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Research article

Sustainability metrics and a hybrid decision-making model for selecting lean manufacturing tools

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ABSTRACT

The literature review reveals that lean manufacturing tool selection models still have some gaps. These models lack the criteria for selecting LM tools. Only a few of these models adopted hybrid multi-criteria decision-making (MCDM) methods. Obtaining reliable criteria weights in these models is complicated. They lack the consideration of grey uncertainty. Thus, this study is the first to propose a hybrid model for selecting a set of LM tools based on their effect on sustainability. This model combines the best-worst method (BWM) for weighting the criteria and the grey technique for order of preference by similarity to the ideal solution (Grey-TOPSIS) method to rank the alternatives and address the grey uncertainty problem. A set of sustainability metrics (selection criteria) was determined based on a literature review and expert evaluation to prioritize a set of LM tools. An Iraqi cement company was utilized to evaluate the proposed model. The ranking results showed that the value stream mapping (VSM) tool was the most important, whereas the single-minute exchange of die (SMED) tool was the least important. The rankings of the remaining LM tools ranged between these two tools depending on their effects on sustainability. The study conducted a sensitivity analysis using three strategies that verified the model's robustness and reliability. This research provides 16 applicable sustainability metrics and 12 LM tools that could function as a knowledge foundation for future research. It can help researchers and manufacturers maximize sustainability performance by delivering a hybrid MCDM model to select the appropriate LM tools.

1. Introduction

Sustainable performance is considered one of the significant indicators in fulfilling the need for environmentally and socially aware organizations because it concentrates on improving the company's economic, environmental, and social aspects (Kishawy et al., 2018). Sustainability can be achieved by implementing sustainable performance in enterprises (Jafarzadeh et al., 2022). Sustainability aims to address pressing issues like economic inefficiency, environmental degradation, and potential health and safety dangers to people and other living things (Tasdemir and Gazo, 2018).

Numerous initiatives have been made over the past decades to advance sustainable manufacturing processes, and lean manufacturing (LM) is one of these important solutions (Vinodh et al., 2011a). LM is one of the most popular manufacturing approaches comprising a broad diversity of tools (Leksic et al., 2020). LM enables managers to run their organizations and enterprises more efficiently while adhering to resource limits (Marie et al., 2022). LM can meet the metrics of the three pillars of sustainability as a feasible and complete concept (Marques et al., 2022; Tăucean et al., 2019).

LM attempts to improve performance and effectiveness by perpetually eliminating non-value-added processes (Qin and Liu, 2022). Thus, LM tools reduce many negative economic, environmental, and social consequences associated with manufacturing operations (Cherrafi et al., 2016; Chiarini, 2014). However, one of the biggest issues is that many organizations have trouble selecting the right LM tools (Anvari et al., 2014a). There are a growing number of LM tools that can assist firms and their products to remain sustainable, but not all of these tools offer the same results, and no tool is ideal for every business (Jing et al., 2018; Maware and Parsley, 2022).

LM implementation, like many other strategies for improvement, has not been used successfully everywhere (Benkarim and Imbeau, 2021). Despite LM's immense popularity, the methodology's record of a successful application is, at best, patchy. According to some recent studies, lean manufacturing failure rates are between 50 and 90 percent (Esfandyari and Osman, 2010; Gerger and Firuzan, 2012; Secchi and Camuffo, 2019). Misuse of various LM tools and a failure to comprehend the environment in which the chosen tools should be used are two of the main causes of failure (Salonitis and Tsinopoulos, 2016; Da Wan and Chen, 2008). Therefore, there is a need to select the right set of LM tools in the manufacturing system.

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In this respect, experts have devised various methods to select the most appropriate LM tools, including traditional methods and multi-criteria decision-making (MCDM) methods (Naeemah and Wong, 2021). However, the existing literature reveals that models for LM tool selection still have certain limitations. LM tools were selected based on their impact on economic performance metrics, removing waste, or both, where LM tools were not selected based on their effect on triple bottom line (TBL) sustainability metrics because the environmental and social sustainability metrics were overlooked. Therefore, these models lack the criteria for choosing LM tools.

The literature review also revealed that only a tiny proportion of existing studies that used MCDM methods have hybridized MCDM methods together or with uncertainty treatment methods (Naeemah and Wong, 2021). Moreover, most existing hybrid models of LM tool selection depend on some MCDM methods such as the analytic hierarchy process (AHP) method and the analytic network process (ANP) for weighing the criteria or metrics (Chamarthi et al., 2016). These methods often include complex and inconsistent comparisons which lead to unreliable results (Rezaei, 2015).

Furthermore, only a small percentage of the reviewed studies addressed uncertainty. However, there is no available MCDM model for selecting LM tools that addresses grey uncertainty (insufficient information) that occurs through the decision-making process because all the reviewed studies solved one category of uncertainty, which is fuzziness.

The major questions of this study can be summarized as follows:

1. What is the suitable set of applicable TBL sustainability metrics (criteria) that help in the selection of LM tools?
2. How can a hybrid model be developed for selecting and ranking the proper set of LM tools (alternatives) depending on their impact on TBL sustainability metrics (criteria), obtaining reliable values of criteria weights, and treating the grey uncertainty problem?
3. How can the reliability and robustness of the developed model for selecting the LM tools be evaluated and validated?

As such, the objectives of this study are to:

1. Develop a set of applicable sustainability metrics as selection criteria.
2. Develop a new hybrid model for selecting and ranking a set of LM tools (alternatives) depending on their effect on sustainability metrics (criteria). This model can avoid inconsistent comparisons and get reliable criteria weights by using the best-worst method (BWM). This model can also treat the "grey uncertainty" problem during decision-making by using the grey technique for order of preference by similarity to the ideal solution (Grey-TOPSIS) method.
3. Evaluate and validate the reliability and robustness of the proposed model in the real-life case study.

This research contributes to the body of knowledge by developing a set of applicable metrics for TBL-based sustainability aspects that can function as a foundation for future research on selecting LM tools. This study could also be a knowledge base for researchers to support sustainable efforts by providing a hybrid MCDM model to choose the most suitable LM tools that boost sustainability in companies for a safe environment and community in the future. From a practical viewpoint, this study allows companies to choose the most suitable set of LM tools. As a result, their company's sustainability benefits are maximized. Finally, the case study results provided experiential proof of the applicability of the proposed method.

The rest of the article is structured as follows: Section 2 briefly presents the literature review, and Section 3 illustrates the study methodology. Section 4 reviews the criteria for the selection of LM tools. Section 5 displays the suggested model. Section 6 explains the evaluation and validation of the proposed model. Section 7 addresses the implications of the study. Finally, Section 8 presents the conclusions.

2. Literature review

2.1. Integration between lean manufacturing and sustainability

LM is an approach that emphasizes the elimination of waste during the complete value stream of the product (Thanki et al., 2016). As a result, better products and services can be produced with less money and effort. Another definition of LM is a work strategy that boosts process efficiency, increases customer confidence, and produces better outcomes (Shah and Ward, 2007). Eight forms of waste can be reduced or eliminated by LM. For instance, waiting, unneeded inventory, inappropriate processing, unutilized talent, unnecessary motion, transport, overproduction, and defects (Cherrafi et al., 2016).

Various LM tools have been applied to increase intra and inter-company sustainability performance effectiveness and improve sustainability metrics to achieve competitive manufacturing performance characteristics (Carvajal-Arango et al., 2019). These tools aim to implement the LM guiding principles, which include reducing non-value-added activities, boosting productivity, lowering variability, speeding up production cycles, and streamlining procedures by reducing the number of parts and steps (Qin and Liu, 2022). The LM tools can also improve the working environment and worker wellbeing while lowering customer complaints.

Additionally, LM tools can reduce air and water pollutants and enhance the use of materials, energy, and water (Afum et al., 2021). According to the literature review, studies discussing the likelihood of achieving true sustainability by utilizing an LM thinking philosophy to create sustainable manufacturing are rare (Yusup et al., 2015). Although there have been various recent attempts to combine sustainability and LM (Souza and Alves, 2018), much of the research on sustainability and LM is based on a limited understanding of the three dimensions of sustainability (Abualfaraa et al., 2020).

TBL sustainability concepts have been added to the LM definition in response to production's growing ecological and social consciousness. Sustainability has attracted great attention in most industries and studies worldwide, especially after the publication of the written report of the World Commission of Environment and Development (WCED), "Our Common Future"(Naeemah and Wong, 2022). Sustainability can be defined as meeting existing requirements without jeopardizing the coming generations' capacity to satisfy their own (Cherrafi et al., 2017).

In order to meet present and future generations' social, economic, and environmental needs, sustainability establishes and preserves the conditions under which human beings and nature can coexist (Poudyal and Adhikari, 2021). To ensure that human use of natural resources or raw materials does not result in poor quality of life on the planet due to damage, a lack of future economic prospects and negative consequences on society and the environment, sustainability attempts to design human and industrial systems in such a way that one does not negatively impact the other (Birkin et al., 2021).

LM and sustainability work together to optimize manufacturing and boost competitiveness. LM represents a comprehensive perspective of sustainability and streamlines operations in terms of prices, time, waste, and quality while also considering social and environmental quality (Thanki et al., 2016). LM fulfils other sustainability principles like preserving the environment, recycling wastes, and cutting air emissions (Awad et al., 2022). Sustainable development requires LM, as reducing energy use, environmental pollution, and material use promote sustainability (Yusup et al., 2015).

The same waste-reduction and efficiency-improvement strategies are used by both LM and sustainability, albeit in different ways (Naeemah and Wong, 2022). LM is a quick method since it offers good performance during the manufacturing process. In contrast, sustainability principles may be long-term and apply to the entire life cycle of a product. Furthermore, LM provides various tools that support sustainability (Souza and Alves, 2018).

In brief, LM achieves sustainability in three dimensions: 1. Economically, by conserving materials, effort, time, and money; 2. Socially, by

Table 1
The LM tools.

LM Tools	Definition	References
(7S) (*A*1)	A tool that helps companies achieve corporate goals through identifying seven necessary elements (set in order, sort, shine, standardize, spirit team, safety, sustain)	Souza and Alves (2018), Tasdemir et al. (2020), Vinodh et al. (2011a)
Just in Time (JIT) (*A*2)	A tool that helps plan the production process to minimize inventory to near zero and supply the required components and items for workstations on time	Dieste et al. (2019), Iranmanesh et al. (2019), Leksic et al. (2020)
Kanban (*A*3)	A tool that utilized cards to represent the number of things that needed to be manufactured	Cherrafi et al. (2016), Tăucean et al. (2019), Vinodh et al. (2011a)
Visual Control/Visual Management (*A*4)	This tool allows a manufacturer to build a system with simple indicators to see and realize them with ease, letting supervisors grasp the state of the manufacturing line and track shop floor activities	Helleno et al. (2017), Tasdemir and Gazo (2018), Tăucean et al. (2019)
Value Stream Mapping (VSM) (*A*5)	A tool to recognize value-added and non-value-added activities in the value stream to reduce unnecessary activities	Cherrafi et al. (2016), Chiarini (2014), Vinodh et al. (2011a)
Kaizen (*A*6)	A tool for achieving continual and gradual improvements without making a big capital expenditure	Cherrafi et al. (2016), Souza and Alves (2018), Tasdemir and Gazo (2018)
Poka-yoke (*A*7)	A tool that either prohibits mistakes or defects from taking place and focuses on deleting the reasons for their occurrence	Iranmanesh et al. (2019), Naeemah and Wong (2022), Yusup et al. (2015)
Six Sigma (*A*8)	A method for attaining quality control and reducing variance in manufacturing operations that is consistently organized	Helleno et al. (2017), Leksic et al. (2020), Tasdemir and Gazo (2019)
Total Productive Maintenance (TPM) (*A*9)	A tool that was created to optimize the effective use of equipment throughout the manufacturing process while minimizing downtime	Cherrafi et al. (2016), Chiarini (2014), Thanki et al. (2016)
Production Smoothing (Heijunka) (*A*10)	A scheduling tool for minimizing batch sizes of production	Leksic et al. (2020), Naeemah and Wong (2022), Yusup et al. (2015)
Single-Minute Exchange of Die (SMED) (*A*11)	A technique for reducing the amount of time it takes to replace equipment	Chiarini (2014), Iranmanesh et al. (2019), Yusup et al. (2015)
Cellular Manufacturing (*A*12)	A tool for creating similar products in one cell to reduce the time, energy, and effort	Iranmanesh et al. (2019), Tăucean et al. (2019), Vinodh et al. (2011a)

concentrating on the health, safety, contentment, and well-being of consumers and society, and through collaboration with stakeholders; and 3. Environmentally, by boosting waste minimization, contamination decrease, and resource preservation (Helleno et al., 2017).

2.2. Tools employed for lean manufacturing sustainability

Various organizations have used diverse sets of LM tools to accomplish good performance because of the competitive demand of the market (Tasdemir and Gazo, 2019). LM tools have recently gained popularity as manufacturing sectors improve (Leksic et al., 2020). Many benefits can be gained by choosing and implementing the most appropriate LM techniques. This is due to their ability to improve performance quality, profitability, and productivity (Behrouzi and Wong, 2013). Choosing the proper LM tools saves time and can help enhance efficiency by decreasing or removing waste and improving performance metrics. It also helps businesses achieve sustainable performance by reducing negative environmental effects and saving costs, water, energy, and raw materials.

Moreover, it improves the health and safety of the manufacturing industries' communities, employees, and customers (Cherrafi et al., 2017; Chiarini, 2014). However, not every LM tool yields the same outcomes, and not every business can use them. The 12 LM tools with the most effects on sustainability were determined by conducting a comprehensive literature review. Numerous earlier studies that tracked and identified the significance of these tools and repeatedly proved their impacts, either on one, two, or three aspects of sustainability, were a key factor in the selection of these 12 tools (Cherrafi et al., 2017; Naeemah and Wong, 2022).

These 12 LM tools help manufacturers improve their businesses' efficiency and effectiveness by making them more sustainable. A collection of 12 LM tools has been culled from the literature. Table 1 summarizes the definition of each tool. Understanding the functional purpose of each tool is necessary for the proper selection of LM tools to achieve sustainability.

For example, 7S can reduce effort, cost, and lead and transportation time. 7S helps to save energy, materials, and effort (Manzanares-Cañizares et al., 2022). Also, it helps to maintain safety procedures and alleviate stress (Chiarini, 2014). JIT can help to preserve inventory, improve on-time delivery, reduce labour and other costs associated with raw material handling before manufacturing products, and increase worker involvement (Dieste et al., 2019).

Kanban can reduce all inventories, transportation costs, setup time, raw materials, and waste. Kanban also allows for better utilization of workshop space (Cherrafi et al., 2016). Visual control helps monitor plant activities; reduce defects, downtime, material usage, energy, and injuries; improve team spirit; and enhance the value to the customer (Naeemah and Wong, 2022). Value stream mapping (VSM) can decrease cost, time, labour, energy, defects, inventory, liquid and solid waste, and air emissions (Wang et al., 2022). Also, VSM can increase quality, working conditions, health, and safety (Souza and Alves, 2018).

Kaizen can assist in promoting production and improving time, profit, quality, and efficiency (Queiroz et al., 2022). Kaizen helps to reduce raw material and energy usage. Kaizen improves employee participation, working conditions, and teamwork (Yusup et al., 2015). Poka-Yoke positively impacts production sustainability by reducing setup errors, lowering emissions rates, and improving customer satisfaction and worker attitude (Tăucean et al., 2019).

Six sigma can reduce product errors, minimize cost, maximize quality, minimize air emissions, and increase customer retention (Cherrafi et al., 2016). Total productive maintenance (TPM) can decrease machine malfunctions, expenses, errors, and oil leakage on the floor (Queiroz et al., 2022). TPM also helps to extend the life of the equipment, and increase material and energy efficiency (Chiarini, 2014).

The production smoothing technique keeps the manufacturing process pace constant to reduce inventory, effort, cost, materials, and energy (Yusup et al., 2015). The single-minute exchange of die (SMED) tool aids in minimizing equipment downtime, and increasing productivity and flexibility (Dieste et al., 2019; Fonda and Meneghetti, 2022). The cellular manufacturing technique conserves setup, changeover, and transportation time. Also, this tool saves effort, materials, and energy (Tasdemir and Gazo, 2019).

