X_t^* for each industry will be the maximum value from each sustainability (SDG) attribute in each industry t, as in expression (16).

$$X_t^* = \left\{ \max_i \phi_{i,k}^t \right\} \tag{16}$$

Using expression (16) for this case problem we have: $X_{t,k=}^*$ { 0.765, 1.291, 0.596, 0.814, 0.270, 0.415, 0.000, 0.508, 0.617, 0.860, 0.850, 0.114, 0.860, 0.228 }

Table 5
The cumulate decision weights of the value function among I4.0T for SDG attribute c_1 (EP) in the automobile industry.

I4.0T	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
X1	0.023	0.149	0.057	0.120	0.149	0.057	0.149	0.023	0.120	0.057	0.023	0.099	0.120	0.057
X2	0.057	0.149	0.057	0.120	0.149	0.057	0.149	0.057	0.120	0.057	0.057	0.099	0.120	0.057
X3	0.057	0.163	0.023	0.133	0.163	0.023	0.163	0.057	0.133	0.023	0.057	0.046	0.133	0.023
X4	0.057	0.149	0.057	0.120	0.149	0.057	0.149	0.057	0.120	0.057	0.057	0.099	0.120	0.057
X5	0.057	0.149	0.057	0.120	0.149	0.057	0.149	0.057	0.120	0.057	0.057	0.099	0.120	0.057
X6	0.057	0.163	0.023	0.133	0.163	0.023	0.163	0.057	0.133	0.023	0.057	0.046	0.133	0.023
X7	0.057	0.149	0.057	0.120	0.149	0.057	0.149	0.057	0.120	0.057	0.057	0.099	0.120	0.057
X8	0.023	0.149	0.057	0.120	0.149	0.057	0.149	0.023	0.120	0.057	0.023	0.099	0.120	0.057
X9	0.057	0.149	0.057	0.120	0.149	0.057	0.149	0.057	0.120	0.057	0.057	0.099	0.120	0.057
X10	0.057	0.163	0.023	0.133	0.163	0.023	0.163	0.057	0.133	0.023	0.057	0.046	0.133	0.023
X11	0.023	0.149	0.057	0.120	0.149	0.057	0.149	0.023	0.120	0.057	0.023	0.099	0.120	0.057
X12	0.057	0.163	0.023	0.133	0.163	0.023	0.163	0.057	0.133	0.023	0.057	0.046	0.133	0.023
X13	0.057	0.149	0.057	0.120	0.149	0.057	0.149	0.057	0.120	0.057	0.057	0.099	0.120	0.057
X14	0.057	0.163	0.023	0.133	0.163	0.023	0.163	0.057	0.133	0.023	0.057	0.046	0.133	0.023

Table 6
The cumulative prospect value of each I4.0T for automobile industry along each SDG.

I4.0T	EP	ZH	GHW	QE	GE	CWS	ACE	DWEG	III	RI	SCC	RCP	LBW	LL
Additive manufacturing	0.765	−0.572	0.596	−1.439	−1.388	0.415	0.000	−2.189	0.617	−1.341	−2.357	−3.418	−1.341	0.228
Artificial intelligence	−0.031	−0.572	−0.507	0.116	0.270	−0.338	0.000	−0.707	−0.608	0.170	0.201	0.114	0.170	0.228
Augmented reality	−1.470	−0.572	0.596	−1.439	−1.388	0.415	0.000	0.508	0.617	−1.341	0.201	0.114	−1.341	−3.162
Autonomous robots	−0.031	−0.572	−0.507	0.116	0.270	0.415	0.000	−0.707	−0.608	0.170	0.201	0.114	0.170	0.228
Big data and analytics	−0.031	0.563	−0.507	0.116	0.270	−0.338	0.000	−0.707	−0.608	0.170	0.201	0.114	0.170	0.228
Blockchain	−1.470	−0.572	0.596	0.814	−1.388	−2.094	0.000	0.508	0.617	−1.341	0.201	0.114	−1.341	−3.162
Cloud	−0.031	0.563	−0.507	0.116	0.270	−0.338	0.000	−0.707	−0.608	0.170	0.201	0.114	0.170	0.228
Cybersecurity	0.765	−0.572	0.596	−1.439	−1.388	0.415	0.000	−2.189	0.617	−1.341	−2.357	−3.418	−1.341	0.228
Industrial Internet of Things	−0.031	−0.572	−0.507	0.116	0.270	0.415	0.000	0.508	−0.608	0.170	−1.112	0.114	0.170	0.228
Mobile Technology	−1.470	−0.572	0.596	−1.439	−1.388	0.415	0.000	0.508	0.617	−1.341	0.201	0.114	−1.341	−3.162
Nanotechnology	0.765	1.291	0.596	−1.439	−1.388	−2.094	0.000	0.508	0.617	0.860	0.201	0.114	0.860	0.228
RFID	−1.470	−0.572	0.596	0.116	−1.388	−0.338	0.000	−0.707	0.617	−1.341	0.850	0.114	−1.341	0.228
Sensors and actuators	−0.031	−0.572	−0.507	0.116	0.270	−0.338	0.000	0.508	−0.608	0.170	−1.112	0.114	0.170	0.228
Simulation	−1.470	−0.572	−1.935	−1.439	−1.388	0.415	0.000	0.508	0.617	−1.341	−2.357	0.114	−1.341	−3.162

