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# **Hierarchical Analysis of Barriers in Additive Manufacturing Implementation with Environmental Considerations under Uncertainty**

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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.

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## **Abstract**

Notwithstanding additive manufacturing has been gaining momentum in the industry, particularly during the fourth industrial revolution, their widespread implementation as a disruptive production technology has brought impacts on the environment. Considering this issue, the research for this paper was built upon the discussion concerning life cycle assessment (LCA) adoption in implementing additive manufacturing (AM). The capability of LCA to achieve environmental goals is a vivid illustration of why it has given researchers and practitioners an extensive impetus. However, to actualize such an effective approach, it is necessary to identify and face the barriers impeding its implementation in AM. Thus, this research aims to identify, classify, and analyze the most critical barriers hindering LCA adoption in AM implementation. To do so, the fuzzy analytical hierarchy process, along with a comprehensive literature review and thorough interviews with the relevant experts, was used to achieve the research purposes. The results revealed twenty-two barriers within five classifications, where the lack of financial resources to conduct LCA study on AM is the most dominant barrier, followed by the lack of LCA expertise in the AM context and the lack of laws and directives for LCA application in AM, respectively. The findings would be useful to decision-makers to develop suitable mitigation strategies and make more informed decisions with individual and/or cluster concentrations. This study can be fruitfully exploited as a guiding reference since no article has hitherto discussed, identified, or analyzed barriers in the understudied area.

## **Keywords**

Additive manufacturing, Life cycle assessment, Barriers, Automotive sector, Environmental sustainability, Fuzzy AHP, Sensitivity analysis

## 1. Introduction

Industrial metabolism, defined as the transformation of inputs like matter, energy, and labor into outputs like goods, services, waste, and ambient emissions, has made significant contributions in terms of value while having a detrimental effect on the environment and society due to consuming an inordinate amount of precious resources and generating hazardous wastes and emissions (Peng et al., 2018; Gholami et al., 2020). The field of additive manufacturing (AM), also known as 3D printing, has been gaining momentum in the industry, particularly during the fourth industrial revolution (Industry 4.0), which has developed to maximize industrial productivity. With the use of this technology, the creation of prototypes and proof-of-concept designs can be streamlined and accelerated for developing new products (Bourhis et al., 2013; Colorado et al., 2020). In comparison to conventional means, AM has been affirmed as a green technology (Peng et al., 2018) since it holds the potential to reduce the life cycle impacts such as material usage, energy consumption, and emissions, as well as enable greater engineering functionality by reducing the need for specialized tooling in part fabrication, speeding up tool production, and minimizing material waste (Peng et al., 2018; Bechmann, 2014; Faludi et al., 2015; Huang et al., 2016). In product-level sustainability, it is contended by Gholami et al. (2022) that AM enhances the capabilities for manufacturing sustainable products, enables shorter lead times for products, and decreases the requirement for product and component assembly and thus for customizing complex product designs.

However, AM is not necessarily more environmentally beneficial (Faludi et al., 2015; Kellens et al., 2017a; Colorado et al., 2020) since it also entails several inherent drawbacks such as energy usage (Gutowski et al., 2017; Gholami et al., 2022). According to Rejeski et al. (2018), AM carries potential environmental impacts due to the emissions generated from materials and energy consumption. Referring to Peng et al. (2018), the essential environmental factors to be examined as potential environmental impacts of AM include materials demands, process energy, life cycle energy, recyclable waste, non-recyclable waste, process emissions, and life cycle emissions. According to ISO 14001 (2015), environmental impact entails “the changes to the environment, whether adverse or beneficial, wholly or partially resulting from an organization's environmental aspects”. Therefore, it is essential to holistically evaluate the potential environmental impacts of AM so as to support decision-makers in making environmentally informed decisions. Following the viewpoints of Agustí-Juan and Habert (2017), Bekker and Verlinde (2018), and Saade et al. (2020), the current literature on assessing AM's environmental impacts appears to be scant, hence requiring

movements to generate significant outlooks since, based on Arvidsson et al. (2018), such assessments have been of critical importance to sustainable development, but also difficult due to the inherent uncertainties and lack of effective appraisal tools.

Life cycle assessment (LCA), which was first developed in the 1990s, is a widely accepted approach for measuring the potential environmental impact of various business operations and products (ISO14040, 2006; Böckin and Tillman, 2019; Gouveia et al., 2022). Contrary to other environmental impact assessment techniques such as Carbon Assessment or Design for the Environment, LCA enables quantifying the environmental impact of a global system effectively and with different criteria (Bourhis et al., 2013). Despite its growing use in the manufacturing context, studies examining the potential environmental impacts of AM using LCA are very limited (Ma et al., 2018; Saade et al., 2020; Gouveia et al., 2022), e.g., Faludi et al. (2017) conducted an LCA technique to examine the environmental impacts of AM machines and powder production. Further investigations into the environmental effects of AM using LCA are likewise called for (Frazier, 2014; Saade et al., 2020), particularly empirical investigations that offer systematic guidelines for succeeding in its adoption (Huang et al., 2017; Bekker and Verlinde, 2018). The effectiveness of LCA to meet environmental objectives exemplify why it has given researchers and practitioners an extensive impetus. However, to actualize such an effective approach, it is necessary to identify and face the barriers hindering its successful implementation (Hetherington et al., 2014; Long et al., 2016; Farooque et al., 2020).

Understanding the potential environmental impacts of AM from a life cycle perspective is found to be complicated since AM is an interdisciplinary technological field and, more importantly, there are always emerging barriers that pose serious challenges to LCA adoption in implementing AM in terms of managerial, organizational, technical knowledge, legal, and methodological aspects (Bekker et al., 2016; Pinna et al., 2018). According to Pinna et al. (2018), companies that already have management and employee commitment to sustainability values and business practices based on assumptions of potential environmental impacts will be able to successfully utilize LCA in the AM context. Meanwhile, the environmental knowledge required by LCA is rather advanced for design engineers to possess (Bhander et al., 2003). Such barriers are often interrelated or carry some significant weight. Therefore, it is critical to recognize key barriers and their level of importance to mitigate or overcome them during the appraisal process. This issue was also brought up by Dwivedi et al. (2017), who stated that in order to take the required preventative or corrective steps, it is crucial to scrutinize potential obstacles.

Thus, this research aims to identify, classify, and analyze the most critical barriers hindering LCA adoption in implementing additive manufacturing within automotive manufacturing systems. The automotive industry is an ideal setting for the analysis due to its size and impact on the ecosystem, considering that the usage of AM technology in this sector is expected to grow intensely (Böckin and Tillman, 2019). Yet, there is no research addressing the aforementioned noble aim at this moment, while, based on Schmidt and Sullivan (2002) and Farooque et al. (2020), there are significant obstacles to putting LCA into practice. To effectively implement AM with environmental considerations using this method, practitioners must first address the potential barriers to LCA adoption. (Ma et al., 2018; Saade et al., 2020). Thus, the contribution of this paper entails presenting a particular topic that is underexposed in the literature. In this regard, the fuzzy analytical hierarchy process (AHP), outlined as a fuzzy modification of AHP intended to remedy its deficiencies in handling ambiguity and uncertainty (Buckley, 1985), is applied due to its significance for determining the important weights of the identified barriers under fuzzy environments (Mangla et al., 2017).

