



Digital transformation in the defense industry: A maturity model combining SF-AHP and SF-TODIM approaches

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ABSTRACT

As an inevitable process, digitalization has become a priority for many companies. The measurement of digital maturity is the first step toward adequately executing this. Although digital maturity models (DMM) have been developed for different sectors in the literature, such studies in the defense industry are lacking due to sector-specific dynamics. This study aims to close this gap and proposes a digital maturity model specific to the defense industry. In this study, a novel model was developed that combines the SF-AHP and SF-TODIM methods due to the uncertainty and hesitancy contained in the evaluation. The validity of the presented novel model has been demonstrated in a prominent defense company in Turkey. According to the results, the most notable digital maturity dimensions are the evaluation of opportunities and alignment with stakeholders. In addition, the model indicates that the company owns the required soft skills, such as leadership, organizational culture, and strategic determination for digital transformation (DT). On the other hand, essential hard skills such as technology and operational competencies are yet to be improved. Lastly, sensitivity and comparison analyses are conducted to validate and verify the obtained results' stability and robustness.

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1. Introduction

The rapid change in information and communication technologies has enforced the digitalization of the business environment. Digital technologies improve operational processes and add value to the business [1]. As an inevitable process, digital transformation provides managers with the necessary tools to enable their organizations to expand into new markets, increase stakeholder engagement, and reduce costs. Businesses benefiting from the advantage of DT will soon be essential actors in the digital age.

With the increase in digitalization activities in many different business lines, the concept of sustainability has gained a different meaning. A deliberate DT supports a firm's sustainability endeavor from different perspectives, such as a more secure job environment, less scrap, closer customer contact, more reliable products and services, a more resilient supply chain network, more careful supervision of fair trade standards, and so on. Businesses face various paradoxical challenges to increase their competitiveness; reducing costs while improving quality, shortening time-to-market, integrating the upper and lower tiers of the entire supply chain, understanding new customer experiences,

and creating efficient business models. Undoubtedly, DT plays a key role while overcoming these challenges [2].

One of the most critical factors in gaining sustainable competitive advantage is adopting Industry 4.0-related technologies. Companies with no investment in Sustainable Digital transformation developments will soon perish. Today, Industry 4.0 refers to integrating digital technologies in all aspects of production and service operations where cyber-physical systems with smart applications are at heart. Industry 4.0 process encompasses the design of higher value-added processes rather than productivity gains. It can be said that Industry 4.0 has fundamentally changed the established value chains and created its economy [3]. In addition, Industry 4.0 enables the collection and detailed analysis of data in the production environment.

The defense industry has been a vital driver of technological advancements that transformed our daily life. However, defense firms delay their DT journeys mainly due to data integrity and security concerns and rely on more traditional management tools. Nevertheless, digitalization is an inevitable milestone for any defense firm trying to gain a competitive advantage, improve operational efficiency, increase revenue, and encourage innovation [4]. With this transformation, developing more efficient and well-equipped products and systems in this sector will be possible. To this end, companies in the sector must analyze their existing digital abilities and competencies well before initializing

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a new DT journey. Digital Maturity Models (DMM) help determine an organization's maturity level in digitalization to draw a practical roadmap.

In light of previous studies, the primary motivations for this study are the following:

- The main motivation of this study is to propose a valid and reliable DMM for defense sector companies to evaluate their performance and ability through the digitalization journey.
- It is vital for defense companies, where technology and security have a significant place, to measure their digital transformation maturity levels and to determine a roadmap accordingly. However, in the literature, it is seen that the studies carried out in recent years with digital transformation maturity models are generally carried out in the logistics, human resources, manufacturing, and aviation sectors [5–9]. There is a wide gap in the literature in terms of developing a DMM for defense industry companies. The defense industry has different dynamics, especially privacy and security, compared to other sectors. Despite its strategic importance, this topic has rarely been addressed.
- The fuzzy state set was ignored in previous studies on the DMMs. They have developed their framework in a context that cannot effectively cope with vague, indeterminate, and inconsistent information. Thus, one of the motivations of this study is to introduce a novel multi-criteria decision-making approach based on fuzzy numbers to handle information uncertainty.

This study aims to fill this gap where we develop an applicable DMM considering different factors of a multifaceted concept, such as organization, culture, leadership, strategy, and operation. To this end, we propose a novel DMM for the defense industry, which hybridizes the Analytical Hierarchy Process (AHP) [10] and TODIM [11] in the Spherical Fuzzy Sets (SFSs) domain due to the subjective judgments of experts. AHP, one of the most popular Multi-Criteria Decision Making (MCDM) methods, is criticized for its incapability to handle uncertainty and subjectivity in human judgment in its initial form [12]. SFSs have recently become more prevalent in various fields to address this drawback. The main logic behind SFS is to let decision-makers generalize a further extension of fuzzy sets by defining a membership function on a spherical surface and independently assigning the parameters of that membership function by providing a more extensive domain [13]. SFS is a synthesis of Pythagorean Fuzzy Sets (PFS) [14] and Neutrosophic Fuzzy Sets (NFS) [15]. Thus, a SFS is a more appealing option to represent expert opinion in a high degree of indeterminacy environment.

The main contributions of this study are as follows:

- To the best of authors' knowledge, there is the first study that hybridizes AHP and TODIM methods based on SFS to evaluate the digital maturity model. The spherical fuzzy AHP method is applied in the first stage to determine the criteria weights. Then, the spherical fuzzy TODIM algorithm is employed in the second stage to evaluate the alternatives.
- It will be a pioneering study that develops a novel DMM for the defense industry by obtaining real-world data from one of the leaders of the sector in Turkey.
- Thirdly, the model will guide experts and practitioners in the defense sector and provide valuable insights while implementing DT projects.
- The spherical fuzzy AHP-TODIM method can be deployed in group and individual decision-making.
- To verify the validity of the developed method, we compared the SF-AHP & SF-CODAS approach and the proposed SF-AHP & SF-TODIM approach.

- We conducted a sensitivity analysis to reveal the robustness of the presented methodology to the variation.

This study contains five sections after the introduction. Section 2 presents a literature review on digital maturity, while Section 3 explains the methodology used in the study. Next, Section 4 applies the proposed model in a real-world case study. Then, we provide a sensitivity analysis in Section 4.2. Lastly, Section 5 concludes the research and presents future research directions.

2. Literature review

In recent years, several studies have been published on modeling DT maturity. This section provides a comprehensive literature review on the topic. The reviewed keywords are “digital maturity”, “digital transformation”, and “digitalization”. We consider those studies published in academic journals indexed in SCOPUS and Google Scholar after 2015.

Most studies evaluate the DT maturity on company level [16–19] while some others consider the problem on sector level [5, 20–24] or in country level [25,26].

Company-level studies usually focus on a case study in a sector. [27] created an Industry 4.0 maturity model based on the evaluations of the German Mechanical Engineers Industry Association experts and various sector representatives. The model is developed for manufacturing companies to see how ready they are for Industry 4.0. [16] developed a maturity model to assess the Industry 4.0 maturity of an Austrian company that designs and manufactures aerospace materials. [17] analyzed the current situation of a company before investing in Industry 4.0 technologies. Afterward, the readiness for Industry 4.0 technologies was evaluated, and a roadmap was determined. [5] developed a maturity model for companies that aim to digitalize through smart products and cyber-physical systems in the manufacturing industry. Alternatively, [28] focused on risk management in the context of Industry 4.0.

[18] measured the Industry 4.0 maturity level of a company operating in the retail sector. Similarly, [29] measured the digital maturity of a company that manufactures machinery in Sakarya province in Turkey. In addition, they identified the strengths and weaknesses of the company to be addressed. [23] determined the Industry 4.0 readiness/maturity level of a company in the apparel industry by determining the criterion weights with AHP and using the TOPSIS method. [30] analyzed the Industry 4.0 maturity level of an Indian manufacturing company with the Fuzzy AHP technique.

The second group of studies addresses the problem on the sector level and creates sector-specific models. [7] proposed a two-stage maturity model to evaluate the adaptation level of companies in the logistics sector to the digital transformation process. The study used the Best Worst Method. [22] evaluated the Industry 4.0 maturity level of the defense industry with the Hesitant Fuzzy AHP technique. [21] measured the Industry 4.0 maturity of 12 companies in the Defense sector and proposed a model which is based on IMPULS and Digital Operations Self-Assessment Models. [31] proposed a new model to help manufacturing companies determine their digital maturity level before transitioning to Industry 4.0. Afterward, the importance levels of the main and sub-criteria were found using AHP. [32] evaluated the Industry 4.0 maturity level of seven manufacturing companies from the aviation, automobile, plastic packaging, and heavy vehicle sectors. [33] evaluated the factors relevant for logistics companies during the transition to Industry 4.0. They used the Fuzzy DEMATEL method. [34] proposed two different approaches to assess the Industry 4.0 maturity level of logistics companies with the IMPULS maturity model. [8] measured the

digital maturity level of logistics companies for digital transformation. A recent study [19] analyzed digital readiness in a multinational manufacturing organization. [9] examined dimensions of digital transformation in airlines. The authors found the dimensions of digital transformation in the civil aviation industry and determined the Digital Transformation Maturity (DTM) levels of aviation companies by proposing a DTM evaluation tool. [24] determined the importance level of Industry 4.0 criteria for small and medium-sized enterprises and developed a quantitative maturity model. The AHP was used to calculate the weights of the maturity dimensions.

Another focal point of the studies in the extant literature is to evaluate the countries' DTM. [35] measured the Industry 4.0 maturity level of a total of 24 companies from 7 different sectors in Germany and France and evaluated the problems of Industry 4.0 for these countries. [36] focused on existing Industry 4.0 maturity models and analyzed them. They defined a new universal Industry 4.0 maturity model designed for SMEs in the Czech Republic. [37] presented a maturity model for Smart Product-Service System and compared solutions. They used twelve dimensions and conducted a case study. [38] identified why the Industry 4.0 maturity model was not as used as expected and what should be done to motivate or support users to use it more often. [39] discussed an evaluation framework for the motherboard industry from the digital transformation perspective.

[25] compared the Industry 4.0 levels of the G-20 countries by using the COPRAS method, a MCDM technique. [26] examined the current state of the digitalization process in the world and in Turkey with an Industry 4.0 perspective.

Lastly, some recent works address the issue from a different angle aiming to provide an overall picture of alternative maturity models developed so far. [40] analyzed various industry 4.0 maturity models. [41] have identified the most widely used Industry 4.0 maturity model. This paper aims to give an overview of available Industry 4.0 maturity models and empirically test their dissemination in business practice. Finally, [42] determined the best Industry 4.0 maturity model with Fuzzy TOPSIS.

2.1. The research gaps

To sum up, many studies have been conducted on the concept of industry 4.0, and DTM measurement models. Some studies have evaluated digital maturity levels in the transition phase of manufacturing enterprises to Industry 4.0. In contrast, some others have identified the firms' business readiness, capabilities, opportunities, and challenges. Techniques used to measure digitalization levels in studies are of a wide variety; survey, interview, and various MCDM methods. The prominent studies in the literature are summarized in Table 1.

The current research attempts are dispersed in different sectors, such as human resource management, logistics, manufacturing, and aviation. We observed that the studies carried out primarily in the defense industry are scarce. It is vital for defense companies where technology is at the forefront to analyze their digital maturity level and determine a roadmap to implement accordingly. Despite its strategic importance, this topic has rarely been addressed.

In addition, previous studies have developed their model under a context that cannot effectively consider vague, indeterminate, and inconsistent information except in limited studies. Therefore, there is a need to introduce a novel multi-criteria decision-making approach based on fuzzy numbers to effectively handle the membership, nonmembership, and hesitancy information.

3. Research methodology

This study used the Analytical Hierarchy Process (AHP) [48, 49], one of the most popular MCDM methods, and TODIM. But MCDM methods are criticized for their incapability to handle uncertainty in human judgments [12]. The use of fuzzy sets theory in MCDM methods helps in capturing the vagueness in preference [50,51]. The fuzzy set theory is widely deployed in selection and evaluation problems to tackle information uncertainty in the literature [15] AHP method have been addressed some extensions of fuzzy sets: Type-2 fuzzy sets [52,53]; intuitionistic fuzzy sets [54,55]; neutrosophic fuzzy sets [56–59]; hesitant fuzzy sets [60,61]; Pythagorean fuzzy sets [62–64]; orthopair fuzzy sets [65–67]. These fuzzy sets have some limitations in that they only consider information using a membership function and do not take into account the degree of non-membership and the indeterminacy/degree of hesitancy. One of the recent extensions of the fuzzy sets theory is the spherical fuzzy sets (SFS) proposed by Kutlu Gundogdu and Kahraman as an extension of intuitionistic fuzzy sets, picture fuzzy sets, and Pythagorean fuzzy sets particularly to consider uncertainty. SFS provides higher accuracy in evaluating alternatives in decision-making [68]. SFS is a powerful tool to tackle uncertainty by providing a larger decision-making domain and identifying hesitancy [69]. That is why we used Spherical fuzzy sets (SFS) based AHP and TODIM methods due to eliminating the disadvantages of AHP and TODIM, fuzzy and intuitionistic fuzzy AHP-TODIM in terms of indeterminacy of information. A spherical set is a better option to represent expert opinion with a high degree of indeterminacy. The SF-AHP enables decision-makers to independently reflect their hesitancies in the decision process by using a linguistic evaluation scale based on spherical fuzzy sets.