Step 7: Determine sustainability (SDG) attribute weights

In this case, we use a simple and exact normalization formula for determining the weight of SDG attribute k using expression (17):

$$w_k = \frac{V_k}{\sum\limits_{k=1}^{m} V_k} \tag{17}$$

where $V_k = \frac{1}{T^* n^2}\sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j=1}^{n} d(h^t_{i,k}, h^t_{j,k})$ is the average difference between I4.0T for an SDG attribute k. n is the total number of I4.0T. $d(h^t_{i,k}, h^t_{j,k})$ is the Hamming distance measure between $h^t_{i,k}$ and $h^t_{j,k}$ which is defined in expression (3).

The overall attribute weight summary results appear in Table 7.

Step 8: Calculate the group utility S_i and the maximal regret Q_i in an industry

The values S_i and Q_i are calculated using expressions (11) and (12). For example, sustainability attribute c_1 (EP) of I4.0T x_1 is calculated as $w_1(\left|X^+_{1,1} - \phi^1_{1,1}\right|)/(\left|X^+_{1,1} - X^-_{1,1}\right|) = 0.104^*\left(0.765 - 0.765/_{0.765+1.470}\right) = 0$. The value S_1 for I4.0T x_1 in automobile industry t is $\sum_{k=1}^{m}[w_k(\left|X^+_{1,k} - \phi^1_{1,k}\right|)/(\left|X^+_{1,k} - X^-_{1,k}\right|)] = 0.530$ for all attributes. The value Q_1 for I4.0T x_1 in the automobile industry is the max of above values and calculation result is $w_8(\left|X^+_{1,8} - \phi^1_{1,8}\right|)/(\left|X^+_{1,8} - X^-_{1,8}\right|) = 0.087^*\left(0.86 + 1.341/_{0.86+1.341}\right) = 0.087$ for attribute c_8(DWEG).

Table 7
Average difference and weight for each sustainability attribute.

Sustainability attributes	Average difference	Weights
End Poverty (EP)	0.690	0.104
End Hunger (EH)	0.443	0.067
Good Health and Well-being (GHW)	0.395	0.060
Quality Education (QE)	0.310	0.047
Gender Equality (GE)	0.418	0.063
Clean Water and Sanitation (CWS)	0.602	0.091
Affordable and Clean Energy (ACE)	0.133	0.020
Decent Work and Economic Growth (DWEG)	0.495	0.075
Industry, Innovation and Infrastructure (III)	0.649	0.098
Reduced Inequalities (RI)	0.577	0.087
Sustainable Cities and Communities (SCC)	0.423	0.064
Responsible Consumption and Production (RCP)	0.270	0.041
Life Below Water (LBW)	0.573	0.087
Life on Land (LL)	0.643	0.097
Sum	6.622	1

Step 9: Compute R_i (sustainability index) in an industry

In our application, we set parameter $\nu = 0.5$, which implies the maximum group utility weight equals the individual regret weight. We then get $S^+ = 0.214$, $S^- = 0.675$, $Q^+ = 0.087$, and $Q^- = 0.104$. The value R_1 of I4.0T x_1 $R_i = \nu(S^- - S_i)/(S^- - S^+) + (1-\nu)(Q^- - Q_i)/(Q^- - Q^+) = 0.658$. The values S_i, Q_i, and R_i for other I4.0T appear in Table 8 across various industries.