To further showcase the research contributions, this article is systematized as follows: Section 2 presents a literature review on barriers; Section 3 explains the applied methods; Section 4 reveals the results and elaborates a discussion on the findings and implications; and, Section 5 delivers conclusions and recommendations.

## **2. Literature review**

This study investigates a topic that has yet to be explored in the literature. Hitherto, i.e., Dec. 2022, searches performed using the academic databases Scopus and Web of Science, which are the largest indexer of global research content and include titles and abstracts from plenty more leading publishers worldwide (Lee et al., 2021; Gholami et al., 2021), found no articles clearly discussing, identifying, and/or analyzing barriers hindering LCA adoption in the context of AM, as we debate below, considering that the query string used for the search has been ( ("Barriers" OR "Obstacles") AND ("Life Cycle Assessment" OR " Life Cycle Analysis" OR "LCA") AND ("Additive Manufacturing" OR "3D Printing" OR "AM") ) for titles and abstracts without restrictions or limitations.

### **2.1. Barriers to LCA adoption in AM**

Additive manufacturing (AM), outlined as the “procedure of combining materials layer by layer, to produce parts from 3D model data” (ISO 52900, 2015), is a cutting-edge technology holding the potential to significantly disrupt or revolutionize a wide range of

industries (Böckin and Tillman, 2019; Colorado et al., 2020). Nonetheless, it also entails a number of inherent drawbacks such as energy usage at a high level or restrictions on the types of materials and sizes that can be 3D-printed (Gutowski et al., 2017; Kellens et al., 2017b). Taking this into account, along with the expected expansion and development of AM, the implementation of metal AM across different industrial sectors requires careful consideration of the potential environmental and resource implications. In spite of the extensive literature discussing AM's energy usage, which is larger than that of conventional manufacturing, it appears that scholars show a higher interest in carbon-related information than primary energy usage in an LCA study. On such topics and assessments, very few reports have been contributed (Agustí-Juan and Habert, 2017; Saade et al., 2020).

It is expected that the number of published life cycle assessments (LCA) applied to AM will rise as environmental constraints become more important in employing manufacturing technologies. LCA is instrumental in determining the most efficient manufacturing method and appears to serve as a valuable lens to guarantee the environmental competitiveness of AM (Saade et al., 2020). It is an approach to comprehending the potential environmental impacts of a product or service throughout each of its life cycle stages (UNEP, 2015). The life cycle entails the raw materials' extraction and development through designing, processing, manufacturing, use, and end-of-life disposal (Ma et al., 2018). It is widely used in the public as well as private sectors, and it has developed from the initial energy analysis to impact and costing models and finally to a fully-fledged LCA in the twenty-first century (Guinée et al., 2011).

Nonetheless, there are a variety of hindrances arising when planning and conducting an LCA study, and these barriers have the potential to affect its effective adoption. According to Schmidt and Sullivan (2002) and Farooque et al. (2020), there are significant obstacles to putting LCA into practice, such as the fact that the accuracy of an LCA analysis is directly proportional to the quality of input data. Based on ISO 14044 (2006), "Data quality requirements shall be specified to enable the goal and scope of the LCA to be met." The requirements for data quality encompass time-related coverage, geographical coverage, technology coverage, etc. (Curran, 2017). Although promoting the value of such a systemic approach may be advantageous, performing the method precisely and producing a significant result requires attentiveness in terms of managerial, organizational, technical knowledge, legal, and methodological aspects. Practitioners must first confront the potential obstacles to LCA adoption, in order to effectively depict the benefits and loads of AM through this method (Ma et al., 2018; Saade et al., 2020). In the literature, no study exists on the

identification, classification, and analysis of barriers to LCA adoption in AM, as mentioned earlier. In pursuit of the research purpose, this section hence deals with the identification and classification of the key barriers in the context based on the review and interviews with experts, who were chosen on the basis of a methodological approach (see Section 3). The outcomes of this appraisal, which are discussed below, are systematically presented in Table 1.

### ***2.1.1. Management barriers***

Baldwin and Lin (2002) contend that an optimistic managerial mindset is essential for the effective introduction of cutting-edge technology. Existing environmental values in a company, particularly those acknowledging that sustainability must go beyond compliance, tend to facilitate the implementation of LCA (Heiskanen, 2000; Hunkeler et al., 2003; KPMG, 2005). There is a gap between the importance of environmental perspectives to a company's bottom line and the attention that upper management is willing to devote to them due to their busy schedules and inability to keep up with global developments in environmental legislation and markets (Schaper, 2002). Management's incessant fixation on productivity and production targets stifles innovation and new technological development. Since LCA is capital intensive and necessitates the acquisition of new software, expert knowledge, and real-time effective data collection, the authority to accept or implement LCA falls with the organization's management team. Lack of management awareness to recognize the benefit of LCA and a low understanding of products' environmental value will prevent them from deciding on the implementation of necessary environmental assessment (Testa et al., 2022). Thus, the linking of company objectives with LCA is critical to act as a backbone for the successful adoption of LCA within a company (Yao and Huang, 2019).

### ***2.1.2. Organizational barriers***

According to Rex and Baumann (2008), the effectiveness of LCA adoption is influenced by key employees' belief in their ability to transform and reshape the organization's structure and business sectors. Although key members of the team may be technically proficient as such, they often lack the interpersonal and organizational skills required for LCA implementation (Baumann, 2000; Frankl and Rubik, 1999). In this regard, the lack of financial resources has mainly been reported as a dominant barrier to organizations adopting environmentally sustainable practices (Kaswan and Rathi, 2021) since determining the appropriate investment amount and calculating the return on investment are always regarded as a matter of organizational concern. Implementing LCA in AM is costly due to the unpredictability of the market, which is caused by a scarcity of AM service

providers and the introduction of novel AM technology (Baumers et al., 2016; Berman, 2012). The lack of readiness models to evaluate their preparedness prior to adopting LCA is viewed as one of the other major barriers to its adoption in the AM context. The maturity of LCA adoption can be determined by referring to the technology readiness level acting as a qualitative grading system for assessing a technology's maturity level (Upadhyayula et al., 2018).