2.3. Selection methods for lean manufacturing tools

The process of determining and selecting from a set of options based on the preferences of the decision-maker(s) is referred to as decision-making (Rezaei, 2016). There are two approaches that past research has taken when selecting LM tools. The first category is the conventional approach, in which the decision-makers use analytical mathematical procedures and programs to make judgments that sometimes require their understanding, insight, and intuition (Naeemah and Wong, 2021). Numerous traditional techniques have been employed in the reviewed studies. For example, the stepwise multiple linear regression model (SMLR), the Rasch model (RM), etc.

MCDM methods are the second category of methods used to choose LM tools. MCDM methods are decision-making strategies that examine several competing criteria and allow for the involvement of many decision-makers. Two types of MCDM methods were used in the reviewed studies:

1. Single MCDM methods such as the multi-objective decision-making (MODM) method (Bidhendi et al., 2018), the analytic hierarchy process (AHP) method (Saaty, 1987) the analytic network process (ANP) method (Saaty, 2004) and many other MCDM methods that are mentioned in Table 2. There have also been several MCDM methods developed recently. For instance, the base-criterion method (BCM) (Haseli et al., 2020; Haseli and Sheikh, 2022), the ordinal priority approach (OPA) (Ataei et al., 2020), and the combined compromise solution (COCOSO) method (Yazdani et al., 2019). However, these methods were not used for the purpose of choosing LM tools.

2. Hybrid MCDM methods that have hybridized MCDM methods together or with uncertainty treatment methods. For example, Jing et al. (2018) combined the AHP technique to define the weights of criteria and the fuzzy-VlseKriterijuska Optimizacija I Komoromisno Resenje (Fuzzy-VIKOR) technique to prioritize LM tools. Also, Mohammad et al. (2021) integrated the entropy method to determine the weights of criteria and the simple additive weighting (SAW) method and VIKOR method to rank LM tools, in addition to some other hybrid methods that were used in the studies of LM tool selection, as shown in Table 2. Moreover, there were other hybrid MCDM methods (Cheraghalipour et al., 2017; Hosseini et al., 2021) but they were not developed for the purpose of selecting LM tools.

Each decision-maker has unique skills, knowledge, and perceptions about the related significance of the various criteria and the relative importance of the many choices. The selection of LM tools, therefore, becomes an MCDM problem that involves various kinds of uncertainty such as grey and fuzzy uncertainty (Naeemah and Wong, 2021). Therefore, incorporating uncertainty treatment approaches can help to overcome the uncertainty problems that sometimes occur in some single MCDM techniques because of human qualitative assessments and incomplete preferences (Naeemah and Wong, 2021; Zavadskas et al., 2016b,a).

Also, hybrid MCDM methods, due to their capabilities in combining different individual MCDM techniques, can depend on more than one type of decision-making process and assist in addressing various information when considering preferences (Zavadskas et al., 2016b,a). Therefore, researchers in various fields have begun to use hybrid MCDM approaches that integrate two or more MCDM methods with uncertainty treatment methods to maximize the advantages of each method and solve different types of decision-making problems. A review of prior studies of selection methods of LM tools revealed that these tools (alternatives) are ranked depending on the value of their impact on performance metrics (criteria), wastes, or both. The decision-making methods, criteria, uncertainty, and countries that were used in 27 previous studies on the selection methods of LM tools are shown in Table 2.

2.4. Research gaps

After conducting a comprehensive review of the studies of LM tool selection in Section 2.3, the next step is to figure out the gaps in the methods and criteria of LM tool selection. Table 2 reveals some gaps and limitations that this study tries to bridge. The main research gap is that the selection of LM tools in the prior studies was based on performance metrics (economic metrics), waste, or both. However, the environmental and social metrics were not considered.

A small percentage of the reviewed studies utilized hybrid MCDM methods, as most studies have focused on some individual MCDM methods that can treat certain decision-making issues. Also, most of the hybrid models adopted some types of MCDM methods that require high numbers of pairwise comparisons and consume a huge amount of data, leading to a lack of consistency in the comparisons.

Moreover, a small percentage of the reviewed studies treated uncertainty in decision-making and focused on fuzziness while overlooking other types of uncertainty. Further, while previous studies covered various industries in different countries, no study has addressed the selection of LM tools in the Iraqi cement industry. The assumptions made in this study are as follows:

- Assumption 1: For the first time in this field, LM tools can be selected based on their effect on sustainability metrics.
- Assumption 2: A hybrid MCDM model for selecting and ranking LM tools can address some weaknesses of single MCDM methods, provide reliable results, and treat the grey uncertainty issue.

Hence, this study is the first in this field to attempt to develop a hybrid model that integrates the BWM and Grey-TOPSIS methods to select the most suitable set of LM tools in a cement company in Iraq depending on their effects on applicable sustainability metrics. This model can avoid inconsistent pairwise comparisons and get credible results when calculating the criteria weights. It can also solve the problem of grey uncertainty in the decision-making process.

3. A brief overview of BWM, TOPSIS, and grey numbers

3.1. Best-Worst Method (BWM)

The BWM is one of the most current MCDM techniques (Rezaei, 2015). This approach uses pairwise comparisons that are performed in a specially organized manner so that not only is minimum data needed, but the comparisons are often more consistent (Rezaei, 2016). In BWM, the best and the worst criteria are distinguished first by the decision-maker (Mahmoudi et al., 2020). Pairwise comparisons are then made between the best and worst criteria on the one hand and the remaining options on the other hand (Rezaei, 2016). After that, the problem of mini-max is formulated, and the study determines the weights of various criteria by using the model of BWM (Rezaei, 2015).

BWM includes two consistency ratios: the input-based consistency ratio (CR^I) (Liang et al., 2020); the output-based consistency ratio (CR^O) (Rezaei, 2015). Both ratios are used to check the reliability of the results. BWM has numerous features and characteristics, making it a more durable and desirable method for determining criteria weights (Liang et al., 2020; Rezaei, 2016, 2015).

1. BWM depends on fewer pairwise comparisons compared to other pairwise comparison MCDM methods.
2. BWM's final weights are often reliable because BWM allows for more consistent comparisons.
3. Only integers are utilized in the BWM, making it considerably easier.
4. Unlike other weighting methods such as AHP and ANP, BWM relies on the two types of consistency ratios (CR^O, CR^I) to ensure the reliability of the results and avoid errors in the evaluation.

Table 2
Detailed attributes and properties of LM tools selection studies.

Method	Sector and industry	Criteria	Country	Uncertainty aspect	References
Entropy + SAW + VIKOR methods	Services sector-hospital management	Performance metrics (economic metrics)	Iran	Not considered	Mohammad et al. (2021)
SMLR model	Manufacturing sector-automotive industry	Waste	Croatia	Not considered	Leksic et al. (2020)
Multi-objective decision-making (MODM) method	Manufacturing sector-electrical & electronics industry	Waste	India	Not considered	Deshpande and Rao (2019)
Lean fuzzy failure Mode and effects analysis (LFMEA)	Manufacturing sector-machining & casting industry	Waste	India	Considered (fuzzy uncertainty)	Kumar and Parameshwaran (2019)
MODM method	Construction sector	Performance metrics (economic metrics) and waste	Australia	Not considered	Bidhendi et al. (2018)
AHP + Fuzzy VIKOR methods	Estate sector	Performance metrics (economic metric) and waste	China	Considered (fuzzy uncertainty)	Jing et al. (2018)
Fuzzy failure mode and effects analysis (FMEA)+ fuzzy quality function deployment (FQFD)	Manufacturing sector-plastic industry	Waste	India	Considered (fuzzy uncertainty)	Kumar and Parameshwaran (2018)
AHP method	Services sector-hotel management	Performance metrics (economic metrics) and waste	United Arab Emirates	Not considered	Al-Aomar and Hussain (2018)
AHP method	Manufacturing sector -screw industry	Waste	India	Not considered	Chamarthi et al. (2016)
MODM method	Manufacturing sector-drinks industry	Performance metrics (economic metrics)	Libya	Not considered	Alaskari et al. (2016)
AHP method	Manufacturing sector	Performance metrics (economic metrics)	India	Not considered	Thanki et al. (2016)
AHP method	Services sector-hospital management	Waste	United Arab Emirates	Not considered	Hussain and Malik (2016)
VIKOR methods	Manufacturing sector-dairy industry	Performance metrics (economic metrics)	China	Not considered	Jing et al. (2015)
ANP method	Manufacturing sector (hypothetical case)	Performance metrics (economic metrics)	Colombia	Not considered	Wan et al. (2014)
VIKOR method	Manufacturing sector-automotive industry	Performance metrics (economic metrics)	Iran	Not considered	Anvari et al. (2014a)
AHP method+ data envelopment analysis (DEA)	Manufacturing sector-automotive industry	Performance metrics (economic metrics)	Iran	Not considered	Anvari et al. (2014b)
Weighted average method (WAM)	Manufacturing sector-automotive industry	Waste	India	Not considered	Arunagiri and Gnanavelbabu (2014)
Rasch Model	Manufacturing sector-food industry	Waste	Malaysia	Not considered	Khusaini et al. (2014)
Lean decision support tool (LDST) + AHP method	Simulation study for manufacturing sector	Performance metrics (economic metrics)	USA	Not considered	da Wan and Tamma (2013)
MODM method	Manufacturing sector- electrical & electronics industry	Waste	Australia	Not considered	Amin and Karim (2013)
MODM method	Manufacturing sector- electrical & electronics industry	Waste	Australia	Not considered	Amin and Karim (2011)
AHP method	Manufacturing sector- electrical & electronics industry	Performance metrics (economic metrics)	India	Not considered	Vinodh et al. (2011b)

(*continued on next page*)

Table 2 (*continued*).

Method	Sector and industry	Criteria	Country	Uncertainty aspect	References
Lean web-based decision support (DS) tool	Manufacturing sector	Performance metrics (economic metrics)	USA	Not considered	da Wan and Chen (2009)
House of quality matrix (HQM) tool	Manufacturing sector- machine tools industry	Performance metrics (economic metrics) and waste	USA	Not considered	Inanjai and Farris (2009)
Quality function deployment (QFD) + balanced scorecard (BSC) + life cycle cost analysis (LCCA)+ MCDM	Manufacturing sector-timber industry	Performance metrics (economic metrics) and waste	Sweden	Not considered	(Al-Hamed and Qiu, 2007)
Fuzzy AHP method	Manufacturing sector-die casting industry	Waste	India	Considered (fuzzy uncertainty)	(Singh et al., 2006)
Productivity needs analysis (PNA) + training needs analysis (TNA)+ manufacturing needs analysis (MNA)	Manufacturing sector-automotive industry	Performance metrics (economic metrics)	UK	Not considered	(Herron and Braiden, 2006)

5. BWM has fewer violations and overall deviations and requires less time to fill out questionnaires than the AHP and ANP methods.
6. BWM includes consistency thresholds to specify the dependability of the outcomes.

3.2. Technique for order preference by similarity to ideal solution (TOPSIS)

The TOPSIS method was suggested by Hwang and Yoon (1981). The TOPSIS method is one of the best methods of MCDM. In this MCDM method, (i) alternatives are assessed by (j) criteria (Hwang and Yoon, 1981). The idea of the method is that the alternatives are ranked depending on their distances from positive and negative ideal solutions (Yoon and Hwang, 1985). The best alternative is considered to be the one that has the closest distance to the positive ideal solution and has the longest distance from the negative ideal solution (Yoon and Hwang, 1985). The TOPSIS method is a compensative aggregation method that ranks a group of alternatives with regard to a group of criteria. The TOPSIS method has several features that distinguish it from the other ranking methods (Shamsuzzoha et al., 2021).

1. The TOPSIS method has a simple procedure.
2. Regardless of the number of attributes or criteria, the number of TOPSIS steps remains constant.
3. The TOPSIS method provides a rational ranking for alternatives.
4. The TOPSIS method can rank the alternatives based on relative closeness values (CC_i) from the best to the worst.
5. The TOPSIS method produces stable performance results even when the input data oscillates.

3.3. Grey number

The basic notion of uncertainty is a quantitative measure of variation in information. That is, uncertainty indicates the notion that all information has a scope of anticipated values, as opposed to an exact point value (Naeemah and Wong, 2021). It is difficult to obtain all the information about decision-making in reality. Also, decision-makers are unaware of all the available alternatives, the outcomes of each alternative, or their probabilities. Hence, decision-making on practical problems is always exposed to a lack of information (grey uncertainty) (Mahmoudi et al., 2020).

The existing studies did not treat this type of uncertainty. Therefore, this study tries to address this issue (Naeemah and Wong, 2021). Grey uncertainty can be treated by using the grey system theory which is a mathematical theory founded on the notion of the grey set (Julong, 1982). Grey systems demonstrate a level of data and relationships between black and white systems (Julong, 1989). In grey system theory, numbers whose definite value is not distinguished are shown as grey numbers. $\otimes A$ is a grey number with known lower and upper limits, and it is denoted as $[\underline{A}, \overline{A}]$ (Liu et al., 2012).

If $\otimes A = [\underline{A}, \overline{A}]$ and $\otimes B = [\underline{B}, \overline{B}]$ are two grey numbers, then mathematical actions can be formulated as follows (Ikram et al., 2020):

$$\otimes A + \otimes B = [\underline{A} + \underline{B}, \overline{A} + \overline{B}] \tag{1}$$

$$\otimes A - \otimes B = [\underline{A} - \overline{B}, \overline{A} - \underline{B}] \tag{2}$$

$$\otimes A \times \otimes B = \{\text{Min } [\overline{A}\,\overline{B}, \underline{A}\,\underline{B}, \underline{A}\,\overline{B}, \overline{A}\,\underline{B}],\ \text{Max } [\overline{A}\,\overline{B}, \underline{A}\,\underline{B}, \underline{A}\,\overline{B}, \overline{A}\,\underline{B}]\} \tag{3}$$

$$\otimes A / \otimes B = \otimes A \times \otimes B^{-1} = \{\text{Min } [\underline{A}/\underline{B}, \overline{A}/\overline{B}, \overline{A}/\underline{B}, \underline{A}/\overline{B}],\ \text{Max } [\underline{A}/\underline{B}, \overline{A}/\overline{B}, \overline{A}/\underline{B}, \underline{A}/\overline{B}]\} \tag{4}$$

$$C \times \otimes A = [C \times \underline{A}, C \times \overline{A}] \quad C \in R \tag{5}$$

4. Sustainability metrics for selecting LM tools

To achieve success in the prioritization of the best set of LM tools that boost different sustainability aspects in LM companies, it is critical to choose the right collection of sustainability metrics (criteria) that help to identify the best set of LM tools (Jing et al., 2018). To examine the appropriateness of sustainability metrics for LM organizations, it is necessary to assess the applicability of performance metrics in the manufacturing sector (Ahmad et al., 2019). A comprehensive review of the literature was conducted to recognize and extract the sustainability metrics.

The criteria for selecting LM tools must be compatible with the overall purpose (Bidhendi et al., 2018). These metrics mirror the objectives of the company's sustainability and meet the requirements of the decision-makers to use them as criteria (Naeemah and Wong, 2022). The sustainability metrics should be characterized by some features such as easiness, robustness, order, and consistency so that they are very beneficial in decision making (Al-Aomar and Hussain, 2018).

These metrics should reflect the three sustainability aspects (Naeemah and Wong, 2022). The metrics were picked based on their usage in the literature, importance, and relevance to the manufacturing industry (Ahmad et al., 2019). Every aspect of sustainability includes metrics to evaluate the sustainable performance of the industry (Helleno et al., 2017). A set of sustainability metrics were collected. After the preparatory screening, these metrics were filtered and edited.

As a result, an initial list of sustainability metrics (18 metrics) was compiled and categorized based on three sustainability aspects (7

Table 3
Proposed sustainability metrics for selecting LM tools.