Step 10: Calculate Cross-Industry Aggregated Index Values R_i for I4.0T

The cross-industry cumulative prospect value for I4.0T based on the sustainability (SDG) measures is calculated using expression (18).

$$R_i = \frac{1}{\mathrm{T}}\sum_{t=1}^{T} R^t_i \tag{18}$$

The calculated aggregated degrees R_i of I4.0T are shown in Table 8 (last column) and Fig. 1. The results show that overall – based on the cross-industry, cross-application case report – mobile technology has the highest degree in contributing to sustainability attributes with a score of 0.593. Augmented reality has the lowest sustainability degree with a score of 0.030.

4.3. Sensitivity analysis

A joint HFS, CPT and VIKOR method is used to evaluate I4.0T. In this section, sensitivity analysis is completed to determine methodological robustness by evaluating variations of the methodology. We develop three models and compare them with the original method to show that the three approaches – HFS, CPT and VIKOR – we complementarily integrate are each necessary. The three models include: Model 1 – we apply a triangular fuzzy number $\tilde{z} = (l, m, r)$ instead of HFS; Model 2 – we remove CPT from the original method; Model 3 – we do not apply the VIKOR method from the original method. We only evaluate these three model versions for the automotive industry for sensitivity illustrative purposes. The final results are summarized in Table 9.

We find that rank results from the Model 1 variation causes a very significant change. As can be seen by the rankings the discriminatory power of the first model decreases versus the HFS model. That is, there are many ties in the rankings. This result shows that triangular fuzzy

Table 8
The index values for each I4.0T in four industries.

I4.0T	Automotive			Electronics	Food and beverage	Textiles, apparel and footwear	Aggregated
	S_i	Q_i	R_i^1	R_i^2	R_i^3	R_i^4	R_i
Additive manufacturing	0.530	0.087	0.658	0.148	0.270	0.707	0.446
Artificial intelligence	0.371	0.098	0.511	0.034	0.476	0.752	0.443
Augmented reality	0.565	0.104	0.120				0.030
Autonomous robots	0.344	0.098	0.540	0.055	0.000	0.092	0.172
Big data and analytics	0.330	0.098	0.555	0.034	0.643	0.823	0.514
Blockchain	0.609	0.104	0.072	0.231	0.791	0.747	0.460
Cloud	0.330	0.098	0.555	0.695	0.292	0.774	0.579
Cobotic systems				0.177			0.044
Cybersecurity	0.530	0.087	0.658				0.164
Drones					0.513	1.000	0.378
GPS					0.432	0.951	0.346
Industrial Internet of Things	0.336	0.098	0.548	0.000	0.468	0.842	0.464
Mobile Technology	0.565	0.104	0.120	1.000	0.330	0.923	0.593
Nanotechnology	0.214	0.091	0.887	0.776		0.069	0.433
RFID	0.483	0.104	0.208	0.231	0.154		0.148
Sensors and actuators	0.363	0.098	0.519	0.055	0.739	0.860	0.543
Simulation	0.675	0.104	0.000		1.000	0.973	0.493

"" (Null value) represent that this I4.0T is not applied in this field in our sample data.

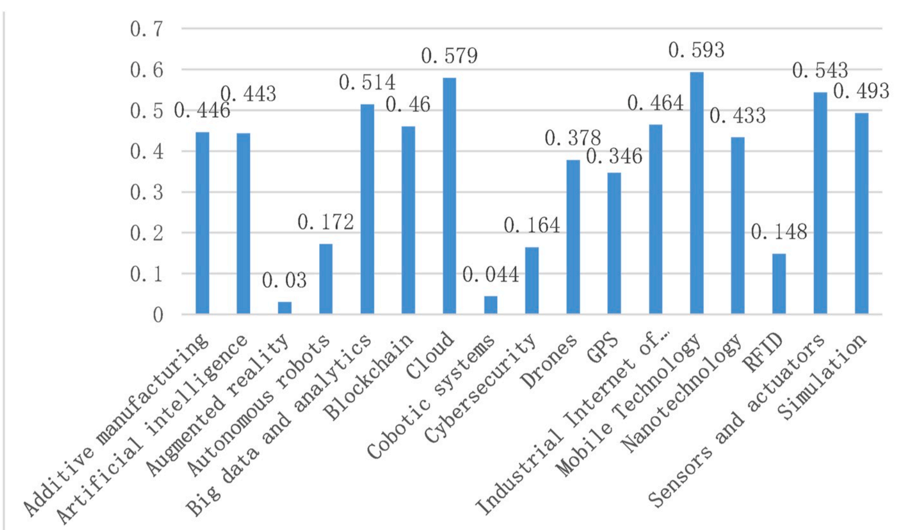

Fig. 1. The sustainability degree for each I4.0T across four industries.

