Augmented Reality Application Selection Framework Using Spherical Fuzzy COPRAS Multi Criteria Decision Making

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Abstract: One of the key aspects of digitalization brought by Industry 4.0 is driven by the Internet of Things. Perhaps, the most interesting component of digital transformation is Augmented Reality. Augmented reality is merging the digital and physical worlds in the same experience. This new technology is accepted and applications are initiated in various areas including manufacturing. The main usage area in manufacturing is planning, execution, and verification of the assembly and maintenance operations. Likewise, augmented reality is used in the training of inexperienced people and to guide them by remote expert support. However, the augmented reality application selection, especially for non-technology savvy manufacturing organizations is challenging. Detailed and time-consuming analyses are required to understand the key features to compare and select the most suitable augmented reality application. In this paper, the most critical nine augmented reality software selection criteria are identified. To help organizations to apply such criteria and make a selection that is most suitable for the enterprise, a multi criteria decision-making approach is suggested. The suggested method is based on a fuzzy spherical number. The complex proportional assessment method is used to calculate the rankings. Therefore, the suggested method is called SF-COPRAS. Moreover,
the detailed definition of augmented reality features and terminologies is explained. Several augmented reality use-case scenarios are discussed for manufacturing organizations on their Industry 4.0 initiatives. This paper aims to guide decision makers on their augmented reality software selection journey. The offered framework aims to save time for investigating augmented reality solution features systematically and objectively.

**Subjects:** Human Computer Intelligence; Computer Engineering; Computer Graphics & Visualization; Computer Science; General; Engineering Education; Industrial Engineering & Manufacturing; Machine Science & Technology

**Keywords:** Industry 4.0; internet of things; augmented reality; multi-criteria decision-making; SF-COPRAS

1. Introduction

The key challenge in manufacturing is to balance between increasing and complex demands from customers while carefully consuming the limited natural resources. The fourth industrial revolution is shaping enterprises, tools, and long-term smart manufacturing strategies. Internet of Things (IoT) is the turning point for the traditional approaches by helping the integration between forefront systems (Alcácer & Cruz-Machado, 2019). Digitalization is not only affecting the firms but the competition as well. Due to increasing customization demand and complexity of the products and production; product development times are shortened with higher cost cuts (Kohn & Harborth, 2018; Quandt et al., 2018; Zigart & Schlund, 2020). To stay strong and exist in this competing race, all firms but especially the industrial companies need to be more efficient and effective in the way they work. Augmented Reality (AR) is one of the key components which helps enterprises to become more efficient and effective (Brunner et al., 2020; Sony & Naik, 2019; Uva et al., 2018). AR is a key enabling technology of Industry 4.0 and nominated as the main technology by the European Union (De Amicis et al., 2018; Egger & Masood, 2020). Based on a forecast done by IDC group, the revenue is expected to be around $162 billion by 2020 (Brunner et al., 2020). Perhaps among many other areas, the manufacturing domain is the most critical field. In which the AR could improve the current state dramatically (Plakas et al., 2020; Zigart & Schlund, 2020). It is a smart and novel interface for interacting with people in the world of smart factories (Egger & Masood, 2020). As manufacturing becomes complex, the need for experienced workers increases. However, one of the struggles for the firms is to find such talented individuals or to train them in-house (Lai et al., 2020). AR is providing the required information inventively to employees. As a consequence, the employee easily understands complex processes such as maintenance manuals. By providing intuitive illustrated content and real-time feedback, human errors are reduced as well as the costs of such operations (Ceruti et al., 2019; Elia et al., 2016).

AR is a technology that integrates the physical world we are living with the virtual world we are experiencing in a single display (Speicher et al., 2019; Zigart & Schlund, 2020). The virtual world is computer-generated information such as video, sound, 3D CAD (computer-aided design) models and markers (Amin & Govilkar, 2015; Aydin, 2018; Berryman, 2012; Chi et al., 2013; Plakas et al., 2020). Superimposing virtually created content in the real life is firstly introduced by Azuma and Malibu (Azuma & Malibu, 1997) and affecting our lives daily (Chi et al., 2013). Besides the term AR, there are other very similar and common names such as Virtual Reality and Mixed Reality. The taxonomy can be confusing for many people. In many instances, the AR and VR terminologies are used wrongly. The detailed interviews with AR/VR experts prove that there is no common understanding (Speicher et al., 2019). The Figure 1, created by Milgram and Kishino explains the taxonomy perfectly (Milgram & Kishino, 1994).
In order to clarify the virtual and real environments in the Figure 1, the modeling diagram can be used. Figure 2, is demonstrating superimposition taxonomy with a different perspective (Milgram & Kishino, 1994).

Using AR in manufacturing offers various benefits. The complexity of products and increasing variants cause assembly operations to become convoluted. The learning curve for shop floor people is certainly steeper than it used to be. Moreover, the operators are required to have real-time information and instructions to do their jobs. The corrective action suggested by AR systems is reducing errors or avoiding mistakes before they could occur (Egger & Masood, 2020). There are various manufacturing pilot projects. These projects provide quicker production, higher quality, and more efficient maintenance operations by naturally merging virtual and real objects (Arbeláez-Estrada & Osorio-Gómez, 2013; Caricato et al., 2014; Elia et al., 2016; Ivaschenko et al., 2018). As the complexity of operation increases, the benefit of using an AR system inflates (Zigart & Schlund, 2020). Oftentimes, the traditional, paper-based operation manuals cannot clearly explain the procedures (Ceruti et al., 2019). AR provides an intuitive teaching method that allows learning by doing the tasks (Bower et al., 2014; Wang et al., 2016).

Among many benefits that are discussed earlier, AR systems are still far away from perfection. However, they are becoming more and more mature with the advancements in the hardware and software technologies (Elia et al., 2016). The promising future of AR is expected to be so advanced that observers would not distinguish between what is augmented and what is real (Amin & Govilkar, 2015). Besides the technical challenges, perhaps the most crucial aspect of complex IT system evaluation lies in the decision problem (Caricato et al., 2014). Moreover, technical aspects need to be integrated with organizational technology adoption. Organizational challenges, requirements, and strategies need to be mapped with the selected solution capabilities to utilize the new tool (Bueno Espíndola et al., 2013). It is very difficult to find a systematic way of evaluating such systems in terms of beneficial measures relative to their cost and return on the investment (Caricato et al., 2014).

To guide the organizations to select the best AR application that is aligned with their strategies and needs; the Multi Criteria Decision Making (MCDM) approach is provided as a guideline. The detailed AR features are identified by extended research reviews. The most important features are
explained in detail. Organizations that require AR solutions could potentially apply the suggested framework on the defined criteria list and pick the best alternative. The article aims to contribute to the literature in two ways:

- A detailed literature investigation and explanation of AR capabilities would enable a better understanding of the technology

- The novel Spherical Fuzzy (SF) COmplex PRoportional ASsessment (COPRAS) MCDM model named SF-COPRAS eliminates subjective judgment for individuals. Therefore, it helps organizations to determine the best possible AR solution selection based on actual needs and requirements

The remainder of this paper is organized as follows. Section 2 is devoted to the literature review for AR and fuzzy MCDM methods. Section 3 provides a detailed overview of the AR challenges, reasons to use AR, and AR use-cases. Subsection 3.4 explains the most important AR application features considered for MCDM. Section 4, explains the methodology step by step followed by Section 5, an illustrative example of the method. Followed by discussing the result of the outcomes in Section 6. Lastly, Section 7 demonstrate the sensitivity analysis followed by Section 8, future work suggestions and concluding remarks.

2. Literature review
This section deliberates the literature review about AR and fuzzy MCDM methods focused on SF numbers (SFN).

2.1. Augmented reality
AR as a research area is rapidly growing with many published papers (Zigart & Schlund, 2020). To correctly understand how the AR is used in different sectors; various AR use cases, reviews, and technical papers were investigated. The focus was on the last decades’ researches to provide the most up-to-date information. Some review papers provide extensive metrics on how the papers are categorized. In the broad overview of AR papers, Bottani and Vignali suggest that the most common AR use cases are assembly and maintenance operations. Almost one-third of all investigated papers focus on these use cases. If the other fields such as training/learning, design, safety instructions, and expert guidance are added; more than half of the papers will be relevant to the manufacturing industry (Bottani & Vignali, 2019). Among the provided applications, the most important benefits are time reduction and quality improvement. According to the research done by Kohn and Harborth some companies reduce the time of operations by 80%. The reduction in errors is increased to 96% (Kohn & Harborth, 2018). As interesting as it gets, these high numbers are not reflecting the average. According to other studies, time reduction generally lies between 10% and 30% in average (Egger & Masood, 2020; Lai et al., 2020; Uva et al., 2018; Zigart & Schlund, 2020).