Economic metrics	Mean of applicability scores	References	Environmental metrics	Mean of applicability scores	References	Social metrics	Mean of applicability scores	References
1. cost ($C1$)	4.2	(Kishawy et al., 2018; Tasdemir et al., 2020; Tasdemir and Gazo, 2018)	1. Material usage ($C6$)	4	(Kishawy et al., 2018; Tasdemir and Gazo, 2019; Vinodh et al., 2011a)	1.Work condition ($C12$)	4.2	(Ahmad et al., 2019; Kishawy et al., 2018; Souza and Alves, 2018)
2. Profit ($C2$)	4.2	(Ahmad et al., 2019; Cherrafi et al., 2016; Helleno et al., 2017)	2. Energy usage ($C7$)	4.4	(Cherrafi et al., 2017; Helleno et al., 2017; Yusup et al., 2015)	2. Health and safety ($C13$)	4.6	(Ahmad et al., 2019; Carvajal-Arango et al., 2019; Tasdemir et al., 2020)
3. Flexibility ($C3$)	3.9	(Carvajal-Arango et al., 2019; Cherrafi et al., 2017; Shrivastava, 2017)	3. Water usage ($C8$)	4	(Carvajal-Arango et al., 2019; Cherrafi et al., 2017; Naeemah and Wong, 2022)	3. Labour wellbeing and satisfaction ($C14$)	4.2	(Chiarini, 2014; Helleno et al., 2017; Naeemah and Wong, 2022)
4. Eight wastes ($C4$)	4.3	(Chiarini, 2014; Tasdemir and Gazo, 2018; Vinodh et al., 2011a)	4.Air emissions ($C9$)	4.5	(Cherrafi et al., 2016; Dieste et al., 2019; Kishawy et al., 2018)	4. Society wellbeing and satisfaction ($C15$)	4.2	(Cherrafi et al., 2017, 2016; Tasdemir and Gazo, 2019)
5. Productivity ($C5$)	4.2	(Helleno et al., 2017; Naeemah and Wong, 2022; Tasdemir et al., 2020)	5. Wastewater ($C10$)	3.9	(Ahmad et al., 2019; Shrivastava, 2017; Vinodh et al., 2011a)	5. Customer wellbeing and satisfaction ($C16$)	4.1	(Chiarini, 2014; Helleno et al., 2017; Souza and Alves, 2018)
			6. Solid waste ($C11$)	4.1	(Cherrafi et al., 2016; Dieste et al., 2019; Naeemah and Wong, 2022)			

economic metrics, 6 environmental metrics, and 5 social metrics). By considering the frequency of each metric, analysing these metrics, removing redundancy and surplus, and merging similar types of metrics, a list of 16 metrics was proposed. The evaluation tool was designed to determine the applicability scores of the proposed metrics.

The applicability of metrics was evaluated based on a 5-point Likert scale (Ahmad et al., 2019). Fourteen experts from different countries responded to this evaluation. These fourteen experts include six academic experts and eight industrial experts, four of whom were from the Iraqi cement industry, to create a balance between academic and industrial experience. Usually, an evaluation by fourteen experts provides a sufficient sample. The number of judging experts should not be excessive, and generally, between 5 and 15 experts are sufficient (Anvari et al., 2014a).

These experts have relevant experience and qualifications with regard to sustainable manufacturing performance, such as scientific research and practical experience. The comments of experts were taken into account when editing metrics. The mean applicability score for each metric has been calculated by collecting the applicability values for each proposed sustainability metric (criterion) evaluated by experts and dividing them by the number of experts as shown in Table 3. There was no metric with an applicability score of less than 2.5. The experts' answers were collected by sending the evaluation tool and receiving the answers by email. Fig. 1 also shows all the mean applicability scores of sustainability metrics (criteria).

5. Proposed research model

5.1. Determining the weights of the criteria using the best-worst method (BWM)

The first step in developing the hybrid MCDM model is to determine the weights of criteria (metrics) by adopting the BWM (Rezaei, 2020). In order to implement the BWM in all four stages mentioned previously, there are specific procedures for the BWM as follows (Kheybari and Ishizaka, 2022; Rezaei, 2016):

1. Identifying a group of decision criteria $\{C_1, C_2, \ldots, C_n\}$.
2. Identifying the best and worst criteria by experts.
3. Conducting the pairwise comparison between the best criterion and the other criteria (BO) utilizing numbers between 1 and 9.
4. Conducting the pairwise comparison between the other criteria and the worst criterion (OW) utilizing numbers between 1 and 9.
5. Calculating the CR^I to examine the consistency for each pairwise comparison and comparing this ratio with the fixed threshold. Table A.1 in the Appendix shows thresholds for a different number of criteria and scales for CR^I (Liang et al., 2020).

$$CR^I = \max CR_j^I$$
$$CR_j^I = \begin{cases} \frac{|a_{bj}\times a_{jw} - a_{bw}|}{a_{bw}\times a_{bw} - a_{bw}} & a_{bw} > 1 \\ 0 & a_{bw} = 1 \end{cases} \tag{6}$$

where CR^I is the global ratio for all criteria, and CR_j^I is the local ratio associated with criterion C_j, $(0 \leq CR^I \leq 1)$ (Liang et al., 2020).

6. Determining the optimal weights using the BWM model (Rezaei, 2015).

$$\begin{aligned} &\min \xi \\ &\text{s.t} \\ &\quad \left|\frac{w_b}{w_j} - a_{bj}\right| \leq \xi, \text{ for all } j \\ &\quad \left|\frac{w_j}{w_w} - a_{jw}\right| \leq \xi, \text{ for all } j \\ &\quad \sum_j w_j = 1 \\ &w_j \geq 0, \text{ for all } j \end{aligned} \tag{7}$$

7. Calculating CR^O to double-check the results' reliability and comparing it with the fixed threshold (Mohammadi and Rezaei, 2020).

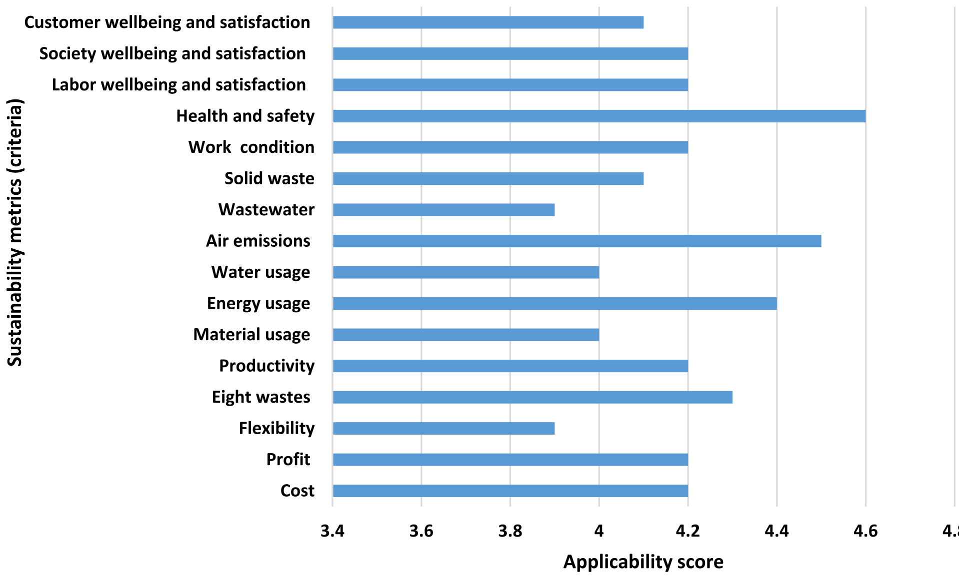

Fig. 1. The mean applicability score for sustainability metrics (criteria).

$$CR^O = \frac{\xi}{CI} \tag{8}$$

where ξ is the maximum objective value of the BWM model and CI represents the consistency index for different scales (a_{bw}). Table A.2 in the Appendix shows the consistency index (CI) of CR^O (Rezaei, 2016). Also, Table A.3 in the Appendix displays thresholds for a different number of criteria and scales for CR^O (Liang et al., 2020). The study later utilized the global weights of the criteria obtained from BWM in the Grey-TOPSIS method.

5.2. Ranking LM tools using the grey-TOPSIS method

The second step of the proposed model is to rank the alternatives (LM tools). There are specific procedures in Grey-TOPSIS (Lin et al., 2008b,a) to achieve the ranking as follows:

1. Evaluating the importance of the alternatives ($\otimes g_1$, $\otimes g_2, \ldots,$ $\otimes g_i$) linguistically (see the Appendix, Table A.4) by the experts. The group of experts (K) assesses each alternative with regard to each criterion (Ikram et al., 2020; Zakeri and Keramati, 2015).
2. Converting the linguistic assessments to grey numbers.
3. Building a combined grey decision matrix using the arithmetic mean method (Shamsuzzoha et al., 2021).

$$\otimes g_{ij} = \frac{1}{K}[\otimes g_{ij}^1 + \otimes g_{ij}^2 + \ldots\ldots + \otimes g_{ij}^k] \tag{9}$$

where $\otimes g_{ij}^k$ ($i = 1,2,\ldots\ldots, m,\ j = 1,2,\ldots\ldots n$) is an evaluation of alternatives with respect to each criterion by the k^{th} (decision maker) (Bai and Sarkis, 2018).

$$\otimes F = \begin{bmatrix} \otimes g_{11} & \otimes g_{12} & \cdots & \otimes g_{1n} \\ \otimes g_{21} & \otimes g_{22} & & \otimes g_{2n} \\ \vdots & & \ddots & \vdots \\ \otimes g_{m1} & \otimes g_{m2} & \cdots & \otimes g_{mn} \end{bmatrix} \tag{10}$$

where $\otimes g_{ij}$ indicates the importance value of the ith alternative with respect to the jth criteria.

4. Normalizing the grey decision matrix (Oztaysi, 2014)

$$\otimes F^* = \begin{bmatrix} \otimes g_{11}{}^* & \otimes g_{12}{}^* & \cdots & \otimes g_{1n}{}^* \\ \otimes g_{21}{}^* & \otimes g_{22}{}^* & & \otimes g_{2n}{}^* \\ \vdots & & \ddots & \vdots \\ \otimes g_{m1}{}^* & \otimes g_{m2}{}^* & \cdots & \otimes g_{mn}{}^* \end{bmatrix} \tag{11}$$

For the beneficial type criteria.

$$\otimes g_{ij}^* = \frac{\otimes g_{ij}}{g_j^{\max}} = [\frac{\underline{g}_{ij}}{g_j^{\max}}, \frac{\overline{g}_{ij}}{g_j^{\max}}] \text{ where } (g_j^{\max}) = \max_{1\le i\le m}\{\overline{g}_{ij}\} \tag{12}$$

For the non-beneficial type criteria.

$$\otimes g_{ij}^* = \frac{g_j^{\min}}{\otimes g_{ij}} = [\frac{g_j^{\min}}{\overline{g}_{ij}}, \frac{g_j^{\min}}{\underline{g}_{ij}}] \text{ where } (g_j^{\min}) = \min_{1\le i\le m}\{\underline{g}_{ij}\} \tag{13}$$

5. Formulating a weighted normalized grey decision matrix (Nyaoga et al., 2016).

$$\otimes Z = \begin{bmatrix} \otimes z_{11} & \otimes z_{12} & \cdots & \otimes z_{1n} \\ \otimes z_{21} & \otimes z_{22} & & \otimes z_{2n} \\ \vdots & & \ddots & \vdots \\ \otimes z_{m1} & \otimes z_{m2} & \cdots & \otimes z_{mn} \end{bmatrix}, \text{ where } \otimes z_{ij} = \otimes g_{ij}^* \times w_j \tag{14}$$

where w_j represents the weights of criteria (C_1, C_2, …., C_n) obtained from BWM.

6. Identifying the positive and negative ideal solutions of alternatives (Shamsuzzoha et al., 2021).

$$\otimes R^{max} = \{[\max_{1\le i\le m} \underline{Z}_{i1}, \max_{1\le i\le m} \overline{Z}_{i1}], [\max_{1\le i\le m} \underline{Z}_{i2}, \max_{1\le i\le m} \overline{Z}_{i2}], \ldots, [\max_{1\le i\le m} \underline{Z}_{in}, \max_{1\le i\le m} \overline{Z}_{in}]\} \tag{15}$$

$$\otimes R^{min} = \{[\min_{1\le i\le m} \underline{Z}_{i1}, \min_{1\le i\le m} \overline{Z}_{i1}], [\min_{1\le i\le m} \underline{Z}_{i2}, \min_{1\le i\le m} \overline{Z}_{i2}], \ldots, [\min_{1\le i\le m} \underline{Z}_{in}, \min_{1\le i\le m} \overline{Z}_{in}]\} \tag{16}$$

7. Calculating the Euclidean distances between the alternatives and the ideal solutions, both positive and negative (d_i^+, d_i^-) (Zolfani and Antucheviciene, 2012).

$$d_i^+ = \sqrt[P]{\frac{1}{2}\sum_{j=1}^{n}[\left(Z_j^+ - \underline{Z}_{ij}\right)^P + \left(Z_j^+ - \overline{Z}_{ij}\right)^P]} = \sqrt{\frac{1}{2}\sum_{j=1}^{n}[\left(Z_j^+ - \underline{Z}_{ij}\right)^2 + \left(Z_j^+ - \overline{Z}_{ij}\right)^2]} \tag{17}$$

$$d_i^- = \sqrt[P]{\frac{1}{2}\sum_{j=1}^{n}[\left(Z_j^- - \underline{Z}_{ij}\right)^P + \left(Z_j^- - \overline{Z}_{ij}\right)^P]} = \sqrt{\frac{1}{2}\sum_{j=1}^{n}[\left(Z_j^- - \underline{Z}_{ij}\right)^2 + \left(Z_j^- - \overline{Z}_{ij}\right)^2]} \tag{18}$$

8. Computing the relative closeness, CC_i for each alternative (Lin et al., 2008b).

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, 3, \ldots, m \tag{19}$$

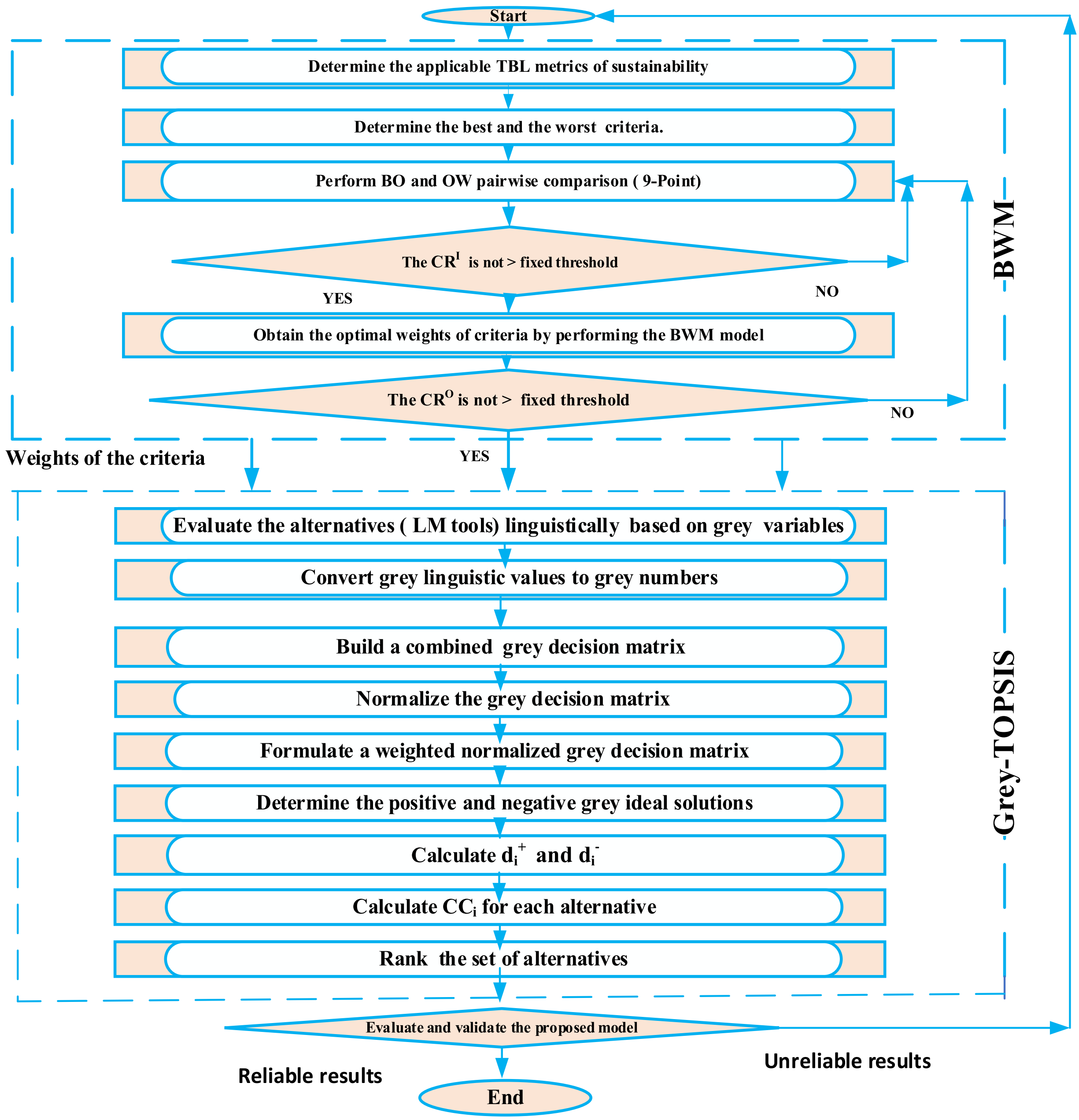

Fig. 2. Hybrid MCDM model.

where $0 \leq CC_i \leq 1$ and the greater the index value is, the better the assessment of alternative will be.