### ***2.1.3. Knowledge-based barriers***

LCA adoption necessitates extensive LCA knowledge and skills to yield the most accurate results. Part orientation, build volume maximization, layering strategy, and support generation are examples of AM process planning parameters that require manual intervention (Munguía et al., 2008). AM processes, particularly those involving metals and new-to-date technologies, are challenging. Materials including polymers, ceramics, and metals are all viable options for AM processes. Among the mentioned materials, metallic materials are drawing more attention from researchers and industries due to the fact that engineering centers employing metal-based additive technologies can create more durable tooling, allowing for the wider production of parts (Anderson et al., 2021). Metal AM may offer certain environmental benefits such as reduced waste, improved quality, lower pollutant emissions, and the ability to produce parts on demand. Based on Vafadar et al. (2021), four important challenges concerning the implementation of metal AM technology are production volume, standard compliance, product quality, and post-processing. The LCA study compares the current state of AM implementation to a potential future state to examine the future technological development of AM. According to Anderson et al. (2021), knowledge of the dimensions of 3D-printed parts and the potential effects of materials on various parameters, such as global warming potential, acidification potential, aquatic eco-toxicological risk, human toxicity, and stratospheric ozone depletion, is essential. All the LCA software parameters demanded a level of expertise that could only be provided by a trained professional. Aside from that, it is a challenging task to allocate someone knowledgeable about operating a precise LCA study (Kaswan and Rathi, 2021), particularly in the AM context since the environmental expertise demanded to conduct LCA studies, in the opinion of critics, is beyond the scope of design engineers (Bhander et al., 2003). Proper training is hence required to instill advanced abilities to this end (Rossi et al., 2016).

### ***2.1.4. Legal/Stakeholder barriers***

An effective framework to raise organizational awareness of the importance of LCA in AM is required to consolidate government policy on environmental issues (Rejeski et al.,

2018). Existing government policies and regulatory frameworks do not currently encourage its adoption in AM. Government agencies must provide aid in the form of financial incentives and encouragement for the manufacturing industry to move toward more sustainable methods of production (Lorek and Spangenberg, 2014; Parent et al., 2013). Furthermore, the government can encourage LCA developments in AM technology by emphasizing the importance of community management, moral appeals, and incentives. For example, if all competitors are required to pay pollution taxes, the cost-effectiveness of machinery and other LCA costs seems to be more achievable (Sharfman et al., 1997). A failure to actively engage with those in positions of authority undermines efforts to implement comprehensive systems for adopting policies and programs that promote sustainable development. Thus, a strong directive policy, regulatory framework, and financial penalties are mandatory to advance LCA in the AM context. To ensure the credibility and transparency of LCA studies, as well as to prevent non-expert stakeholders (e.g., the general public, funding agencies, marketing departments, and policymakers) from making skewed interpretations of the data, a greater emphasis on uncertainty communication is also needed (Ravikumar et al., 2018; Igos et al., 2019).

#### ***2.1.5. LCA adoption barriers***

When it comes to adopting LCA in the AM implementation, less formal operating procedures and processes are common in the context since there are very few studies investigating the topic. LCA initiatives may easily "fall through the cracks" if they are not well communicated, followed, and/or monitored (Seidel et al., 2009). The lack of a dedicated LCA method to decide the conduct of an LCA study in AM is a barrier that needs to be dealt with. Despite ongoing efforts to improve the LCA methodology, businesses continue to struggle with it due to a variety of issues, including the time and cost associated with accessing and analyzing data, as well as difficulties in maintaining a consistent set of standards (Remmen, 2003) and addressing different types of uncertainty and variability in LCA phases that can be derived from parameter, model, and scenario considerations (Huijbregts, 1998; Björklund, 2002; Rosenbaum et al., 2018). The final result of LCA is also affected by other factors such as the quality of input data and subjective interpretation techniques. Data quality issues, like a lack of transparency and data variation, can affect the reliability and consistency of LCA results. Furthermore, inconsistencies in functional units and system boundaries can lead to ambiguous LCA results (Hetherington et al., 2014).

### **3. Research Methodology**

In this research, a four-phase methodological approach is being considered for achieving the research purposes. It began with the literature study consisting of a review of previous studies on barriers, as discussed above. Next, the content validity was performed with an expert group. The fuzzy analytical hierarchy process (AHP), which is a fuzzy modification of AHP intended to remedy its deficiencies in handling ambiguity and uncertainty (Buckley, 1985), was further applied to analyze the identified barriers due to being sound logic and capable of decomposing the complexity of a decision-making problem under the fuzzy environment. The fuzzy set theory introduced by Zadeh (1965) is advantageous for addressing uncertainty in decision-making, allowing membership in a partial set instead of a crisp set. When comparing two alternatives, it is challenging for individuals to assign exact ratios; hence, fuzzy numbers automatically incorporate such ambiguity (Buckley, 1985). Following the fuzzy AHP and to examine the outputs, a sensitivity analysis was also carried out. The methodological phases taken in this study are further explained below.

### ***3.1. Barriers' identification and classification***

Based on a critical review of the most relevant studies; the studies investigating barriers to LCA adoption in various fields, in particular in the technological and manufacturing fields, since there is a lack of research on the topic (as discussed in Section 2), a checklist of 25 barriers was created, as shown in Table 1. These barriers have been classified into five main classes due to the representative characteristics of the identified barriers in the same class, namely: management barriers, organizational barriers, knowledge-based barriers, legal/stakeholder barriers, and lastly, LCA adoption barriers.

### ***3.2. Content validity***

To confirm the classifications and the relevancy of identified barriers, the checklist including 25 barriers and five classifications was assessed by a group of six academics, who had a direct relation to this research project, through the following criteria (Johnson and Morgan, 2016; Letchumanan et al., 2022): 1) each barrier's applicability and relevance, 2) clarity and coherence of each barrier with respect to the scale's objective, 3) use of simple, understandable terminology, 4) remove ambiguous words and phrases, 5) avoid an overabundance of technical or non-practitioner terms, and 6) removing jargon, colloquialisms, slang, and acronyms. The main amendments recommended by this experts' group were to improve the writing of the barriers that engage more relevant terms as well as to exclude three barriers that were regarded inappropriate - see Table 1.

### ***3.3. Barriers' analysis using fuzzy AHP***

AHP was initiated by Saaty (1980) as a quantitative method for making multi-criteria decisions. It is the most often applied approach for analyzing, prioritizing, planning, and developing (Wang et al., 2010; Dhingra et al., 2022). However, as a result of the unbalanced judgment scale and the absence of uncertainty, AHP has some limitations when used in a crisp environment; e.g., based on Wang et al. (2010), it is inapplicable once decision-makers confront a complex and uncertain issue and present their comparison decisions as uncertain ratios; thus, AHP is not very useful in the presence of uncertainty. This problem necessitates the application of the fuzzy approach, i.e., fuzzy AHP. In recent years, a number of researchers have taken advantage of this fuzzy-based method in a variety of fields. For instance, Dhingra et al. (2022) employed a fuzzy AHP-based analysis for the prioritization of barriers to offshore wind energy. Mangla et al. (2017) prioritized the barriers to achieving sustainable consumption and production trends in supply chains using fuzzy AHP. It is believed this method is more straightforward, scalable, and adaptable to a wide range of problem sizes as it does not rely on a large amount of data to be performed in comparison with the other multi-criteria decision-making methods (Ayhan, 2013; Dhingra et al., 2022). Rather than dictating the correctness or incorrectness of a decision, it aids decision-makers in analyzing complex systems and identifying the best alternative to meet the problem's stated objectives under conditions of uncertainty. Apart from that, it boosts expert participation and mutual cooperation, thus allowing the synthesis of multiple perspectives, trade-offs in determining the relative importance of attaining the best solution, and consensus for reaching the ultimate decision.