Besides the benefits obtained in manufacturing, many other papers focus on the challenges of implementing AR solutions (Egger & Masood, 2020). For managers and stakeholders to analyze AR application requirements, there are only a few papers in the literature (Caricato et al., 2014). Each paper analyses AR in terms of a single use-case. However, to verify the company-wide ROI, a thorough analysis of such systems is required (Elia et al., 2016). For the majority of people, AR is all about devices that one wears to experience superimposed virtual objects. By all means, the hardware is a crucial element when it comes to augmentation. However, focusing AR selection only on the hardware side limits the potential that could be achieved by the software. Perhaps due to that, all MCDM papers are only focusing on hardware selection criteria (Aydin, 2018; Caricato et al., 2014; Elia et al., 2016). Even though such evaluation is important and beneficial for
enterprises, the gap of not considering the software is critical. As the maturity of the hardware is not yet satisfactory, the only way to adopt AR applications early in its life cycle is to focus on correct software selection. The acceptance of the AR solution is based on the approval of the two levels of stakeholders. Those are corporate level and shop floor level. While the corporate level focuses on strategic and financial aspects, the shop floor focuses on ease of use (Brunner et al., 2020). Furthermore, many other challenges need to be considered. The details of AR are explained in Section 3.

2.2. Fuzzy COPRAS MCDM

The MCDM is a broad and constantly growing area. The main aim is to collect information from decision makers (DM) systematically. Once that is completed, by applying various methods, the alternatives are ranked based on the provided metrics. The benefit of using such methods is to provide a decision, based on facts and objective evaluation. However, human judgment is not easily converted into metric form. In order to overcome such a challenge, fuzzy logic is suggested (Zadeh, 1965). The fuzzy numbers contain the membership degrees. Throughout the years, various extensions are introduced to enclose even more information possible. The SFNs introduced by Kutlu Gündoğdu and Kahraman contain the membership degree as well as non-membership degree and hesitancy. The main difference is in the ability to provide hesitancy value independently. The SF number is an extension based on multiple fuzzy numbers such as Pythagorean Fuzzy Number (PFS) and Neutrosophic Fuzzy Number (NFN; Kutlu Gündoğdu & Kahraman, 2019, 2020). The SF number handles further uncertainty of the DMs (Mathew et al., 2020). The SF number has certain parameters. For example, the sum of squared features is between zero and one. Due to such preference, normalization operations are not needed. Most MCDM models require a normalization operation. Since the SF number helps to skip such steps, the overall process becomes easier.

SFN used in multiple MCDM methods such as TOPSIS, VIKOR, MULTIMOORA, WASPAS, TODIM and AHP (Ayyıldız & Taskin Gumus, 2020; Ju et al., 2021; Kutlu Gündoğdu, 2020; Kutlu Gündoğdu & Kahraman, 2019, 2020; Mathew et al., 2020).

The COPRAS method was firstly introduced by Zavadskas et al. Moreover, both crisp and fuzzy versions of COPRAS method are used in various MCDM papers (Garg et al., 2019; Ghose et al., 2019; Kazimieras Zavadskas et al., 1994; Keshavarz Ghorabaee et al., 2014; Roozbehani et al., 2020; Turanoglu Bekar et al., 2016). It is also common to combine the COPRAS method with other methods such as TOPSIS, AHP, and MULTIMOORA. The aim is to provide hybrid versions or simply compare the outputs (Aikan & Karadag Albayrak, 2020; Dhiman & Deb, 2020). The fuzzy extensions used in these studies vary from type-I fuzzy number to all kinds of fuzzy extensions. SF number is used with COPRAS once in the literature by Ashraf et al. in their work to evaluate COVID19 cases (Ashraf et al., 2020). The method suggested is a combination of TOPSIS and COPRAS and uses only the distance measure which is normally used in TOPSIS methodology (Kutlu Gündoğdu & Kahraman, 2019). In this paper, the aim is to provide regular COPRAS steps by using the SF number and to obtain the SF-COPRAS method. The provided illustrative example also uses the distance measures suggested by Ashraf et al. as an alternative for comparison purposes. In the next section, a detailed investigation of AR is explained.

3. Augmented reality

In this section, the details of the AR use cases, challenges, features, and explanation of why AR is preferred to other realities such as VR are explained.
3.1. Challenges of AR

In any new technology selection, the management is not certain about the impacts, issues, and budgetary constraints. Besides the managerial uncertainties, end users are typically skeptical about their privacy and the benefits of such changes (Brunner et al., 2020). The hardware is mostly the main criterion of the AR selection process. The weight and balance of the devices, issues related to hardware and ease of content creation are the main focus areas of many papers (Alcácer & Cruz-Machado, 2019; De Amicis et al., 2018; Ferrati et al., 2019; Kassahun Bekele et al., 2018; Mengoni et al., 2018; Nee et al., 2012; Quandt et al., 2018; Rabah et al., 2018; Wang et al., 2016). Since most of the manufacturing happens indoors, the lighting conditions, accuracy measures, dirt, dust, moving objects, ergonomics, accuracy, and calibration are some major bottlenecks (Wang et al., 2016; Zigart & Schlund, 2020). However, the most important worry without any doubt is safety. Current robotics are not designed for collaborative operations (Egger & Masood, 2020). AR can provide information related to safety; such as safe working areas, visual and verbal danger indications, and robot movement path illustrations (Michalos et al., 2016). These safety challenges are the top reasons why AR is superior to other virtualization aspects which are explained more in Section 3.2.

3.2. Why AR?

As shown earlier with the two Figures 1 and 2, AR is the only possible way of observing virtual content while still being aware of the physical world, whereas, in the virtual world, the user feels like being in a game or a movie, therefore, cannot focus on what is going on around (Amin & Govilkar, 2015). The VR study of Dreamer-Boats company is a good example of the sadly occurring accidents due to not seeing the stairs and hitting head to ship propeller because of disorientation (Brunner et al., 2020). Most other employees felt dizziness, eye strain, and other types of aches in VR usage. Another challenge of VR is the amount of time required to model augmented content as well as the environment (single work-cell to entire factory) that the operations will be conducted (Ong et al., 2008). Even if the model of the environment was created, the realistic experience would be absent (Wang et al., 2016). As the interaction with real machines is required for maintenance and operations, AR is the right technology for manufacturing organizations due to high user intuition (Egger & Masood, 2020; Zigart & Schlund, 2020). Due to the above-mentioned reasons, AR is preferred instead of VR. In Section 3.3, the various usage areas of the AR application will be discussed.

3.3. Where AR can be used?

Even though there is no specific limit of where the AR can be used, the most common areas of AR are on medical (surgery training; Zigart & Schlund, 2020), tourism (Gun A. Lee et al., 2012), fashion (Arbeldez-Estrada & Osorio- Gómez, 2013), markets and museums (Berryman, 2012), education (Wang et al., 2016; Woo Seo & Yeol Lee, 2013), construction and civil engineering (Zigart & Schlund, 2020), supply chain management Egger and Masood, Plakas et al., Karlsson et al. and foremost the manufacturing (De Amicis et al., 2018; Blaga & Tamas, 2018; Brunner et al., 2020; Böttner et al., 2017; Caricato et al., 2014; Ceruti et al., 2019; Egger & Masood, 2020; Ferrati et al., 2019; Frigo et al., 2016; Hyunsoo Lee, 2019; Karlsson et al., 2017; Kollatsch et al., 2014; Mengoni et al., 2018; Ong et al., 2008; Quandt et al., 2018; Rabah et al., 2018; Uva et al., 2018). Among many areas, the smart manufacturing focuses on digitalization of supply chain and production. In that regard, most important areas of use is on maintenance operations (Bottani & Vignali, 2019; Brunner et al., 2020; Caricato et al., 2014; Ceruti et al., 2019; Elia et al., 2016; Kohn & Harborth, 2018; Uva et al., 2018), assembly operations (Blattgerste et al., 2017; Bottani & Vignali, 2019; Brunner et al., 2020; Caricato et al., 2014; Funk et al., 2017; Kohn & Harborth, 2018), quality assurance (Bottani & Vignali, 2019; Elia et al., 2016; Quandt et al., 2018), logistic and other areas (Egger & Masood, 2020; Elia et al., 2016; Hyunsoo Lee, 2019; Kohn & Harborth, 2018; Plakas et al., 2020; Wang et al., 2016). Based on the literature review done by Egger and Masood the 75% of all
the relevant papers are focused on assembly operations and maintenance tasks (Egger & Masood, 2020). This both includes the training to prepare for such operations and actual operation being carried out including the remote support guidance. Some sectors such as automotive uses AR for product design of the interior cabin. The only available aspect of the car prior to prototype phase are the 3D models and testing on prototype is expensive and appears later in the product life-cycle (Zigart & Schlund, 2020).