9. Ranking the preference order by choosing an alternative with maximum CC_i. Fig. 2 shows the proposed hybrid MCDM model.

6. Evaluation and validation of the proposed model

6.1. Case study

To test and evaluate the proposed hybrid MCDM model, a case study of one of Iraq's largest cement manufacturing companies was used to prove that the model can be applied to choose and rank the most suitable set of LM tools. The plant has two production lines. The factory's annual production is about 2,000,000 tons of cement, or more than 7500 tons per day of sulfate-resistant cement. The plant operates on the dry technique of cement production. Approximately 700 people with different specializations work in this company. The cement industry has always been critical to a country's socioeconomic prosperity. It has mostly led to improved affluence and expanded job and livelihood options (Shrivastava, 2017). However, cement is one of the main industries contributing to environmental contamination (Uddin, 2020).

The cement industry has been accused of accelerating the use of fossil fuels while also polluting the local and international environment by emitting liquid, solid, and gaseous pollutants (Majeed and Mazhar, 2021; Shrivastava, 2017). One of the essential considerations for the cement industry's long-term viability is the consumption of natural resources, such as raw materials, water, and energy (Majeed and Mazhar, 2021). The cement production process passes through numerous workstations, including crushing raw materials, grinding raw materials, burning the materials in a rotary kiln, grinding cement in the mills, packing the products, and other backing units, such as cement silos, water treatment units, and the main power station. Several studies have discussed the effective role of lean manufacturing in the cement industry (Amrina and Lubis, 2017; Isaksson and Taylor, 2014; Masmali, 2021).

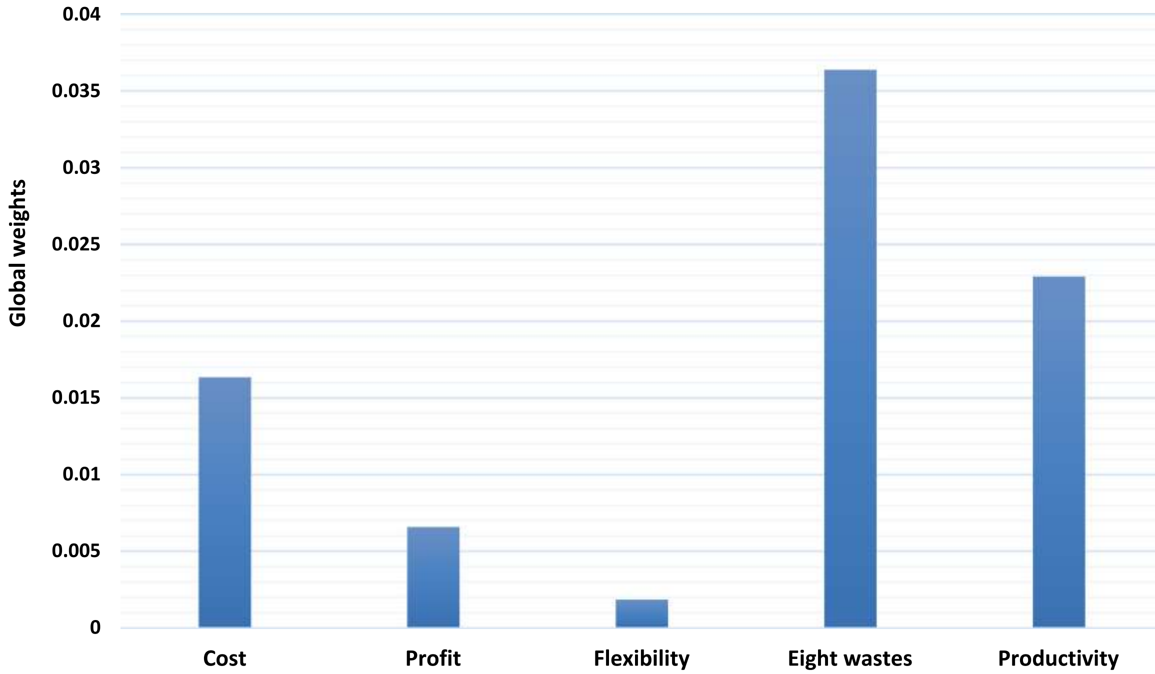

Fig. 3. Global weights of the economic criteria.

The purpose of implementing LM tools is to develop and improve the operations in cement factories by minimizing waste and non-value activities that enhance sustainability performance (Cherrafi et al., 2016). For instance, 7S can help cement companies reduce the space needed for operations and draw attention to environmental waste. 7S can help businesses save costs, energy, and materials, improve the company's hazardous material storage, and decrease the danger of spills and mistreatment. 7S can assist firms in minimizing dangers to health and safety (Tasdemir et al., 2020). To reduce individual bias, it is advised that more than one expert be included in the decision-making process.

Two experts from the company have been accredited because the evaluation process for criteria and alternatives using the BWM and Grey-TOPSIS methods requires sufficient experience and knowledge about LM tools and sustainability metrics that are available only to a very small number of engineers working in the company as heads of department (s). Two experts in this company who work as production and maintenance managers participated in the assessment process. The number of years of experience was calculated from their first job in the industry. These experts have sufficient experience more than 20 years and have headed various departments during their working careers.

6.2. Weights of the criteria

Expert 1

Stage 1: Weight values of sustainability aspects

The environmental aspect was chosen as the best and the economic aspect as the worst. Table 4 shows the BO and OW pairwise comparisons (preferences) and the CR_j^I ratio for each comparison.

The study calculated the CR_j^I (using Eq. (6)) for the three aspects. The value of the CR_j^I was equal to zero; therefore, all pairwise comparisons are fully consistent and acceptable. After that, the optimal weight of each aspect was determined using the BWM model (using Eq. (7)) as follows:

$w_{\text{environmental aspect}} = 0.61035$
$w_{\text{social aspect}} = 0.30517$
$w_{\text{economic aspect}} = 0.08448$
$\xi = 0.08545$

Then the CR^O was determined ($CR^O = \frac{0.08545}{4.47} = 0.01911$). The CR^O was very close to zero, and when the value of CR^O was compared with the fixed threshold associated with scale (8) and the number of criteria (3) (see the Appendix, Table A.3), the value was smaller than the fixed threshold ($0.01911 < 0.2267$); therefore, the results were acceptable.

Stage 2: Weight values of criteria in each aspect of sustainability

In terms of the economic aspect, the eight wastes criterion was chosen as the best and the flexibility criterion as the worst. Table 5 shows the BO and OW pairwise comparisons and the CR_j^I ratio for each pairwise comparison.

$CR^I = \max CR_j^I$
$CR^I = 0.07142$

The CR^I ratio was compared with a fixed threshold that is associated with the scale (8) and the number of criteria (5) ($0.07142 < 0.2958$) (see the Appendix, Table A.1), and this indicates the consistency of pairwise comparisons. The local weights of economic criteria were calculated using the BWM model as follows.

$w_{\text{cost}} = 0.16330$
$w_{\text{profit}} = 0.08165$
$w_{\text{flexibility}} = 0.02021$
$w_{\text{eight wastes}} = 0.48989$
$w_{\text{productivity}} = 0.24495$
$\xi = 0.01845$
$CR^O = \frac{0.01845}{4.47} = 0.00412$

The value of CR^O was close to zero and not greater than the fixed threshold (0.4029) (see the Appendix, Table A.3); therefore, the results were reliable. The study calculated the weights of environmental and social aspects for the first expert by using the same formulas. All previous procedures were also applied to the second expert. Table 6 displays the criteria' local weights, average local weights, and average global weights values. Table 6 also displays the values of ξ, CR^I, and CR^O for both experts.

Table 6 shows that all values of CR^I and CR^O for the main sustainability aspects and the criteria in each aspect are less than the fixed thresholds (see the Appendix, Tables A.1 and A.3). This means that pairwise comparisons are consistent and the results are reliable. The sum of the local weights for criteria in each aspect of sustainability is equal to one, and the sum of the global weights for all criteria is equal to one, indicating that the results are also reliable. Figs. 3 to 5 show the average global weights for each criterion.

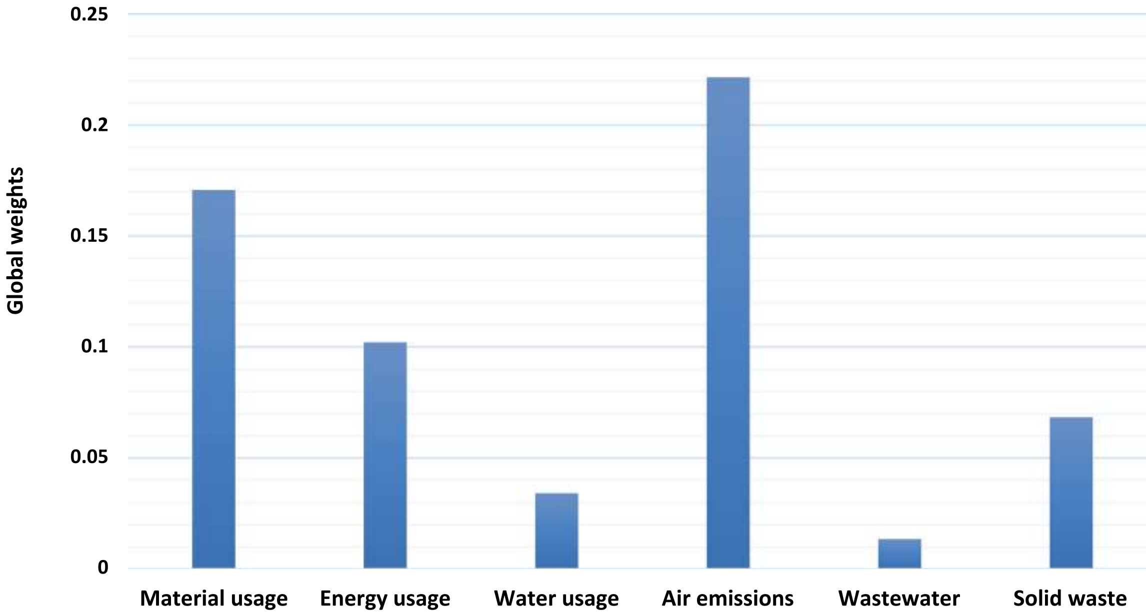

Fig. 4. Global weights of the environmental criteria.

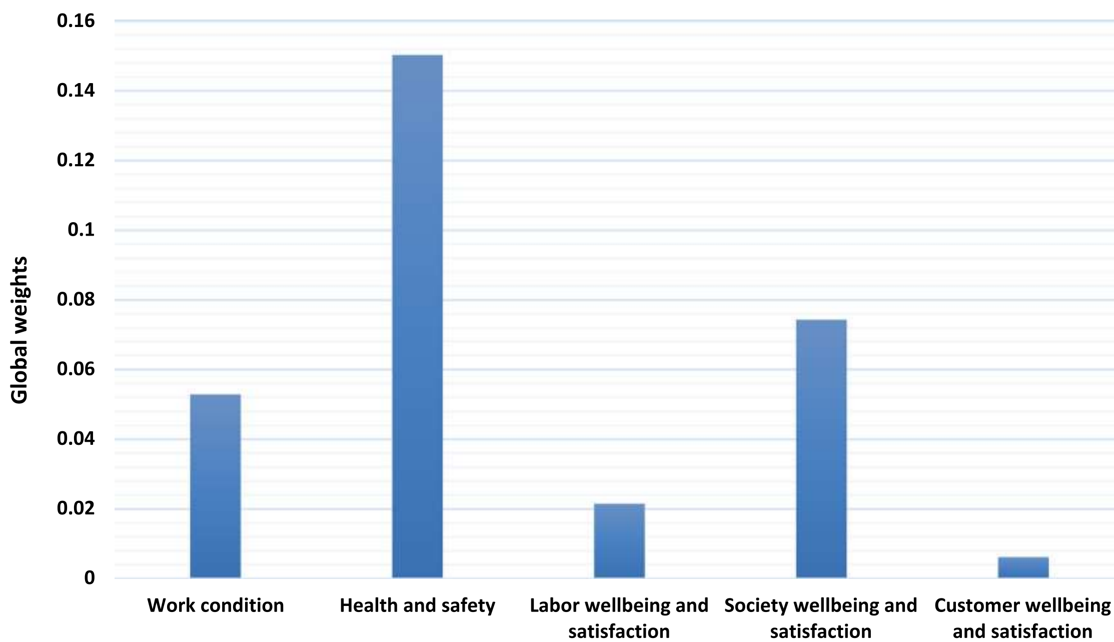

Fig. 5. Global weights of the social criteria.

Table 4
BO and OW pairwise comparisons and CR_j^I for sustainability aspects.

	Environmental aspect	Social aspect	Economic aspect
a_{bj}	1	4	8
a_{jw}	8	2	1
CR_j^I	0	0	0

Table 5
BO and OW pairwise comparisons and CR_j^I for economic criteria.

	Cost ($C1$)	Profit ($C2$)	Flexibility ($C3$)	Eight wastes ($C4$)	Productivity ($C5$)
a_{bj}	4	5	8	1	2
a_{jw}	3	2	1	8	6
CR_j^I	0.07142	0.03571	0	0	0.07142

6.3. Ranking LM tools using the grey-TOPSIS method

After evaluating the importance of the alternatives concerning each criterion linguistically, the study converted the linguistic assessment to grey numbers as shown in Tables A.5 and A.6 in Appendix. First, the combined grey decision matrix was built, and then the study normalized the grey decision matrix ($\otimes F^*$) as revealed in Table A.7 in Appendix. Second, the weighted normalized grey decision matrix ($\otimes Z$) was formulated as displayed in Table A.8 in Appendix. Third, the grey positive and negative ideal solutions ($\otimes R^{max}$, $\otimes R^{min}$) were also identified using Eqs. (15) and (16), as shown in Table A.9 in Appendix.

Fourth, the d_i^+, d_i^-, and CC_i were calculated for each alternative as shown in Table 7. Last, the alternatives were ranked based on values of

Table 6
The local weights, average local and global weights, ξ, CR^I, and CR^O.