SF-TODIM method, which is based on prospect theory, considers the subjectivity of DM's behaviors and can provide the dominance of each alternative over others with particular operation formulas, and is more reasonable and scientific in the application of MCDM problems [70]. Also, the method presents the limited rationality behavior character of the decision maker.

3.1. Spherical Fuzzy sets: Preliminaries

Spherical Fuzzy Sets (SFS) as a generalization of Pythagorean Fuzzy Sets and Neutrosophic Sets were presented by Kutlu and Kahraman in 2018. In spherical fuzzy sets, while the squared sum of membership, nonmembership, and hesitancy parameters can be between 0 and 1, each of them can be defined between 0 and 1 independently [10,13,44]. Thus, SFS provides a larger preference domain for decision-makers by the novel concept [10]. For instance, a decision-maker may assign his/her preference for an alternative with respect to a criterion as (0.5, 0.4, 0.6). In this case, the sum of the parameters is larger than one, whereas the squared sum is 0.77. In SFS, the decision-maker should define a hesitancy degree just like other dimensions, with membership and nonmembership degrees. Fig. 1 illustrates the historical background of fuzzy sets.

In the following section, we provide a review of the basic definitions and notations of the linguistic variable SFS and its operations [10,13,71]:

Definition 1. In SFS, \tilde{A}_s of the universe of discourse U is defined by the following expression;

$$u_{\tilde{A}_s} : U \rightarrow [0, 1], v_{\tilde{A}_s} : U \rightarrow [0, 1], \pi_{\tilde{A}_s} : U \rightarrow [0, 1]$$

Table 1
Summary of literature review on DTM.

Year	Author(s)	Objective of the study	Applied methods	Dimensions of study
2015	Lichtblau et al. [27]	Existing readiness model redesigned with contributions from workshops and formed in six Industry 4.0 dimensions by adding two dimensions to the previous model "Smart products", "Data-driven services" and "Employees"	Questionnaire survey	The dimensions are Strategy and organization, Smart factory, Smart operations, Smart products, Data-driven services, Employees.
2016	Schumacher et al. [16]	Presenting a model and applying to assess Industry 4.0 maturity	Questionnaire survey	The model consists of 9 dimensions and 62 items. These dimensions: people, culture, products, leadership, customers, technology, strategy, and governance. The first four dimensions are for evaluating key providers, the others are for evaluating organizational elements.
2017	De Carolis et al. [17]	Proposing a framework to investigate companies' digital maturity	Scoring method	The dimensions are; organization, technology, monitoring and control, and process.
2017	Klötzer and Pflaum [5]	Developing a maturity model concerning the digital transformation of companies within the manufacturing industry's supply chain.	Maturity model for Digitalization	The dimensions are; innovation culture, cooperation, strategy development, process organization, complementary IT system, smart product/factory, offering to the customer, competencies, and structural organization.
2017	Bostrom and Celik [6]	Determining the digital business factors and developing a digital maturity model	Review	Provide practitioners a conceptual framework and give insight for researchers on digital business strategies.
2017	Tupa et al. [28]	Conducting research on risk management related to the concept of Industry 4.0 and identifying all aspects of the relevant risk management practice.	Risk management	The dimensions are; finance, information, technical, security, people, legal, environmental
2018	Akdil et al. [18]	Reviewing the existing maturity models for Industry 4.0 transformation and proposing a new Industry 4.0 maturity model	Questionnaire survey	The dimensions are; Smart Products and Services, Smart Business Processes, Strategy, and Organization.
2017	Von Leipzig et al. [20]	Identifying the problems and difficulties encountered in digitalization	Review	The dimensions are; strategy, leadership, products, operations, culture, people, governance, and technology.
2017	Wibowo and Taufik [43]	Providing a self-assessment tool for companies to measure their maturity level	Delphi method, AHP method	The dimensions are; organizational and culture, risk management processes, risk management resources, risk management implementation. Examples of sub-criteria are; budget, competence, risk perception, and stakeholder relationship.
2018	Ataman [22]	Evaluating the Industry 4.0 maturity level of the defense industry with the Hesitant Fuzzy AHP.	AHP, Fuzzy AHP, Hesitant Fuzzy AHP	Five main criteria and 17 sub-criteria are determined. The main criteria are; Strategy, Management and Organization, Human and R&D Culture, Product and Technology, and Operation. Examples of sub-criteria; Quick Response, Assortment Industry, 4.0 Workforce Planning, Knowledge Sharing, and Teamwork.
2018	Eke [7]	Proposing a two-stage maturity model to evaluate the adaptation level of companies in the logistics sector to the digital transformation process.	Best-Worst method	Four main criteria have been determined in the Logistics 4.0 estimation. The end-to-end supply chain was taken into account when determining the criteria. The main criteria are; Smart Procurement, Smart Logistics Systems, Smart Business Culture, and Smart Sales & Marketing. Examples of sub-criteria are; Technologies used in product - service supply, Level of technology use in logistics, Digital transformation education, Level of meeting customer expectations

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Table 1 (continued).

Year	Author(s)	Objective of the study	Applied methods	Dimensions of study
2018	Bibby and Dehe [21]	Developing an assessment model to measure the level of implementation of Industry 4.0 technologies in defense manufacturing firm.	Questionnaire survey, Scoring method	The main criteria are; factory of the future, people and culture, strategy. Examples of Sub-criteria are; cloud, big data, innovation openness, and manufacturing strategy.
2019	Şahin [25]	Comparing the Industry 4.0 levels of the G-20 countries.	COPRAS	Various criteria have been determined to determine the Industry 4.0 levels of the countries. Some of these criteria are; Open market index, information and communication technologies development index, world economic freedom index, e-government development index, globalization index, global competitiveness index, networked readiness index, e-participation index, the share of medium-high technology production in total production, global innovation index, global entrepreneurship monitor
2019	Keskin et al. [23]	Presenting an analytical model that provides an overall estimation of organizational readiness to Industry 4.0	AHP and TOPSIS	The dimensions are; Product and services, Manufacturing and Operations, Strategy and Organization, Supply Chain, Business Model, Legal Considerations
2019	Kayar [31]	Proposing a new model to guide the production companies to determine their digital maturity levels before moving to Industry 4.0.	AHP	The main criteria are; strategy, innovation, organization, technology, operations, and personnel. examples of sub-criteria are; employee motivation, interdepartmental cooperation, technology investment budget, creation of the business model
2019	Koyuncu et al. [38]	Seven properties of the models are compared and analyzed in a solar cell manufacturing company	Fuzzy TOPSIS (FTOPSIS) and Intuitionistic fuzzy TOPSIS (IFTOPSIS)	Comparison criteria are; the number of dimensions, maturity level, release date, content, the definition of measurement properties, assessment expenditures, and assessment method
2020	Büyükoğkan ve Güler [44] (2020)	Providing a scientific method that helps to determine the most important criteria for companies' digital maturity.	Hesitant Fuzzy Linguistic (HFL) Analytic Hierarchy Process (AHP) and HFL Additive Ratio assessment (ARAS)	The main criteria are; Culture, Organization, Technology, and Insights. Examples of sub-criteria are; Competitive strategy's dependency on digital, Best qualified staff in digital functions, and implementation of digital tools to promote the employee.
2020	Hizam-Hanafiah et al. [45]	Conducts a systematic literature review to explore the breadth and depth of existing Industry readiness models first and then to identify the most common dimensions from these models	Review	The study proposes six dimensions (Technology, People, Strategy, Leadership, Process, and Innovation) that can be considered the most important dimensions for organizations.
2020	Baltacı [8]	With the proposed model, an evaluation method has been developed to measure the digital maturity level of logistics companies.	AHP	The main criteria are; Strategy and Management of Digital Processes, Organization, Digital infrastructure and Integrations, Digital Technologies and Digital Utility Models, Digital Applications. Examples of sub-criteria are; Strategy and Management of Digital Processes, Digital transformation awareness, Mobile usage and Platform applications, Ensuring product traceability, and University collaborations
2020	Ömürgönülşen et al. [33]	Evaluating the factors to be considered in the adaptation process of logistics companies to Industry 4.0.	Fuzzy DEMATEL	Factors in the Industry 4.0 Adaptation Process are as follows; Competencies e.g.; Senior management Support, Adaptability, Requirements; Digitalization Level, Infrastructure; Financial resources. External Factors; Public Incentives

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Table 1 (continued).

Year	Author(s)	Objective of the study	Applied methods	Dimensions of study
2020	Baki and Serdar [34]	Propose two different approaches to evaluate the Industry 4.0 maturity levels of logistics firms with the IMPULS maturity model	AHP-TOPSIS and AHP-VIKOR	The main criteria are; Strategy and organization, Smart factory, Smart transactions, Smart products, Data-driven Services, and Employees. Examples of Sub-criteria are; Innovation Management, Cloud Usage, Level of data used
2020	Wagire et al. [30]	Measuring the industry 4.0 maturity level of an Indian manufacturing company	Fuzzy AHP	The main criteria are; people and culture, industry 4.0 awareness, organizational strategy, value chain and processes, smart manufacturing technology, product and services oriented technology, and industry 4.0 base technology. Examples of sub-criteria are; leadership support, collaboration, blockchain technology, industrial cyber security
2020	Kaya et al. [46]	Determining the best strategy in the transition process to the industry 4.0 for organizations by using a MCDM methodology	Interval valued intuitionistic fuzzy AHP and IVIF-TOPSIS	The main criteria are; leadership, customer, product, c4: operation, culture, people, governance, technology, quality, organization. Examples of sub-criteria are; management competencies and methods, knowledge sharing, and openness of employees to new technology.
2021	Etkeser and Apilioğulları [24]	Developing an Industry 4.0 maturity model for SMEs	AHP	The main criteria are; strategy and organization, employees, smart production, manufacturing technologies and systems, information and communication technology infrastructure, vertical and horizontal integration, industrial internet of things, cyber security, data processing and storage. Examples of Sub-criteria are; industry 4.0 roadmap, leadership skill, digital modeling, communication and network systems
2021	Borštinar, and Pucihar [47]	Assessing digital maturity for SMEs. For this purpose, they developed a multi-attribute model for assessment of the digital maturity of an SME.	DSR approach and the DEX method, which belongs to a group of multi-attribute utility theory method	The main categories: use of technology, role of informatics, digital business model, and strategy. human resources, management
2022	Kırıklık et al. [9]	Examining the role of DT's sub-dimensions in the civil airline industry and proposing a Digital Transformation Maturity (DTM) self-assessment tool for airline firms	IT2F-AHP, Interval type-2 Fuzzy AHP, Factor Analysis	The dimensions are; customer, competition, data, innovation, value, organization, digital ecosystem, technology, strategy
2022	Simetinger, F., & Basl, J. [36]	Defining of a new universal Industry 4.0 maturity model designed for SMEs in the Czech Republic.	Questionnaire survey	The dimensions are; Strategy, Value Chain, Organization, Human Resources, Technology and 19 sub-criteria
2022	Heinz et al. [37]	Presenting a maturity model for Smart Product-Service System and compare solutions	Scale and an assessment questionnaire	The dimensions are; technical enablers (smart product, Realization of value (smartservice), integration into business (product-service system) and 12 sub-criteria
2022	Ting, et al. [39]	Discussing an evaluation framework for the motherboard industry from the perspective of digital transformation	Fuzzy AHP	The dimensions are; procurement management, research and development design, manufacturing, logistics warehousing, aftersales service, customer demand, relationship maintenance, and 21 evaluation criteria
This study	Nebati et al.	Proposing a DMM in defense industry and applying it on a major defense company	SF-AHP & SF TODIM	

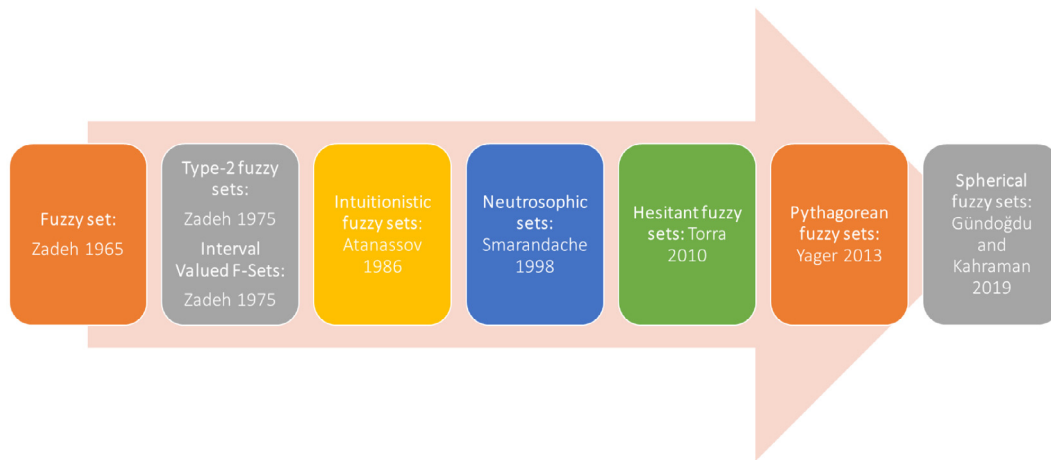


Fig. 1. Fuzzy sets' historical background.

and

$$0 \leq u_{\tilde{A}_s}^2(u) + v_{\tilde{A}_s}^2(u) + \pi_{\tilde{A}_s}^2(u) \leq 1 \quad (u \in U)$$

$$\tilde{A}_s = \{ \langle u, (u_{\tilde{A}_s}(u), v_{\tilde{A}_s}(u), \pi_{\tilde{A}_s}(u)) \mid u \in U \}$$

For each u , the value $u_{\tilde{A}_s}(u)$, $v_{\tilde{A}_s}(u)$, and $\pi_{\tilde{A}_s}(u)$ are the degree of membership, nonmembership, and hesitancy of u to \tilde{A}_s , respectively [10].