Besides automotive, aircraft and other manufacturing industries are also heavily using AR. Even though only a few production-ready systems are available, a high number of proof of concept applications exist (Bottani & Vignali, 2019; Frigo et al., 2016). Companies like Audi, BMW, Bosch, Ford, Porsche, Lockheed Martin, VW, ThyssenKrupp, Volvo, Boeing, and Airbus are early adapters of AR in their digitalization strategy (Kohn & Harborth, 2018). By applying AR, companies can increase efficiency with reduced time and fewer quality errors. Visualization of the digital twin of the manufacturing environment helps achieve effective decision-making for companies (Zhu et al., 2019). In occasional cases, AR is integrated with advanced neural network algorithms to increase tool detection capabilities with high accuracy of 85% (Lai et al., 2020). The broad usage area of AR requires extensive capabilities. Most papers are focusing on single use-cases and identify the features associated with them. This paper aims to define company-wide AR features to be used in MCDM. Section 3.4 explains the most important features and their corresponding reference in the literature.

### 3.4. Features of AR software

Previous sections explain the importance of AR application in the digitalization strategy of smart manufacturing. In order to implement such crucial software in place, all potential challenges need to be evaluated. Some key challenges are defined but not limited to: expensive authoring, tracking of items, issues with placing virtual items, latency, lack of interaction, and accuracy limitations (Wang et al., 2016; Zigart & Schlund, 2020). AR applications are generally built upon software development kits (SDK). There are six most popular AR SKD's and those are Vuforia, ARToolKit, Wikitude, DroiAR, Layar, PanicAR (Kassahun Bekele et al., 2018). Various other applications are built on top of the SDKs. Manufacturing companies are generally not interested in building their applications based on SDKs. Rather, the focus is generally on purchasing the solution built on top of SDKs. To purchase the right available solution, enterprises are required to understand how to evaluate the alternatives. One of the important aims of this paper is to identify the top technical features of the AR application evaluation. The most important features to evaluate AR applications are listed in Table 1, with the corresponding reference from the literature.

AR experience consists of four main phases. These are scene capturing, recognition, processing, and display (Aydin, 2018). The key for each section is to have efficiency, usability, and high quality. Among AR software features, some can be categorized as enabling technologies such as tracking and registration (Zigart & Schlund, 2020). The next sections will explain each AR software feature in detail. Moreover, what would be required for top AR applications will be provided.

#### 3.4.1. Hardware support

Perhaps, the most important element of AR is to display information. AR is differentiated from many other information displays due to its superimposing feature of virtual content in real life. The human eye is not capable of visualizing virtual elements without hardware. Based on the usage perspective, hands-free control can be required. In some cases, only one hand would suffice but in other cases, especially in production facilities, both hands are favored to be free. The most high-level grouping of AR hardware can be under three categories. These are; Head-Mounted Displays (HMD), Handheld display (HHD), Spatial Displays (SD; Milgram & Kishino, 1994). In some cases, the grouping can be extended to five options by including haptic feedback and user tracking (Caricato
Haptic feedback provides instant response to users. The user tracking recognizes how human actions are performed. However, these two categories can be implemented under other main categories. For example, HHD devices can provide haptic feedback via vibration or track users with accelerometers and other sensors. Therefore, it is removed from the grouping in this paper. On the other hand, haptic feedback and user tracking provide an interaction capability. Such benefits will be discussed further in the Interaction & Collaboration subsection. Content creation is generally done on static screens. As they are not a part of actual AR visualization, they are not added to the hardware support section.

HMD's future is the most bright and requires many advancements moving forward (Brunner et al., 2020). HMD's can be grouped into two categories as 3D and 2D wearables. The benefit of
using HMD is to have hands-free use. However, wearing such devices can be cumbersome after long hours. Moreover, these devices are very costly and their industrial use is limited as of today. HHD is typically a mobile phone or a tablet that augments virtual information and shares sensor values such as gyroscope, accelerometers, and GPS for further accuracy Egger and Masood. They are easy to use for most people as they do not require any training. They are very intuitive and lightweight but in most cases, users need to hold them with one hand and the actual work can only be done with the other free hand. However, this burden can be cleared by mounting the devices on tripods (Chi et al., 2013). Due to their ease of use and socially acceptable nature, they are the most preferred option among the three (Egger & Masood, 2020). Users are familiar and such devices rarely cause distractions Zigart and Schlund. Such devices do not require any weird gestures or hand motions which can sometimes be awkward for the users. The price advantage is definitely a key decision criterion. SD has a different aspect that does not require individuals to wear or hold any hardware. The information is displayed using led or laser projectors (Caricato et al., 2014). Those devices are bulky and information privacy is heavily affected. Therefore, among the three options, they are the least preferred.

Table 2, shows a comparison between hardware options and their capabilities. As long as the human sense can interact with the AR application, it does not matter which hardware is used (Alcácer & Cruz-Machado, 2019) as long as it is ergonomic (Zigart & Schlund, 2020). However, a good AR software should be able to support, multiple options and various brands of hardware to be flexible. Perhaps, the best AR software is the one that is hardware agnostic.

3.4.2. Content support
AR applications superimpose virtual objects into physical context. The virtual objects can be 2D content like pdf, video, and image files or 3D content like CAD models and markers like arrows and pointers. Moreover, 3D CAD model-based simulations, illustrations, and animations are heavily used. This will help to visualize operations such as assembly tasks and maintenance operations, especially in complex circumstances. Such animations greatly help to understand manufacturing systems in a better way (Karlsson et al., 2017). Accuracy issues are generally dependent on CAD software and content quality (Wang et al., 2016). Creating such content is generally time-consuming and difficult but it sits in the heart of the AR experience. The high-quality AR application is the one that supports various multimedia. This will allow flexibility to authors to create the most intuitive and easiest experiences for the end-users. 3D CAD models have common formats and native formats depending on the preferred software of the manufacturers. Supporting native formats is key in providing higher quality. To ease the authoring, AR applications should allow various formats and types of multimedia to be used in the application.

3.4.3. Authoring
Once the AR hardware and content supports are defined, authors are in need of creating custom AR experiences for the users of the enterprise. Since AR solves complex tasks, the applications cannot be simple. Creating such experiences can be time-consuming and requires a lot of

| Table 2. AR hardware comparison (Zhu et al., 2019) |
|-----------------------------------------------|
| Mobility | HMDs | HHDs | Projectors |
|----------|------|------|-----------|
|          | X    | X    |           |
| 3D Space Registration | X | X |           |
| Hands-free | X | | X |
| Real-time data transmission | X | X | X |
knowledge in authoring. The authoring topic in the AR domain is a growing area. The investment required for the authoring of AR application is heavy for the enterprises (Egger & Masood, 2020). There are conceptual studies in the creation of automated, context-aware AR content. The aim is to make smart AR systems that can understand users’ intentions. Promptly, it offers AR-enabled manuals for operations. This emerging concept of auto content creation is not yet fully tested in production and is still in the conceptual phase. Until it gets fully matured, it is still beneficial to have easier authoring which does not require advanced software programming skills (Wang et al., 2016). As AR is an emerging area, finding authoring experts is difficult. Generally, the content is created offline by authors. The techniques to enable AR content creation without the need for actual work experience is key (Ahmet Erkayuncu et al., 2017). The preferred AR solution should allow ease of authoring capabilities such as requiring no software coding, ease of integration, and navigation within the experience and enable feedback to the end-users.

3.4.4. Tracking

In order to initiate the created AR experiences, various approaches can be taken. These approaches are called tracking. The tracking has the aim to be easily recognized by the hardware. The aim is to be accurate while augmenting the virtual content in the correct placement of the physical world. The most common tracking method is to use markers. The markers are specific figures that can be posted in the real world. They are then scanned by the AR app. After the scanning, the location and size of the marker provide information about the real world. Later on, all virtual objects will be superimposed based on the location of the marker. It is the easiest and most accurate tracking mechanism. Besides finding the exact location, other information such as angles and distances can be calculated. Therefore, it is the most commonly used method (Amin & Govilkar, 2015; Egger & Masood, 2020). Moreover, such a tracking mechanism can differentiate any specific object. For example, the marker could provide information on the device and real-time sensor readings. This information can also be augmented in the AR experience. However, industrial environments are not the cleanest places. Dirt, dust, oil, and other factors can tear out the marker; hence, markers become unusable (Egger & Masood, 2020). Markers cause occlusion, which is to see such markers in real-life, even when they are not required. Another downside is to find markers with contrasting colors against the surface. High contrast colors help AR applications to recognize markers easily. If the surface is too small to post a marker, this option cannot be used. Their positions need to be remembered and if they are lost, the experience cannot be initiated.