Aspect of sustainability	Criteria	Expert 1	Expert 2	Average local weights	Average global weights
		0.08448	0.08370	0.08409	
	Cost	0.16330	0.22518	0.19424	0.01633
	Profit	0.08165	0.07506	0.07835	0.00658
	Flexibility	0.02021	0.02421	0.02221	0.00186
Economic aspect	Eight wastes	0.48989	0.37530	0.43259	0.03637
	Productivity	0.24495	0.30024	0.27259	0.02290
	ξ	0.01845	0.01803	0.01824	
	CR^I	0.07142	0.15277	0.11209	
	CR^O	0.00412	0.00344	0.00378	
		0.61035	0.61087	0.61061	
	Material usage	0.28775	0.27155	0.27965	0.17075
	Energy usage	0.17165	0.16293	0.16729	0.10214
	Water usage	0.05755	0.05431	0.05593	0.03415
	Air emissions	0.34530	0.38016	0.36273	0.22148
Environmental aspect	Wastewater	0.02166	0.02243	0.02205	0.01346
	Solid waste	0.11510	0.10862	0.11185	0.06829
	ξ	0.01785	0.01746	0.01766	
	CR^I	0.12500	0.15277	0.13888	
	CR^O	0.00399	0.00334	0.00366	
		0.30517	0.30543	0.30530	
	Work condition	0.15063	0.19607	0.17335	0.05292
	Health and safety	0.52722	0.45750	0.49236	0.15032
	Labour wellbeing and satisfaction	0.07531	0.06535	0.07033	0.02147
Social aspect	Society wellbeing and satisfaction	0.22595	0.261430	0.24369	0.074320
	Customer wellbeing and satisfaction	0.02088	0.01963	0.02026	0.00618
	ξ	0.01865	0.01848	0.01856	
	CR^I	0.12500	0.08330	0.10415	
	CR^O	0.00412	0.00353	0.00383	
ξ (for three aspects)		0.08545	0.08569	0.08557	
CR^I (for three aspects)		0	0.02380	0.02380	
CR^O (for three aspects)		0.01911	0.02297	0.02104	

Table 7
d_i^+, d_i^-, CC_i and ranking of alternatives.

Alternatives	d_i^+	d_i^-	CC_i	Ranking
$A1$	0.1602	0.5745	0.7819	6
$A2$	0.3077	0.6052	0.6630	10
$A3$	0.1488	0.5761	0.7948	5
$A4$	0.2606	0.6050	0.6989	9
$A5$	0.0577	0.6158	0.9144	1
$A6$	0.0713	0.6089	0.8952	2
$A7$	0.1205	0.5940	0.8313	3
$A8$	0.1414	0.5790	0.8037	4
$A9$	0.1588	0.5686	0.7817	7
$A10$	0.1785	0.5677	0.7607	8
$A11$	0.5020	0.6252	0.5547	12
$A12$	0.4578	0.6000	0.5672	11

CC_i as shown in Table 7. Table 7 shows that the 5th alternative (VSM) was ranked 1st, and the 6th alternative (Kaizen) was ranked 2nd, while the 11th alternative (SMED) was ranked 12th, and the 12th alternative (cellular manufacturing) was ranked 11th. Fig. 6 displays the relationship between the CC_i values and the ranking of alternatives. Fig. 7 also shows the relationship between positive and negative distances (d_i^+, d_i^-) and CC_i values.

6.4. Sensitivity analysis

In this subsection, a sensitivity analysis was performed to display the model's robustness

6.4.1. Impact of different distances on the alternatives' ranking

Sensitivity analysis plays a crucial role in the decision-making process. In this section, sensitivity analysis is performed by estimating the change in the Grey-TOPSIS method's final ranking of alternatives when using different distance measurements between alternatives and positive and negative ideal solutions to investigate the effect of different distances on the ranking of alternatives and test the robustness of the suggested model's results. This can be achieved using the Minkowski formula's general form (Lin et al., 2008b). Therefore, the form of determining the distance between two grey numbers can be shown below.

In order to see the effects of the change in distance measurement on the ranking of alternatives, the study used different values for P. In the case where $P = 1$, the distance is equivalent to the Manhattan distance. In the case where $P = 2$, the distance is equivalent to the Euclidean distance that was used in calculating the distances in Section 6.3 previously. Also, the same calculations were applied using Minkowski distance, where $P = 3$, $P = 4$, and $P = 5$ to see the change in the ranking of alternatives.

when $P = 1$

$$d_i^+ = \frac{1}{2}\sum_{j=1}^{n}[|\left(Z_j^+ - \underline{Z}_{ij}\right)| + |\left(Z_j^+ - \overline{Z}_{ij}\right)|],$$
$$d_i^- = \frac{1}{2}\sum_{j=1}^{n}[|\left(Z_j^- - \underline{Z}_{ij}\right)| + |\left(Z_j^- - \overline{Z}_{ij}\right)|], \tag{20}$$

when $P = 3$

$$d_i^+ = \sqrt[3]{\frac{1}{2}\sum_{j=1}^{n}[|\left(Z_j^+ - \underline{Z}_{ij}\right)^3| + |\left(Z_j^+ - \overline{Z}_{ij}\right)^3|]},$$
$$d_i^- = \sqrt[3]{\frac{1}{2}\sum_{j=1}^{n}[|\left(Z_j^- - \underline{Z}_{ij}\right)^3| + |\left(Z_j^- - \overline{Z}_{ij}\right)^3|]}, \tag{21}$$

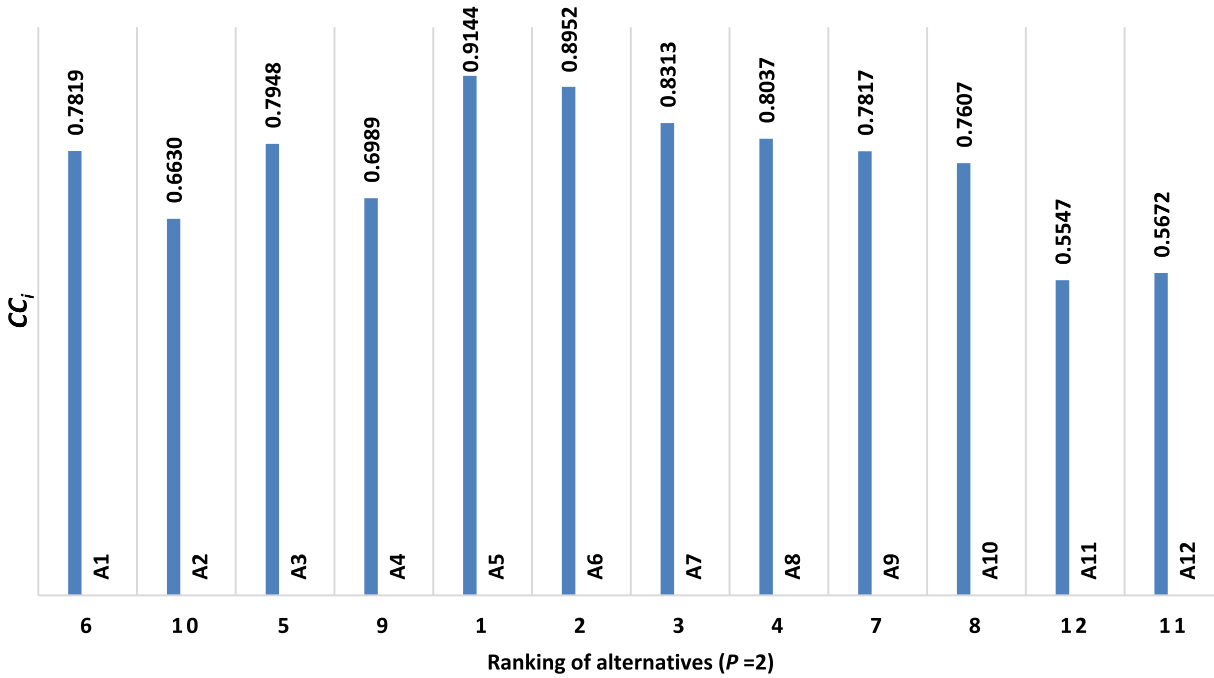

Fig. 6. The relationship between CC_i values and alternative ranking.

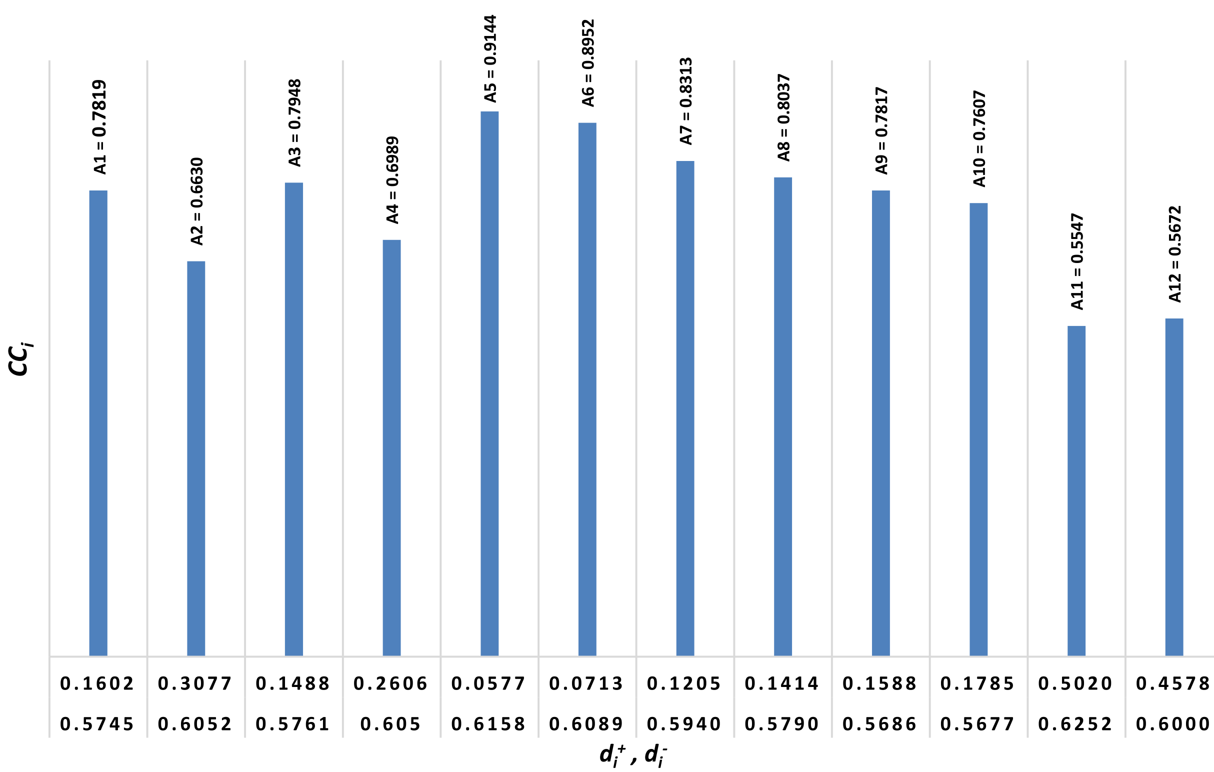

Fig. 7. The relationship between d_i^+,d_i^- and CC_i values.

when $P = 4$

$$d_i^+ = \sqrt[4]{\frac{1}{2}\sum_{j=1}^{n}[|\left(Z_j^+ - \underline{Z}_{ij}\right)^4| + |\left(Z_j^+ - \overline{Z}_{ij}\right)^4|]},$$
$$d_i^- = \sqrt[4]{\frac{1}{2}\sum_{j=1}^{n}[|\left(Z_j^- - \underline{Z}_{ij}\right)^4| + |\left(Z_j^- - \overline{Z}_{ij}\right)^4|]}, \quad (22)$$

when $P = 5$

$$d_i^+ = \sqrt[5]{\frac{1}{2}\sum_{j=1}^{n}[|\left(Z_j^+ - \underline{Z}_{ij}\right)^5| + |\left(Z_j^+ - \overline{Z}_{ij}\right)^5|]},$$
$$d_i^- = \sqrt[5]{\frac{1}{2}\sum_{j=1}^{n}[|\left(Z_j^- - \underline{Z}_{ij}\right)^5| + |\left(Z_j^- - \overline{Z}_{ij}\right)^5|]}, \quad (23)$$

Table 8
Manhattan distance (P =1).

Alt.	d_i^+	d_i^-	CC_i	Ranking
$A1$	0.1315	0.4310	0.7662	7
$A2$	0.2584	0.5238	0.6696	10
$A3$	0.1252	0.4577	0.7852	5
$A4$	0.2166	0.5134	0.7033	9
$A5$	0.0511	0.5015	0.9075	1
$A6$	0.0612	0.4882	0.8886	2
$A7$	0.0991	0.4682	0.8254	3
$A8$	0.1210	0.4605	0.7919	4
$A9$	0.1331	0.4365	0.7663	6
$A10$	0.1528	0.4496	0.7463	8
$A11$	0.4202	0.5841	0.5816	12
$A12$	0.3839	0.5569	0.5920	11

Table 9
Minkowski distance (P = 3).

Alt.	d_i^+	d_i^-	CC_i	Ranking
$A1$	0.1767	0.6396	0.7835	7
$A2$	0.3385	0.6478	0.6568	10
$A3$	0.1625	0.6398	0.7974	5
$A4$	0.2867	0.6526	0.6948	9
$A5$	0.0616	0.6820	0.9172	1
$A6$	0.0767	0.6753	0.8980	2
$A7$	0.1328	0.6586	0.8322	3
$A8$	0.1542	0.6430	0.8066	4
$A9$	0.1741	0.6334	0.7844	6
$A10$	0.1951	0.6296	0.7634	8
$A11$	0.5530	0.6444	0.5382	12
$A12$	0.5083	0.6264	0.5542	11

Table 10
Minkowski distance (P = 4).

Alt.	d_i^+	d_i^-	CC_i	Ranking
$A1$	0.1866	0.6756	0.7836	7
$A2$	0.3575	0.6723	0.6528	10
$A3$	0.1710	0.6769	0.7984	5
$A4$	0.3026	0.6800	0.6920	9
$A5$	0.0641	0.7212	0.9184	1
$A6$	0.0799	0.7143	0.8994	2
$A7$	0.1402	0.6954	0.8322	3
$A8$	0.1623	0.6804	0.8074	4
$A9$	0.1836	0.6704	0.7850	6
$A10$	0.2055	0.6655	0.7640	8
$A11$	0.5842	0.6552	0.5286	12
$A12$	0.5321	0.6427	0.5471	11

Table 11
Minkowski distance (P= 5).

Alt.	d_i^+	d_i^-	CC_i	Ranking
$A1$	0.1931	0.6983	0.7834	7
$A2$	0.3699	0.6879	0.6503	10
$A3$	0.1765	0.7007	0.7987	5
$A4$	0.3129	0.6974	0.6903	9
$A5$	0.0657	0.7465	0.9191	1
$A6$	0.0820	0.7393	0.9001	2
$A7$	0.1451	0.7188	0.8320	3
$A8$	0.1676	0.7042	0.8077	4
$A9$	0.1898	0.6939	0.7852	6
$A10$	0.2125	0.6884	0.7642	8
$A11$	0.6045	0.6621	0.5227	12
$A12$	0.5506	0.6532	0.5426	11

The study calculated the d_i^+ and d_i^- for all alternatives and calculated the values of (CC_i) for all alternatives as shown in Tables 8 to 11.

From Tables 8 to 11, it can be seen that both the values of d_i^+, and d_i^- for each alternative increase with increasing the P value. However, the CC_i values were increased disproportionately, where Tables 8 to 11 reveal that some CC_i values of alternatives were smaller even when using bigger P values. Nevertheless, although an extra four different distances were used by using four different values of P (P = 1, P = 3, P = 4, and P = 5) to rank the alternatives, the ranking of all alternatives remained similar to the rankings based on Euclidean distance (P = 2) except for $A1$ and $A9$ as they took each other's ranking.

Based on the new four scenarios, the VSM tool ($A5$) was ranked 1st and the Kaizen tool ($A6$) was ranked 2nd, while the SMED tool ($A11$) was ranked 12th and the cellular manufacturing tool ($A12$) was ranked 11th. The $A1$ was ranked 6th when the Euclidean distance (P = 2) was used, while it was ranked 7th when (P = 1, P = 3, P = 4, and P = 5) were used, while the A9 was ranked 7th when (P = 2) was used, and it was ranked 6th when (P = 1, P = 3, P = 4, and P = 5) were used. This indicates the stability and robustness of the model such that, despite using different values of distances that differ from the Euclidean distance through changes in the P values, the ranking of the alternatives did not change, except for the $A1$ and $A9$. Table 12 compares the rankings of the alternatives at the different P values.