Using linguistic variables, the experts' judgments are made uncertain and imprecise by fuzzy AHP (Dhingra et al., 2022). In this regard, a set of triangular fuzzy numbers is determined to proceed with the application. Table 2 shows the triangular fuzzy number of linguistic variables used in this study following the work of Ayhan (2013). The expert group has to make the pairwise comparison of all criteria and sub-criteria, ranging from 'very low' to 'excellent'. At this point, industry experts have been brought together to form an expert group. The demographic profile of the experts is shown in Table 3. The expert group includes eight professionals, comprising three senior managers, three managers, and two senior engineers with considerable knowledge and experience in metal additive manufacturing within automotive manufacturing systems and environmental management – LCA.

Among others, these eight experts have accepted the interview session for data collection purposes; the data were collected within 35 days of the commencement date in 2022. The interview questionnaire seized two sections. The first section was about their

professional information such as educational qualification, occupation category, work experience, work profile classification, etc. In the second section, they were requested to assign a linguistic variable to the (sub)criteria on the fuzzy AHP pairwise comparison tables. The linguistic variables are then translated into the assigned triangular fuzzy numbers, as indicated in Table 2. Fuzzy AHP encapsulates the implementation process in some simple, logical, and common sense-based steps (Buckley, 1985; Ayhan, 2013), as follows:

**Step 1.** The pairwise comparison matrix is shown below:

$$\tilde{A} = \begin{bmatrix} \tilde{d}_{11} & \cdots & \tilde{d}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{d}_{n1} & \cdots & \tilde{d}_{nn} \end{bmatrix} \quad (1)$$

**Step 2.** According to Buckley (1985), Eq.2 below will be used to calculate the geometric mean of fuzzy comparison values in each criterion. In this context,  $\tilde{r}_i$  represents the triangular values for each (sub)criterion.

$$\tilde{r}_i = \left( \prod_{j=1}^n \tilde{d}_{ij} \right)^{1/n}, \quad i = 1, 2, \dots, n \quad (2)$$

**Step 3.** Each criterion's fuzzy weight can be obtained using Eq. 3, by comprising the following three steps.

**Step 4.** Calculate the vector summation of each  $\tilde{r}_i$ .

**Step 5.** Find the (-1) power of each vector summation and arrange the reverse vector summation in ascending order.

**Step 6.** To obtain the fuzzy weight of criterion  $i$  ( $\tilde{w}_i$ ), multiply each  $\tilde{r}_i$  with the reverse vector summation, which is in ascending order, as shown in the equation below:

$$\begin{aligned} \tilde{w}_i &= \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \cdots \oplus \tilde{r}_n)^{-1} \\ &= (lw_i, mw_i, uw_i) \end{aligned} \quad (3)$$

**Step 7.** Since  $\tilde{w}_i$  remain as fuzzy triangular numbers, the defuzzification needs to be done using the center of area method (Ayhan, 2013), by applying Eq. 4 below:

$$M_i = \frac{lw_i + mw_i + uw_i}{3} \quad (4)$$

**Step 8.** Normalization is necessary for normalizing risk attributes' ratings and normalizing the maturity attributes' values. The  $M_i$  achieved in the previous step is a non-fuzzy number, but it needs to be normalized by the following equation:

$$N_i = \frac{M_i}{\sum_{i=1}^n M_i} \quad (5)$$

The steps discussed above are performed to achieve the normalized weights of criteria and sub-criteria respectively. The final global value can be obtained by multiplying the sub-criteria weight with the relative criteria weight.

### **3.4. Sensitivity analysis**

Sensitivity analysis refers to the examination of how the 'outputs' of a system or model are associated with and affected by its 'inputs' (Razavi et al., 2021). Based on Saltelli et al. (2021), it is the instrument used to evaluate how the inference derived from a model depends on the underlying assumptions and characteristics. In general, there is a great deal of imprecision and fuzziness in the data obtained for multi-criteria decision-making issues; thus, a minor adjustment in relative weights might result in substantial alterations to the final ranking or decision (Mangla et al., 2017). In this study, sensitivity analysis is performed to monitor the priority ranking of key barriers hindering LCA adoption in implementing AM. In addition, it can reveal even a slight change in the ranking as a result of alterations to the relative weights of the criterion (Dhingra et al., 2022; Gholami et al., 2022).

## **4. Results and Discussion**

Automotive manufacturing industries have been under pressure in recent decades to enhance their sustainable performance due to unsustainable products and protocols that could harm the environment and society (Gholami et al., 2022). In order to mitigate the such type of harm, it is recommended that the auto industry moves toward sustainable manufacturing practices; hence, environmental initiatives should be implemented throughout the entire production process to lessen the potential environmental impacts and increase ecological efficiency in the automotive industry. Thus, the automotive industry was an ideal setting for the study due to its size and impact on the ecosystem, considering that the usage of AM technology in this sector is evolving over the years (Böckin and Tillman, 2019).

The research methodology used (see Section 3) in this context helps achieve the research purpose that takes into account several implications for those decision-makers who intend to identify, classify, and analyze the most critical barriers hindering LCA adoption in implementing AM within automotive manufacturing systems. Twenty-two barriers were accordingly identified through a critical review of the most relevant studies after performing the content validity, as discussed in Section 3.2. These barriers have been classified into five main classes (see Table 1) due to the representative characteristics of the identified barriers in the same class, including management barriers (MB), organizational barriers (OB), knowledge-based barriers (KB), legal/stakeholder barriers (LSB), and LCA adoption barriers (LAB).

Therefore, 22 sub-barriers were selected within 5 barriers to be further analyzed using the fuzzy AHP application (see Section 3.3). As shown in Table 2, the linguistic variable ratings employed range from ‘very low’ to ‘excellent’. The fuzzy comparison matrixes of barriers and their sub-barriers, along with the calculated weights, are consequently given in Tables 3–8. Table 10 shows the final global ranking for all 22 sub-barriers by multiplying the sub-barriers’ weight with the relative barrier’s weight. The analysis and prioritization of the barriers have been done by observing the highest weightage value, which shows the ranking for all barriers. As demonstrated in Table 4, the ranking order of the five barriers is: OB > KB > LSB > LAB > MB. Thus, ‘OB’ is ranked first among all barriers.