The current direction in AR applications is to move from marker tracking to marker-less tracking (Wang et al., 2016). Many novel approaches are implemented in marker-less tracking (Murithi Runji & Lin, 2020). The most common marker-less tracking method is to use 2D or 3D content. Generally, AR applications transform the 3D CAD models into 2D sketches and use edges, corners, and other dimensional factors to initiate the experience when the model is found in the environment. As there is no marker, problems of environmental conditions are minimized. The downside is to differentiate between similar-looking models. Imagine starting an AR experience that searches a model like a bottle. Most bottles look similar and have a cylindrical shape. AR application could start a wrong experience based on tracking a model that looks similar. On the other hand, the processing power required in such applications is higher (Amin & Govilkar, 2015).

The third option is to use a natural recognition mechanism. In this approach, the AR application is similarly using objects in the environment. Contrary to marker-less tracking, a 3D CAD model does not require to be previously provided. This approach is not commonly used in industrial AR applications due to the lack of recognition and efficiency. However, if this approach is enhanced, it could be the leading tracking method. The advantage of not being required to provide a 2D or 3D CAD model of the equipment can simplify the process.
The last tracking method is the hybrid option. It is the most advanced and conceptually successful method. In this method, a combination of multiple methods defined earlier is integrated. Besides combining tracking methods, other sensor information such as GPS location, compass, and accelerometers can be of great help in positioning (Amin & Govilkar, 2015). The only downside of this approach is the high processing needs. It is required to have advanced algorithms in place to calculate multiple sensor values and tracking methods in milliseconds (Carmigniani et al., 2011). A good AR application should support both marker and marker-less tracking at the same time. The application should also be efficient and quick in tracking capabilities. The tracking should not be lost if the user moves slightly away from the tracker. Selecting the correct tracking method for any AR application is key to its success and accuracy. Therefore, authors should not be limited to certain types of tracking methods and be flexible in their selection. As a result, due to different reasons and needs for various scenarios, the AR application should allow different tracking methods.

3.4.5. Registration
The tracking initiates the AR experience and registration of virtual images in the physical environment takes place. The correct registration increases the accuracy and provides efficient calibration (Wang et al., 2016). All possible sensors such as GPS, compass, and others are used to detect the locations and surfaces to register the objects (Chi et al., 2013). As a result, the registration defines a virtual coordinate space and uses it for virtual item positioning. Among other features, perhaps the registration is the hardest to evaluate for non-experienced users. However, the strong AR application is the one that registers the item efficiently and rapidly. After registration, it is critical to keep the virtual items in the physical environments and links should not be lost easily. Because registration is the key feature to provide high-quality AR applications by high precision, accuracy, and low latency.

3.4.6. Integration & real-time data
Among many other Industry 4.0 applications, the main benefits are observed when the integration and real-time data are provided and implemented. The service-oriented architecture (SOA) is offering flexibility to gather data from various systems. SOA, without duplication; updates the values on the various target systems. AR applications can be integrated with product life-cycle management, IOT, manufacturing execution systems, and enterprise resource planning systems for enhanced use cases (Caricato et al., 2014; Chi et al., 2013; Nee et al., 2012). This approach will be beneficial in AR applications as well. The integration and real-time data connections are handled in the processing unit. One of the most advanced usages of real-time data is predictive-based, preventive maintenance operations. Instead of fixing schedules, this approach tracks the sensor readings and optimizes the best maintenance schedule accordingly. This information can be displayed and used in AR applications. Showing the correct data at the correct time improves the AR experience. Especially when the remote experts are integrated into the AR sessions for guidance (Egger & Masood, 2020). Another strong integration benefits reside in providing quality and operational data from the target devices. In this approach, users not only visualize static models but also view dynamic information. These approaches satisfy easier AR interactions and ease the use by natural sense involvements (Woo Seo & Yeol Lee, 2013). A strong AR system is one, which integrates easily with other systems. The sensor values that are collected from machinery can be displayed in AR applications in real-time to improve the experience.

3.4.7. Interaction & collaboration
AR applications can help inexperienced individuals to learn and perform certain tasks. However, just experiencing written or AR-enabled documentation is not enough most of the time. Collaboration with experts in the field can be of great support. For example, during a maintenance operation, an experienced user can be connected to the session and suggest AR-
based hasten guidance (Egger & Masood, 2020). This will allow a remote technician to view the problem in real-time and provide input on the fly. This is a critical approach in making the collaboration more efficient. Also, interaction with AR experiences can be difficult. Most AR hardware requires certain gestures or voice controls that are not natural. To improve the interaction, additional hardware is also considered like gloves, wristbands, and so forth. These devices certainly improve the input provided. But their ponderous design, the need for calibration, and the requirement to wear for long hours can distract the users (Kassahun Bekele et al., 2018). In the future, interaction with such devices without the need for calibration or usage of extra tools will make the usage more intuitive (Wang et al., 2016). AR system interaction should be value-added and not interfere with the users (Carmigniani et al., 2011). As a result, the AR application should be able to easily interact with natural control and provide easy to understand user graphical interface. They should also allow collaboration with experts, robots, and workspaces when needed for best performance and extended information sharing De Amicis et al., Chi et al.

3.4.8. Architecture & deployment
The last technical capability for AR and any other industrial solution is the architectural capabilities and deployment options. The solution should provide high security and privacy (Brunner et al., 2020). Due to misinformation, AR users believe that AR experiences are not there to support their work but to keep track of their working actions and have these actions used against them. Even though this is not correct, privacy is unquestionably a critical component. The system should be easy to use, reliable and affordable to maintain. User-based access management levels should be configurable (Quandt et al., 2018). Lastly, the need for cloud is increasing in the industry 4.0 initiatives. Most companies are either currently utilizing the cloud or considering the cloud for the future. The system should provide different deployment options such as cloud, on-premise, or hybrid. Moreover, these systems should be able to load-balance the workload and offer high availability (Zigart & Schlund, 2020).

3.4.9. Cost/Affordability
The cost is certainly important and sometimes the main feature of the MCDM process. The cost is a very wide term. Generally, only the licensing costs are considered by the firms while making decisions. However, the cost is broader and should include the actual license costs as well as maintenance costs, hardware requirements cost, implementation costs, and any cost that would occur due to issues caused by the system or not solved by the system. The details of the cost and return of the investment are out of the scope of this paper. However, this feature is still important in assessing the best AR solution alternative for enterprises.

4. Methodology
In this section, the step-by-step methodology of SF-COPRAS is explained. SF-COPRAS is the only method provided and used in this paper. By following the same steps, the same numbers can be calculated. To make the calculation easier, software like excel can be used.

4.1. Spherical Fuzzy Number
The SFN is an extension of the mixture of two fuzzy numbers, PFN and NFN. Let the \( \tilde{A} \) be the SFN of the universe of \( U \) (Kutlu Gündoğdu & Kahraman, 2019).

\[
A_3 = \{ (u, (\mu_{A_3}(u), \nu_{A_3}(u), \pi_{A_3}(u))) | u \in U \}
\]

Membership, non-membership, and hesitancy can be provided independently. Their squared sum should be between 0 and 1 (Kutlu Gündoğdu & Kahraman, 2019).
\[
0 < \mu_{A_i}^2(u) + \nu_{A_i}^2(u) + \pi_{A_i}^2(u) < 1
\]

The geometric shape of the SFN and other extensions are shown in Figure 3. There are various calculations needed to be applied. These are addition, multiplication, weighted arithmetic mean and defuzzification using scoring (Kutlu Gündoğdu & Kahraman, 2019).