Definition 2. Let U_1 and U_2 be two universes. Let \tilde{A}_s and \tilde{B}_s be two SFSs of the universe of discourse U_1 and U_2 . Geometrical representation of SFS and distances between \tilde{A}_s and \tilde{B}_s are illustrated in Fig. 2 [72,73].

$$D(\tilde{A}_s, \tilde{B}_s) = \frac{2}{\pi} \sum_{i:1}^n \arccos \left(1 - 0.5 \times \left[(u_{\tilde{A}_s} - u_{\tilde{B}_s})^2 + (v_{\tilde{A}_s} - v_{\tilde{B}_s})^2 + (\pi_{\tilde{A}_s} - \pi_{\tilde{B}_s})^2 \right] \right)$$

$$0 \leq D(\tilde{A}_s, \tilde{B}_s) \leq n$$

by using $u_{\tilde{A}_s}^2 + v_{\tilde{A}_s}^2 + \pi_{\tilde{A}_s}^2 = 1$, we can obtain the normalized distances between \tilde{A}_s and \tilde{B}_s as following:

$$D_n(\tilde{A}_s, \tilde{B}_s) = \frac{2}{n\pi} \sum_{i:1}^n \arccos \left(u_{\tilde{A}_s}(u_i) \times u_{\tilde{B}_s}(u_i) + v_{\tilde{A}_s}(u_i) \times v_{\tilde{B}_s}(u_i) + \pi_{\tilde{A}_s}(u_i) \times \pi_{\tilde{B}_s}(u_i) \right)$$

$$0 \leq D_n(\tilde{A}_s, \tilde{B}_s) \leq 1$$

Definition 3. The algebraic operations are defined as follows [13]:

Addition:

$$\tilde{A}_s \oplus \tilde{B}_s = \left\{ \sqrt{u_{\tilde{A}_s}^2 + u_{\tilde{B}_s}^2 - u_{\tilde{A}_s}^2 \cdot u_{\tilde{B}_s}^2}, v_{\tilde{A}_s}^2 \cdot v_{\tilde{B}_s}^2, \sqrt{\left((1 - u_{\tilde{B}_s}^2) \pi_{\tilde{A}_s}^2 + (1 - u_{\tilde{A}_s}^2) \pi_{\tilde{B}_s}^2 - \pi_{\tilde{A}_s}^2 \cdot \pi_{\tilde{B}_s}^2 \right)} \right\}$$

Multiplication:

$$\tilde{A}_s \otimes \tilde{B}_s = \left\{ u_{\tilde{A}_s}^2 \cdot u_{\tilde{B}_s}^2, \sqrt{v_{\tilde{A}_s}^2 + v_{\tilde{B}_s}^2 - v_{\tilde{A}_s}^2 \cdot v_{\tilde{B}_s}^2}, \sqrt{\left((1 - v_{\tilde{B}_s}^2) \pi_{\tilde{A}_s}^2 + (1 - v_{\tilde{A}_s}^2) \pi_{\tilde{B}_s}^2 - \pi_{\tilde{A}_s}^2 \cdot \pi_{\tilde{B}_s}^2 \right)} \right\}$$

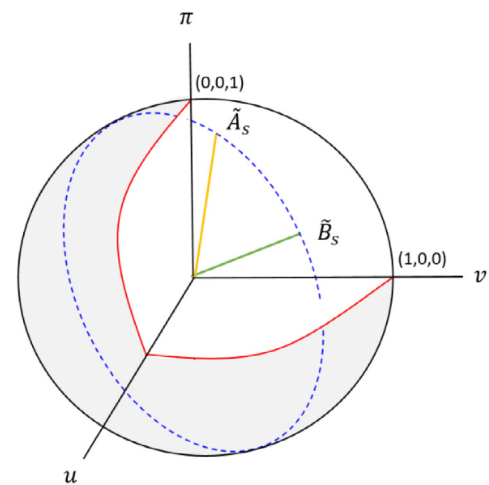


Fig. 2. 3D geometrical representation of Spherical Fuzzy Sets.

Multiplication by a scalar:

$$\tilde{A}_s \otimes x = \left\{ \sqrt{1 - (1 - u_{\tilde{A}_s}^2)^x}, v_{\tilde{A}_s}^x, \sqrt{\left((1 - u_{\tilde{A}_s}^2)^x - (1 - u_{\tilde{A}_s}^2 - \pi_{\tilde{A}_s}^2)^x \right)} \right\}$$

x. Power of \tilde{A}_s :

$$\tilde{A}_s^x = \left\{ u_{\tilde{A}_s}^x, \sqrt{1 - (1 - v_{\tilde{A}_s}^2)^x}, \sqrt{\left((1 - v_{\tilde{A}_s}^2)^x - (1 - v_{\tilde{A}_s}^2 - \pi_{\tilde{A}_s}^2)^x \right)} \right\}$$

Union;

$$\tilde{A}_s \cup \tilde{B}_s = \left\{ \max(u_{\tilde{A}_s}^2, u_{\tilde{B}_s}^2), \min(v_{\tilde{A}_s}^2, v_{\tilde{B}_s}^2), \min \left(1 - \left(\left(\max(u_{\tilde{A}_s}^2, u_{\tilde{B}_s}^2) \right)^2 + \left(\min(v_{\tilde{A}_s}^2, v_{\tilde{B}_s}^2) \right)^2 \right), \max(\pi_{\tilde{A}_s}^2, \pi_{\tilde{B}_s}^2) \right) \right\}$$

Table 2
Linguistic scale, its Score Index and corresponding SF sets [10].

Linguistic term	Score Index (SI)	(u, v, π)
Absolutely more importance (AMI)	9	(0.9,0.1,0.0)
Very high importance (VHI)	7	(0.8,0.2,0.1)
High importance (HI)	5	(0.7,0.3,0.2)
Slightly more importance (SMI)	3	(0.6,0.4,0.3)
Equally importance (EI)	1	(0.5,0.4,0.4)
Slightly low importance (SLI)	1/3	(0.4,0.6,0.3)
Low importance (LI)	1/5	(0.3,0.7,0.2)
Very low importance (VLI)	1/7	(0.2,0.8,0.1)
Absolutely low importance (ALI)	1/9	(0.1,0.9,0.0)

Table 3
Experts' positions and expertise.

Expert	Position	Experience (Year)
Expert 1	Tactic level manager	22
Expert 2	Tactic level manager	20
Expert 3	Strategic level manager	40

Intersection;

$$\tilde{A}_s \cap \tilde{B}_s = \left\{ \min(u_{\tilde{A}_s}^2, u_{\tilde{B}_s}^2), \max(v_{\tilde{A}_s}^2, v_{\tilde{B}_s}^2), \min \left(1 - \left(\left(\min(u_{\tilde{A}_s}^2, u_{\tilde{B}_s}^2) \right)^2 + \left(\max(v_{\tilde{A}_s}^2, v_{\tilde{B}_s}^2) \right)^2 \right), \min(\pi_{\tilde{A}_s}^2, \pi_{\tilde{B}_s}^2) \right) \right\}$$

Definition 4. The Basic operators in SFs are defined as follows [13]:

$$\begin{aligned} \tilde{A}_s \oplus \tilde{B}_s &= \tilde{B}_s \oplus \tilde{A}_s \\ \tilde{A}_s \otimes \tilde{B}_s &= \tilde{B}_s \otimes \tilde{A}_s \\ x(\tilde{A}_s \oplus \tilde{B}_s) &= x.\tilde{A}_s \oplus x.\tilde{B}_s \\ x_1.\tilde{A}_s \oplus x_2.\tilde{A}_s &= (x_1 + x_2).\tilde{A}_s \\ (\tilde{A}_s \otimes \tilde{B}_s)^x &= \tilde{A}_s^x \otimes \tilde{B}_s^x \\ \tilde{A}_s^{-x} \otimes \tilde{A}_s^{-y} &= \tilde{A}_s^{-x-y} \end{aligned}$$

Definition 5. Spherical Weighted Arithmetic Mean (SWAM) with respect to $w = (w_1, w_2, \dots, w_n)$; $\sum_{i:1}^n w_i = 1$, is defined as follows [13]:

$$\begin{aligned} SWAM_w(\tilde{A}_{s1}, \tilde{A}_{s2}, \dots, \tilde{A}_{sn}) &= w_1\tilde{A}_{s1} + w_2\tilde{A}_{s2} + \dots + w_n\tilde{A}_{sn} \\ &= \left\{ \sqrt{1 - \prod_{i:1}^n (1 - u_{\tilde{A}_{si}}^2)^{w_i}}, \prod_{i:1}^n v_{\tilde{A}_{si}}^{w_i}, \sqrt{\prod_{i:1}^n (1 - u_{\tilde{A}_{si}}^2)^{w_i} - \prod_{i:1}^n (1 - u_{\tilde{A}_{si}}^2 - \pi_{\tilde{A}_{si}}^2)^{w_i}} \right\} \end{aligned}$$

Definition 6. Spherical Weighted Geometric Mean (SWGM) with respect to $w = (w_1, w_2, \dots, w_n)$; $\sum_{i:1}^n w_i = 1$ is defined as follows [13]:

$$\begin{aligned} SWGM_w(\tilde{A}_{s1}, \tilde{A}_{s2}, \dots, \tilde{A}_{sn}) &= \tilde{A}_{s1}^{w_1} + \tilde{A}_{s2}^{w_2} + \dots + \tilde{A}_{sn}^{w_n} \\ &= \left\{ \prod_{i:1}^n u_{\tilde{A}_{si}}^{w_i}, \sqrt{1 - \prod_{i:1}^n (1 - v_{\tilde{A}_{si}}^2)^{w_i}} \right\} \end{aligned}$$

$$\left\{ \sqrt{\prod_{i:1}^n (1 - v_{\tilde{A}_{si}}^2)^{w_i} - \prod_{i:1}^n (1 - v_{\tilde{A}_{si}}^2 - \pi_{\tilde{A}_{si}}^2)^{w_i}} \right\}$$

Definition 7. Score functions and accuracy function of sorting SFs are defined with [13];

$$\begin{aligned} \text{Score}(\tilde{A}_s) &= (u_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2 - (v_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2 \\ \text{Accuracy}(\tilde{A}_s) &= u_{\tilde{A}_s}^2 + v_{\tilde{A}_s}^2 + \pi_{\tilde{A}_s}^2 \end{aligned}$$

Note that: $\tilde{A}_s < \tilde{B}_s$ if and only if $\text{Score}(\tilde{A}_s) < \text{Score}(\tilde{B}_s)$ or $\text{Score}(\tilde{A}_s) = \text{Score}(\tilde{B}_s)$ and $\text{Accuracy}(\tilde{A}_s) < \text{Accuracy}(\tilde{B}_s)$

3.2. DMM with SF-AHP and SF-TODIM

The suggested hybrid methodology, SF-AHP and SF-TODIM, consists of seventeen steps, as given in Fig. 3.

Stage 1: SF-AHP

Step 1 Determine criteria weights using SF-AHP

Step 2. Establish the hierarchical structure of the DMM.

Step 3. Construct a pairwise comparison matrix with spherical fuzzy judgment matrices based on the linguistic terms given in Table 2. Eqs. (1) and (2) are used to obtain the score indices (SI) in Table 2.

For AMI, VHI, HI, SMI, and EI

$$SI = \sqrt{\left| 100 \times \left((u_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2 - (v_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2 \right) \right|} \tag{1}$$

For EI; SLI; LI; VLI; and ALI;

$$SI^{-1} = 1 / \sqrt{\left| 100 \times \left((u_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2 - (v_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2 \right) \right|} \tag{2}$$

Step 4. Estimate the spherical fuzzy global and local weights of main and sub-criteria using SWAM operator given in Definition 5. The weighted arithmetic mean is used to compute the spherical fuzzy weights.

Stage 2: Extension of TODIM with SFs

In the conventional TODIM, the decision-makers express the assessment of the alternatives' performances and weights of the criteria using crisp values. An integrated generalized TODIM method is applied to the MCDM analysis [74]. TODIM is derived from prospect theory, which considers the psychological behaviors of decision-makers [75]. However, the decision maker may remain undecided. So, the DM's judgment affirmation, negation, and hesitation characteristics are manifested. For this reason, it is more appropriate to show the performance and criterion weights of the alternatives with SFs. Furthermore, SFs can clearly define DMs' preferences while representing ambiguous information efficiently. The score function is effective in comparing most SFs, but can sometimes be insufficient. According to [10] changed the score function for this situation, and the score function can sometimes give a negative value. In order to evaluate decision matrices and SF weights, alternative evaluation functions that give non-negative values are needed. [76] proposed an evaluation function for Intuitive Fuzzy Sets (IFSs). Information reliability is measured by the degree of hesitation and the amount of information by the distance from the positive ideal alternative. The function is given by $f(\tilde{A}_i) = 0.5(1 + \pi)(1 - \mu)$. The smaller the value of $f(\tilde{A}_i)$, the greater the IFS.