Table 9
Sensitivity analysis of three models in automotive industry.

I4.0T	Original method		Model1		Model2		Model3	
	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking
Additive manufacturing (3D printing)	0.658	2	1.000	1	0.660	2	0.315	9
Artificial intelligence	0.511	8	0.362	4	0.417	8	0.659	7
Augmented reality	0.120	10	0.000	5	0.113	10	0.240	10
Autonomous robots	0.540	6	0.362	4	0.467	4	0.719	5
Big data and analytics	0.555	4	0.362	4	0.454	5	0.748	2
Blockchain	0.072	11	0.000	5	0.064	11	0.144	11
Cloud	0.555	4	0.362	4	0.454	5	0.748	2
Cybersecurity	0.658	2	1.000	1	0.660	2	0.315	9
Industrial Internet of Things	0.548	5	0.362	4	0.485	3	0.735	4
Mobile Technology	0.120	10	0.000	5	0.113	10	0.240	10
Nanotechnology	0.887	1	0.775	2	0.887	1	1.000	1
RFID	0.208	9	0.000	5	0.178	9	0.416	8
Sensors and actuators	0.519	7	0.362	4	0.435	7	0.676	6
Simulation	0.000	12	0.000	5	0.000	12	0.000	12

numbers does not reliably express clearly defined rankings for different technologies and is not as suitable for decision-making or policy setting.

From amongst the three alternative sensitivity models, Model 2 has the smallest change in ranks. But there are subtle differences. This result shows that human decision behavior under uncertainty or risk should be considered in this evaluation.

We found that some I4.0T valuations have changed fundamentally when applying Model 3. For example, additive manufacturing and cybersecurity changed from a two ranking to a nine ranking. This result shows that although the overall performances of these two I4.0T are low, the performance is relatively balanced without too many very poor attributes. VIKOR can evaluate these I4.0T from a holistic perspective and avoid some risks that derives from poor performance of some sustainability attributes. Overall, our conclusion is that it is necessary to address sustainability concerns from a holistic perspective with multiple complementary methodologies (Bai and Sarkis, 2019).

5. Case study results and discussion

The method proposed (see Section 3) and the case study application (see Section 4) allows us to compare various I4.0T in terms of their contribution to the three dimensions of sustainability (economic, environmental and social) across different industries.

The results are based on the input data – drawn from the WEF report – which reflect opinions of the experts contributing to the WEF study. We present and discuss them in order to show: (a) the capacity of the proposed methodology to comprehensively evaluate I4.0T; and (b) some preliminary results of the comparisons of I4.0T in terms of their contribution to sustainability. We complete three comparative analyses: among industries (Section 5.1), among sustainability dimensions (Section 5.2), and among sustainability dimensions and industries (Section 5.3).

5.1. Comparative analysis among industries

The first comparative analysis is the impact of I4.0T to sustainability across different industries. The calculated degrees R_i of I4.0T industry sustainability impacts are shown in Table 8 and Fig. 1.

This analysis shows that I4.0T have a very different sustainability impact – from 0.030 of augmented reality to 0.593 of mobile technology – with a strong industry context dependence (see Table 8). Unfortunately we cannot compare this finding with previous Industry 4.0 studies since this study paper is – to the best of our knowledge – the first one to compare various I4.0T in terms of their contribution to society's sustainability.

This result will have two significant implications for future Industry 4.0 research. First, while extant Industry 4.0 literature has usually considered I4.0T as a group of technologies without making distinctions among them (e.g., Kagermann et al., 2011; Xu et al., 2018), it seems that a more granular approach considering each I4.0T separately can provide additional insights. Second, a more contingency-based, multi-contextual approach – at least with reference to the industry – is advisable since I4.0T have very different applications and impacts in different industries (see below).

As far as the automotive industry is concerned, nanotechnology is the best I4.0T for improving sustainability with a sustainability score equal to 0.887; see Table 8. This result – which is not surprising – is due to the potential contribution of nanotechnology to the development of lightweight bio-based plastics and composites. This outcome can contribute to reduce the fuel consumption, the CO2 emissions of vehicles and the use of petroleum-based plastics, relating to economic and environmental sustainability. It may also improve the livelihoods for farmers; relating to social sustainability (World Economic Forum (WEF)Accenture, 2018).