**Addition:** (Kutlu Gündoğdu & Kahraman, 2019)

\[
\hat{A}_s \oplus \hat{B}_s = \left\{ \sqrt{\mu_{A_i}^2 + \mu_{B_i}^2 - \mu_{A_i}^2 \mu_{B_i}^2 + \nu_{A_i} \nu_{B_i} \sqrt{\left(1 - \mu_{A_i}^2\right)\pi_{A_i}^2 + \left(1 - \mu_{B_i}^2\right)\pi_{B_i}^2}} \right\}
\]

(1)

**Multiplication:** (Kutlu Gündoğdu & Kahraman, 2019)

\[
\hat{A}_s \otimes \hat{B}_s = \left\{ \mu_{A_i} \mu_{B_i} \sqrt{\nu_{A_i}^2 + \nu_{B_i}^2 - \nu_{A_i}^2 \nu_{B_i}^2} \sqrt{\left(1 - \nu_{A_i}^2\right)\pi_{A_i}^2 + \left(1 - \nu_{B_i}^2\right)\pi_{B_i}^2} \right\}
\]

(2)

**SWAM:** Spherical weighted arithmetic mean takes the weighting of DMs (w) and SFN (A_s) and provides weighted average values as shown (Kutlu Gündoğdu & Kahraman, 2019):

\[
w = (w_1, w_2, \ldots, w_n); \; w_i \in [0, 1]; \sum_{i=1}^{n} w_i = 1
\]

\[
SWAM_w(\hat{A}_{s1}, \hat{A}_{s2}, \ldots, \hat{A}_{sn}) = w_1 \hat{A}_{s1} + w_2 \hat{A}_{s2} + \ldots + w_n \hat{A}_{sn}
\]

Figure 3. Fuzzy extension graphical representation (Kutlu Gündoğdu & Kahraman, 2019).
Score and Accuracy: The score function defuzzify the SF number into the crisp form. To compare the two numbers, firstly the score function results are compared. The larger value indicates a bigger number. If the score values are equal, the higher accuracy states the bigger number.

\[
\text{Score}(\tilde{A}_s) = (\mu_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2 - (\nu_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2
\]

\[
\text{Accuracy}(\tilde{A}_s) = \frac{\mu_{\tilde{A}_s}^2 + \nu_{\tilde{A}_s}^2 + \pi_{\tilde{A}_s}^2}{W}
\]

4.2. Extension of COPRAS with Spherical Fuzzy sets

The crisp COPRAS method consists of several steps which are covered and explained in this chapter. Since the crisp numbers are converted to SFS the section explains the proposed SF-COPRAS Method. The steps of the SF-COPRAS method are shown in Figure 4. The calculation results are shown in Section 5.

Table 2, shows the linguistic terms and the SF number equivalent. Let \( X = \{x_1, x_2, \ldots, x_m\} \) be a set of \( m \) discrete alternatives where \( m \geq 2 \). \( C = \{C_1, C_2, \ldots, C_n\} \) be a set of criteria, and \( w = \{w_1, w_2, \ldots, w_n\} \) be a set of weight vector for criteria that supports \( 0 \leq w_j \leq 1 \) and \( \sum_{j=1}^{n} w_j = 1 \).

Step 1: The first step is to build the decision matrix and criteria evaluation matrix. Let DMs fill in the matrices using linguistic terms given in Table 3 (Keshavarz Ghorabaee et al., 2014).

Step 2: The weighting matrix for the DMs \( W_p \) is constructed as follows:

\[
W_p = |W_m| = \begin{bmatrix}
W_1 \\
W_2 \\
\vdots \\
W_m
\end{bmatrix}
\]

where \( 0 \leq w_m \leq 1 \) and \( \sum_{j=1}^{m} w_j = 1 \).

Step 3: The decision matrix is averaged among normalized weights for each DM. The more experienced DMs can be assigned higher weighting or each person can get the same weighting. The function defined in Equation 3) is used to generate a weighted average decision matrix. The weights are gathered from the matrix shown in Equation 6. This step can be ignored if all DMs are weighted equally (Kutlu Gündoğdu & Kahraman, 2019). Decision matrix is constructed by the judgements of DMs as shown in Equation 7.

\[
D = (C_j(X_i))_{m \times n} = \begin{bmatrix}
(\mu_{11}, \nu_{11}, \pi_{11}) & (\mu_{12}, \nu_{12}, \pi_{12}) & \cdots & (\mu_{1n}, \nu_{1n}, \pi_{1n}) \\
(\mu_{21}, \nu_{21}, \pi_{21}) & (\mu_{22}, \nu_{22}, \pi_{22}) & \cdots & (\mu_{2n}, \nu_{2n}, \pi_{2n}) \\
\vdots & \vdots & \ddots & \vdots \\
(\mu_{m1}, \nu_{m1}, \pi_{m1}) & (\mu_{m2}, \nu_{m2}, \pi_{m2}) & \cdots & (\mu_{mn}, \nu_{mn}, \pi_{mn})
\end{bmatrix}
\]
Figure 4. COPRAS steps.

Table 3. Linguistic terms and their spherical equivalent (Kutlu Gündoğdu & Kahraman, 2019)

| Linguistic Terms                        | $(\mu, \nu, \pi)$ |
|----------------------------------------|-------------------|
| Absolutely more Importance (AMI)       | $(0.9, 0.1, 0.1)$ |
| Very High Importance (VHI)             | $(0.8, 0.2, 0.2)$ |
| High Importance (HI)                   | $(0.7, 0.3, 0.3)$ |
| Slightly More Importance (SMI)         | $(0.6, 0.4, 0.4)$ |
| Equally Importance (EI)                | $(0.5, 0.5, 0.5)$ |
| Slightly Low Importance (SLI)          | $(0.4, 0.6, 0.4)$ |
| Low Importance (LI)                    | $(0.3, 0.7, 0.3)$ |
| Very Low Importance (VLI)              | $(0.2, 0.8, 0.2)$ |
| Absolutely Low Importance (ALI)        | $(0.1, 0.9, 0.1)$ |
Step 4: The criteria weights are weighted by the DMs' weighting. The function defined in Equation 3 is used to generate weighted average criteria weights. This step can be ignored if all DMs are weighted equally (Kutlu Gündoğdu & Kahraman, 2019).

Step 5: Weighted decision matrix based on SWAM operation is generated with each weighted criteria (Kutlu Gündoğdu & Kahraman, 2019). The aggregated weighted SF decision matrix is calculated by using Equation 2 and displayed as shown in Equation 8.

\[
D = (C_j(X_i))_{m \times n} = \begin{bmatrix}
\mu_{11w} & \mu_{12w} & \ldots & \mu_{1nw} \\
\mu_{21w} & \mu_{22w} & \ldots & \mu_{2nw} \\
\vdots & \vdots & \ddots & \vdots \\
\mu_{mw} & \mu_{mw} & \ldots & \mu_{mnw}
\end{bmatrix}
\]

(8)

4.2.1. COPRAS ranking methods

Step 6: In this step, all weighted decision matrix criteria are divided into two categories, \(S_{+i}\) and \(S_{-i}\). If a cost attribute is reversed, then all attributes can be treated as benefit attributes. The sum of all alternatives for beneficial and cost criteria are calculated (Keshavarz Ghorabaee et al., 2014). This is the novel step to differentiate the calculation from the other MCDM approaches. To calculate the total of benefit and cost attributes Equation 1 is used.

\[
S_{+i} = \sum_{j=1}^{n} C_j^+
\]

(9)

\[
S_{-i} = \sum_{j=1}^{n} C_j^-
\]

(10)

where \(C^+\) indicates benefit attributes and \(C^-\) indicates cost attributes.

Step 7: Once the sum of the weighted decision matrix is calculated, to compare benefit and cost attributes effect together, the relative significance of the alternatives is calculated. If all attributes are beneficial attributes, this step can be ignored (Keshavarz Ghorabaee et al., 2014).

\[
Q_i = \frac{S_{+i}}{S_{+i} + \frac{S_{-i} \sum_{j=1}^{m} S_{-j}}{S_{+i} \sum_{j=1}^{m} (S_{+i} / S_{+i})}}
\]

(11)

Step 8: In this last step, the quantity utility with respect to other elements are calculated (Keshavarz Ghorabaee et al., 2014).

\[
U_i = \left(\frac{Q_i}{Q_{max}}\right) \times 100\%
\]

(12)
4.2.2. Spherical Fuzzy ranking methods
In this section, distance-based SF ranking method steps are explained. The method is provided by Ashraf et al. and Kutlu Gündoğdu and Kahraman in the SF-TOPSIS calculations (Ashraf et al., 2020; Kutlu Gündoğdu & Kahraman, 2019). Later, the results obtained from COPRAS ranking and SF rankings will be compared.