Thus, the weights of the criteria express an SFS, the degree of agreement and disagreement, and the degree of hesitation about the importance of a criterion. The SFS representing the ideal weight (IW) is (1; 0; 0), i.e. 100% agreement, 0% disagreement, and 0% hesitancy. A short distance to IW determines the

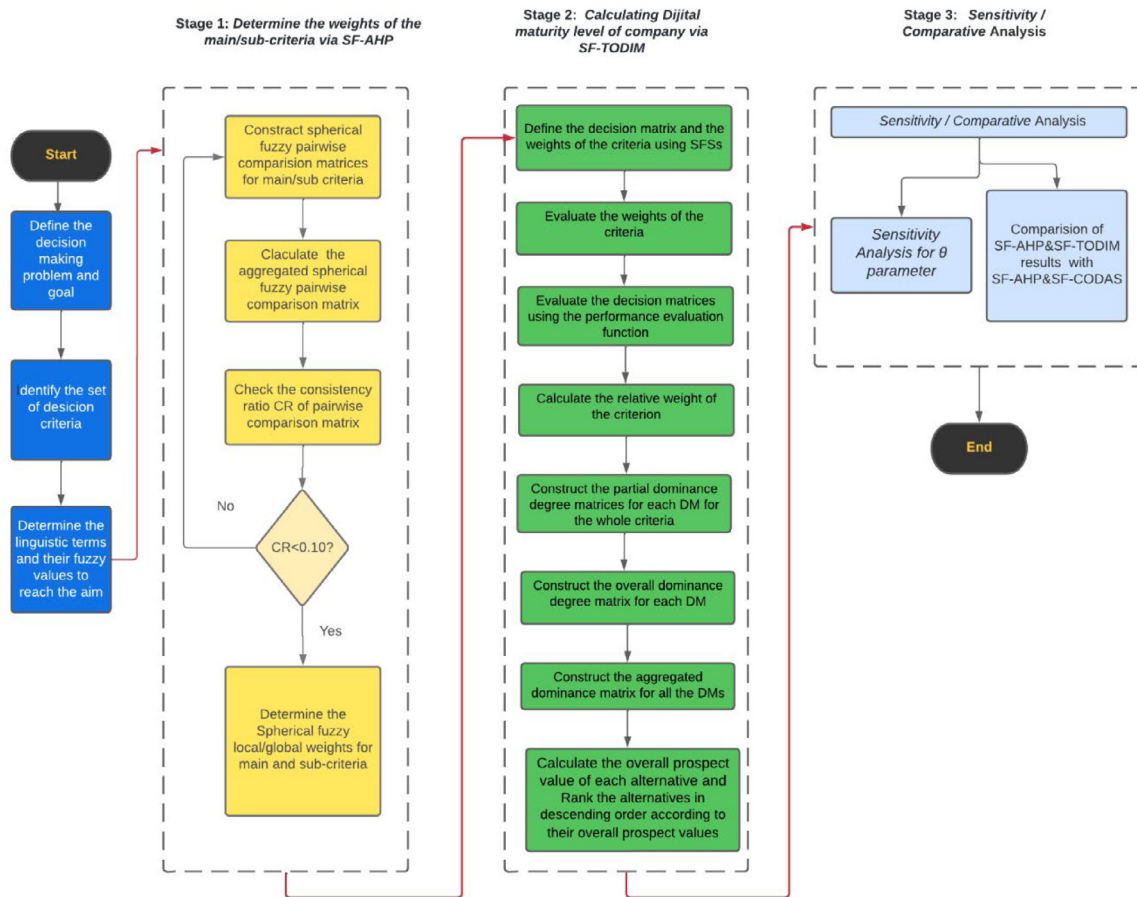


Fig. 3. Flowchart of the proposed DMM based on SF-AHP and SF-TODIM.



Fig. 4. Hierarchical structure for digital maturity model.

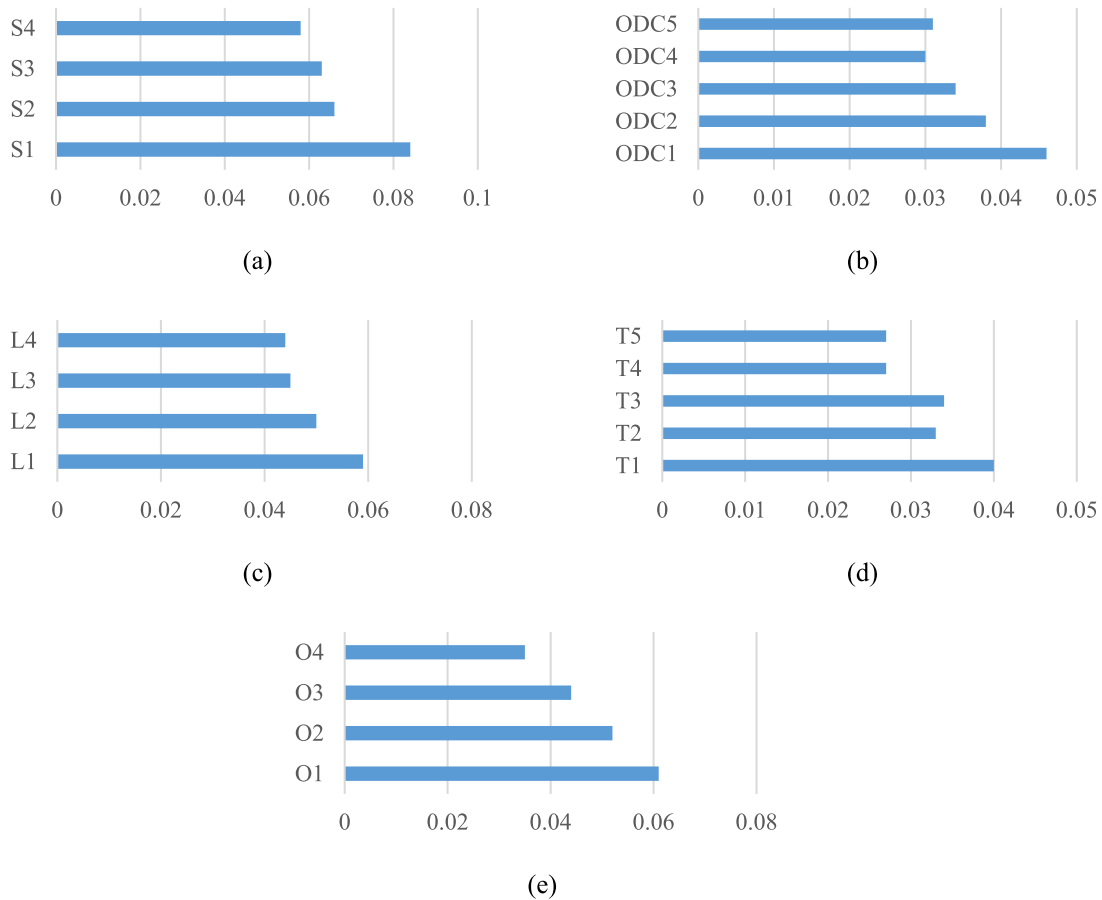


Fig. 5. (a-e) The spherical fuzzy global weights sub-criteria calculated with SF-AHP.

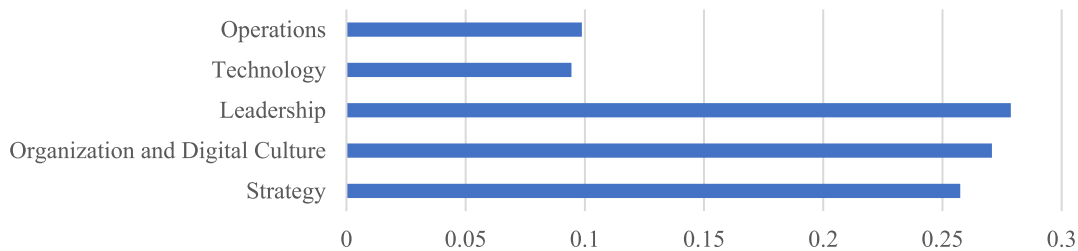


Fig. 6. Normalized prospect values for the main criteria.

Table 4
Aggregated evaluations of three experts on the main criteria.

	S			ODC			L			T			O		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
S	0.5	0.4	0.4	0.71	0.2	0	0.7	0.29	0.18	0.8	0.18	0	0.68	0.25	0.16
ODC	0.22	0.66	0	0.5	0.4	0.4	0.39	0.55	0.29	0.56	0.36	0.32	0.46	0.46	0.36
L	0.29	0.7	0.18	0.5	0.4	0.4	0.5	0.4	0.4	0.59	0.36	0.29	0.55	0.42	0.26
T	0.18	0.8	0	0.42	0.48	0.32	0.39	0.55	0.29	0.5	0.4	0.4	0.39	0.55	0.29
O	0.27	0.63	0.16	0.53	0.4	0.36	0.42	0.55	0.26	0.59	0.36	0.29	0.5	0.4	0.4

importance of the criterion. Therefore, the weight of a criterion increases as the distance between the IW and that criterion decreases. For a SF weight $\tilde{w} = (\mu_w, \nu_w, \pi_w)$, the importance evaluation function is given by

$$F(\tilde{w}) = 1 - d_{\tilde{w}} = 1 - \sqrt{\frac{1}{2} [(1 - \mu_w)^2 + (\nu_w)^2 + (\pi_w)^2]} \quad (3)$$

The distance between the amount of information measured in the significance evaluation function and the positive ideal weight is sufficient. The reliability of the information measured by the degree of hesitation is unimportant.

On the contrary, the margin of hesitation plays a crucial role when concerned with the performance of alternatives for criteria.

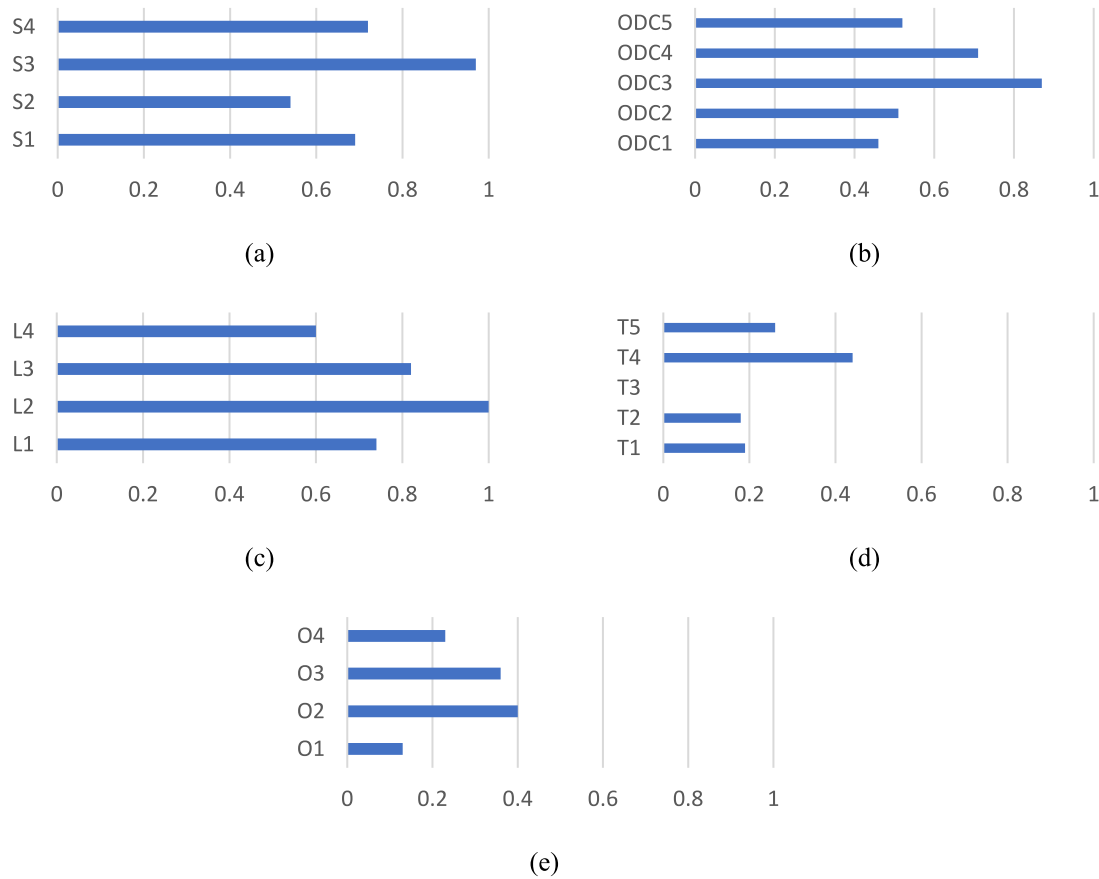


Fig. 7. (a–e) Overall prospect values.