Similarly, mobile technology appears as the highest scoring I4.0T in the electronics industry with an overall sustainability score equal to 1; see Table 8. This result is related to contribution of this technology to the traceability of (rare) minerals used in this industry as well as to the autonomous disassembly of electronics equipment to recycle/reuse their components. Both of these activities have significant implications for all the three sustainability dimensions (World Economic Forum (WEF) Accenture, 2018).

More surprising results appear in the food and beverage, and the textiles, apparel and footwear industries. Interestingly, simulation is the I4.0T with greatest implications for improving sustainability in the food and beverage industry; a sustainability score equal to 1 in Table 8. This reason behind this high scoring for simulation is related to its potential contribution to genome editing. This application might lead to increased yield which is an economic and social sustainability contribution; for example through SDG2 zero hunger. It can also lead to decreased water usage; an environmental sustainability measure. Genome editing can contribute to increased tolerance to challenging weather conditions (World Economic Forum (WEF)Accenture, 2018).

Drones are the most sustainable I4.0T in the textiles, apparel and footwear industry; with a sustainability score equal to 1, see Table 8. Drones have potential contribution to advance bio farming and precision agriculture for fiber crops (World Economic Forum (WEF)Accenture, 2018).

5.2. Comparative analysis among sustainability dimensions

The second comparative analysis is the impact of I4.0T across the TBL sustainability dimensions. The aggregated degrees R_i of I4.0T are shown in Fig. 2 for economic (a), environmental (b) and social (c) dimensions.

We found that blockchain technology is the most economically sustainable I4.0T (score of 0.632); confirmed by recent literature (Zhang, 2019; Grigoras et al., 2018; Cocco et al., 2017). According to Fig. 2, blockchain technology is followed by mobile technology with a score of 0.605. This is also underpinned by literature with example applications such as reduction of food waste in restaurant chains, enabling smart urban mobility and increasing productivity by means of the fifth generation of mobile technology (5G) (Hajjdiab et al., 2018; Lyons, 2018; Annunziato, 2015).

Our findings show that sensors and actuators are the most environmentally sustainable I4.0T – sustainability score of 0.692. This score is closely followed by artificial intelligence (0.670), big data and analytics (0.635), and cloud (0.621). These technologies provide both hard (sensors and actuators) and soft (artificial intelligence, big data and analytics, and cloud) infrastructure for addressing energy and resource efficiency in production activities.

The impact of cloud technology on environmental sustainability – from higher efficiency in materials usage, reduced use of toxic materials, and lower impact on effluents and wastes – was highlighted in Schniederjans and Hales (2016).

Finally, cloud technology is the most socially sustainable I4.0T with a score of 0.646. Big data and analytics follows with a score of 0.623. This result – somewhat unexpected considering the ethics, privacy and personal autonomy issues related to the sharing of data and applications on the cloud (e.g., Isaias, 2015) – can be explained by the experts' opinions that both cloud and big data and analytics significantly contribute to various socially influential applications. These applications include augmented workforce, robotic disassembly for remanufacturing bio-based plastics and composites, digital traceability of minerals, advanced electronic design automation, precision agriculture, and advanced bio-farming and vertical farming (World Economic Forum (WEF)Accenture, 2018). Future research is needed on these aspects, in particular with a more complete consideration of the potential negative sustainability impacts of each technology.

5.3. Comparative analysis among dimensions in each industry

A complete comparative analysis of sustainability degrees R_i of each I4.0T across different sustainability dimensions in each industry is summarized in Table 10.

Considering the economic sustainability perspective, Industrial Internet of Things (IoT) has a high score in the food and beverage industry (Table 10). IoT is used with other technologies such as GPS, soil sensors and weather data in the field of precision agriculture to integrate