*Organizational barriers*—consisting of six sub-barriers, which are orderly ranked as follows: OB3 > OB1 > OB2 > OB5 > OB4 > OB6. As presented in Table 5, it is revealed that OB3 – lack of financial resources to conduct LCA study on AM – with the normalized weight of 0.488 is the most critical barrier in this highest-ranked classification, while OB6, by contrast, has had the lowest weight, i.e., 0.046. Based on the comment of the expert, implementing LCA in AM is costly due to the unpredictability of the market, which is caused by a scarcity of AM service providers. Thus, it is mainly reported as a fundamental barrier to organizations that adopt environmentally-sustainable techniques and tools (Kaswan and Rathi, 2021). Next to the top barrier is the OB1, i.e., lack of LCA readiness in AM scope. Effective adoption of LCA necessitates comprehensive readiness from the whole organization and all involved team members. OB2, i.e., lack of proper organizational structure and support, appears next on the priority list. Rex and Baumann (2008) contend that proper organizational structure and support influence the effectiveness of the LCA study, as key employees should be well informed of their responsibilities in this LCA implementation. The fourth-ranked barrier is OB5, i.e., insufficient team effort across supply chain networks to

collect relevant data, followed by OB4 and OB6, i.e., lack of inventory data and lack of effective data assimilation, respectively. The results highlight a key adoption factor of LCA, which is the necessity for inter-organizational collaboration to supervise the potential environmental impacts of a product along its entire lifecycle. An organization needs to put efforts beyond the current circumstances and perform business responsibilities from environmental perspectives. Going through the final global ranking of sub-barriers (see Table 10) indicates that out of a total of 22 barriers, only one barrier under organizational barriers falls into global rank five – OB3 occupied the top first global rank as such.

*Knowledge-based barriers*—consisting of four sub-barriers, which are orderly ranked as follows: KB2 > KB1 > KB3 > KB4. As presented in Table 6, it is revealed that KB2 – lack of LCA expertise in the AM context – with the normalized weight of 0.484 is the most critical barrier in this classification. Based on the comment of the expert, it is a challenging task to allocate someone, who is qualified to run a precise LCA application in AM since there is a significant paucity of knowledge as such. However, according to Bhandar et al. (2003), the environmental expertise demanded to conduct an LCA study is beyond the scope of design engineers. The second-ranked barrier is the KB1 – lack of LCA knowledge in the AM area. To conduct LCA in the AM context, a certain level of knowledge regarding the potential effects of materials on various parameters needs to be mastered such as global warming potential, acidification potential, aquatic eco-toxicological risk, human toxicity, and stratospheric ozone depletion (Anderson et al., 2021). Subsequently, barrier KB3 – lack of training on LCA software – is ranked next. Intensive training on LCA software is needed for the employee to become familiar with its operation (Rossi et al., 2016). Finally, barrier KB4 – LCA training difficulty – is last on the list. Hence, the absence of a knowledge base to comprehend LCA is considered one of the major barriers in additive manufacturing that needs to be dealt with. Sufficient knowledge, skills, and experience will transform the employees into proficient LCA experts. Going through the final global ranking of sub-barriers indicates that two barriers under knowledge-based barriers – KB2 and KB1 – occupied the second and fourth global ranks, respectively (Table 10).

*Legal/stakeholder barriers*—consisting of five sub-barriers, which are orderly ranked as follows: LSB2 > LSB1 > LSB4 > LSB3 > LSB5. As presented in Table 7, it is revealed that LSB2 – lack of laws and directives for LCA application in AM – with the normalized weight of 0.473 is the most critical barrier in this classification. Based on the comment of the expert, the main goal of a company is to maximize profit and minimize cost; thus, if the LCA adoption is not mandatory and enforced by any regulatory law, financial resources will not be

allocated to this end. Therefore, the government's role is extremely essential to ensure promising sustainable practices among industrial companies (Parent et al., 2013). The next barrier LSB1 – lack of government supportive policies on remanufacturing environmental assessment – which ranked second in this category. Besides regulatory frameworks, the government should introduce supportive policies as well as financial incentives and encouragement to boost LCA adoption in the manufacturing industry (Lorek and Spangenberg, 2014; Parent et al., 2013). LSB4 – lack of standard LCA practices for AM – appears next in this priority list. The lack of standardization can be a major deterrent for LCA practitioners, and it is necessary to understand and clarify issues such as conflicting LCA practices (Zakaria et al., 1999). The fourth-ranked barrier is LSB3 – lack of public attention to environmental issues. Government policy on environmental issues needs to be integrated into an effective framework to raise public awareness regarding the importance of implementing LCA studies on AM technology (Rejeski et al., 2018). The last rank in this category is LSB5 – communication of LCA results to a wide range of stakeholders with uncertain implications. The government, which acts as a country's backbone, is obliged to incorporate necessary initiatives and efforts such as strong directive policies, regulatory framework, and standard LCA practices in order to support the LCA adoption in the AM context. Going through the final global ranking of sub-barriers indicates that LSB2 occupied the third global rank (Table 10).

*LCA adoption barriers*—consisting of three sub-barriers, which are orderly ranked as follows: LAB2 > LAB1 > LAB3. As presented in Table 8, it is revealed that LAB2 – lack of dedicated LCA method to decide the conduct of LCA study in AM – with the normalized weight of 0.469 is the most critical barrier in this classification. Based on the comment of the expert, since AM is an emerging technology, there are insufficient industrial examples and experiences to draft an appropriate LCA study in AM. Based on Seidel et al. (2009), LCA initiatives may easily "fall through the cracks" if they are not well communicated, followed, or monitored. Following this, the second-ranked barrier in this category is LAB1 – inconsistency of LCA results. The final LCA result can be affected by factors such as data quality issues and inconsistencies in functional units and system boundaries (Hetherington et al., 2014). The last barrier is LAB3 – LCA is time-intensive, and assessment time is essential to support technology development. LCA is rather time-consuming during the rapidly changing stages of product development. Most resource commitments are made early in the design process, thereby complicating the precise environmental parameter evaluation and

cost-performance trade-offs (McAloone & Evans, 1997). Going through the final global ranking of sub-barriers indicates that LAB2 occupied the fifth global rank (Table 10).

*Management barriers*—consisting of four sub-barriers, which are orderly ranked as follows: MB4 > MB3 > MB1 > MB2. As presented in Table 9, it is revealed that MB4 – lack of synergy between LCA-AM and company objectives – with the normalized weight of 0.419 is the most critical barrier in this classification. Based on the comment of the expert, the synergy of LCA-AM should be incorporated into the company’s blueprint in order to draw the management team’s attention. Subsequently, the second-ranked barrier is MB3 – lack of environmental awareness about the AM business model. A low understanding of management on products’ environmental value will discourage their decisions on environmental initiatives (Testa et al., 2022). The third-ranked barrier is MB1 – insufficient management support. LCA implementation requires the purchase of new software, expert knowledge, and real-time effective data collection. Hence, insufficient management support will hinder its effective adoption (Kaswan & Rathi, 2021). The last barrier in this category is MB2 – resistive culture to use LCA to assess AM technology. The resistive culture of management to adopting LCA within the company is considered a barrier, and changing existing management core values within an organization is challenging. Based on ISO 14001 (2015), the success of the adoption of an environmental management system necessitates commitment from all levels and functions of the organization, which is led by top management. Going through the final global ranking of sub-barriers indicates that MB2 occupied the last global rank (Table 10).