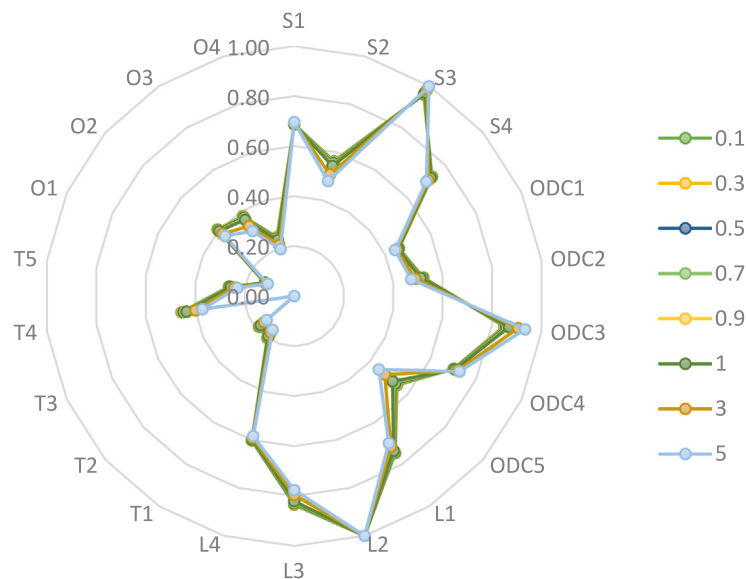


Fig. 8. Digital maturity scores of criteria for different θ values.

Consideration should be given to the extent to which an alternative meets the requirements. Thus, the reliability and the amount of information are used in the performance evaluation function.

SFS represents the performance of the ideal alternative (IA) for a criterion is (1; 0; 0), for example; an alternative fulfills a criterion 100%, an alternative does not fulfill a criterion 0%, and 0% hesitation margin. For an alternative with performance

$\tilde{r}_{ij} = (\mu_r, \nu_r, \pi_r)$ the amount of information is measured by the membership and nonmembership degree; reliability is measured by the degree of hesitation. The higher the fulfillment degree, the lower the nonfulfillment degree, and the amount of information increases. Besides, the smaller the hesitancy degree, the reliability of an SFS is greater. Also, the smaller the degree of hesitation, the higher the reliability of an SFS.

Table 5
Aggregated pairwise matrix for **strategy** sub-criteria.

	S1			S2			S3			S4		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
S1	0.5	0.4	0.4	0.66	0.32	0.21	0.63	0.36	0.26	0.66	0.32	0.21
S2	0.32	0.66	0.21	0.5	0.4	0.4	0.52	0.46	0.3	0.56	0.4	0.33
S3	0.36	0.63	0.26	0.46	0.52	0.3	0.5	0.4	0.4	0.53	0.4	0.36
S4	0.32	0.66	0.21	0.43	0.52	0.33	0.46	0.46	0.36	0.5	0.4	0.4

Table 6
Aggregated pairwise matrix for **organization and digital culture** sub-criteria.

	ODC1			ODC2			ODC3			ODC4			ODC5		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
ODC1	0.5	0.4	0.4	0.68	0.23	0	0.73	0.26	0.16	0.7	0.29	0.18	0.65	0.25	0
ODC2	0.25	0.63	0	0.5	0.4	0.4	0.63	0.36	0.26	0.62	0.32	0.23	0.58	0.36	0.21
ODC3	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.52	0.46	0.3	0.42	0.5	0.21
ODC4	0.29	0.7	0.18	0.34	0.58	0.23	0.46	0.52	0.3	0.5	0.4	0.4	0.48	0.48	0.26
ODC5	0.27	0.6	0	0.36	0.58	0.21	0.5	0.42	0.21	0.48	0.48	0.26	0.5	0.4	0.4

Table 7
Aggregated pairwise matrix for **leadership** sub-criteria.

	L1			L2			L3			L4		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
L1	0.50	0.40	0.40	0.66	0.33	0.23	0.62	0.32	0.23	0.56	0.36	0.32
L2	0.33	0.66	0.23	0.50	0.40	0.40	0.58	0.36	0.21	0.55	0.42	0.26
L3	0.34	0.58	0.23	0.36	0.58	0.21	0.50	0.40	0.40	0.56	0.40	0.33
L4	0.42	0.48	0.32	0.42	0.55	0.26	0.43	0.52	0.33	0.50	0.40	0.40

Table 8
Aggregated pairwise matrix for **technology** sub-criteria.

	T1			T2			T3			T4			T5		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
T1	0.5	0.4	0.4	0.66	0.32	0.21	0.68	0.23	0	0.7	0.29	0.18	0.63	0.33	0.25
T2	0.32	0.66	0.21	0.5	0.4	0.4	0.58	0.36	0.21	0.62	0.32	0.23	0.53	0.4	0.2
T3	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.65	0.29	0.2	0.54	0.36	0.23
T4	0.29	0.7	0.18	0.34	0.58	0.23	0.31	0.61	0.2	0.5	0.4	0.4	0.53	0.4	0.2
T5	0.36	0.58	0.25	0.4	0.53	0.2	0.39	0.5	0.23	0.4	0.53	0.2	0.5	0.4	0.4

Table 9
Aggregated pairwise matrix for **operations** sub-criteria.

	O1			O2			O3			O4		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
O1	0.50	0.40	0.40	0.66	0.33	0.23	0.76	0.21	0.00	0.65	0.29	0.20
O2	0.33	0.66	0.23	0.50	0.40	0.40	0.66	0.33	0.23	0.66	0.33	0.23
O3	0.21	0.76	0.00	0.33	0.66	0.23	0.50	0.40	0.40	0.66	0.33	0.23
O4	0.31	0.61	0.20	0.33	0.66	0.23	0.33	0.66	0.23	0.50	0.40	0.40

The absolute value of the natural logarithmic function is used to count the reliability relative to the margin of hesitation. Therefore, depending on the increase in the margin of hesitation, the performance evaluation function decreases. Given by the evaluation function

$$F(\tilde{r}_{ij}) = \begin{cases} 0.1\mu_r (1 - \nu_r) |\ln \pi| & \text{if } \pi_r \geq 0.05 \\ 0.3\mu_r (1 - \nu_r), & \text{if } \pi_r < 0.05 \end{cases} \quad (4)$$

To reduce the effect of the natural logarithmic function, the constant 0.1 is added with a steep descent in the range (0.1). SF-TODIM steps are explained as follows.

Step 1. The decision matrix is defined in each DMs and weights of criteria using SFSSs.

$$C_1 \quad C_2 \quad C_m$$

$$\tilde{D}_p = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} \begin{bmatrix} \tilde{r}_{11}^p & \tilde{r}_{12}^p & \dots & \tilde{r}_{1m}^p \\ \tilde{r}_{21}^p & \tilde{r}_{22}^p & \dots & \tilde{r}_{2m}^p \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{r}_{n1}^p & \tilde{r}_{n2}^p & \dots & \tilde{r}_{nm}^p \end{bmatrix}, \text{ and} \quad (5)$$

$$w = \tilde{w}_1^p, \tilde{w}_2^p, \dots, \tilde{w}_m^p,$$

where $\tilde{r}_{ij}^p = (\mu_r, \nu_r, \pi_r)$ is the rating of i th alternative, $i = \{1, \dots, N\}$, for the j th criterion, $j = \{1, \dots, M\}$, as evaluated by the p th DM, $p = \{1, \dots, P\}$. Additionally, $\tilde{w}_j^p = (\mu_w, \nu_w, \pi_w)$ is the weight of j th criterion assigned by the p th DM.

Step 2. The weights of the criteria are evaluated using the importance evaluation function (3). With using the normalized Euclidean distance (6), the distance of the spherical fuzzy weight $\tilde{w}_j^p = (\mu_w, \nu_w, \pi_w)$ to ideal weight (1,0,0) is calculated.

$$d_{\tilde{w}_j^p} = \sqrt{\frac{1}{2} [(1 - \mu_w)^2 + (\nu_w)^2 + (\pi_w)^2]} \quad (6)$$

The shorter the distance to the ideal weight, the more the criterion's weight. Therefore, the distance from 1 is subtracted.

$$F(\tilde{w}_j^p) = 1 - d_{\tilde{w}_j^p} = 1 - \sqrt{\frac{1}{2} [(1 - \mu_w)^2 + (\nu_w)^2 + (\pi_w)^2]} \quad (7)$$

Then, the weights are normalized to satisfy the condition, $w_j > 0$ and $\sum_{j=1}^m w_j = 1$. Hence, the weight is given by:

$$\tilde{w}_j^p = \frac{F(\tilde{w}_j^p)}{\sum_{j=1}^m F(\tilde{w}_j^p)} \quad (8)$$

Table 10
The SF decision matrix and the weights of the criteria assigned by DMs.

	DM ₁				DM ₂				DM ₃			
	μ	ν	π	w ₁	μ	ν	π	w ₂	μ	ν	π	w ₃
S1	0.7	0.3	0.3	0.064	0.7	0.3	0.3	0.081	0.2	0.8	0.2	0.102
S2	0.5	0.5	0.5	0.059	0.5	0.5	0.5	0.075	0.5	0.5	0.5	0.059
S3	0.4	0.6	0.4	0.050	0.9	0.1	0.1	0.064	0.5	0.5	0.5	0.073
S4	0.3	0.7	0.3	0.050	0.8	0.2	0.2	0.064	0.4	0.6	0.4	0.059
ODC1	0.6	0.4	0.4	0.052	0.6	0.4	0.4	0.046	0.2	0.8	0.2	0.040
ODC2	0.5	0.5	0.5	0.038	0.7	0.3	0.3	0.044	0.2	0.8	0.2	0.031
ODC3	0.9	0.1	0.1	0.034	0.5	0.5	0.5	0.034	0.4	0.6	0.4	0.031
ODC4	0.8	0.2	0.2	0.037	0.4	0.6	0.4	0.028	0.4	0.6	0.4	0.027
ODC5	0.5	0.5	0.5	0.050	0.5	0.5	0.5	0.024	0.4	0.6	0.4	0.025
L1	0.4	0.6	0.4	0.055	0.8	0.2	0.2	0.052	0.3	0.7	0.3	0.067
L2	0.7	0.3	0.3	0.049	0.8	0.2	0.2	0.043	0.3	0.7	0.3	0.062
L3	0.5	0.5	0.5	0.046	0.8	0.2	0.2	0.052	0.3	0.7	0.3	0.042
L4	0.6	0.4	0.4	0.042	0.7	0.3	0.3	0.052	0.2	0.8	0.2	0.038
T1	0.5	0.5	0.5	0.034	0.4	0.6	0.4	0.045	0.2	0.8	0.2	0.039
T2	0.4	0.6	0.4	0.033	0.5	0.5	0.5	0.028	0.2	0.8	0.2	0.036
T3	0.4	0.6	0.4	0.031	0.3	0.7	0.3	0.032	0.2	0.8	0.2	0.035
T4	0.4	0.6	0.4	0.029	0.5	0.5	0.5	0.030	0.4	0.6	0.4	0.025
T5	0.5	0.5	0.5	0.023	0.2	0.8	0.2	0.041	0.4	0.6	0.4	0.019
O1	0.5	0.5	0.5	0.073	0.2	0.8	0.2	0.053	0.3	0.7	0.3	0.059
O2	0.3	0.7	0.3	0.057	0.6	0.4	0.4	0.045	0.4	0.6	0.4	0.053
O3	0.4	0.6	0.4	0.049	0.4	0.6	0.4	0.037	0.4	0.6	0.4	0.045
O4	0.4	0.6	0.4	0.044	0.4	0.6	0.4	0.030	0.3	0.7	0.3	0.033

Table 11
Defuzzification of the decision matrices for each DM.

	DM ₁	DM ₂	DM ₃	w ₁	w ₂	w ₃
S1	0.059	0.059	0.006	0.877	1.000	1.000
S2	0.017	0.017	0.017	0.814	0.928	0.580
S3	0.015	0.187	0.017	0.687	0.783	0.718
S4	0.011	0.103	0.015	0.687	0.783	0.580
ODC1	0.033	0.033	0.006	0.712	0.566	0.393
ODC2	0.017	0.059	0.006	0.518	0.538	0.300
ODC3	0.187	0.017	0.015	0.470	0.425	0.302
ODC4	0.103	0.015	0.015	0.505	0.347	0.269
ODC5	0.017	0.017	0.015	0.691	0.294	0.242
L1	0.015	0.103	0.011	0.759	0.643	0.657
L2	0.059	0.103	0.011	0.676	0.525	0.604
L3	0.017	0.103	0.011	0.627	0.643	0.407
L4	0.033	0.059	0.006	0.582	0.643	0.368
T1	0.017	0.015	0.006	0.463	0.553	0.381
T2	0.015	0.017	0.006	0.457	0.342	0.355
T3	0.015	0.011	0.006	0.433	0.399	0.340
T4	0.015	0.017	0.015	0.400	0.365	0.243
T5	0.017	0.006	0.015	0.321	0.511	0.185
O1	0.017	0.006	0.011	1.000	0.656	0.581
O2	0.011	0.033	0.015	0.782	0.556	0.523
O3	0.015	0.015	0.015	0.680	0.459	0.442
O4	0.015	0.015	0.011	0.603	0.367	0.324

Step 3. Decision matrices are evaluated using the performance function (4).