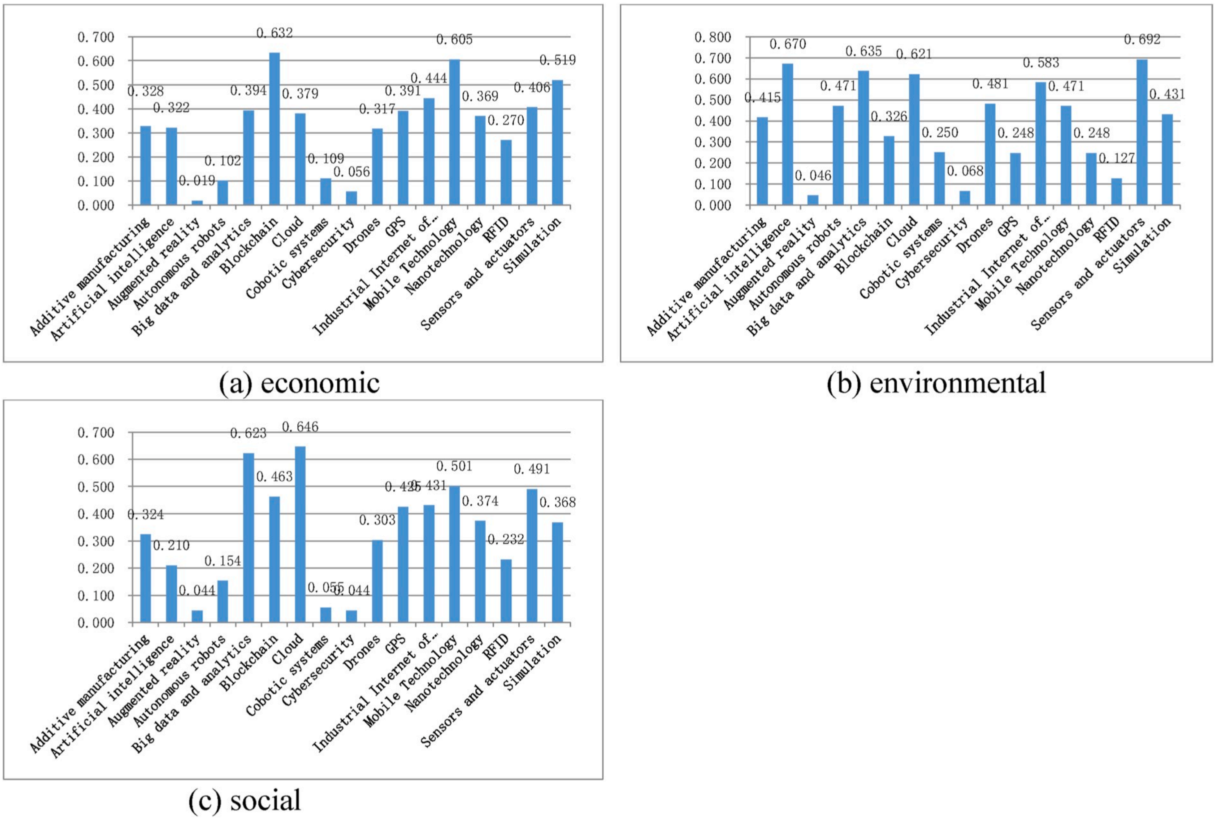

Fig. 2. The sustainability degree for each I4.0T along the three dimensions of sustainability.

data and analytics with crop science to enable scientific farming decisions (World Economic Forum (WEF)Accenture, 2018). As such, it supports the optimization of resource usage in the fields of fertilizer, irrigation, harvesting time and seed spacing (Sambo et al., 2019).

Alternatively, nanotechnology has a very low impact on increasing the economic sustainability in the textiles, apparel and footwear industry even given the medium-term perspective (5–10 years) developments; nano-tech enhanced fabrics are expected (World Economic Forum (WEF)Accenture, 2018).

For the environmental sustainability dimension, autonomous robots and cobotic systems seem to have a high impact in the automotive and electronics industries (Table 10). Cobotic systems can support production in an energy and resource efficient way of electronic components. This may especially be true for silicon wafer fabrication and microchips, especially in emerging markets where there is a significant potential for efficiency gains (World Economic Forum (WEF)Accenture, 2018).

Alternatively, autonomous robots seem to have little influence to increase environmental sustainability in the food and beverage industry (Table 10). This result can be explained by considering that this industry can be classified as a process industry that is generally characterized by a high-automation degree and a continuous production flow.

Finally, for the social sustainability dimension, big data and analytics seem to have the highest impact in the automotive industry. Recent applications in this field are the systematic gathering and analysis of car consumer reviews to figure out the perceived advantages and disadvantages of selected vehicles (Dremel et al., 2018; Kim and Chun, 2019). Alternatively, artificial intelligence seems have little influence of I4.0T for improving social sustainability in the food and beverage industry. Even if artificial intelligence could make a significant contribution in the (analysis) and extrapolation of meaningful information from field data, the agriculture industry is faced by relatively more unpredictable events like changing weather conditions, changes in soil quality, and the unexpected influence of pests and diseases. As such, farmers may feel that their harvest will be good, but until that day arrives, the outcome will always be uncertain (Byrum, 2017). As a result, a limited impact of this technology to the social dimension can be expected because an extreme quantity of factors needs to be considered and two environments are improbably likely to be exactly the same. This environment makes the testing, validation and successful implementation of these technologies much more difficult than in other industries (Byrum, 2017).