#### **4.1. Sensitivity analysis**

Sensitivity analysis, regarded as the hermeneutics of mathematical modeling (Saltelli et al., 2021), is employed to prove the validity of the applied methodology’s robustness (Dhingra et al., 2022). Based on Gholami et al. (2022), it is utilized by introducing slight changes to the weights’ values to observe their impacts on the decision and verify the reliability of the conclusions drawn from the data. As shown in Table 4, among all five classifications, the organizational barriers (OB) has the highest ranking, with a weight of 0.303, implying that any modification to the organizational barriers can potentially influence the ranking of other barriers. The use of sensitivity analysis allows for measuring the influence of organizational barriers on the other barriers and also on the sub-barriers in each classification. As exposed in Table 11, the weight of OB varied from 0.1 to 0.9; the impact

was also apparent in the other classifications. This analysis was hence conducted to examine the impact of the 22 barriers that are grouped under five classes – see Table 12.

As outlined in Fig. 1, by increasing the weight of OB to 0.9, the barrier OB3 remains the first rank, highlighting that this is one of the dominant barriers that ranked first. Interestingly, the last barrier, i.e., MB2, by increasing the weight of OB to 0.9, remains the same, meaning that had no impact on the organizational barrier's value. But, by increasing the weight of OB, the second rank, which is KB2, will be decreased. Therefore, the sensitivity analysis indicates that any increase in the value of OB has no impact on the rank of the top first sub-barrier, highlighting that undivided attention should be paid by decision-makers to organizational barriers as the most critical barrier.

## ***4.2. Implications***

LCA is an approach to comprehending the potential environmental impacts of a product or service throughout each of its life cycle stages. To remain competitive in the market, manufacturing companies have to pursue rigorous material and energy efficiency improvements. This article is beneficial for additive manufacturing industries, which necessitate the effective adoption of LCA in their processes to improve both operational and sustainable performance. In this context, the results of the study, which are the prioritization of LCA barriers through fuzzy AHP, contribute to LCA practice by facilitating the organization's top management's decisions in identifying, managing, and overcoming any barriers to LCA implementation. Policymakers will also benefit from this since it will help them create more effective policies that help industrial companies on their path to sustainability.

### ***4.2.1. Theoretical Implications***

This article has theoretical implications for future researchers and newcomers to LCA adoption in the context of additive manufacturing. It extends the literature by utilizing fuzzy AHP, a multiple-criterion decision-making method, to analyze the severity of various barriers to LCA adoption in the AM. Furthermore, this expands researchers' theoretical understanding of LCA, which is regarded as one of the most effective environmental assessments in the manufacturing industry, and will fuel efforts to create a variety of adoption measures that will boost LCA implementation in the additive manufacturing sector.

### ***4.2.2. Practical Implications***

Through a systematic understanding of the barriers involved, the appraisal approach makes it possible for industrial companies and managers to adopt LCA effectively. By

establishing financial institutions to facilitate better access to financing for industrial settings that intend to adopt LCA for environmental performance assessment, the barrier of "lack of financial resources" can be overcome. The manufacturing industry can employ a variety of strategies to boost internal competencies for LCA implementation in the AM context. The company should create a memorandum of understanding in conjunction with environmental organizations, academic and research institutes in order to gain access to funding, technical knowledge, and capacity improvement through educational programs. This cooperative strategy will mitigate the costs associated with attaining training from external agencies as well as eliminate barriers of resistive culture, lack of LCA readiness, lack of training, lack of knowledge, insufficient environmental awareness of management, and several other mentioned barriers. Making team members in the company accountable for LCA adoption and fostering a culture of mutual learning and cooperation that aids in the collection of useful data and thus develops expertise knowledge is therefore a successful strategy for overcoming LCA's primary adoption barriers. The appropriate laws and regulations, as well as supportive government policies, will effectively devote to the wide implementation of LCA in the context of the additive manufacturing industry. The current work will benefit society in terms of enhanced health and motivation for industrial work owing to lower emissions, which will contribute to a healthy society and a better planet for living beings.

## **5. Conclusion and Recommendations**

It is appeared that the investigation on assessing AM's environmental impacts is rather limited, necessitating further rhythms to develop this research stream along with environmental considerations since such an assessment has been of critical importance to sustainable development; however, due to the inherent uncertainties and lack of efficient appraisal methods, it is also observed to be challenging. In this regard, LCA is reported to be a competent methodology in measuring the potential environmental impact of various business operations and products; yet, there are very few studies investigating the environmental effects of AM using LCA. Going through the literature via the most reliable academic databases – Scopus and Web of Science – indicated even that no articles explicitly discuss and/or systematically examine barriers impeding LCA adoption in the AM context. To be conscious and cognizant of the obstacles to take the necessary actions to prevent or to unravel them is what motivated the current research. Thus, the contribution of this study entails identifying, classifying, and analyzing the most critical barriers hindering LCA adoption in additive manufacturing implementation. In doing so, the fuzzy analytical

hierarchy process (AHP) method, which is a fuzzy adaptation of AHP to remedy its deficiencies in addressing ambiguity and uncertainty, was applied, along with a sensitivity analysis to examine the outputs.

In line with the research objectives, twenty-two barriers were identified through a critical review of the most relevant studies after performing the content validity. These barriers have been classified into five main classes due to the representative characteristics of the identified barriers in the same class, namely: management barriers, organizational barriers, knowledge-based barriers, legal/stakeholder barriers, and LCA adoption barriers. The results obtained by the fuzzy AHP application revealed that the 'organizational barriers' is ranked first among all barriers. It is also uncovered that 'lack of financial resources', with a global value of 0.14791, is the most dominant sub-barrier, followed by the 'lack of LCA expertise in the AM context' and the 'lack of laws and directives for LCA application in AM, respectively. Moreover, the sensitivity analysis indicated that any increase in the value of organizational barriers has no impact on the rank of the topmost sub-barrier, highlighting that undivided attention should be paid to organizational barriers as the most critical one. The findings would be useful to decision-makers to develop suitable mitigation strategies and make more informed decisions with individual and/or cluster focus.