The spherical fuzzy rating, $\tilde{r}_{ij}^p = (\mu_r, \nu_r, \pi_r)$, is evaluated using the following formula:

$$\tilde{r}_{ij} = \begin{cases} 0.1\mu_r(1 - \nu_r)|\ln\pi| & \text{if } \pi_r \geq 0.05 \\ 0.3\mu_r(1 - \nu_r), & \text{if } \pi_r < 0.05 \end{cases} \quad (9)$$

Step 4. The relative weight of the C_j criterion with respect to the C_r reference criterion is calculated by.

$$w_{jr} = \frac{w_j}{w_r}, \quad (j = 1, 2, \dots, m), \quad (10)$$

where w_j is the weight of the criterion C_j and $w_r = \max\{w_j\}$.

Step 5. Partial dominance matrices with are generated for all criteria

$$A_1 \quad A_2 \quad A_n$$

$$\phi_j^p(A_i, A_k) = [\phi_{ik}^p] = \begin{matrix} A_1 & \begin{bmatrix} 0 & \tilde{\phi}_{12}^p & \dots & \phi_{1n}^p \\ \tilde{\phi}_{21}^p & 0 & \dots & \tilde{\phi}_{2n}^p \\ \vdots & \vdots & \ddots & \vdots \\ A_n & \phi_{n1}^p & \phi_{n2}^p & \dots & 0 \end{bmatrix} \end{matrix} \quad (11)$$

The dominance of alternative *i* over the alternative *k* with respect to the criterion *j* is defined as

$$\phi_j^p(A_i, A_k) = \begin{cases} \sqrt{\frac{w_{jr}}{\sum_{j=1}^n w_{jr}} (r_{ij} - r_{kj})}, & \text{if } (r_{ij} - r_{kj}) > 0 \\ 0, & \text{if } (r_{ij} - r_{kj}) = 0 \\ -\frac{1}{\theta} \sqrt{\frac{w_{jr}}{\sum_{j=1}^n w_{jr}} (r_{kj} - r_{ij})}, & \text{if } (r_{ij} - r_{kj}) < 0 \end{cases} \quad (12)$$

where $d(r_{ij}, r_{pj})$ is the distance between r_{ij} and r_{pj} .

Step 6. The overall dominance matrix is generated for each DM

$$\phi^p(A_i, A_k) = \sum_{j=1}^m \phi_j^p(A_i, A_k) \quad (13)$$

Step 7. The aggregated dominance matrix is for each DMs.

$$\Psi(A_i, A_k) = \sum_{p=1}^s \lambda_p \phi_p(A_i, A_k). \quad (14)$$

where λ_p stands for the importance attached to the *p*th DM.

Step 8. The overall probability value must be calculated for each alternative A_i

$$\psi_i = \frac{\sum_{i=1}^n \Psi(A_i, A_k) - \min_i \{\sum_{i=1}^n \Psi(A_i, A_k)\}}{\max_i \{\sum_{i=1}^n \Psi(A_i, A_k)\} - \min_i \{\sum_{i=1}^n \Psi(A_i, A_k)\}} \quad (15)$$

Step 9. Rank the alternatives according to the decreasing values in the overall expectation values. If the value of ψ_i is high, the alternative value of A_i. will increase at the same rate.

Table 12
The aggregated dominance matrix.

C	S1	S2	S3	S4	ODC1	ODC2	ODC3	ODC4	ODC5	L1	L2	L3	L4	T1	T2	T3	T4	T5	O1	O2	O3	O4
S1	0.00	-0.11	-0.67	-0.43	0.02	0.01	-0.79	-0.50	-0.10	-0.37	-0.41	-0.41	0.01	0.03	0.02	0.03	-0.15	-0.17	-0.04	-0.10	-0.10	-0.08
S2	-0.52	0.00	-0.60	-0.42	-0.35	-0.34	-0.73	-0.50	0.00	-0.40	-0.73	-0.45	-0.52	0.01	0.01	0.01	0.01	0.01	0.02	-0.16	0.01	0.01
S3	-0.24	-0.04	0.00	0.03	-0.16	-0.06	-0.71	-0.48	-0.04	0.03	-0.29	-0.05	-0.19	-0.06	0.03	0.03	0.03	-0.09	-0.02	0.04	0.03	0.03
S4	-0.26	-0.16	-0.59	0.00	-0.19	-0.12	-0.73	-0.50	-0.10	-0.08	-0.32	-0.12	-0.22	-0.12	-0.09	-0.09	-0.10	-0.16	-0.07	0.02	-0.07	-0.07
ODC1	-0.42	-0.12	-0.72	-0.51	0.00	-0.27	-0.85	-0.60	-0.11	-0.45	-0.73	-0.50	-0.26	0.02	0.02	0.02	-0.16	-0.18	-0.06	-0.11	-0.11	-0.09
ODC2	-0.27	-0.13	-0.68	-0.44	-0.17	0.00	-0.88	-0.65	-0.12	-0.38	-0.71	-0.43	-0.20	0.01	0.02	0.02	-0.16	-0.18	-0.06	-0.11	-0.12	-0.09
ODC3	-0.23	-0.04	-0.65	-0.40	-0.15	-0.31	0.00	0.02	0.03	-0.37	-0.40	-0.42	-0.29	0.03	0.03	0.03	0.02	0.03	0.05	-0.14	0.03	0.04
ODC4	-0.25	-0.12	-0.67	-0.42	-0.17	-0.33	-0.61	0.00	-0.05	-0.39	-0.42	-0.43	-0.31	0.02	-0.07	0.03	-0.08	0.02	0.04	-0.16	0.02	0.02
ODC5	-0.53	-0.07	-0.68	-0.43	-0.36	-0.34	-0.73	-0.50	0.00	-0.40	-0.73	-0.45	-0.52	0.01	0.01	0.01	0.00	0.01	0.01	-0.17	0.01	0.01
L1	-0.25	-0.16	-0.55	-0.09	-0.17	-0.07	-0.83	-0.60	-0.15	0.00	-0.31	-0.08	-0.20	-0.07	0.02	0.02	-0.10	-0.23	-0.04	-0.06	-0.07	0.02
L2	0.02	-0.07	-0.53	-0.08	0.04	0.03	-0.73	-0.45	-0.05	0.02	0.00	0.01	0.03	0.03	0.03	0.03	-0.09	-0.11	0.05	-0.05	-0.05	0.04
L3	-0.24	-0.09	-0.54	-0.09	-0.16	0.02	-0.83	-0.59	-0.07	0.00	-0.30	0.00	-0.18	0.02	0.02	0.02	-0.10	-0.12	0.03	-0.06	-0.07	0.02
L4	-0.21	-0.12	-0.67	-0.43	0.01	0.01	-0.85	-0.60	-0.11	-0.38	-0.65	-0.42	0.00	0.02	0.02	0.02	-0.16	-0.18	-0.05	-0.10	-0.11	-0.08
T1	-0.54	-0.21	-0.76	-0.57	-0.38	-0.43	-0.90	-0.66	-0.21	-0.51	-0.84	-0.56	-0.54	0.00	-0.09	0.01	-0.27	-0.19	-0.07	-0.31	-0.13	-0.10
T2	-0.54	-0.21	-0.76	-0.56	-0.38	-0.43	-0.90	-0.66	-0.21	-0.50	-0.85	-0.63	-0.54	-0.09	0.00	0.00	-0.18	-0.30	-0.14	-0.29	-0.13	-0.10
T3	-0.56	-0.32	-0.77	-0.58	-0.41	-0.46	-1.05	-0.77	-0.33	-0.52	-0.86	-0.65	-0.57	-0.20	-0.15	0.00	-0.33	-0.30	-0.14	-0.33	-0.23	-0.20
T4	-0.53	-0.14	-0.68	-0.43	-0.37	-0.43	-0.74	-0.51	-0.08	-0.41	-0.74	-0.53	-0.54	-0.08	0.01	0.01	0.00	-0.11	-0.05	-0.17	0.00	0.01
T5	-0.56	-0.21	-0.70	-0.45	-0.41	-0.38	-0.92	-0.66	-0.15	-0.43	-0.76	-0.48	-0.56	-0.16	-0.18	-0.12	-0.20	0.00	0.01	-0.22	-0.13	-0.14
O1	-0.56	-0.25	-0.74	-0.54	-0.41	-0.39	-1.03	-0.77	-0.24	-0.43	-0.77	-0.48	-0.56	-0.16	-0.18	-0.12	-0.32	-0.13	0.00	-0.30	-0.22	-0.14
O2	-0.49	-0.17	-0.75	-0.39	-0.21	-0.41	-0.74	-0.51	-0.11	-0.45	-0.72	-0.53	-0.49	-0.13	-0.10	-0.10	-0.11	-0.17	-0.08	0.00	-0.08	-0.08
O3	-0.54	-0.21	-0.69	-0.43	-0.39	-0.44	-0.83	-0.51	-0.15	-0.41	-0.75	-0.53	-0.55	-0.09	-0.09	0.01	-0.10	-0.11	-0.05	-0.18	0.00	0.00
O4	-0.54	-0.25	-0.73	-0.53	-0.39	-0.44	-0.94	-0.62	-0.24	-0.42	-0.76	-0.54	-0.55	-0.09	-0.09	0.01	-0.22	-0.24	-0.06	-0.27	-0.09	0.00

Table 13
Overall prospect values of the criteria.

Criteria	Overall prospect values
S1	0.69
S2	0.54
S3	0.97
S4	0.72
ODC1	0.46
ODC2	0.51
ODC3	0.87
ODC4	0.71
ODC5	0.52
L1	0.74
L2	1.00
L3	0.82
L4	0.60
T1	0.19
T2	0.18
T3	0.00
T4	0.44
T5	0.26
O1	0.13
O2	0.40
O3	0.36
O4	0.23

Table 14
Overall prospect values and rankings with different ranking methods.

Criteria	SF-AHP & SF-TODIM		SF-AHP & SF-CODAS	
	Overall prospect values	Rank	Overall prospect values	Rank
S1	0.69	8	1.192	1
S2	0.54	10	0.949	3
S3	0.97	2	1.655	2
S4	0.72	6	0.556	6
ODC1	0.46	13	-0.075	10
ODC2	0.51	12	-0.198	13
ODC3	0.87	3	0.518	7
ODC4	0.71	7	-0.170	12
ODC5	0.52	11	-0.342	15
L1	0.74	5	0.560	5
L2	1.00	1	0.723	4
L3	0.82	4	0.383	8
L4	0.60	9	0.039	9
T1	0.19	19	-0.582	17
T2	0.18	20	-0.755	19
T3	0.00	22	-1.147	22
T4	0.44	14	-0.709	18
T5	0.26	17	-0.941	21
O1	0.13	21	-0.331	14
O2	0.40	15	-0.096	11
O3	0.36	16	-0.418	16
O4	0.23	18	-0.813	20

4. Application

4.1. A DMM for a Turkish defense firm

This study suggests an integrated methodology of SF-AHP and SF-TOPSIS for a defense company's digital maturity level evaluation.

4.1.1. Stage one: SF-AHP

In the first stage, SF-AHP determines the relative importance of various digital maturity metrics.

Step 1. Construct the Hierarchical Structure:

The hierarchical structure for DMM is constructed based on the recent studies in the literature. We benefited from recent studies, industry reports, and experts' views [8,16,21,22,27,77–81]. The complete list of evaluation criteria and the references from the literature are given in Table A.1, whereas Fig. A.1 contains detailed definitions of the criteria in the Appendix. The final hierarchical structure consists of five main criteria and 22 sub-criteria, as depicted in Fig. 4.

Step 2. Construct Pairwise Comparisons Matrix:

The pairwise comparison matrices for primary and sub-criteria are determined by three experts using the linguistic scale in Table 2 [10]. The data was collected from three experts through a structured survey. Their positions and expertise in the defense industry are shown in Table 3. Tables A.2–A.7 give the experts' opinions on the pairwise relevances of the main criteria and subcriteria expressed in SFSs [10,13,71], respectively.

Aggregated fuzzy pairwise comparison matrix for the main criteria is constructed as per Table 4.

Next, the aggregated fuzzy pairwise comparison matrices for the sub-criteria are calculated as in Tables 5–9.

Step 3. Estimate the spherical fuzzy global and local weights of main and sub-criteria:

We use the SWAM operator given in Definition 5. The weighted arithmetic mean is used to compute the spherical fuzzy weights (See Table A.8 in the Appendix). According to Table A.8, the most important main criterion for the digital maturity model is Strategy (0.271). In addition, the most prominent sub-criteria under the main titles are providing incentive and long-term financing (0.309), training a qualified digital workforce (0.255), openness to new innovative ideas (0.297), the infrastructure of information technology (0.249), and autonomous and flexible processes (0.316), respectively.

Fig. 5(a–e) depicts the global weights of sub-criteria. According to the figure, most prominent five sub-criteria are providing incentive and long-term financing ($w_{S1} = 0.084$), developing an R&D strategy for digital technologies ($w_{S2} = 0.066$), alignment

Table A.1
Criteria used in the study and the references from the literature.