5.4. *Implications for business and government*

The proposed multi-contextual decision-making method for evaluating the impact of I4.0T on the three sustainability dimensions – economic, environmental and social – can be applied by both managers and policy makers for evaluating sustainability priorities and which technologies to adopt or to foster through policy interventions. The evaluation focus is enlarged from a merely economic perspective to a broader– although more complex – view in terms of environmental and social sustainability dimensions.

The proposed method and results are for an empirical case, using secondary published data from a WEF report (World Economic Forum - Accenture, 2018). This information allowed us to provide insights for both managers and policy makers. Insights include evidence of the potential impact of different technologies across various sustainability dimensions and attributes in four key industries – automotive, electronics, food and beverage, textiles, apparel and footwear. As an example, according to our results (see Section 5.3) companies in the automotive industry may decide to invest in autonomous robots and cobotic systems to improve industrial and organizational environmental sustainability dimensions. Big data and analytics in this industry can effectively address social sustainability concerns. In this way we significantly support organizations and industry in their decision-making processes.

Policy makers – depending on their relative concerns and community

Table 10
The index values for each I4.0T in four industries along the three dimensions of sustainability.

I4.0T	Economic				Environmental				Social			
	Automotive	Electronics	Food and beverage	Textiles, apparel and footwear	Automotive	Electronics	Food and beverage	Textiles, apparel and footwear	Automotive	Electronics	Food and beverage	Textiles, apparel and footwear
Additive manufacturing	0.222	0.050	0.512	0.527	0.270	0.268	0.182	0.940	0.176	0.257	0.059	0.805
Artificial intelligence	0.094	0.143	0.475	0.575	0.944	0.527	0.701	0.510	0.380	0.081	0.000	0.378
Augmented reality	0.075				0.184				0.176			
Autonomous robots	0.094	0.026	0.000	0.287	1.000	0.790	0.000	0.095	0.380	0.176	0.059	0.000
Big data and analytics	0.094	0.143	0.687	0.651	0.944	0.527	0.404	0.667	1.000	0.081	0.605	0.805
Blockchain	0.075	0.869	0.746	0.840	0.000	0.000	0.948	0.354	0.313	0.500	0.918	0.121
Cloud	0.094	0.440	0.332	0.651	0.944	0.760	0.220	0.560	1.000	0.256	0.525	0.805
Cobotic systems		0.437				1.000				0.219		
Cybersecurity	0.222				0.270				0.176			
Drones			0.516	0.752			1.000	0.923			0.212	1.000
GPS			0.811	0.752			0.257	0.736			0.700	1.000
Industrial Internet of Things	0.169	0.026	0.980	0.603	0.862	0.527	0.257	0.685	0.380	0.000	0.700	0.642
Mobile Technology	0.075	1.000	0.594	0.752	0.184	0.790	0.172	0.736	0.176	0.450	0.578	0.800
Nanotechnology	1.000	0.465		0.012	0.415	0.577		0.000	0.419	0.954		0.121
RFID	0.000	0.869	0.210		0.427	0.000	0.081		0.271	0.500	0.158	
Sensors and actuators	0.169	0.026	0.748	0.682	0.807	0.790	0.484	0.685	0.380	0.176	0.765	0.642
Simulation	0.075		1.000	1.000	0.081		0.795	0.850	0.000		1.000	0.471

"" (Null value) represent that this I4.0T is not applied in this field in our sample data.

or constituent pressures they face – can incentivize and support development of particular technologies in a given industry. From a supply chain perspective companies and industrial sectors may gain competitive advantage through building sustainability performance; making companies in regions and industries more competitive for those product families and supply chains seeking to build more sustainable products and materials.

Finally, the empirical case results highlights the existence of interrelationships and sometimes trade-offs between the impacts of the different I4.0T on the three sustainability dimensions These interrelationships and tradeoffs vary across different industrial sectors. The interrelationship make policy decision-making processes more complex, difficult, and with greater uncertainty. For instance, if regulators decide to support industry investment in autonomous robots and cobotic systems– increasing environmental sustainability – the resulting impact may be a negative effect on the level of employment in the automotive industry; thus, decreasing the social sustainability. The methodology provides some insights into these varying interrelationships and tradeoffs that may not only exist across technologies and sustainability dimensions, but also across industries.