**Step 9:** Once the weighted decision matrix is generated, the score values are calculated using Equation 4 and highest and lowest values are identified for \( X^+ \) and \( X^- \) (Kutlu Gündoğdu & Kahraman, 2019).

\[
X^+ = \{ C_j, \max_i (\text{Score}(C_j(X_{wi}))) \} \quad j = 1, 2, \ldots, n \tag{13}
\]

\[
X^- = \{ C_j, \min_i (\text{Score}(C_j(X_{wi}))) \} \quad j = 1, 2, \ldots, n \tag{14}
\]

**Step 10:** Once the positive and negative endpoints are identified, the Euclidean distance can be calculated using the below equations (Kutlu Gündoğdu & Kahraman, 2019).

\[
D(X_i, X^+) = \sqrt{\frac{1}{2n} \sum_{i=1}^{n} (\alpha^2 + \beta^2 + \theta^2)} \tag{15}
\]

where;

\[
\alpha = (\mu_{ai} - \mu_{x^+}), \beta = (\nu_{ai} - \nu_{x^+}), \theta = (\pi_{ai} - \pi_{x^+})
\]

\[
D(X_i, X^-) = \sqrt{\frac{1}{2n} \sum_{i=1}^{n} (\alpha^2 + \beta^2 + \theta^2)} \tag{16}
\]

where;

\[
\alpha = (\mu_{ai} - \mu_{x^-}), \beta = (\nu_{ai} - \nu_{x^-}), \theta = (\pi_{ai} - \pi_{x^-})
\]

**Step 11:** Determine the maximum distance for \( X^- \) and minimum distance for \( X^+ \) (Kutlu Gündoğdu & Kahraman, 2019).

\[
D_{max}(X_i, X^-) = \max_{1 \leq i \leq n} D(X_i, X^-) \tag{17}
\]

\[
D_{min}(X_i, X^+) = \min_{1 \leq i \leq n} D(X_i, X^+) \tag{18}
\]
**Step 12:** After calculating the maximum and minimum distances by Equation 17) and (Equation 18) the closeness ratio can be calculated to rank the alternatives (Kutlu Gündoğdu & Kahraman, 2019). The result is between zero and positive values therefore the bigger is better.

\[
\epsilon(X_i) = \frac{D(X_i, X^*)}{D_{\text{min}}(X_i, X^*)} - \frac{D(X_i, X^*)}{D_{\text{max}}(X_i, X^*)}
\]  

(19)

5. **Illustrative example of SF-COPRAS**

In this section, an illustrative example is provided to demonstrate how the methodology defined earlier can be used with SFNs. The studied firm is a multinational, leading premium car and truck manufacturer. The enterprise is in the top 20 for the largest number of productions worldwide. Total vehicles sold before the pandemic was more than three million and the heritage of the company is expanded over a century. The key strategy of the firm is to maintain sustainability by protecting the environment as well as building inspiring vehicles for its customers. Since digitalization is one of the significant strategies for sustainable growth, investment in AR technologies is given a very high priority. In order to select the most suitable AR solution, Table 3 is provided to DMs to rate both criteria importance and the strength of the alternatives based on various criteria. The selection criteria are displayed in Table 1. In this study, all criteria are used for evaluation. Three DMs are assigned for the evaluation; they are named DM1, DM2, and DM3 throughout the paper. DM1 is assumed to be an expert from the field with 20 years of experience in software consultancy. Moreover, DM1 participated in several evaluations for application selection in manufacturing enterprises. DM2 is an academician with 30 years of experience in the field. The main interest areas include digital transformation and AR. Lastly, DM3 is an employee of the studied manufacturing firm. DM3 is the sponsor and main responsible person with 7 years of experience in the field. DM3 is running an evaluation study for the first time in her career.

To select the best AR solution, four alternatives are selected to the shortlist. The four alternatives are Vuforia, Wikitude, Amazon Sumerian and ARCore. Other options that were considered and not selected to the shortlist were ARKit and ARToolKit due to failure in satisfying the requirements generated by the firm. The aim of the study is not to compare alternatives overall, but to choose the best alternative for the studied organization based on its needs and requirements. Therefore, the alternatives are randomly named A1, A2, A3, and A4 throughout the paper to protect their reputation. The selection and comparison of alternatives are only valid for the studied organization and other firms’ assessments could have different ranking results. As the DMs weights, criteria weights, and selection factors are subjective, the ranking results are only valid for the studied enterprise.

Criteria are defined as C1 (Hardware Support), C2 (Content Support), C3 (Authoring), C4 (Tracking), C5 (Registration), C6 (Integration & Real-time data), C7 (Interaction & Collaboration), C8 (Architecture & Deployment) and C9 (Cost/Affordability). The last criterion C9 is also considered as benefit criteria and users are asked to evaluate not the cost of the product but its affordability. Highly affordable alternatives (easier payment terms, cheaper maintenance and license costs, etc.) will be ranked higher. Each DMs judgements of criteria and alternative are listed in Tables 5, 7 and 9 respectively. The linguistic terms are converted to SF number forms using Table 3. The SF number equivalent of the judgements are displayed in Table 6, for DM1, Table 8 for DM2 and Table 10 for DM3. Based on experience, age, or other factors, different weights can be assigned to DMs. To demonstrate different weighting for DMs, the normalized weights are generated and displayed in Table 4 using Equation 6.
Based on the corresponding weights of each DM and their respective judgments, the average decision matrix is calculated using SWAM operation defined in Equation 3. The calculated output is displayed in Table 11 as displayed in Equation 7.

The criteria weights are filled by each DM by linguistic terms defined in Table 3 and converted to SFN. The weights of criteria for all DMs are shown in Table 12. Afterwards, all DMs criteria weight judgements are combined with their corresponding weights defined in Table 4, using SWAM operations defined in Equation 3 and displayed in Table 13.

Once all the information is gathered, the last step is to generate weighted decision matrix based on weighted criteria and average DMs judgements. The Equation 2 is used to multiply two tables of Tables 11 and 12. The results are displayed in Table 13 as shown in Equation 8.

Once the weighted average decision matrix is created, there are three possibilities to calculate the preferred alternatives with respective rankings.

In the first option “Alternative A”, the defuzzified values are compared. Using score function as defined in Equation 4 and accuracy function as defined in Equation 5, the SFNs are converted into crisp equivalents (Kutlu Gündoğdu & Kahraman, 2019). This operation is followed by summing up all criteria (C1, C2, C9) for each alternative. Table 15 shows the crisp score values of each alternative’s criteria and the totals. The totals are used in the final ranking. As all the criteria are beneficial, summing them all up is meaningful. The ranking of the alternatives based on the total score is displayed in Table 16 and A3 > A1 > A2 > A4 is the suggested result of this method.

The second alternative “Alternative B”, calculates the ratings based on $S_{si}$ and $S_{i}$ scores (Keshavarz Ghorabaee et al., 2014) as shown in Equation 9 and (Equation 10). This is the main differentiating step of the COPRAS method from other MCDM methods such as TOPSIS. In this paper, COPRAS method with the SF number application is firstly introduced using $S_{si}$ and $S_{i}$ scores. In order to rank the alternatives, the relative significance is calculated by Equation 11. If all the criteria are beneficial and no cost criterion is involved, there is no need to calculate $S_{i}$ and the relative significance. The values from Table 14, are taken and by using addition operation defined in Equation 3, all categories can be aggregated. Since the current method does not allow multiple addition operation at once, all categories need to be added two by two. $C_{1,2} = C_{1} + C_{2}, C_{3,4} = C_{3} + C_{4}, C_{5,6} = C_{5} + C_{6}, C_{7,8} = C_{7} + C_{8}$ and lastly $C_{1:2345678:9} = C_{1:2345678:9}$ is calculated. The result of $C_{1:2345678:9}$ is displayed in Table 17. Based on the values calculated, using the score function described in Equation 4, the values are defuzzified. The quantitative utilities are calculated using Equation 12. The scores, quantitative utility and rankings of alternatives are displayed in Table 18. In this method, the first two options’ place is replaced and final ranking is suggested as A1> A3> A2> A4.