Criteria	References
Strategy	[8,16,21,22,27,31,34,45,73–75]
Providing Incentive and Long-Term Financing	[8,16,21,27,73–75]
Developing an R&D strategy for Digital Technologies	[16,21,27,73–75]
Alignment with stakeholders	[8,16,27,43,73–75]
Set a roadmap	[16,27,30,31,73–75]
Organization and digital culture	[5,21,22,27,30,31,34,43,44,73,76]
Training a qualified digital workforce	[8,16,27,44,73–75]
Creating a digital ecosystem in the institution	[8,16,27,44,73–75]
Developing new business models	[8,16,27,31,73–75]
Horizontal hierarchy	[8,16,27,30,73–75]
Creating a working group	[16,27,31,73–75]
Leadership	[8,16,27,41,73–75]
Openness to new innovative ideas	[16,27,73–75]
Evaluation of opportunities	[8,16,27,73–75]
Digital vision	[16,27,30,73–75]
Providing motivation	[16,27,31,73–75]
Technology	[8,16,31,44,67,76]
Infrastructure of information technology	[16,27,30,73–75]
Technology investment financing	[16,21,27,30,73–75]
Cyber security technologies	[16,27,34,73–75]
Fast access to data	[16,22,27,73–75]
Smart Products or Existence of Modern Information Technologies	[5,16,27,34,73–75]
Operations	[16,22,27,31,73–75]
Autonomous and flexible process	[16,27,30,73–75]
Cooperation between departments	[5,16,22,27,30,73–75]
Information-sharing	[16,22,27,30,73–75]
Big data and advanced analytics	[16,21,27,30,73–75]

Table A.2
The pairwise comparison matrices for the main criteria.

		S			ODC			L			T			O		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM1	S	0.5	0.4	0.4	0.5	0.4	0.4	0.6	0.4	0.3	0.7	0.3	0.2	0.5	0.4	0.4
	ODC	0.5	0.4	0.4	0.5	0.4	0.4	0.4	0.6	0.3	0.7	0.3	0.2	0.5	0.4	0.4
	L	0.4	0.6	0.3	0.5	0.4	0.4	0.5	0.4	0.4	0.6	0.4	0.3	0.4	0.6	0.3
	T	0.3	0.7	0.2	0.3	0.7	0.2	0.4	0.6	0.3	0.5	0.4	0.4	0.3	0.7	0.2
	O	0.5	0.4	0.4	0.5	0.4	0.4	0.6	0.4	0.3	0.7	0.3	0.2	0.5	0.4	0.4
DM2	S	0.5	0.4	0.4	0.8	0.2	0.1	0.8	0.2	0.1	0.8	0.2	0.1	0.8	0.2	0.1
	ODC	0.2	0.8	0.1	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4
	L	0.2	0.8	0.1	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.7	0.3	0.2
	T	0.2	0.8	0.1	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4
	O	0.2	0.8	0.1	0.5	0.4	0.4	0.3	0.7	0.2	0.5	0.4	0.4	0.5	0.4	0.4
DM3	S	0.5	0.4	0.4	0.9	0.1	0	0.7	0.3	0.2	0.9	0.1	0	0.8	0.2	0.1
	ODC	0.1	0.9	0	0.5	0.4	0.4	0.3	0.7	0.2	0.5	0.4	0.4	0.4	0.6	0.3
	L	0.3	0.7	0.2	0.5	0.4	0.4	0.5	0.4	0.4	0.7	0.3	0.2	0.6	0.4	0.3
	T	0.1	0.9	0	0.5	0.4	0.4	0.3	0.7	0.2	0.5	0.4	0.4	0.4	0.6	0.3
	O	0.2	0.8	0.1	0.6	0.4	0.3	0.4	0.6	0.3	0.6	0.4	0.3	0.5	0.4	0.4

with stakeholders ($w_{S3} = 0.063$), autonomous and flexible process ($w_{O1} = 0.061$), and openness to new innovative ideas ($w_{L1} = 0.059$).

4.1.2. Stage two: The evaluation of the criteria using SF-TODIM

Steps 1–2. Each DM defines the decision matrix and the normalized weights of the criteria in linguistic terms are attached from the previous stage. The resulting data is given in Table 10 [10].

Steps 3–4. Evaluate the decision matrices using Eq. (9), and calculate the relative weight, w_1 , w_2 , and w_3 , of the criterion C_j to the reference criterion C_r by Eq. (10) [10]. The final outcome of these steps is shown in Table 11.

Steps 5–6. Partial dominance matrices are calculated for each criterion with Eqs. (11)–(12). Then, Eq. (13) is used to obtain the overall dominance matrix for each DM [10]. The resulting matrices are given in Tables A.9–A.11.

Step 7. An aggregate dominance matrix is obtained for all DMs with Eq. (14) [10] (See Table 12).

Steps 8–9. The overall prospect value of each alternative A_i is calculated using Eq. (15) [10]. Alternatives are ranked in descending order of their overall expectation value. The resulting values are shown in Table 13.

According to Table 13, the ranking of the criteria with respect to overall prospect values is as follows: $L2 > S3 > ODC3 > L3 > L1 > S4 > S1 > ODC4 > L4 > S2 > ODC2 > ODC5 > ODC1 > T4 > O2 > O3 > T5 > O4 > T1 > T2 > O1 > T3$

The normalized total prospect values of the main criteria are shown in Fig. 6. According to the figure, the leadership capabilities of the focal firm are greatly appreciated by the experts and assessed as satisfactory for digital transformation, whereas the technology is evaluated as a critical resource that the firm must invest in. The respondents are high- and mid-level managers in the company. A significant challenge the managers face

Table A.3
Pairwise comparison matrix for sub-criteria of **strategy** criteria.

		S1			S2			S3			S4		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM1	S1	0.5	0.4	0.4	0.6	0.4	0.3	0.6	0.4	0.3	0.6	0.4	0.3
	S2	0.4	0.6	0.3	0.5	0.4	0.4	0.6	0.4	0.3	0.6	0.4	0.3
	S3	0.4	0.6	0.3	0.4	0.6	0.3	0.5	0.4	0.4	0.5	0.4	0.4
	S4	0.4	0.6	0.3	0.4	0.6	0.3	0.5	0.4	0.4	0.5	0.4	0.4
		S1			S2			S3			S4		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM2	S1	0.50	0.40	0.40	0.60	0.40	0.30	0.60	0.40	0.30	0.60	0.40	0.30
	S2	0.40	0.60	0.30	0.50	0.40	0.40	0.60	0.40	0.30	0.60	0.40	0.30
	S3	0.40	0.60	0.30	0.40	0.60	0.30	0.50	0.40	0.40	0.50	0.40	0.40
	S4	0.40	0.60	0.30	0.40	0.60	0.30	0.50	0.40	0.40	0.50	0.40	0.40
		S1			S2			S3			S4		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM3	S1	0.5	0.4	0.4	0.8	0.2	0.1	0.7	0.3	0.2	0.8	0.2	0.1
	S2	0.2	0.8	0.1	0.5	0.4	0.4	0.4	0.6	0.3	0.5	0.4	0.4
	S3	0.3	0.7	0.2	0.6	0.4	0.3	0.5	0.4	0.4	0.6	0.4	0.3
	S4	0.2	0.8	0.1	0.5	0.4	0.4	0.4	0.6	0.3	0.5	0.4	0.4

Table A.4
Pairwise comparison matrix for sub-criteria of **organization and digital culture** criteria.

		ODC1			ODC2			ODC3			ODC4			ODC5		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM1	ODC1	0.5	0.4	0.4	0.7	0.3	0.2	0.8	0.2	0.1	0.7	0.3	0.2	0.5	0.4	0.4
	ODC2	0.3	0.7	0.2	0.5	0.4	0.4	0.6	0.4	0.3	0.5	0.4	0.4	0.4	0.6	0.3
	ODC3	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.4	0.6	0.3	0.2	0.8	0.1
	ODC4	0.3	0.7	0.2	0.5	0.4	0.4	0.6	0.4	0.3	0.5	0.4	0.4	0.3	0.7	0.2
	ODC5	0.5	0.4	0.4	0.6	0.4	0.3	0.8	0.2	0.1	0.7	0.3	0.2	0.5	0.4	0.4
		ODC1			ODC2			ODC3			ODC4			ODC5		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM2	ODC1	0.5	0.4	0.4	0.5	0.4	0.4	0.7	0.3	0.2	0.8	0.2	0.1	0.9	0.1	0
	ODC2	0.5	0.4	0.4	0.5	0.4	0.4	0.7	0.3	0.2	0.8	0.2	0.1	0.8	0.2	0.1
	ODC3	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.6	0.4	0.3	0.6	0.4	0.3
	ODC4	0.2	0.8	0.1	0.2	0.8	0.1	0.4	0.6	0.3	0.5	0.4	0.4	0.6	0.4	0.3
	ODC5	0.1	0.9	0	0.2	0.8	0.1	0.4	0.6	0.3	0.4	0.6	0.3	0.5	0.4	0.4
		ODC1			ODC2			ODC3			ODC4			ODC5		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM3	ODC1	0.5	0.4	0.4	0.9	0.1	0	0.7	0.3	0.2	0.6	0.4	0.3	0.6	0.4	0.3
	ODC2	0.1	0.9	0	0.5	0.4	0.4	0.6	0.4	0.3	0.6	0.4	0.3	0.6	0.4	0.3
	ODC3	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.6	0.4	0.3	0.6	0.4	0.3
	ODC4	0.4	0.6	0.3	0.4	0.6	0.3	0.4	0.6	0.3	0.5	0.4	0.4	0.6	0.4	0.3
	ODC5	0.4	0.6	0.3	0.4	0.6	0.3	0.4	0.6	0.3	0.4	0.6	0.3	0.5	0.4	0.4

Table A.5
Pairwise comparison matrix for sub-criteria of **leadership** criteria.

		L1			L2			L3			L4		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM1	L1	0.5	0.4	0.4	0.7	0.3	0.2	0.6	0.4	0.3	0.5	0.4	0.4
	L2	0.3	0.7	0.2	0.5	0.4	0.4	0.6	0.4	0.3	0.6	0.4	0.3
	L3	0.4	0.6	0.3	0.4	0.6	0.3	0.5	0.4	0.4	0.6	0.4	0.3
	L4	0.5	0.4	0.4	0.4	0.6	0.3	0.4	0.6	0.3	0.5	0.4	0.4
		L1			L2			L3			L4		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM2	L1	0.5	0.4	0.4	0.6	0.4	0.3	0.5	0.4	0.4	0.5	0.4	0.4
	L2	0.4	0.6	0.3	0.5	0.4	0.4	0.4	0.6	0.3	0.4	0.6	0.3
	L3	0.5	0.4	0.4	0.6	0.4	0.3	0.5	0.4	0.4	0.5	0.4	0.4
	L4	0.5	0.4	0.4	0.4	0.6	0.3	0.5	0.4	0.4	0.5	0.4	0.4
		L1			L2			L3			L4		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM3	L1	0.5	0.4	0.4	0.7	0.3	0.2	0.8	0.2	0.1	0.7	0.3	0.2
	L2	0.3	0.7	0.2	0.5	0.4	0.4	0.8	0.2	0.1	0.7	0.3	0.2
	L3	0.2	0.8	0.1	0.2	0.8	0.1	0.5	0.4	0.4	0.6	0.4	0.3
	L4	0.3	0.7	0.2	0.3	0.7	0.2	0.4	0.6	0.3	0.5	0.4	0.4

Table A.6
Pairwise comparison matrix for sub-criteria of the **technology** criteria.

		T1			T2			T3			T4			T5		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM1	T1	0.5	0.4	0.4	0.6	0.4	0.3	0.5	0.4	0.4	0.6	0.4	0.3	0.7	0.3	0.2
	T2	0.4	0.6	0.3	0.5	0.4	0.4	0.6	0.4	0.3	0.6	0.4	0.3	0.7	0.3	0.2
	T3	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.7	0.3	0.2	0.5	0.4	0.4
	T4	0.4	0.6	0.3	0.4	0.6	0.3	0.3	0.7	0.2	0.5	0.4	0.4	0.7	0.3	0.2
	T5	0.3	0.7	0.2	0.3	0.7	0.2	0.5	0.4	0.4	0.3	0.7	0.2	0.5	0.4	0.4
DM2	T1	0.5	0.4	0.4	0.8	0.2	0.1	0.7	0.3	0.2	0.7	0.3	0.2	0.5	0.4	0.4
	T2	0.2	0.8	0.1	0.5	0.4	0.4	0.4	0.6	0.3	0.5	0.4	0.4	0.3	0.7	0.2
	T3	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.4	0.6	0.3
	T4	0.3	0.7	0.2	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.3	0.7	0.2
	T5	0.5	0.4	0.4	0.7	0.3	0.2	0.6	0.4	0.3	0.7	0.3	0.2	0.5	0.4	0.4
DM3	T1	0.5	0.4	0.4	0.6	0.4	0.3	0.9	0.1	0	0.8	0.2	0.1	0.7	0.3	0.2
	T2	0.4	0.6	0.3	0.5	0.4	0.4	0.8	0.2	0.1	0.8	0.2	0.1	0.7	0.3	0.2
	T3	0.5	0.4	0.4	0.5	0.4	0.4	0.5	0.4	0.4	0.8	0.2	0.1	0.8	0.2	0.1
	T4	0.2	0.8	0.1	0.2	0.8	0.1	0.2	0.8	0.1	0.5	0.4	0.4	0.7	0.3	0.2
	T5	0.3	0.7	0.2	0.3	0.7	0.2	0.2	0.8	0.1	0.3	0.7	0.2	0.5	0.4	0.4

Table A.7
Pairwise comparison matrix for sub-criteria of the **operations** criteria.