6. Conclusion

The applications of Industry 4.0 technologies for sustainable development seem to attract increasing attention from practitioners and scholars (Beltrami and Orzes, 2019). This attention will increase given industry's global influence on sustainability through its supply chains, products, and processes.

Some current literature examines Industry 4.0 predominantly from an organizational sustainability perspective, whereas few articles consider aspects of overall society's sustainability; especially using the United Nations' Sustainable Development Goals (SDGs). However, it is essential to understand the potential of I4.0T for achieving society's sustainability through successful technology adoption and diffusion.

There is also a realization that I4.0T will be differently applied across industries, with varying implications. In multiple situations, it is difficult to effectively evaluate the impact of these I4.0T on society's sustainability. In this context, a multi-context analytical approach is introduced to broadly understand the sustainable performance of I4.0T. The main conclusions and contributions of this paper include:

(1) We proposed a framework for evaluating I4.0T sustainability degrees using the United Nations Sustainable Development Goals and expert opinion (see Section 3). Sustainability is grouped into the three TBL categories, economic, environmental, and social impacts. The results provide a deeper understanding of the relationship between I4.0T and sustainability. This framework helps stakeholders to evaluate I4.0T, and can assist practitioners benchmarking existing I4.0T; helping to develop technology roadmapping.
(2) We introduced a multi-context method using multiple methodologies – HFE, CPT and VIKOR – that help to determine the sustainability degree of I4.0T (see Section 3). HFE effectively takes into account I4.0T performance across applications. Cumulative prospect theory (CPT) is employed to consider decision maker psychological characteristics under risk and uncertain environments; integrating these possibilities into I4.0T evaluation. The value function of CPT has been modified to deal with HFE calculations. VIKOR helps to arrive at a sustainability degree value of I4.0T along a [0,1] range.
(3) We applied the proposed method in a case study based on secondary data from a report of the World Economic Forum (Section 4). This allowed us not only to show the capacity of the method to comprehensively evaluate I4.0T but also to obtain some preliminary results of the comparisons of I4.0T in terms of their contribution to sustainability. According to the results of the

study, mobile technology seems to have the greatest impact on sustainability (see Table 8). If we then consider the different industries, we obtain that nanotechnology, mobile technology, simulation and drones have the highest impact on sustainability in the automotive, electronics, food and beverage, and textile, apparel and footwear industries, respectively. Considering the analysis among sustainability dimensions, blockchain and mobile technology resulted to have the highest impact on the economic perspective (Fig. 2). Sensors and actuators followed by artificial intelligence, big data and analytics and cloud had the highest impact on the environmental sustainability dimension, whereas cloud technology and big data and analytics showed impacting most the social sustainability dimension. In sum, according to the presented results, it can be seen that the sustainability impact of Industry 4.0 varies significantly based on the specific technology, industry, and sustainability dimension considered.

Given these initial findings, the present study has some limitations related to both the proposed method and the case study application, which provide opportunities for further research.

Considering the proposed method, the first limitation is that it does not consider the interdependencies between I4.0T and their combined effects on the three sustainability dimensions. Future research should introduce advanced MADM methods to address this issue. For example, tools such as DEMATEL method and ANP method can look at various interdependencies and influences on these technologies to provide a broader integrative set of relationships. Next, the time perspective (short-, medium and long-term developments) is not considered explicitly in the model. Future research should try to integrate in the model the maturity degree of the considered I4.0T. Finally, the method uses 7 parameters altogether, such as α, β, λ, γ, δ, ϕ in CPT, and ν in VIKOR. We selected the most commonly used values based on past experience. A sensitivity analysis with different parametric settings should be implemented to analyze the effects of these parameters on the results.

Considering the case study application, the results presented in section 5 are based on the (partial) opinion of experts considered in the WEF study. While this study considered a very wide panel of worldwide experts in different application domains of Industry 4.0 and sectors (see World Economic Forum (WEF)Accenture, 2018: 47–49), future research could collect additional primary data to further validate the model and these preliminary results.

Overall, our study proposes a valuable model that provides important initial insight and understanding of the role of Industry 4.0 technologies and their impact to society's sustainability. We clearly need to further evaluate these relationships since man's future will be dependent on the technology and social choices we make today.

CRediT authorship contribution statement

Chunguang Bai: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Patrick Dallasega:** Writing - original draft, Writing - review & editing, Conceptualization. **Guido Orzes:** Writing - original draft, Writing - review & editing, Conceptualization. **Joseph Sarkis:** Conceptualization, Writing - original draft, Writing - review & editing.

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