In the third and last alternative “Alternative C”, the largest and smallest distances are calculated and Euclidean distance measure is used to define the ranking of alternatives. The comparison using distance as a measure is observed in TOPSIS methodology (Ashraf et al., 2020; Kutlu Gündogdu & Kahraman, 2019). In order to compare the outcome of the COPRAS approach suggested by Ashraf et al. with the COPRAS approach proposed in “Alternative B” this step is defined. Comparing the results of “Alternative B” and “Alternative C” can be considered as a sensitivity test as well. The values from Table 14 are used in Equation 4 to calculate the score values similarly as shown in Table 15. Based on the scores, the highest and lowest points are identified using Equation 13) and (Equation 14), respectively. These values are listed in Table 19. Afterwards, all the distances of all alternatives to their corresponding criteria are displayed in
Table 5. Judgements of DM1

| DM1   | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|-------|----|----|----|----|----|----|----|----|----|
| SLI   | VHI| ALI| AMI| ALI| VHI| VHI| SLI| EI |    |
| EI    | EI | HI | VLI| ALI| SLI| EI | EI | SMI|    |
| EI    | VLI| HI | VHI| AMI| HI | VHI| LI | VLI|    |
| AMI   | ALI| HI | VLI| SLI| EI | LI | SLI| VHI|    |
Table 6. Judgements of DM1 in SFN

| DM1 | C1    | C2    | C3    | C4    | C5    | C6    | C7    | C8    | C9    |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| A1  | (0.4,0.6,0.4) | (0.8,0.2,0.2) | (0.1,0.9,0.1) | (0.9,0.1,0.1) | (0.1,0.9,0.1) | (0.8,0.2,0.2) | (0.8,0.2,0.2) | (0.4,0.6,0.4) | (0.5,0.5,0.5) |
| A2  | (0.5,0.5,0.5) | (0.5,0.5,0.5) | (0.7,0.3,0.3) | (0.2,0.8,0.2) | (0.1,0.9,0.1) | (0.4,0.6,0.4) | (0.5,0.5,0.5) | (0.5,0.5,0.5) | (0.6,0.4,0.4) |
| A3  | (0.5,0.5,0.5) | (0.2,0.8,0.2) | (0.7,0.3,0.3) | (0.8,0.2,0.2) | (0.9,0.1,0.1) | (0.7,0.3,0.3) | (0.8,0.2,0.2) | (0.3,0.7,0.3) | (0.2,0.8,0.2) |
| A4  | (0.9,0.1,0.1) | (0.1,0.9,0.1) | (0.7,0.3,0.3) | (0.2,0.8,0.2) | (0.4,0.6,0.4) | (0.5,0.5,0.5) | (0.3,0.7,0.3) | (0.4,0.6,0.4) | (0.8,0.2,0.2) |
respectively. Lastly, using Equation 19, the closeness ratio is calculated for each alternative on the

| Table 7: Judgements of DM2 | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|----------------------------|----|----|----|----|----|----|----|----|----|
| DM2 Alternative 1          | AMI| ELI| VHI| VHI| VHI| VHI| ELI| VHI| SLI|
| DM2 Alternative 2          | AMI| ELI| VHI| VHI| VHI| VHI| ELI| VHI| SLI|
| DM2 Alternative 3          | AMI| ELI| VHI| VHI| VHI| VHI| ELI| VHI| SLI|
| DM2 Alternative 4          | AMI| ELI| VHI| VHI| VHI| VHI| ELI| VHI| SLI|
Similar to "Alternative B", the ranking appears as distances. The result is displayed in Table 22. Similar to "Alternative B", the ranking appears as

| DM2 | C1       | C2       | C3       | C4       | C5       | C6       | C7       | C8       | C9       |
|-----|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| A1  | (0.9,0.1,0.1) | (0.5,0.5,0.5) | (0.8,0.2,0.2) | (0.3,0.7,0.3) | (0.1,0.9,0.1) | (0.8,0.2,0.2) | (0.3,0.7,0.3) | (0.2,0.8,0.2) | (0.3,0.7,0.3) |
| A2  | (0.7,0.3,0.3) | (0.6,0.4,0.4) | (0.8,0.2,0.2) | (0.1,0.9,0.1) | (0.5,0.5,0.5) | (0.8,0.2,0.2) | (0.4,0.6,0.4) | (0.1,0.9,0.1) |
| A3  | (0.4,0.6,0.4) | (0.9,0.1,0.1) | (0.6,0.4,0.4) | (0.6,0.4,0.4) | (0.6,0.4,0.4) | (0.8,0.2,0.2) | (0.3,0.7,0.3) | (0.4,0.6,0.4) | (0.3,0.7,0.3) |
| A4  | (0.1,0.9,0.1) | (0.1,0.9,0.1) | (0.4,0.6,0.4) | (0.4,0.6,0.4) | (0.2,0.8,0.2) | (0.5,0.5,0.5) | (0.5,0.5,0.5) | (0.4,0.6,0.4) | (0.5,0.5,0.5) |
| DM3   | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|-------|----|----|----|----|----|----|----|----|----|
| Alterative 1 | EI | AMI | LI | HI | VHI | SMI | LI | VHI | ALI |
| Alterative 2 | VHI | AHI | AMI | HI | LI | SLI | AMI | EI | LI |
| Alterative 3 | VLI | VHI | VLI | VHI | VLI | SMI | VHI | SLI | VHI |
| Alterative 4 | SLI | SMI | EI | VLI | HI | ALI | SLI | EI | VLI |
Table 10. Judgements of DM3 in SFN

| DM3 | C1    | C2    | C3    | C4    | C5    | C6    | C7    | C8    | C9    |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| A1  | 0.505 | 0.505 | 0.307 | 0.307 | 0.307 | 0.307 | 0.307 | 0.307 | 0.307 |
| A2  | 0.802 | 0.802 | 0.703 | 0.703 | 0.703 | 0.703 | 0.703 | 0.703 | 0.703 |
| A3  | 0.802 | 0.802 | 0.703 | 0.703 | 0.703 | 0.703 | 0.703 | 0.703 | 0.703 |
| A4  | 0.406 | 0.406 | 0.505 | 0.505 | 0.505 | 0.505 | 0.505 | 0.505 | 0.505 |
|     | C1       | C2       | C3       | C4       | C5       | C6       | C7       | C8       | C9       |
|-----|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| A1  | (0.7, 0.3, 0.0) | (0.8, 0.2, 0.3) | (0.5, 0.5, 0.2) | (0.8, 0.2, 0.2) | (0.4, 0.7, 0.2) | (0.8, 0.2, 0.2) | (0.7, 0.4, 0.2) | (0.5, 0.5, 0.3) | (0.4, 0.6, 0.4) |
| A2  | (0.7, 0.4, 0.4) | (0.5, 0.5, 0.4) | (0.8, 0.2, 0.2) | (0.6, 0.4, 0.2) | (0.2, 0.9, 0.2) | (0.4, 0.6, 0.4) | (0.7, 0.3, 0.3) | (0.5, 0.5, 0.5) | (0.5, 0.6, 0.3) |
| A3  | (0.4, 0.6, 0.4) | (0.7, 0.3, 0.2) | (0.5, 0.5, 0.3) | (0.8, 0.2, 0.2) | (0.7, 0.3, 0.2) | (0.7, 0.3, 0.2) | (0.4, 0.6, 0.4) | (0.5, 0.6, 0.2) | (0.5, 0.6, 0.2) |
| A4  | (0.8, 0.3, 0.2) | (0.3, 0.8, 0.2) | (0.6, 0.4, 0.4) | (0.3, 0.7, 0.3) | (0.5, 0.6, 0.3) | (0.5, 0.6, 0.5) | (0.4, 0.6, 0.4) | (0.4, 0.6, 0.4) | (0.7, 0.3, 0.3) |
However, the relative distances between A1 and A3 alternatives are very short. Therefore, suggesting A1 = A3 > A2 > A4 can also be the outcome of this method.

### 6. Results and findings

As a result, the SF-COPRAS method is utilized to help organizations identify the right AR solutions to be selected. The linguistic terms provided by three DMs are converted to SF numbers and various operations are conducted. Lastly, three comparison alternatives are applied to select the most suitable alternative based on DMs judgments, DMs weights, and criteria weights. In this illustrative example, the first option (“Alternative A”) suggests A3 > A1 > A2 > A4 as the final ranking. The other two alternatives “Alternative B” and “Alternative C” suggest A1 > A3 > A2 > A4 ranking result. The comparison metrics are provided in all ranking tables, Tables 16, 18, 22. Since the distance in “Alternative C” has the closest metric between A1 and A3 they can be considered equally preferred. All of the results are consistent with each other. As the “Alternative A” directly converts the values into the crisp form, besides the computational advantage; the difference in the ranking shows that the usage of additional information of SF number is not utilized.

