

## Article

# Fermatean Fuzzy CRITIC-COPRAS Method for Evaluating the Challenges to Industry 4.0 Adoption for a Sustainable Digital Transformation

Mahyar Kamali Saraji <sup>1,\*</sup>, Dalia Streimikiene <sup>1,\*</sup> and Grigorios L. Kyriakopoulos <sup>2</sup><sup>1</sup> Kaunas Faculty, Vilnius University, Muitines 8, LT-44280 Kaunas, Lithuania<sup>2</sup> School of Electrical and Computer Engineering, Electric Power Division, Photometry Laboratory, National Technical University of Athens, 9 Heron Polytechniou Street, 15780 Athens, Greece; gregkyr@chemeng.ntua.gr

\* Correspondence: Mahyar.Kamali@knf.stud.vu.lt (M.K.S.); Dalia.streimikiene@knf.vu.lt (D.S.)

**Abstract:** Decision and policymakers are looking at the potential of Industry 4.0 smart technologies to create a green economy as the European Commission aims to deliver the European Green Deal by rethinking policies for clean energy supply. Industry 4.0 will eventually be applied to all aspects of life; however, it is necessary to identify the challenges to the adoption of Industry 4.0 for a sustainable digital transformation. In this vein, the present study aims to identify the challenges to the adoption of Industry 4.0 in fintech companies and to develop a novel Fermatean fuzzy CRITIC-COPRAS method to rank the identified challenges and evaluate the performance of companies concerning the weighted challenges based on three decision experts' support. The results indicated that "difficulty in coordination and collaboration" is the most significant challenge to the adoption of Industry 4.0 out of the fourteen identified challenges, followed by "resistance to change" and "governmental support." In addition, the superiority and efficiency of the proposed method were investigated through comparative analyses.

**Keywords:** sustainable transformation; MCDA; society 5.0; digital society; digitalization



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## 1. Introduction

Challenges related to the environment and climate change have become exciting research fields due to countries' commitments under the Paris Agreement, the United Nations' 2030 Agenda, and the Sustainable Development Goals (SDGs). In this vein, the European Green Deal was proposed to deal with the aforementioned challenges by restarting the European commitments to transforming the E.U. into a prosperous and fair society with a competitive and modern economy concerning sustainability. To this end, a policy reformation is needed for green energy supply across the industry, economy, production, consumption, transport, large-scale infrastructure, agriculture, food, etc. Therefore, the E.U. should promote digital transformation as a crucial enabler of the aforementioned reformation to deliver the European Green Deal [1]. In addition, businesses must decrease non-renewable resource consumption and waste to survive in an intensely competitive global economy. In doing so, integrating novel developing technologies with conventional business strategies is inevitable. Novel strategies have been developed by the advent of the fourth generation of the industry—so-called Industry 4.0—causing fundamental changes in current business models and developing novel ones, which is known as the digital transformation [2,3]. However, there is a lack of studies on challenges and opportunities concerning the implementation of Industry 4.0 in companies [4,5]; thus, it is necessary to provide a deeper analysis of challenges to the adoption of Industry 4.0.

Digital transformation refers to the utilization of novel and developing digital technologies for significant business improvements, such as boosting customer experience,

designing novel business models, etc. [6,7]. Digital transformation is a process for fundamental business changes, not a task for upgrading or improving specific functions in businesses. In addition, organizational strategies, value chains, and structural mechanisms are affected by digital technologies in the digital transformation, causing disruptions in industries and global markets [8]. Moreover, the sustainability triangle, i.e., environmental sustainability, must be considered in the digital transformation, since digital technology development could significantly improve the environment and human health [9]. Environmental sustainability looks to meet needs without any adverse effects on the quality of the environment in order to have a sustained ecosystem for future generations; thus, integrating the principles of environmental sustainability with organizational operations and processes in the digital transformation could create organizational value, thus making digital technologies more valuable [10]. In addition, Vrchota et al. [11] concluded that sustainability is the central aspect in defining Industry 4.0, while Industry 4.0 employs novel technologies by interconnecting equipment and machines with digital data to improve the customization and flexibility of production in sustainable project management [12,13]. The organizational and industrial levels could transcend and extend to the country level through the convergence of environmental sustainability and digitalization. In this vein, ElMassah and Mohieldin [14] conducted research in which the impacts of digital transformation on the Sustainable Development Goals were studied. They concluded that localization could assist the government in following the SDGs, which could be boosted through digital transformation; however, studies on the contributions of digital transformation to the environmental sustainability domain are still scarce [4].