This study can be fruitfully exploited as a guiding reference since no article has hitherto investigated barriers in the understudied area, considering that the academic databases used for the search were Scopus and Web of Science. It may complement the research on developing AM sustainability using LCA, which is the subject of growing interest in the field. However, the research findings, which have been indicative rather than conclusive, are subject to the limits that recommend directions for future studies. Although it is attempted to cover the key barriers by thoroughly reviewing the literature, there may be other critical barriers needing to be considered, classified, and examined in the understudied context. The findings presented in this study were mostly attributable to the expert suggestions; thus, appraisal procedures need to be conducted with careful consideration. The applied fuzzy AHP-based analytical method may be adopted to other industries in order to increase the efficiency of their LCA adoption in the AM context; however, other multi-criteria decision-making techniques such as ANP, ELECTRE, VIKOR, TOPSIS, etc. may also be applied in future research. Future investigations might likewise employ ISM, DEMATEL, and so forth to examine interactions within and between the identified barriers. Considering this, future studies can further be expanded to promote more comprehensive

methodologies scrutinizing barriers and particularly the solutions supporting decision-makers to overcome the barriers across different contexts.

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## Tables Captions

**Table 1**  
Barriers along with criteria and sub-criteria.

Barrier	Code	Sub-barrier	Approved	Removed	References
Management barriers	MB1	Insufficient management support	✓		Clark & de Leeuw (1999); Heiskanen (2000); Baldwin & Lin (2002); Hunkeler et al. (2003); KPMG (2005); Schaper (2002); Lorek & Fuchs (2013); Pinna et al. (2018); Yao & Huang (2019)
	MB2	Resistive culture to use LCA to assess AM technology	✓		
	MB3	Lack of environmental awareness about the AM business model	✓		
	MB4	Lack of synergy between LCA-AM and company objectives	✓		
	MB5	Dissociate the AM-LCA from the company's goal		X	
Organizational barriers	OB1	Lack of LCA readiness in AM scope	✓		Upadhyayula et al. (2018); Frankl & Rubik (1999); Stone (2006); Baumann (2000); Rex & Baumann (2008); Berman (2012); Hetherington et al. (2014); Rejeski et al. (2018); Farooque et al. (2020); Kaswan & Rathi (2021)
	OB2	Lack of proper organizational structure and support	✓		
	OB3	Lack of financial resources to conduct LCA study on AM	✓		
	OB4	Lack of inventory data	✓		
	OB5	Insufficient team effort across supply chain networks to collect relevant data	✓		
	OB6	Lack of effective data assimilation	✓		
	OB7	Difficulty to collect data from supplier		X	
Knowledge-based barriers	KB1	Lack of LCA knowledge in the AM area	✓		Bhander et al. (2003); Munguía et al. (2008); Anderson et al. (2021); Farooque et al. (2020); Kaswan & Rathi (2021)
	KB2	Lack of LCA expertise in the AM context	✓		
	KB3	Lack of training on LCA software	✓		
	KB4	LCA training difficulty	✓		
Legal/Stakeholder barriers	LSB1	Lack of government supportive policies on remanufacturing environmental assessment	✓		Parent et al. (2013); Sharfman et al. (1997); Clark & de Leeuw (1999); Rejeski et al. (2018); Hetherington et al. (2014); Igos et al. (2019); Ravikumar et al. (2018)
	LSB2	Lack of laws and directives for LCA application in AM	✓		
	LSB3	Lack of public attention to environmental issues	✓		
	LSB4	Lack of standard LCA practices for AM	✓		
	LSB5	Communication of LCA results to a wide range of stakeholders with uncertain implications	✓		
LCA adoption barriers	LAB1	Inconsistency of LCA results	✓		Huijbregts (1998); Björklund (2002); Rosenbaum et al. (2018); Hauschild et al. (2018); Hetherington et al. (2014); Remmen (2003); Bhander et al. (2003); Seidel et al. (2009)
	LAB2	Lack of dedicated LCA method to decide the conduct of LCA study in AM	✓		
	LAB3	LCA is time-intensive and assessment time is essential to support technology development	✓		
	LAB4	LCA consumes a longer period for study completion		X	

**Table 2**

Linguistic variables for the rating and comparison matrix.

Linguistic variables	Code	Assigned triangular fuzzy numbers
Equal	EQ	(1, 1, 1)
Very low	VL	(1, 2, 3)
Low	L	(2, 3, 4)
Medium	M	(3, 4, 5)
High	H	(4, 5, 6)
Very high	VH	(5, 6, 7)
Excellent	EXC	(6, 7, 8)

**Table 3**

The demographic profile of the experts.

Position	Educational Qualifications	Work Experience	Work Profile Classification
Senior Manager - Operation	Master	More than 20 years	Private sector (Multinationals)
Senior Manager - Quality	Bachelor's Degree	16 - 20 years	Private sector (Multinationals)
Senior Manager - Engineering	Bachelor's Degree	More than 20 years	Private sector (Multinationals)
Manager - Production	Bachelor's Degree	11-15 years	Private sector (Multinationals)
Manager - Engineering	Bachelor's Degree	16 - 20 years	Private sector (Multinationals)
Manager - Quality	Bachelor's Degree	11-15 years	Private sector (Multinationals)
Senior engineer - Mechanical	Bachelor's Degree	5-10 years	Private sector (Multinationals)
Senior engineer - Quality	Bachelor's Degree	5-10 years	Private sector (Multinationals)

**Table 4**

Comparison matrix of the barriers.

	MB	OB	KB	LSB	LAB	Weight	Rank
MB	(1, 1, 1)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	0.119	5
OB	(1, 2, 3)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	0.303	1
KB	(1, 2, 3)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	0.239	2
LSB	(1, 2, 3)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 2, 3)	0.189	3
LAB	(1, 2, 3)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	0.150	4

**Table 5**

Comparison matrix of the OB sub-barriers.

	OB1	OB2	OB3	OB4	OB5	OB6	Weight	Rank
OB1	(1, 1, 1)	(2, 3, 4)	(0.17, 0.2, 0.25)	(3, 4, 5)	(3, 4, 5)	(4, 5, 6)	0.214	2
OB2	(0.25, 0.33, 0.5)	(1, 1, 1)	(0.17, 0.2, 0.25)	(2, 3, 4)	(2, 3, 4)	(3, 4, 5)	0.125	3
OB3	(4, 5, 6)	(4, 5, 6)	(1, 1, 1)	(4, 5, 6)	(4, 5, 6)	(4, 5, 6)	0.488	1
OB4	(0.2, 0.25, 0.33)	(0.25, 0.33, 0.5)	(0.17, 0.2, 0.25)	(1, 1, 1)	(0.25, 0.33, 0.5)	(1, 2, 3)	0.050	5
OB5	(0.2, 0.25, 0.33)	(0.25, 0.33, 0.5)	(0.17, 0.2, 0.25)	(2, 3, 4)	(1, 1, 1)	(1, 2, 3)	0.077	4
OB6	(0.17, 0.2, 0.25)	(0.2, 0.25, 0.33)	(0.17, 0.2, 0.25)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	0.046	6

**Table 6**

Comparison matrix of the KB sub-barriers.