		O1			O2			O3			O4		
		μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
DM1	O1	0.5	0.4	0.4	0.7	0.3	0.2	0.9	0.1	0	0.5	0.4	0.4
	O2	0.3	0.7	0.2	0.5	0.4	0.4	0.7	0.3	0.2	0.6	0.4	0.3
	O3	0.1	0.9	0	0.3	0.7	0.2	0.5	0.4	0.4	0.7	0.3	0.2
	O4	0.5	0.4	0.4	0.4	0.6	0.3	0.3	0.7	0.2	0.5	0.4	0.4
DM2	O1	0.5	0.4	0.4	0.6	0.4	0.3	0.7	0.3	0.2	0.8	0.2	0.1
	O2	0.4	0.6	0.3	0.5	0.4	0.4	0.6	0.4	0.3	0.7	0.3	0.2
	O3	0.3	0.7	0.2	0.4	0.6	0.3	0.5	0.4	0.4	0.6	0.4	0.3
	O4	0.2	0.8	0.1	0.3	0.7	0.2	0.4	0.6	0.3	0.5	0.4	0.4
DM3	O1	0.5	0.4	0.4	0.7	0.3	0.2	0.7	0.3	0.2	0.7	0.3	0.2
	O2	0.3	0.7	0.2	0.5	0.4	0.4	0.7	0.3	0.2	0.7	0.3	0.2
	O3	0.3	0.7	0.2	0.3	0.7	0.2	0.5	0.4	0.4	0.7	0.3	0.2
	O4	0.3	0.7	0.2	0.3	0.7	0.2	0.3	0.7	0.2	0.5	0.4	0.4

is demonstrating leadership during the digital transformation process and leading organizational change. The firm's leadership competencies per prospect values (see Fig. 7(a-e)) are well regarded. However, technology and operations are two main issues that the management must address while going digital. Overall, the company owns the required soft skills, such as leadership, organizational culture, and strategic determination for DT.

On the other hand, essential hard skills such as technology and operational competencies are yet to be developed. Fig. 7(a-e) gives the vital subfactors from the experts' views for DT. The focal company must invest in critical technologies enabling cyber security, fast data access, and smart production. Other significant challenges are adopting autonomous and flexible processes and utilizing advanced analytics and big data tools in the firm's operational areas.

4.2. Sensitivity analysis

A critical parameter in TODIM is the attenuation factor of the losses, θ . We conducted a sensitivity analysis to reveal the robustness of the presented methodology to the variation. The rankings of the alternatives are listed in Table 14 and depicted

in Fig. 8. The figure shows the ranking orders of criteria with different values of θ ($0 < \theta \leq 5$). $\theta > 1$ weakens the influence of loss.

According to Fig. 8, the trends of the global values for different θ values are consistent. Therefore, it can be seen that different θ values do not lead to a change in ranking orders. Thus, the sensitivity analysis validates the robustness of the proposed method to a certain degree.

4.3. Comparative analysis

To verify the validity of the proposed model, we compared the spherical fuzzy CODAS approach [71] and the proposed approach. From Table 14, it is apparent that the ranking orders obtained by these two methods slightly differ. Using the presented SF-AHP & SF-CODAS and SF-AHP & SF-TODIM methods, the first two best alternatives are the same, L2 and S3, respectively.

4.4. Policy implications

The first stage of the proposed methodology gives the experts' preferences about the main criteria. According to the results,

Table A.8

The spherical fuzzy weights of the main criteria.

Main criteria	Weight	Sub-criteria	Local weight	Global weight
S	0.271	S1	0.309	0.084
		S2	0.243	0.066
		S3	0.232	0.063
		S4	0.216	0.058
ODC	0.179	ODC1	0.255	0.046
		ODC2	0.213	0.038
		ODC3	0.188	0.034
		ODC4	0.169	0.030
		ODC5	0.176	0.031
L	0.198	L1	0.297	0.059
		L2	0.253	0.050
		L3	0.229	0.045
		L4	0.222	0.044
T	0.160	T1	0.249	0.040
		T2	0.208	0.033
		T3	0.210	0.034
		T4	0.166	0.027
		T5	0.166	0.027
O	0.193	O1	0.316	0.061
		O2	0.272	0.052
		O3	0.229	0.044
		O4	0.183	0.035

strategy and leadership are the two most vital main dimensions of DTM. These findings align with the current literature, where the strategy is also highly appreciated [21,22,45].

Surprisingly, the experts evaluated the technology dimension as the least essential while going digital. On the contrary, [45] highlighted the importance of technology. The authors provided a systematic literature review on 30 Industry 4.0 readiness models where six dimensions (Technology, People, Strategy, Leadership, Process, and Innovation) were considered the most important factors for an organization going digital. We believe this incompatibility with the existing literature reveals valuable insights for decision-makers into the DMMs designed explicitly for defense firms. Defense firms have relatively new technological infrastructure compared to other industries, such as manufacturing, logistics, retail, etc., since they are usually in a leading position in reaching and adopting recent technologies. The sector is more technology-oriented than other sectors, and access to new technologies is not hard. Hence, the experts we interviewed do not evaluate the technology dimension as critical as the strategy and leadership dimensions. As for managerial implications, the digital transformation capacity of a defense firm is bottlenecked mainly by its leadership competence and strategic orientation, which deserve real attention. Thus, a significant challenge managers face is demonstrating leadership during the digital transformation process and leading organizational change.

When it comes to the focal firm we evaluated, the firm's leadership competencies per prospect values obtained with SF-TODIM (see Fig. 7) are well regarded. More precisely, the experts greatly appreciate the firm's leadership capabilities and assess them as satisfactory for digital transformation. Indeed, digitalization has been identified as a major strategic priority in the company. As an indication, the company established a digitalization department under the strategy development division. During the last decade, the Turkish defense industry has strengthened its place in the world in a short time with ambitious targets. Therefore, the current leadership of the company sees the industry 4.0-oriented digital transformation as an indispensable process to maintain its competitive advantage and achieve the ambitious targets of the Turkish defense industry.

For this reason, the company's strategic orientation on digitalization was evaluated by experts as a vital dimension. In particular, combining the stakeholders around this strategy will increase the chances of success. Experts stated that the company

stands out, especially in this regard. According to experts, the firm has allocated sufficient long-term financing for DT in line with the issue's importance.

On the other hand, technology and operations are two main issues that the management must address while going digital. The company owns the required soft skills, such as leadership, organizational culture, and strategic determination for DT. On the other hand, the firm has yet to develop essential hard skills such as technology and operational competencies. Therefore, the focal company must invest in critical technologies enabling cyber security, fast data access, and smart production. Other significant challenges are adopting autonomous and flexible processes and utilizing advanced analytics and big data tools in the firm's operational areas.

The outputs of the study will guide researchers and decision-makers working in the field in two ways while solving real problems. First, the study points out which dimensions companies should focus on, which will start the digital transformation process in the defense industry. Second, the proposed method allows firms to approach this process systematically and adequately handle uncertainties in decision-making.

The main objective of DMMs is to identify the starting point and then develop a road map so that the change process can run smoothly. Hence, these valuable insights may shed light on the pitfalls and difficulties of undertaking a DT endeavor.

Emerging digital technologies such as additive manufacturing, the internet of things, big data, and machine learning are transforming the practices of companies in the field of sustainability. Because these new approaches also necessitate the redefinition of production and service processes [82]. Today, companies have to act in accordance with the extended producer responsibility principle. In other words, they should be concerned not only with the production processes, but also with the process after the end of the product's life [83,84]. At this stage, re-evaluation of a product and bringing it into the economy is carried out with 9R circularity strategies. To implement these strategies, activities such as monitoring and recording the product at all stages, analyzing user habits, detecting faulty products in advance, increasing design ergonomics, and reducing waste amounts are necessary. Undoubtedly, the focal company's new capabilities with digital transformation will positively contribute to the circular economy. The firm will be able to collect more data, analyze it correctly, and make optimum decisions based on accurate data [82].

5. Conclusions

During the era of industry 4.0, new technologies have accelerated digitalization endeavors in various sectors. Today, defense industry companies prioritize digital investments and make broad strategic moves to gain a competitive advantage. Therefore, measuring the extent of their processes' digitalization is vital.

Digitalization is a multifaceted concept that requires addressing various issues simultaneously. In the current body of research, measuring digital maturity is considered the very first step of any digitalization journey. After assessing maturity based on the relevant criteria, a concrete road map can be created. With this assessment, developing more efficient and well-designed processes and systems will be possible. In addition, the technology move on the national level will be accelerated with the correct management of the digital transformation in the defense industry technologies.

This study addressed the digital maturity assessment problem and proposed a novel DMM for companies in the defense sector. DMM in the defense industry has rarely been studied in the extant literature, which is the main novelty of the current work. To this end, we extracted relevant factors for a comprehensive digital

Table A.9

The partial/overall dominance degree matrices for DM1.

Table with 22 columns (C, S1-S4, ODC1-ODC5, L1-L4, T1-T5, O1-O4) and 22 rows (S1-S4, ODC1-ODC5, L1-L4, T1-T5, O1-O4) showing dominance degree matrices for DM1.

Table A.10

The partial/overall dominance degree matrices for DM2.

Table with 22 columns (C, S1-S4, ODC1-ODC5, L1-L4, T1-T5, O1-O4) and 22 rows (S1-S4, ODC1-ODC5, L1-L4, T1-T5, O1-O4) showing dominance degree matrices for DM2.

Table A.11

The partial/overall dominance degree matrices for DM3.

Table with 22 columns (C, S1-S4, ODC1-ODC5, L1-L4, T1-T5, O1-O4) and 22 rows (S1-S4, ODC1-ODC5, L1-L4, T1-T5, O1-O4) showing dominance degree matrices for DM3.

maturity evaluation model in the defense sector. The model was based on two pillars: measuring the relevance of the factors and evaluating the overall success of the focal company. The former was calculated with the SF variant of AHP, while the latter utilizes SF-TODIM to incorporate the inherent subjectivity of the evaluation process based on the degrees of membership, nonmembership, and hesitancy.

The model's conformance was assessed with a real-life application on a renowned Turkish defense company. Three top managers of the company evaluated the DMM, consisting of five main and 22 sub-criteria. The results show that the most vital main criterion for the digital maturity model is strategy, while the most critical five sub-criteria are: providing incentive and long-term financing, developing an R&D strategy for digital technologies, alignment with stakeholders, designing autonomous and flexible processes, and openness to new ideas.

Next, the company's digital maturity is evaluated with the proposed model. The most prominent digital maturity dimensions are the evaluation of opportunities and alignment with stakeholders. The company owns the required soft skills, such as leadership, organizational culture, and strategic determination for DT. On the other hand, essential hard skills such as technology and operational competencies are yet to be developed.

Next, we conducted a sensitivity analysis to determine the robustness of the model to specific parameters. The results show that the decision and the rankings of the alternatives obtained by these two methods are almost the same when the threshold parameter of SF-CODAS is varied. However, the company's achievements on different dimensions barely change with alternative methodologies. Thus, the obtained model is robust to model parameters.



Fig. A.1. Definitions of criteria.

The main contributions of this study are as follows. First, a novel model combines SF-AHP and SF-TODIM to estimate the digital maturity model. Secondly, this is the first study that develops a novel DMM for the defense industry by obtaining real-world

data from one of the leading defense firms in Turkey. Thirdly, the model supports experts and decision-makers in the defense sector and provides valuable insights while implementing DT projects. Fourth, SF-AHP and SF-TODIM methods can be deployed

in group and individual decision-making. And sensitivity analysis and comparison with SF-AHP and SF-CODAS methods are employed to verify the obtained results' stability and robustness.

5.1. Limitations and future research directions

Digital maturity assessment in the defense industry requires the evaluation of high-uncertainty criteria by hesitant decision-makers. The proposed method facilitates precisely such decision processes. Similarly, the model can be applied to other decision situations with high uncertainty and hesitation, provided that problem-specific criteria are selected.

Further research can be devoted to comparing different MCDM methods recently emerging in the domain [85–88]. A recent, simple but effective weighting method, the Best-Worst method (BWM), can be an alternative weighting strategy [89,90]. Furthermore, the defense sector contains multiple subfields focusing development of various subcomponents of a single product, such as software, mechanical parts, radars, and detection systems. Obviously, each may prioritize a different set of criteria in the digitalization journey, which can be studied in further research. In addition, the proposed model can be implemented in other companies in the sector, which may provide additional insights into the practical applicability of the model. Furthermore, the proposed DMM should be tested in different cultural settings, as it was initially designed for a Turkish defense company. This issue is also included in our agenda as an essential research question. Another limitation of the study is that the focal company was evaluated only by senior managers. However, the point of view of the other stakeholders, such as suppliers, and customers, is also important. Their opinions can give important clues about the maturity level of the company. In other words, the subject should be evaluated not only from an internal perspective but also from an external perspective.

CRedit authorship contribution statement

Emine Elif Nebati: Methodology, Formal analysis, Resources, Writing – original draft, Visualization. **Berk Ayyaz:** Supervision, Conceptualization, Data curation, Formal analysis, Writing – original draft, Visualization. **Ali Osman Kusakci:** Validation, Visualization, Writing – review & editing.

Declaration of competing interest

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

Appendix

See Fig. A.1, Tables A.1–A.11.

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