On the other hand, the other two alternatives “Alternative B” uses COPRAS sum of alternatives, and “Alternative C” uses distance measures. Both options utilize the SFNs towards the last step. The novel offering of “Alternative B” which uses simpler calculations is computationally easier. Since both alternatives provide the same results, selecting either of them is meaningful. However,

| Criteria | DM1         | DM2         | DM3         |
|----------|-------------|-------------|-------------|
| C1       | (0.8,0.2,0.2) | (0.4,0.6,0.4) | (0.7,0.3,0.3) |
| C2       | (0.9,0.1,0.1) | (0.8,0.2,0.2) | (0.9,0.1,0.1) |
| C3       | (0.9,0.1,0.1) | (0.8,0.2,0.2) | (0.8,0.2,0.2) |
| C4       | (0.6,0.4,0.4) | (0.6,0.4,0.4) | (0.9,0.1,0.1) |
| C5       | (0.4,0.6,0.4) | (0.4,0.6,0.4) | (0.7,0.3,0.3) |
| C6       | (0.5,0.5,0.5) | (0.8,0.2,0.2) | (0.9,0.1,0.1) |
| C7       | (0.7,0.3,0.3) | (0.7,0.3,0.3) | (0.5,0.5,0.5) |
| C8       | (0.4,0.6,0.4) | (0.6,0.4,0.4) | (0.4,0.6,0.4) |
| C9       | (0.6,0.4,0.4) | (0.6,0.4,0.4) | (0.9,0.1,0.1) |

| Criteria | Weights |
|----------|---------|
| C1       | (0.7,0.3,0.3) |
| C2       | (0.9,0.1,0.1) |
| C3       | (0.9,0.1,0.1) |
| C4       | (0.7,0.3,0.3) |
| C5       | (0.5,0.5,0.4) |
| C6       | (0.7,0.3,0.3) |
| C7       | (0.7,0.3,0.3) |
| C8       | (0.5,0.5,0.4) |
| C9       | (0.7,0.3,0.3) |
|   | C1     | C2     | C3     | C4     | C5     | C6     | C7     | C8     | C9     |
|---|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| A1| (0.5,0.4,0.4) | (0.7,0.3,0.3) | (0.5,0.6,0.2) | (0.6,0.4,0.4) | (0.2,0.8,0.3) | (0.6,0.4,0.4) | (0.4,0.5,0.4) | (0.2,0.7,0.4) | (0.3,0.7,0.5) |
| A2| (0.5,0.5,0.4) | (0.4,0.5,0.4) | (0.7,0.3,0.3) | (0.4,0.5,0.4) | (0.1,0.9,0.2) | (0.3,0.6,0.5) | (0.5,0.4,0.4) | (0.2,0.7,0.5) | (0.3,0.6,0.4) |
| A3| (0.3,0.6,0.5) | (0.6,0.3,0.2) | (0.5,0.5,0.3) | (0.5,0.4,0.4) | (0.4,0.6,0.4) | (0.5,0.4,0.4) | (0.5,0.4,0.4) | (0.2,0.8,0.4) | (0.3,0.6,0.3) |
| A4| (0.5,0.4,0.3) | (0.3,0.8,0.3) | (0.5,0.4,0.4) | (0.2,0.8,0.3) | (0.2,0.7,0.4) | (0.3,0.6,0.5) | (0.3,0.7,0.4) | (0.2,0.7,0.5) | (0.5,0.4,0.4) |
| Alternative | C1  | C2  | C3  | C4  | C5  | C6  | C7  | C8  | C9  | Total |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-------|
| A1          | 0.01| 0.16| −0.06| 0.04| −0.21| 0.04| −0.01| −0.05| −0.01| −0.09 |
| A2          | 0   | −0.01| 0.17| −0.02| −0.42| 0.01| 0   | 0.03| −0.04| −0.27 |
| A3          | 0   | 0.16| −0.01| 0.02| −0.02| 0.02| 0.01| −0.07| −0.08| 0.01  |
| A4          | 0.05| −0.27| 0.01| −0.16| −0.06| 0.02| −0.02| −0.01| 0   | −0.43 |
as the original COPRAS method is not based on distance measures, selecting “Alternative C” is not required. In the next section, the conclusion and future work suggestions are defined.

7. Sensitivity analysis

Sensitivity analyses are applied to test the robustness of the suggested SF-COPRAS method. Initially, the weight of the DMs was changed and the observed outcomes were as expected. The score function ranking used in Alternative A was more robust compared to the other ranking methods investigated in this study. However, all methods were robust most of the time and provided similar results. Later on, the sensitivity analysis was applied by changing the ν value (Kutlu Gündoğdu & Kahraman, 2019). Similar results were identified and robustness of the proposed method for SF-COPRAS was observed. Figure 5 shows the changes of ranking using Alternative A the defuzzified values and Figure 6 shows the result of Alternative B, COPRAS sum method. As it is clearly shown, the proposed relative significance aggregation method provides more robust results.

8. Conclusion & future work

AR is a rapidly growing area with various use-cases. The benefits of using AR in manufacturing activities such as maintenance, operations, and warehouse are countless. Due to the complex nature of AR and the lack of available information, the firms are only investigating the 3D wearable hardware. However, even though the hardware is a critical piece, the AR investigations cannot be complete without a detailed analysis of the software applications. To help organizations to identify the right solution, MCDM needs to be applied. The nine most important criteria for AR application selection are identified and suggested to be used in the evaluation process. Moreover, this paper
presented a novel SF-COPRAS MCDM method to help the AR application evaluation. In this SF-

| Table 19. Alternative C—max and min distances |
|---------------------------------------------|
|    | C1    | C2    | C3    | C4    | C5    | C6    | C7    | C8    | C9    |
| --- | ----- | ----- | ----- | ----- | ----- | ----- | ----- | ----- | ----- |
| X^+ | (0.5,0.4,0.3) | (0.7,0.3,0.3) | (0.7,0.3,0.3) | (0.6,0.4,0.4) | (0.4,0.6,0.4) | (0.6,0.4,0.4) | (0.5,0.4,0.4) | (0.2,0.7,0.4) | (0.5,0.4,0.4) |
| X^- | (0.3,0.6,0.5) | (0.3,0.8,0.3) | (0.5,0.6,0.2) | (0.2,0.8,0.3) | (0.1,0.9,0.2) | (0.3,0.6,0.5) | (0.3,0.7,0.4) | (0.2,0.8,0.4) | (0.3,0.7,0.5) |
COPRAS approach, DMs linguistic inputs are transformed to SFNs and COPRAS method steps are performed. Lastly, in order to compare the outcomes, three different ranking methods are suggested and compared.

This paper contributes to the literature in various ways;

—Challenges and benefits of AR applications and various use-cases are discussed
—The literature review of AR software selection criteria are analyzed and listed
—The first systematic MCDM system for AR software solution selection procedure is suggested
—Novel SF-COPRAS method using the sum of category measure is introduced

| Alternative C—distances of alternatives |
|-----------------------------------------|
| **Alternative 1** | **Alternative 2** | **Alternative 3** | **Alternative 4** |
| $D_{\text{max}}$ | $D_{\text{min}}$ | $D_{\text{max}}$ | $D_{\text{min}}$ | $D_{\text{max}}$ | $D_{\text{min}}$ |
| C1 | 0.01 | 0.08 | 0.02 | 0.06 | 0.13 | 0 |
| C2 | 0 | 0.43 | 0.16 | 0.12 | 0.02 | 0.31 |
| C3 | 0.14 | 0 | 0 | 0.14 | 0.11 | 0.01 |
| C4 | 0 | 0.29 | 0.04 | 0.12 | 0 | 0.26 |
| C5 | 0.08 | 0.04 | 0.24 | 0 | 0 | 0.24 |
| C6 | 0 | 0.14 | 0.14 | 0 | 0 | 0.1 |
| C7 | 0.01 | 0.07 | 0 | 0.11 | 0 | 0.11 |
| C8 | 0 | 0.01 | 0.01 | 0.02 | 0.01 | 0 |
| C9 | 0.09 | 0 | 0.05 | 0.01 | 0.06 | 0.02 |

| Table 21. Alternative C—total distance and max-min distances |
|----------------------------------------------------------|
| **Alternative** | $D(X_1, X^*)$ | $D(X_i, X^-)$ |
| Alternative 1 | 0.14 | 0.24 |
| Alternative 2 | 0.19 | 0.18 |
| Alternative 3 | 0.14 | 0.24 |
| Alternative 4 | 0.25 | 0.14 |

| Table 22. Alternative C—ranking of alternatives |
|------------------------------------------------|
| **Alternative** | **Closeness Ratio** | **Ranking** |
| Alternative 1 | 0.00 | 1 |
| Alternative 2 | 0.68 | 3 |
| Alternative 3 | 0.01 | 2 |
| Alternative 4 | 1.25 | 4 |
Provided SF-COPRAS has compared with the distance measure-based method. Despite easier computation, similar and more distinguishing results are obtained. There are limitations of this study which consist of but are not limited to the below items:

—Example illustration can be replaced by industrial case
—The weights and judgments of DMs limit the objectivity
—Besides AR, the VR and MR options can be investigated
—Various other MCDM methods can be used to compare rankings
—Besides the SFNs, other fuzzy extensions can be used for further sensitivity analysis.

—SF-COPRAS outcome can be compared with other methods such as SF-TOPSIS, SF-VIKOR, and SF-AHP.

—Besides manufacturing, other sectors can be analyzed and the suitability of features can be tested

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