	KB1	KB2	KB3	KB4	Weight	Rank
KB1	(1, 1, 1)	(0.33, 0.5, 1)	(2, 3, 4)	(2, 3, 4)	0.297	2
KB2	(1, 2, 3)	(1, 1, 1)	(3, 4, 5)	(4, 5, 6)	0.484	1
KB3	(0.25, 0.33, 0.5)	(0.2, 0.25, 0.33)	(1, 1, 1)	(2, 3, 4)	0.141	3
KB4	(0.25, 0.33, 0.5)	(0.17, 0.2, 0.25)	(0.25, 0.33, 0.5)	(1, 1, 1)	0.0718	4

**Table 7**

Comparison matrix of the LSB sub-barriers.

	LSB1	LSB2	LSB3	LSB4	LSB5	Weight	Rank
LSB1	(1, 1, 1)	(0.2, 0.25, 0.33)	(2, 3, 4)	(1, 2, 3)	(3, 4, 5)	0.217	2
LSB2	(3, 4, 5)	(1, 1, 1)	(3, 4, 5)	(3, 4, 5)	(4, 5, 6)	0.473	1
LSB3	(0.25, 0.33, 0.5)	(0.2, 0.25, 0.33)	(1, 1, 1)	(0.33, 0.5, 1)	(1, 2, 3)	0.098	4
LSB4	(0.33, 0.5, 1)	(0.2, 0.25, 0.33)	(1, 2, 3)	(1, 1, 1)	(2, 3, 4)	0.150	3
LSB5	(0.2, 0.25, 0.33)	(0.17, 0.2, 0.25)	(0.33, 0.5, 1)	(0.25, 0.33, 0.5)	(1, 1, 1)	0.062	5

**Table 8**

Comparison matrix of the LAB sub-barriers.

	LAB1	LAB2	LAB3	Weight	Rank
LAB1	(1, 1, 1)	(0.33, 0.5, 1)	(1, 2, 3)	0.317	2
LAB2	(1, 2, 3)	(1, 1, 1)	(1, 2, 3)	0.469	1
LAB3	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	0.214	3

**Table 9**

Comparison matrix of the MB sub-barriers.

	MB1	MB2	MB3	MB4	Weight	Rank
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MB1	(1, 1, 1)	(2, 3, 4)	(0.25, 0.33, 0.5)	(0.25, 0.33, 0.5)	0.160	3
MB2	(0.2, 0.25, 0.33)	(1, 1, 1)	(0.2, 0.25, 0.33)	(0.25, 0.33, 0.5)	0.087	4
MB3	(2, 3, 4)	(3, 4, 5)	(1, 1, 1)	(0.33, 0.5, 1)	0.334	2
MB4	(2, 3, 4)	(2, 3, 4)	(1, 2, 3)	(1, 1, 1)	0.419	1

**Table 10**  
Final global ranking of sub-barriers.

Barrier	Weight	Sub-barrier	Weight	Global value	Global rank
Organizational barriers	0.303	OB1	0.214	0.06478	6
		OB2	0.125	0.03792	11
		OB3	0.488	0.14791	1
		OB4	0.050	0.01522	19
		OB5	0.077	0.02324	15
		OB6	0.046	0.01386	20
Knowledge-based barriers	0.239	KB1	0.297	0.07117	4
		KB2	0.484	0.11583	2
		KB3	0.141	0.03372	12
		KB4	0.078	0.01868	17
Legal/stakeholder barriers	0.189	LSB1	0.217	0.04107	9
		LSB2	0.473	0.08958	3
		LSB3	0.098	0.01858	18
		LSB4	0.150	0.02836	14
		LSB5	0.062	0.01171	21
LCA adoption barriers	0.150	LAB1	0.317	0.04743	8
		LAB2	0.469	0.07030	5
		LAB3	0.214	0.03206	13
Management barriers	0.119	MB1	0.160	0.01903	16
		MB2	0.087	0.01031	22
		MB3	0.334	0.03955	10
		MB4	0.419	0.04969	7

**Table 11**  
Influence of organizational barriers on other classifications.

Classification	Weights									
	<b>MB</b>	0.11859	0.15311	0.13610	0.11909	0.10207	0.08506	0.06805	0.05104	0.03402
<b>OB</b>	0.30294	0.10000	0.20000	0.30000	0.40000	0.50000	0.60000	0.70000	0.80000	0.90000
<b>KB</b>	0.23939	0.30909	0.27475	0.24040	0.20606	0.17172	0.13737	0.10303	0.06869	0.03434
<b>LSB</b>	0.18930	0.24441	0.21725	0.19010	0.16294	0.13578	0.10863	0.08147	0.05431	0.02716
<b>LAB</b>	0.14978	0.19339	0.17190	0.15041	0.12893	0.10744	0.08595	0.06446	0.04298	0.02149
<b>Total</b>	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

**Table 12**  
Sensitivity analysis used to rank sub-barriers when the main barrier (OB) value changes.

Sub-barriers	Organizational barriers weight utilized in the sensitivity analysis									
	0.1	0.2	0.3	Normalized (0.30294)	0.4	0.5	0.6	0.7	0.8	0.9
MB1	13	15	16	<b>16</b>	18	18	18	18	18	18
MB2	18	20	22	<b>22</b>	22	22	22	22	22	22
MB3	8	9	10	<b>10</b>	11	12	14	14	14	14
MB4	5	6	7	<b>7</b>	8	9	10	11	11	11
OB1	16	10	6	<b>6</b>	3	2	2	2	2	2
OB2	19	14	11	<b>11</b>	7	5	3	3	3	3
OB3	9	3	1	<b>1</b>	1	1	1	1	1	1
OB4	21	21	19	<b>19</b>	16	13	9	7	5	5
OB5	20	18	15	<b>15</b>	12	8	6	4	4	4
OB6	22	22	20	<b>20</b>	17	16	11	8	6	6
KB1	3	4	4	<b>4</b>	5	6	7	9	9	9
KB2	1	1	2	<b>2</b>	2	3	4	5	7	7
KB3	10	11	12	<b>12</b>	13	14	15	15	15	15
KB4	14	16	17	<b>17</b>	19	19	19	19	19	19
LSB1	7	8	9	<b>9</b>	10	11	13	13	13	13
LSB2	2	2	3	<b>3</b>	4	4	5	6	8	8
LSB3	15	17	18	<b>18</b>	20	20	20	20	20	20
LSB4	12	13	14	<b>14</b>	15	17	17	17	17	17
LSB5	17	19	21	<b>21</b>	21	21	21	21	21	21
LAB1	6	7	8	<b>8</b>	9	10	12	12	12	12
LAB2	4	5	5	<b>5</b>	6	7	8	10	10	10
LAB3	11	12	13	<b>13</b>	14	15	16	16	16	16

## Figures Captions

**Fig. 1.** Outcome of sensitivity analysis.