6.4.2. The ranking of alternatives based on the criteria of each aspect of sustainability

An additional scenario was provided for the sensitivity analysis to determine the model's robustness. Alternatives (LM tools) can be ranked based on the criteria of each aspect of sustainability separately, neglecting the other aspects of sustainability. For example, the study ranked the LM tools based on the criteria of the economic aspect of sustainability and ignored the other aspects, and then ranked the LM tools based on environmental and social criteria using the same procedure. This procedure revealed the different rankings for alternatives based on each aspect of sustainability. Table 13 displays d_i^+, d_i^-, CC_i, and three additional rankings of alternatives based on the criteria of each aspect of sustainability separately.

Table 13 reveals a significant change in the ranking of the alternatives when the alternatives were ranked according to the metrics (criteria) of each aspect of sustainability. In the first scenario (ranking based on economic criteria), the $A6$ and $A5$ were ranked 1st and 2nd, respectively, while the $A11$ and $A12$ were ranked 12th and 11th, respectively. In the second scenario (ranking based on the environmental criteria), the $A5$ and $A6$ were ranked 1st and 2nd, respectively, while the $A11$ and $A12$ were ranked 11th and 12th, respectively. The third scenario (ranking based on social criteria) is slightly different, where the $A5$ was ranked 1st, and the $A4$ was ranked 2nd, while the $A6$ was ranked 7th. Also, the $A11$ and $A12$ were ranked 12th and 11th, respectively.

As for the rest of the alternatives, there is a clear change in most of the rankings in the three scenarios. These changes in the ranking provide insights for managers of companies and researchers to carefully consider each of the criteria for the aspects of sustainability when using LM tools according to priority. Table 13 shows how the ranking differed when it was conducted based on each aspect of sustainability separately, as some LM tools can affect the criteria of one aspect of sustainability more than the criteria of other aspects. Therefore, the ranking of the alternatives was different from the previous scenarios. This issue should be taken into account by managers when ranking alternatives.

6.4.3. Comparison of the results of the proposed methods with other methods

The suggested methods (BWM-Grey-TOPSIS) results have been compared with those obtained from other methods. First, the study used the OPA method to calculate the criteria weights and then compared those weights to those obtained from the BWM. The OPA method is one of the newly developed MCDM methods used to calculate the weights of the alternatives, criteria, and experts after some simple steps with no pairwise comparison, normalization, or decision matrix (Ataei et al., 2020; Mahmoudi et al., 2021c). This method utilizes ordinal data as inputs and is based on the linear programming (LP) technique (Mahmoudi et al., 2021a,b).

Table 12
The comparison of the rankings of alternatives using different distances.

Distances	Alternatives ranking											
	*A*1	*A*2	*A*3	*A*4	*A*5	*A*6	*A*7	*A*8	*A*9	*A*10	*A*11	*A*12
Manhattan Distance (P = 1)	7	10	5	9	1	2	3	4	6	8	12	11
Euclidean Distance (P = 2)	6	10	5	9	1	2	3	4	7	8	12	11
Minkowski Distance (P = 3)	7	10	5	9	1	2	3	4	6	8	12	11
Minkowski Distance (P = 4)	7	10	5	9	1	2	3	4	6	8	12	11
Minkowski Distance (P = 5)	7	10	5	9	1	2	3	4	6	8	12	11

Table 13
d_i^+, d_i^-, CC_i, and the ranking based on environmental and social criteria.

	Economic aspect				Environmental aspect				Social aspect			
Alt.	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank
*A*1	0.0134	0.0432	0.7627	5	0.1087	0.3548	0.7655	6	0.0381	0.1765	0.8226	9
*A*2	0.0186	0.0449	0.7069	8	0.2374	0.3870	0.6198	10	0.0517	0.1733	0.7704	10
*A*3	0.0142	0.0430	0.7519	7	0.1047	0.3528	0.7712	5	0.0299	0.1803	0.8577	5
*A*4	0.0240	0.0427	0.6401	9	0.2124	0.3766	0.6394	9	0.0242	0.1857	0.8847	2
*A*5	0.0067	0.0476	0.8765	2	0.0281	0.3831	0.9316	1	0.0228	0.1851	0.8902	1
*A*6	0.0056	0.0488	0.8972	1	0.0318	0.3808	0.9228	2	0.0339	0.1794	0.8412	7
*A*7	0.0138	0.0426	0.7549	6	0.0787	0.3688	0.8241	3	0.0279	0.1826	0.8672	3
*A*8	0.0105	0.0444	0.8092	3	0.1029	0.3531	0.7743	4	0.0280	0.1815	0.8662	4
*A*9	0.0128	0.0435	0.7723	4	0.1134	0.3454	0.7528	7	0.0325	0.1797	0.8466	6
*A*10	0.0243	0.0424	0.6355	10	0.1203	0.3463	0.7422	8	0.0340	0.1790	0.8405	8
*A*11	0.0409	0.0452	0.5252	12	0.2708	0.3772	0.5821	11	0.1903	0.2029	0.5159	12
*A*12	0.0267	0.0419	0.6106	11	0.3105	0.3797	0.5501	12	0.1206	0.1784	0.5967	11

Table 14
The comparison between the results of BWM and OPA.

Aspect of sustainability	Criteria	Average local weights for both experts based on BWM	Average global weights based on BWM	Average local weights for both experts based on OPA	Average global weights based on OPA
Economic aspect		0.08409		0.07576	
	Cost	0.19424	0.01633	0.14709	0.01114
	Profit	0.07835	0.00658	0.07475	0.00566
	Flexibility	0.02221	0.00186	0.02928	0.00221
	Eight wastes	0.43259	0.03637	0.49845	0.03776
	Productivity	0.27259	0.02290	0.25043	0.01897
Environmental aspect		0.61061		0.66029	
	Material usage	0.27965	0.17075	0.44443	0.29345
	Energy usage	0.16729	0.10214	0.24566	0.16221
	Water usage	0.05593	0.03415	0.14627	0.09658
	Air emissions	0.36273	0.22148	0.08830	0.05830
	Wastewater	0.02205	0.01346	0.05186	0.03424
	Solid waste	0.11185	0.06829	0.02347	0.01549
Social aspect		0.30530		0.26394	
	Work condition	0.17335	0.05292	0.13776	0.03636
	Health and safety	0.49236	0.15032	0.50152	0.13237
	Labour wellbeing and satisfaction	0.07033	0.02147	0.07309	0.01929
	Society wellbeing and satisfaction	0.24369	0.07432	0.25901	0.06836
	Customer wellbeing and satisfaction	0.02026	0.00618	0.02863	0.00755

The study has collected additional data to conduct the OPA method from the same two experts in the case company to compute the criteria weights. The study gave both experts equal weight values since they have the same years of experience at the case company. The study adopted and followed the steps and equations of the OPA method given by Ataei et al. (2020). Table 14 compares the weights of the criteria obtained from OPA and BWM.

Table 14 shows that when using the OPA method, the sum of the local weights of criteria in each aspect equals 1, and the sum of the global weights for all criteria is also equal to 1. Table 14 reveals that when comparing the local and global weights of criteria obtained from the BWM and OPA methods, it is obvious that there are differences in the weight values. However, the results are rational and reasonable in both methods, as the most influential metrics are still related to eight wastes in the economic aspect, air emissions in the environmental aspect, and health and safety in the social aspect, although the two methods used different decision-making processes.

As for the rest of the metrics, they have the same order of weights in both methods. However, the BWM provides two types of consistency ratios (CR^O and CR^I) that this study used to justify the reliability of the weights, but the OPA method does not have such measurements for consistency.

Second, the study determined the weight of the criteria using the Grey-BWM and compared them with the criteria weights obtained from the BWM. Therefore, the study combined the grey numbers with the BWM to calculate the criteria weights and consider the uncertainty during decision-making. In order to perform the pairwise comparison in Grey-BWM, the study has adopted grey linguistic variables (see the Appendix, Table A.10) (Bai et al., 2019; Mahmoudi et al., 2020).

After completing the pairwise comparisons, the study calculated $\otimes CR^I$ for each pairwise comparison using the formula for CR^I

Table 15
The local grey weights, average local and global grey weights, $\otimes\ \xi$, $\otimes\ CR^I$, and $\otimes\ CR^O$.

Aspect of sustainability	Criteria	Expert 1	Expert 2	Average local weights	Average global weights
Economic aspect		[0.01939, 0.08785]	[0.07974, 0.08718]	[0.04956, 0.08752]	
	Cost	[0.08239, 0.18108]	[0.21255, 0.23536]	[0.14747, 0.20822]	[0.00730, 0.01822]
	Profit	[0.07243, 0.08238]	[0.06724, 0.08502]	[0.06983, 0.08370]	[0.00346, 0.00732]
	Flexibility	[0.01136, 0.02217]	[0.02226, 0.02490]	[0.01681, 0.02353]	[0.00083, 0.00205]
	Eight wastes	[0.47080, 0.61790]	[0.34740, 0.38259]	[0.40910, 0.50024]	[0.02027, 0.04371]
	Productivity	[0.20596, 0.25351]	[0.29757, 0.30261]	[0.25176, 0.27806]	[0.01247, 0.02433]
	$\otimes\ \xi$	[0.01825, 0.01950]	[0.01790, 0.06261]	[0.01807, 0.04105]	
	$\otimes\ CR^I$	[0.04633, 0.18324]	[0.04098, 0.22891]	[0.04365, 0.20607]	
	$\otimes\ CR^O$	[0.00377, 0.00402]	[0.00298, 0.01043]	[0.00337, 0.00722]	
Environmental aspect		[0.49030, 0.65154]	[0.46013, 0.65175]	[0.47521, 0.65164]	
	Material usage	[0.28266, 0.30553]	[0.26825, 0.28569]	[0.27545, 0.29561]	[0.13089, 0.19263]
	Energy usage	[0.16974, 0.17987]	[0.15872, 0.17070]	[0.16423, 0.17528]	[0.07804, 0.11421]
	Water usage	[0.05139, 0.06789]	[0.04877, 0.06348]	[0.05008, 0.06568]	[0.02379, 0.04279]
	Air emissions	[0.33406, 0.37344]	[0.36580, 0.41267]	[0.34993, 0.39306]	[0.16629, 0.25613]
	Wastewater	[0.01549, 0.02353]	[0.01593, 0.02451]	[0.01571, 0.02402]	[0.00746, 0.01565]
	Solid waste	[0.06789, 0.12848]	[0.06348, 0.12193]	[0.06568, 0.12520]	[0.03121, 0.08158]
	$\otimes\ \xi$	[0.01756, 0.01853]	[0.01724, 0.02394]	[0.01747, 0.02123]	
	$\otimes\ CR^I$	[0.04247, 0.24607]	[0.04247, 0.24607]	[0.04247, 0.24607]	
	$\otimes\ CR^O$	[0.00362, 0.00382]	[0.00287, 0.00399]	[0.00325, 0.00390]	
Social aspect		[0.26061, 0.49030]	[0.26070, 0.46012]	[0.26065, 0.47521]	
	Work condition	[0.08236, 0.16848]	[0.15933, 0.20787]	[0.12084, 0.18817]	[0.03149, 0.08942]
	Health and safety	[0.50544, 0.61770]	[0.44544, 0.54176]	[0.47544, 0.57973]	[0.12392, 0.27549]
	Labour wellbeing and satisfaction	[0.06739, 0.08236]	[0.05939, 0.06673]	[0.06339, 0.07454]	[0.01652, 0.03542]
	Society wellbeing and satisfaction	[0.20590, 0.23587]	[0.22307, 0.26726]	[0.21448, 0.25156]	[0.05590, 0.11954]
	Customer wellbeing and satisfaction	[0.01165, 0.02281]	[0.01211, 0.02002]	[0.01188, 0.021415]	[0.00309, 0.01017]
	$\otimes\xi$	[0.01817, 0.01948]	[0.01687, 0.01929]	[0.01752, 0.01938]	
	$\otimes CR^I$	[0.04247, 0.24607]	[0.04247, 0.24607]	[0.04247, 0.24607]	
	$\otimes CR^O$	[0.00375, 0.00402]	[0.00281, 0.00321]	[0.00315, 0.00337]	
$\otimes\xi$ (for three main aspects)		[0.01932, 0.08658]	[0.08406, 0.08719]	[0.05169, 0.08688]	
$\otimes CR^I$(for three main aspects)		[0.05791, 0.10471]	[0.02010, 0.02877]	[0.03900, 0.06674]	
$\otimes CR^O$ (for three main aspects)		[0.00399, 0.01788]	[0.02055, 0.02131]	[0.01227, 0.01959]	

(Eq. (6)). After that, the study calculated the grey weights of the sustainability aspects and the criteria in each aspect using the BWM model (Eq. (7)). Finally, $\otimes CR^O$ was calculated using the formula of CR^O (Eq. (8)) but in this case, the study used a different consistency index. The equation from Mahmoudi et al. (2020) was used to determine the grey consistency index. Table A.11 in the Appendix shows the grey consistency index ($\otimes CI$). Table 15 shows local grey weights, average local grey weights, and average global grey weights for the sustainability aspects and all criteria for both experts. Table 15 also shows the values of $\otimes\xi$, $\otimes CR^I$, and $\otimes CR^O$ for both experts.

Table 15 reveals that all the values of the criteria weights obtained from the normal BWM method are located inside the values of the grey intervals obtained from Grey-BWM. Also, the values of the grey intervals of the $\otimes CR^I$ and $\otimes CR^O$ are close to zero. Moreover, none of the upper bounds of the intervals of $\otimes CR^I$ and $\otimes CR^O$ are bigger than the fixed thresholds (see the Appendix, Tables A.1 and A.3). Therefore, the pairwise comparisons are consistent, and the results are reliable and acceptable.

Third, the study used the Fuzzy-TOPSIS method to rank the alternatives and compare the results with the results of the Grey-TOPSIS method. Therefore, the study combined the fuzzy numbers with the TOPSIS to rank the alternatives and treat the problem of fuzzy uncertainty. After evaluating the alternatives with the help of experts, the study converted linguistic variables into fuzzy numbers (see the Appendix, Table A.12). After that, the study built the combined matrix to aggregate the assessments of alternatives concerning each criterion (Shamsuzzoha et al., 2021).

Then the study normalized the fuzzy decision matrix and determined the weighted normalized fuzzy decision matrix. The study also identified $R^{\max}$ and R^{min}. After that, the Euclidean distances (d_i^+, d_i^-) were calculated for each alternative using the formula from Shamsuzzoha et al. (2021). Last, the CC_i values were determined to rank the alternatives. Table 16 displays d_i^+, d_i^-, CC_i, and the new rankings of alternatives based on the Fuzzy-TOPSIS method and compares them with the ranking of the Grey-TOPSIS.

Table 16 shows that when using fuzzy numbers with the TOPSIS method to rank the alternatives, the CC_i, d_i^+, and d_i^- values became smaller because a different formula was used to calculate the d_i^+ and d_i^- in Fuzzy-TOPSIS. Nevertheless, Table 16 reveals that when ranking the alternatives using the Fuzzy-TOPSIS method, 10 out of 12 alternatives remained in the same ranking as in the previous method (Grey-TOPSIS).

These alternatives are $A2$, $A3$, $A4$, $A5$, $A6$, $A7$, $A8$, $A10$, $A11$, and $A12$. The other alternatives ($A1$ and $A9$) took each other's rankings. $A1$ was the 7th in Fuzzy-TOPSIS while it was the 6th in Grey-TOPSIS, and $A9$ was the 6th in Fuzzy-TOPSIS while it was the 7th in Grey-TOPSIS. This shows the consistency of the results and the robustness of the model; despite the different scales and methods used to rank the alternatives and treat the problem of uncertainty, most of the alternatives ranked similar to the original ranking.

All previous scenarios conducted in this study reveal that the VSM and Kaizen tools ($A5$ and $A6$) have the highest ranking among the set of LM tools because these tools greatly affect sustainability. For instance, the VSM tool lowers defects, cuts down on several sorts of time (cycle time, setup time, etc.), saves labour expenses, and raises productivity, efficiency, and quality. The VSM helps reduce environmental waste such as wastewater, solid waste, and air emissions by preventing the overuse of materials, water, and energy.

Operators can be aware of the environmental repercussions of industrial processes by using the VSM tool. This leads to instructions on properly using the resources, allowing the cement industry to gain significant environmental benefits. Last, the VSM tool can potentially improve stakeholder communication, ergonomics, and the health and safety of workers.

The Kaizen tool improves efficiency, quality, and production while lowering product defects. The Kaizen tool minimizes the use of raw materials, energy, costs, and production time. The Kaizen lowers inventory and boosts workplace health and safety. Additionally, it boosts employee engagement, enhances the competitive climate, strengthens collaboration within the workplace, and generates a collaborative, innovative, and proactive opportunity for continual development. Moreover, Kaizen encourages a problem-solving culture that is based on

Table 16
d_i^+, d_i^-, CC_i, and ranking of alternatives based on Fuzzy-TOPSIS and Grey-TOPSIS.

Alternatives	Fuzzy-TOPSIS				Grey-TOPSIS			
	d_i^+	d_i^-	CC_i	Ranking	d_i^+	d_i^-	CC_i	Ranking
$A1$	0.2136	0.2040	0.4885	7	0.1602	0.5745	0.7819	6
$A2$	0.2898	0.2066	0.4162	10	0.3077	0.6052	0.6630	10
$A3$	0.2055	0.2223	0.5196	5	0.1488	0.5761	0.7948	5
$A4$	0.2494	0.2127	0.4602	9	0.2606	0.6050	0.6989	9
$A5$	0.0740	0.2087	0.7382	1	0.0577	0.6158	0.9144	1
$A6$	0.0938	0.2134	0.6947	2	0.0713	0.6089	0.8952	2
$A7$	0.1502	0.1980	0.5686	3	0.1205	0.5940	0.8313	3
$A8$	0.1976	0.2171	0.5235	4	0.1414	0.5790	0.8037	4
$A9$	0.2260	0.2169	0.4897	6	0.1588	0.5686	0.7817	7
$A10$	0.2443	0.2240	0.4783	8	0.1785	0.5677	0.7607	8
$A11$	0.4141	0.2099	0.3364	12	0.5020	0.6252	0.5547	12
$A12$	0.4259	0.2330	0.3536	11	0.4578	0.6000	0.5672	11

scientific and systematic thinking, which can help cement companies address environmental issues by improving the performance of supporting flows and lowering the manufacturing process's environmental effects.

In contrast, SMED and cellular manufacturing tools ($A11$ and $A12$) have the lowest ranking among the list of LM tools. Using the SMED tool helps to reduce equipment setup time, overproduction, stock, power, material consumption, and air emissions. SMED decreases many environmental influences of the machines, such as oil leakage and chemical fumes, into the environment. However, because there are few dies to modify throughout cement manufacturing, using this equipment is unusual in cement firms.

Cellular manufacturing assists cement companies in reducing setup times and changing over time. It also reduces material transportation inside the company. Therefore, this tool could lower the cost, effort, resources, energy, and stress on employees. However, using this tool is unusual in cement companies because the cement manufacturing stages are difficult to complete in stages in the form of cells, as in other types of manufacturing industries.

The rankings of the remaining eight LM tools ($A1$, $A2$, $A3$, $A4$, $A7$, $A8$, $A9$, and $A10$) that the experts also evaluated ranged between the VSM and Kaizen tools ($A5$ and $A6$) on the one hand, and the SMED and cellular manufacturing tools ($A11$, and $A12$) on the other hand. This indicates that experts have seen that the impacts of the remaining 8 LM tools on 16 metrics of sustainability ranged between $A5$ and $A6$, which were ranked high, and $A11$ and $A12$, which were ranked low. The impacts of these LM tools on the sustainability of the manufacturing industry have been briefly discussed in Section 2.2.

7. Implications of the study

7.1. Theoretical implications

From the results of this study, it is clear that this research has significant outcomes for researchers, businesses, and manufacturers. This is the first study that has ranked the LM tools depending on their effects on sustainability metrics. This research has produced a set of TBL sustainability metrics (16 metrics) that can be used as a foundation for future research on selecting LM tools based on their impact on sustainability in the manufacturing industry, particularly in the cement industry. This study presented to practitioners and researchers a hybrid MCDM model that combines two methods (BWM and Grey-TOPSIS). This hybrid model can help researchers select and rank LM tools based on their impact on sustainability. In contrast, previous studies have ranked the LM tools based on their impact on economic criteria only.

This study has selected a set of 12 LM tools that show a great impact on the sustainability aspects of the manufacturing sector. The study offered more reliable results for researchers. It helped them select a suitable set of LM tools more accurately by using one of the modern MCDM methods (BWM) to determine the criteria weights, which can avoid the contradictions and inconsistencies of comparisons and lead to more reliable results. Moreover, unlike all of the reviewed research, this study addressed the grey uncertainty problem during the decision-making process of ranking LM tools

7.2. Managerial implications

In practice, the managers of cement companies are currently focusing on choosing approaches that support sustainability in their companies because of the pollution of the environment caused by their companies. When there are so many LM tools available, choosing from among them is a complex decision, thus corporate managers often use experience and common sense to make the selection decision. It can often be a waste of time and money if the incorrect LM tools are chosen. It is necessary to have an appropriate method to help companies select the right set of lean tools. Thus, this research allows businesses and organizations to use the hybrid MCDM model to choose the best collection of LM tools, as manufacturers should prioritize implementing the LM tools as one of the most critical conditions for success in LM employment.

As a result, using the generated ranking of LM tools mentioned in Table 7 can maximize the benefits of sustainability in their business. Therefore, the study will positively impact the economic aspects of companies and organizations by rationalizing and decreasing resource, energy, time, and labour expenses. It also enhances the social aspect by promoting team spirit, increasing employee satisfaction, and improving occupational safety procedures. Furthermore, the environmental aspect can be enhanced by lowering many negative consequences of the manufacturing processes, such as material consumption, liquid and solid waste generation, and water and energy consumption.

8. Conclusions

LM tools are techniques used to make manufacturing systems leaner and more sustainable. Applying unsuitable LM tools increases deficiencies and non-value-added activities in the cement manufacturing processes. The conclusions of this study can be summarized as follows:

- A group of 16 applicable TBL sustainability metrics (selection criteria) was proposed based on a comprehensive literature review and academic and industrial experts' evaluations.
- The study determined a list of 12 LM tools that have the most significant impacts on sustainability aspects.
- This study developed a new hybrid model for choosing and ranking the best set of LM tools based on their impact on sustainability, getting credible criteria weights, and addressing grey uncertainty in the decision-making process.
- To our knowledge, this is the first study to rank LM tools based on sustainability metrics, where the BWM and Grey-TOPSIS techniques were integrated for the first time for this purpose in this field.

Table A.1
Thresholds for a different number of criteria using CR^I.

Scale a_{bw}	Criteria						
	3	4	5	6	7	8	9
3	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
4	0.1121	0.1529	0.1898	0.2206	0.2527	0.2577	0.2683
5	0.1354	0.1994	0.2306	0.2546	0.2716	0.2844	0.2960
6	0.1130	0.1190	0.2643	0.3044	0.3144	0.3221	0.3262
7	0.1294	0.2457	0.2819	0.3029	0.3144	0.3251	0.3403
8	0.1309	0.2521	0.2958	0.3154	0.3408	0.3620	0.3657
9	0.1359	0.2681	0.3062	0.3337	0.3517	0.3620	0.3662

Note: in case of a_{bw} = 1, 2, and n = 2, the threshold is equal to zero.

Table A.2
Consistency index (CI).

Scale (a_{bw})	1	2	3	4	5	6	7	8	9
Consistency index (CI)	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

Table A.3
Threshold for different number of criteria using CR^O.

Scale ($\boldsymbol{a_{bw}}$)	Criteria						
	3	4	5	6	7	8	9
3	0.2087	0.2087	0.2087	0.2087	0.2087	0.2087	0.2087
4	0.1581	0.2352	0.2738	0.2928	0.3102	0.3154	0.3273
5	0.2111	0.2848	0.3019	0.3309	0.3479	0.3611	0.3741
6	0.2164	0.2922	0.3565	0.3924	0.4061	0.4168	0.4225
7	0.2090	0.3313	0.3734	0.3931	0.4035	0.4108	0.4298
8	0.2267	0.3409	0.4029	0.4230	0.4379	0.4543	0.4599
9	0.2122	0.3653	0.4055	0.4225	0.4445	0.4587	0.4747

Note: in case of abw = 1, 2, and n = 2, the threshold is equal to zero.

Table A.4
Grey linguistic variables with grey numbers.

Linguistic term	Very low influence (VLI)	Low influence (LI)	Medium influence (MI)	High influence (HI)	Very high influence (VHI)
Grey interval number	[0,2]	[2,4]	[4,6]	[6,8]	[8,10]

- The proposed model was evaluated at a real-life cement company in Iraq.
- The results of the BWM revealed that the most influential criteria were eight wastes in the economic aspect, air emissions in the environmental aspect, and health and safety in the social aspect.
- The result of the Grey-TOPSIS method showed that the most important alternative was the VSM tool, and the least significant alternative was the SMED tool. The rankings of the other tools ranged between these two based on the experts' estimations of their importance and their impacts on improving the sustainability of the cement industry.
- The study used three scenarios to verify the results. First, it ranked the alternatives using different distances instead of Euclidean distance. Second, it ranked the alternatives based on the criteria of each sustainability aspect. Third, it used other methods to determine the criteria weights and rank the alternatives, then compared the obtained results with those used in the proposed model. The results of the three scenarios verified the proposed model's robustness and reliability.

Although many solutions are presented in this study, there are some limitations. It did not consider the negative impact of some LM tools; only a few LM tools and sustainability metrics were considered; and the number of experts from the cement industry involved in the study was only two.

Several recommendations and directions can be followed in the future. First, future studies can modify and increase the number and types of LM tools that impact sustainability. Second, they can improve or adjust the number and types of sustainability metrics. Third, they could combine fuzzy numbers with BWM to treat fuzziness during pairwise comparisons. Fourth, researchers can use this study's LM tools and metrics in other industries after re-evaluating their applicability since they are generally suitable for the manufacturing sector. Fifth, the number of experts from cement companies can be increased in the evaluation processes of the BWM and TOPSIS methods to improve the reliability of the results. Sixth, the negative impacts of some LM tools, such as increased emissions or stress, can be considered in future studies.

Declaration of competing interest

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

Appendix

See Tables A.1–A.12.

Table A.5
The evaluation of the LM tools' effects on the sustainability metrics using grey numbers (expert 1).

LM tools	Sustainability metrics (criteria)															
(alternatives)	Cost ($C1$)	Profit ($C2$)	Flexibility ($C3$)	Eight wastes ($C4$)	Productivity ($C5$)	Material usage ($C6$)	Energy usage ($C7$)	Water usage ($C8$)	Air emissions ($C9$)	Wastewater ($C10$)	Solid waste ($C11$)	Work condition ($C12$)	Health and safety ($C13$)	Labour wellbeing and satisfaction ($C14$)	Society wellbeing and satisfaction ($C15$)	Customer wellbeing and satisfaction ($C16$)
(7S) ($A1$)	[4,6]	[2,4]	[6,8]	[4,6]	[4,6]	[4,6]	[4,6]	[2,4]	[2,4]	[2,4]	[4,6]	[2,4]	[4,6]	[2,4]	[4,6]	[2,4]
Just in Time (JIT) ($A2$)	[6,8]	[4,6]	[4,6]	[4,6]	[2,4]	[6,8]	[2,4]	[2,4]	[2,4]	[2,4]	[4,6]	[4,6]	[2,4]	[4,6]	[2,4]	[2,4]
Kanban ($A3$)	[4,6]	[4,6]	[2,4]	[4,6]	[2,4]	[6,8]	[4,6]	[2,4]	[2,4]	[4,6]	[4,6]	[4,6]	[4,6]	[6,8]	[4,6]	[4,6]
Visual Control/Visual Management ($A4$)	[2,4]	[2,4]	[2,4]	[4,6]	[2,4]	[4,6]	[4,6]	[2,4]	[2,4]	[2,4]	[2,4]	[4,6]	[8,10]	[2,4]	[4,6]	[2,4]
Value Stream Mapping (VSM) ($A5$)	[6,8]	[4,6]	[4,6]	[8,10]	[4,6]	[6,8]	[6,8]	[4,6]	[8,10]	[4,6]	[6,8]	[6,8]	[4,6]	[4,6]	[6,8]	[4,6]
Kaizen ($A6$)	[6,8]	[6,8]	[4,6]	[8,10]	[6,8]	[6,8]	[6,8]	[4,6]	[6,8]	[4,6]	[4,6]	[4,6]	[4,6]	[6,8]	[6,8]	[6,8]
Poka-yoke ($A7$)	[4,6]	[2,4]	[6,8]	[4,6]	[4,6]	[4,6]	[4,6]	[2,4]	[4,6]	[2,4]	[4,6]	[2,4]	[6,8]	[2,4]	[4,6]	[4,6]
Six Sigma ($A8$)	[4,6]	[6,8]	[6,8]	[4,6]	[4,6]	[4,6]	[2,4]	[2,4]	[2,4]	[4,6]	[8,10]	[4,6]	[4,6]	[2,4]	[4,6]	[4,6]
Total Productive Maintenance (TPM) ($A9$)	[4,6]	[2,4]	[6,8]	[4,6]	[6,8]	[2,4]	[6,8]	[2,4]	[4,6]	[2,4]	[2,4]	[2,4]	[4,6]	[2,4]	[4,6]	[2,4]
Production Smoothing (Heijunka) ($A10$)	[2,4]	[2,4]	[6,8]	[4,6]	[2,4]	[6,8]	[4,6]	[2,4]	[2,4]	[4,6]	[2,4]	[4,6]	[4,6]	[2,4]	[2,4]	[2,4]
Single-Minute Exchange of Die (SMED) ($A11$)	[0,2]	[0,2]	[0,2]	[2,4]	[4,6]	[4,6]	[2,4]	[2,4]	[0,2]	[0,2]	[0,2]	[2,4]	[0,2]	[2,4]	[2,4]	[2,4]
Cellular Manufacturing ($A12$)	[2,4]	[2,4]	[4,6]	[4,6]	[2,4]	[0,2]	[0,2]	[2,4]	[2,4]	[2,4]	[2,4]	[2,4]	[2,4]	[2,4]	[0,2]	[0,2]

Table A.6
The evaluation of the LM tools' effects on the sustainability metrics using grey numbers (expert 2).

LM tools	Sustainability metrics (criteria)															
(alternatives)	Cost ($C1$)	Profit ($C2$)	Flexibility ($C3$)	Eight wastes ($C4$)	Productivity ($C5$)	Material usage ($C6$)	Energy usage ($C7$)	Water usage ($C8$)	Air emissions ($C9$)	Wastewater ($C10$)	Solid waste ($C11$)	Work condition ($C12$)	Health and safety ($C13$)	Labour wellbeing and satisfaction ($C14$)	Society wellbeing and satisfaction ($C15$)	Customer wellbeing and satisfaction ($C16$)
(7S) ($A1$)	[2,4]	[2,4]	[6,8]	[6,8]	[4,6]	[2,4]	[4,6]	[0,2]	[4,6]	[0,2]	[4,6]	[4,6]	[4,6]	[4,6]	[2,4]	[2,4]
Just in Time (JIT) ($A2$)	[4,6]	[6,8]	[4,6]	[6,8]	[2,4]	[4,6]	[0,2]	[2,4]	[0,2]	[2,4]	[4,6]	[4,6]	[4,6]	[6,8]	[2,4]	[2,4]
Kanban ($A3$)	[4,6]	[4,6]	[4,6]	[6,8]	[4,6]	[6,8]	[2,4]	[2,4]	[2,4]	[4,6]	[4,6]	[2,4]	[4,6]	[6,8]	[4,6]	[6,8]
Visual Control/Visual Management ($A4$)	[4,6]	[6,8]	[2,4]	[4,6]	[2,4]	[4,6]	[4,6]	[0,2]	[0,2]	[2,4]	[2,4]	[4,6]	[6,8]	[4,6]	[2,4]	[4,6]
Value Stream Mapping (VSM) ($A5$)	[6,8]	[6,8]	[6,8]	[8,10]	[4,6]	[4,6]	[4,6]	[6,8]	[8,10]	[4,6]	[4,6]	[4,6]	[4,6]	[6,8]	[6,8]	[4,6]
Kaizen ($A6$)	[8,10]	[6,8]	[4,6]	[8,10]	[4,6]	[6,8]	[6,8]	[2,4]	[6,8]	[4,6]	[6,8]	[4,6]	[2,4]	[6,8]	[4,6]	[6,8]
Poka-yoke ($A7$)	[6,8]	[4,6]	[4,6]	[4,6]	[4,6]	[6,8]	[4,6]	[0,2]	[4,6]	[0,2]	[4,6]	[4,6]	[6,8]	[4,6]	[2,4]	[6,8]
Six Sigma ($A8$)	[6,8]	[4,6]	[4,6]	[6,8]	[4,6]	[6,8]	[4,6]	[2,4]	[2,4]	[2,4]	[6,8]	[6,8]	[4,6]	[4,6]	[4,6]	[8,10]
Total Productive Maintenance (TPM) ($A9$)	[6,8]	[4,6]	[4,6]	[4,6]	[4,6]	[2,4]	[4,6]	[2,4]	[2,4]	[2,4]	[4,6]	[4,6]	[6,8]	[4,6]	[2,4]	[2,4]
Production Smoothing (Heijunka) ($A10$)	[4,6]	[2,4]	[4,6]	[4,6]	[2,4]	[4,6]	[2,4]	[2,4]	[2,4]	[2,4]	[2,4]	[6,8]	[4,6]	[4,6]	[4,6]	[2,4]
Single-Minute Exchange of Die (SMED) ($A11$)	[2,4]	[2,4]	[4,6]	[2,4]	[4,6]	[2,4]	[2,4]	[0,2]	[2,4]	[2,4]	[2,4]	[0,2]	[2,4]	[0,2]	[0,2]	[4,6]
Cellular Manufacturing ($A12$)	[2,4]	[2,4]	[2,4]	[4,6]	[2,4]	[2,4]	[2,4]	[0,2]	[2,4]	[0,2]	[0,2]	[2,4]	[2,4]	[0,2]	[2,4]	[2,4]

Table A.7
Normalized grey decision-making matrix ($\otimes F^{*}$).

LM tools (alternatives)	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$	$C11$	$C12$	$C13$	$C14$	$C15$	$C16$
$A1$	[0.2000,0.3333]	[0.2500,0.5000]	[0.2500,0.3333]	[0.2857,0.4000]	[0.3333,0.5000]	[0.2000,0.3333]	[0.1667,0.2500]	[0.3333,1.0000]	[0.2000,0.3333]	[0.3333,1.0000]	[0.1667,0.2500]	[0.2000,0.3333]	[0.1667,0.2500]	[0.2000,0.3333]	[0.2000,0.3333]	[0.2500,0.5000]
$A2$	[0.1429,0.2000]	[0.1429,0.2000]	[0.3333,0.5000]	[0.2857,0.4000]	[0.5000,1.0000]	[0.1429,0.2000]	[0.3333,1.0000]	[0.2500,0.5000]	[0.3333,1.0000]	[0.2500,0.5000]	[0.1667,0.2500]	[0.1667,0.2500]	[0.2000,0.3333]	[0.1429,0.2000]	[0.2500,0.5000]	[0.2500,0.5000]
$A3$	[0.1667,0.2500]	[0.1667,0.2500]	[0.4000,0.6667]	[0.2857,0.4000]	[0.4000,0.6667]	[0.1250,0.1667]	[0.2000,0.3333]	[0.2500,0.5000]	[0.2500,0.5000]	[0.1667,0.2500]	[0.1667,0.2500]	[0.2000,0.3333]	[0.1667,0.2500]	[0.1250,0.1667]	[0.1667,0.2500]	[0.1429,0.2000]
$A4$	[0.2000,0.3333]	[0.1667,0.2500]	[0.5000,1.0000]	[0.3333,0.5000]	[0.5000,1.0000]	[0.1667,0.2500]	[0.1667,0.2500]	[0.3333,1.0000]	[0.3333,1.0000]	[0.2500,0.5000]	[0.2500,0.5000]	[0.1667,0.2500]	[0.1111,0.1427]	[0.2000,0.3333]	[0.2000,0.3333]	[0.2000,0.3333]
$A5$	[0.1250,0.1667]	[0.1429,0.2000]	[0.2857,0.4000]	[0.2000,0.2500]	[0.3333,0.5000]	[0.1429,0.2000]	[0.1429,0.2000]	[0.1429,0.2000]	[0.1000,0.1250]	[0.1667,0.2500]	[0.1429,0.2000]	[0.1429,0.2000]	[0.1667,0.2500]	[0.1429,0.2000]	[0.1250,0.1667]	[0.1667,0.2500]
$A6$	[0.1111,0.1429]	[0.1250,0.1667]	[0.3333,0.5000]	[0.2000,0.2500]	[0.2857,0.4000]	[0.1259,0.1667]	[0.1250,0.1667]	[0.2000,0.3333]	[0.1250,0.1667]	[0.1667,0.2500]	[0.1429,0.2000]	[0.1667,0.2500]	[0.2000,0.3333]	[0.1250,0.1667]	[0.1429,0.2000]	[0.1250,0.1666]
$A7$	[0.1429,0.2000]	[0.2000,0.3333]	[0.2857,0.4000]	[0.3333,0.5000]	[0.3333,0.5000]	[0.1429,0.2000]	[0.1667,0.2500]	[0.3333,1.0000]	[0.1667,0.2500]	[0.3333,1.0000]	[0.1667,0.2500]	[0.2000,0.3333]	[0.1250,0.1667]	[0.2000,0.3333]	[0.2000,0.3333]	[0.1429,0.2000]
$A8$	[0.1429,0.2000]	[0.1429,0.2000]	[0.2857,0.4000]	[0.2857,0.4000]	[0.3333,0.5000]	[0.1429,0.2000]	[0.2000,0.3333]	[0.2500,0.5000]	[0.2500,0.5000]	[0.2000,0.3333]	[0.1111,0.1429]	[0.1427,0.2000]	[0.1667,0.2500]	[0.2000,0.3333]	[0.1667,0.2500]	[0.1250,0.1667]
$A9$	[0.1429,0.2000]	[0.2000,0.3333]	[0.2857,0.4000]	[0.3333,0.5000]	[0.2857,0.4000]	[0.2500,0.5000]	[0.1429,0.2000]	[0.2500,0.5000]	[0.2000,0.3333]	[0.2500,0.5000]	[0.2000,0.3333]	[0.2000,0.3333]	[0.1429,0.2000]	[0.2000,0.3333]	[0.2000,0.3333]	[0.2500,0.5000]
$A10$	[0.2000,0.3333]	[0.2500,0.5000]	[0.2857,0.4000]	[0.3333,0.5000]	[0.5000,1.0000]	[0.1429,0.2000]	[0.2000,0.3333]	[0.2500,0.5000]	[0.2500,0.5000]	[0.2000,0.3333]	[0.2500,0.5000]	[0.1429,0.2000]	[0.1667,0.2500]	[0.2000,0.3333]	[0.2000,0.3333]	[0.2500,0.5000]
$A11$	[0.3333,1.0000]	[0.3333,1.0000]	[0.5000,1.0000]	[0.5000,1.0000]	[0.3333,0.5000]	[0.2000,0.3333]	[0.2500,0.5000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.2000,0.3333]
$A12$	[0.2500,0.5000]	[0.2500,0.5000]	[0.4000,0.6667]	[0.3333,0.5000]	[0.5000,1.0000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.2500,0.5000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.2500,0.5000]	[0.2500,0.5000]	[0.3333,1.0000]	[0.3333,1.0000]	[0.3333,1.0000]

Table A.8
A weighted normalized grey decision-making matrix (⊗Z) matrix.

LM tools (alternatives)	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$	$C11$	$C12$	$C13$	$C14$	$C15$	$C16$
$A1$	[0.0033,0.0054]	[0.0016,0.0033]	[0.0005,0.0006]	[0.0104,0.0145]	[0.0076,0.0114]	[0.0341,0.0569]	[0.0171,0.0256]	[0.0114,0.0342]	[0.0443,0.0738]	[0.0045,0.0135]	[0.0114,0.0171]	[0.0106,0.0176]	[0.0251,0.0376]	[0.0043,0.0072]	[0.0149,0.0248]	[0.0015,0.0031]
$A2$	[0.0023,0.0033]	[0.0009,0.0013]	[0.0006,0.0010]	[0.0104,0.0145]	[0.0114,0.0229]	[0.0244,0.0341]	[0.0341,0.1024]	[0.0085,0.0171]	[0.0738,0.2215]	[0.0034,0.0068]	[0.0114,0.0171]	[0.0088,0.0132]	[0.0301,0.0501]	[0.0031,0.0043]	[0.0186,0.0372]	[0.0015,0.0031]
$A3$	[0.0027,0.0041]	[0.0011,0.0016]	[0.0008,0.0014]	[0.0104,0.0145]	[0.0091,0.0152]	[0.0213,0.0285]	[0.0205,0.0341]	[0.0085,0.0171]	[0.0554,0.1107]	[0.0023,0.0034]	[0.0114,0.0171]	[0.0106,0.0176]	[0.0251,0.0376]	[0.0027,0.0036]	[0.0124,0.0186]	[0.0008,0.0012]
$A4$	[0.0033,0.0054]	[0.0011,0.0016]	[0.0010,0.0021]	[0.0121,0.0181]	[0.0114,0.0229]	[0.0285,0.0427]	[0.0171,0.0256]	[0.0114,0.0342]	[0.0738,0.2215]	[0.0034,0.0068]	[0.0171,0.0341]	[0.0088,0.0132]	[0.0167,0.0215]	[0.0043,0.0072]	[0.0149,0.0248]	[0.0012,0.0021]
$A5$	[0.0020,0.0027]	[0.0009,0.0013]	[0.0005,0.0008]	[0.0073,0.0091]	[0.0076,0.0114]	[0.0244,0.0341]	[0.0146,0.0205]	[0.0049,0.0068]	[0.0221,0.0277]	[0.0023,0.0034]	[0.0098,0.0137]	[0.0076,0.0106]	[0.0251,0.0376]	[0.0031,0.0043]	[0.0093,0.0124]	[0.0010,0.0015]
$A6$	[0.0018,0.0023]	[0.0008,0.0011]	[0.0006,0.0010]	[0.0073,0.0091]	[0.0065,0.0091]	[0.0213,0.0285]	[0.0128,0.0171]	[0.0068,0.0114]	[0.0277,0.0369]	[0.0023,0.0034]	[0.0098,0.0137]	[0.0088,0.0132]	[0.0301,0.0501]	[0.0027,0.0036]	[0.0106,0.0149]	[0.0007,0.0010]
$A7$	[0.0023,0.0033]	[0.0013,0.0022]	[0.0005,0.0008]	[0.0121,0.0181]	[0.0076,0.0114]	[0.0244,0.0341]	[0.0171,0.0256]	[0.0114,0.0342]	[0.0369,0.0554]	[0.0045,0.0135]	[0.0114,0.0171]	[0.0106,0.0176]	[0.0188,0.0251]	[0.0043,0.0072]	[0.0149,0.0248]	[0.0008,0.0012]
$A8$	[0.0023,0.0033]	[0.0009,0.0013]	[0.0005,0.0008]	[0.0104,0.0145]	[0.0076,0.0114]	[0.0244,0.0341]	[0.0205,0.0341]	[0.0085,0.0171]	[0.0554,0.1107]	[0.0027,0.0045]	[0.0076,0.0098]	[0.0076,0.0106]	[0.0251,0.0376]	[0.0043,0.0072]	[0.0124,0.0186]	[0.0007,0.0010]
$A9$	[0.0023,0.0033]	[0.0013,0.0022]	[0.0005,0.0008]	[0.0121,0.0181]	[0.0065,0.0091]	[0.0427,0.0854]	[0.0146,0.0205]	[0.0085,0.0171]	[0.0443,0.0738]	[0.0034,0.0068]	[0.0137,0.0228]	[0.0106,0.0176]	[0.0215,0.0301]	[0.0043,0.0072]	[0.0149,0.0248]	[0.0015,0.0031]
$A10$	[0.0033,0.0054]	[0.0016,0.0033]	[0.0005,0.0008]	[0.0121,0.0181]	[0.0114,0.0229]	[0.0244,0.0341]	[0.0205,0.0341]	[0.0085,0.0171]	[0.0554,0.1107]	[0.0027,0.0045]	[0.0171,0.0341]	[0.0076,0.0106]	[0.0251,0.0376]	[0.0043,0.0072]	[0.0149,0.0248]	[0.0015,0.0031]
$A11$	[0.0054,0.0163]	[0.0022,0.0066]	[0.0010,0.0021]	[0.0181,0.0363]	[0.0076,0.0114]	[0.0341,0.0569]	[0.0256,0.0512]	[0.0114,0.0342]	[0.0738,0.2215]	[0.0045,0.0135]	[0.0228,0.0683]	[0.0176,0.0559]	[0.0501,0.1503]	[0.0072,0.0215]	[0.0248,0.0743]	[0.0012,0.0021]
$A12$	[0.0041,0.0082]	[0.0016,0.0033]	[0.0008,0.0014]	[0.0121,0.0181]	[0.0114,0.0229]	[0.0569,0.1707]	[0.0341,0.1024]	[0.0114,0.0342]	[0.0554,0.1107]	[0.0045,0.0135]	[0.0228,0.0683]	[0.0132,0.0265]	[0.0376,0.0752]	[0.0072,0.0215]	[0.0248,0.0743]	[0.0021,0.0062]

Table A.9
Grey positive and negative ideal solutions of alternatives ($\otimes R^{max}$, $\otimes R^{min}$).

$\otimes R^{max}$	[0.0054,0.0163]	[0.0022,0.0066]	[0.0010,0.0021]	[0.0181,0.0363]	[0.0114,0.0229]	[0.0569,0.1707]	[0.0341,0.1024]	[0.0114,0.0342]	[0.0738,0.2215]	[0.0045,0.0135]	[0.0228,0.0683]	[0.0176,0.0559]	[0.0501,0.1503]	[0.0072,0.0215]	[0.0248,0.0743]	[0.0021,0.0062]
$\otimes R^{min}$	[0.0018,0.0023]	[0.0008,0.0011]	[0.0005,0.0008]	[0.0073,0.0091]	[0.0065,0.0091]	[0.0213,0.0285]	[0.0128,0.0171]	[0.0049,0.0068]	[0.0221,0.0277]	[0.0023,0.0034]	[0.0076,0.0098]	[0.0076,0.0106]	[0.0167,0.0215]	[0.0027,0.0036]	[0.0093,0.0124]	[0.0007,0.0010]

Table A.10
Grey linguistic variables for BWM.

Equally Important (EQI)	Weakly Important (WI)	Slightly important (SI)	Moderately important (MI)	Moderately plus important (MPI)	Strongly important (SI)	Strongly plus important (SPI)	Very strongly important (VSI)	Extremely important (EI)
[1, 1]	[1, 2.5]	[2.5, 3.5]	[3.5, 4.5]	[4.5, 5.5]	[5.5, 6.5]	[6.5, 7.5]	[7.5, 8.5]	[8.5, 10]

Table A.11
The grey consistency index ($\otimes CI$).

Linguistic terms	Equally important (EQI)	Weakly important (WI)	Slightly important (SI)	Moderately important (MI)	Moderately plus important (MPI)	Strongly important (SI)	Strongly plus important (SPI)	Very strongly important (VSI)	Extremely important (EI)
$\otimes (a_{bw})$	[1-1]	[1-2.5]	[2.5-3.5]	[3.5-4.5]	[4.5-5.5]	[5.5-6.5]	[6.5-7.5]	[7.5-8.5]	[8.5-10]
$\otimes (CI)$	0.00	0.708	1.30	1.95	2.64	3.35	4.09	4.84	6.00

Table A.12
Linguistic variables with triangular fuzzy number.

Linguistic term	Very low influence (VLI)	Low influence (LI)	Medium influence (MI)	High influence (HI)	Very high influence (VHI)
Fuzzy numbers	(2,2,4)	(2,4,6)	(4,6,8)	(6,8,10)	(8,10,10)

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