As mentioned above, digital transformation occurs under Industry 4.0 by connecting humans, machines, and objects in order to boost production efficiency, and customers are involved in all processes. The Hannover Technology Fair introduced Industry 4.0 in Hannover, Germany in 2011 and incorporated it into the production processes in Western European countries and the U.S. [15,16]. The enablers of Industry 4.0 comprise the Internet of Things (IoT), cloud computing, big data and data analytics, additive manufacturing or 3D printing, augmented reality, robotics, cybersecurity, machine learning, and simulation [17,18]. In Industry 4.0, decisions are made with minimum human involvement thanks to smart materials, interconnected computers, intelligent machines, and interaction with the environment [19,20]. Digitalizing business processes and manufacturing by utilizing smart devices and machines benefits resource efficiency, manufacturing productivity, and waste reduction [21,22]. However, energy consumption, high resource demands, and pollution concerns may be associated with the increased production rates caused by industrial automation [23,24]. On top of that, the labor market could be adversely affected by digital transformation, since lower-skilled jobs could be eliminated by employing autonomous vehicles, intelligent robots, and cloud solutions, though many job vacancies in various industries and fields could be created through digital transformation, such as control system design, automation engineering, software engineering, and machine learning [20,25,26].

Many scholars have shown their interest in the adoption of Industry 4.0 due to its significant effects on productivity, sustainability, labor markets, business models, etc. Some studies are closely related to the present research. For example, Kumar et al. [27] identified fifteen challenges to the adoption of Industry 4.0 in small and medium enterprises (SMEs) and applied the decision-making trial and evaluation laboratory (DEMATEL) to evaluate the importance of the identified challenges. They applied a conventional DEMATEL to evaluate the identified challenges, while the present study applies a novel extended Fermatean fuzzy method to deal with the uncertainty in decision making in order to provide a reliable and practical framework of challenges to the adoption of Industry 4.0 for a sustainable transformation that is applicable in various industries. Furthermore, Chauhan et al. [28] investigated the barriers to Industry 4.0 adoption concerning operational performance and supply chain competency. In this study, 143 companies were analyzed by using the Analysis of Moment Structure (AMOS), and the results indicated that the intrinsic and extrinsic barriers affect Industry 4.0 adversely. Furthermore, the results

indicated that a lack of motivation for the application of Industry 4.0 technologies is the main challenge. In contrast, in the present paper, the challenges to the adoption of Industry 4.0 are identified, and a multi-criteria decision analysis (MCDA) framework is proposed based on the Fermatean fuzzy environment to evaluate the companies' progress in dealing with the identified challenges. MCDA is a methodology for evaluating options concerning conflicting criteria and combining individual evaluations into one overall evaluation to rank the options [29–31].

Vuksanović Herceg, Kuč, Mijušković, and Herceg [5] identified the challenges to the implementation Industry 4.0 in Serbian companies. The results indicated that resistance to change is not an essential barrier to the adoption of Industry 4.0, and human resources could be a barrier to industry 4.0 adoption. In contrast, the present study proposes a novel MCDA framework to evaluate the companies' progress in terms of the identified challenges related to sustainability goals in order to help top managers redesign business models and strategies and to lead companies towards a sustainable transformation. In addition, Gadre and Deoskar [32] studied the current status of Industry 4.0 to figure out whether the world was ready for Industry 4.0 adoption. On top of that, the challenges to the adoption of Industry 4.0 were identified and analyzed. However, no framework for evaluating the companies was proposed, and the identified challenges were not comprehensive because a reliable methodology was not used, while the present study proposes a comprehensive framework of challenges to Industry 4.0 adoption based on a novel MCDA method.

Furthermore, in the present study, a novel method using Fermatean fuzzy sets (FFSs) is proposed in order to evaluate the challenges to sustainable digital transformation. Scholars have broadly employed fuzzy sets (F.S.s) theory to cope with uncertainty and inaccuracy. The idea of intuitionistic fuzzy sets (IFSs), an extension of conventional fuzzy theory proposed by Atanassov [33], involves the addition of the belongingness degree (B.D.) and non-belongingness degree (NBD), which must be less than or equal to one. Afterward, Yager [34] proposed Pythagorean fuzzy sets (PFSs) to deal with the limitations of IFSs and cope with vagueness, uncertainty, and inaccuracy in real-life problems. In this vein, many scholars have applied PFSs in various fields, such as medical diagnosis [35], medical waste management [36], green supplier selection [37], pharmacological therapy selection [38], and pattern recognition problems [39]. The main advantage of fuzzy methods over conventional methods is their capability of dealing with uncertainty in linguistic variables [40]. On top of that, conventional methods cannot deal with qualitative parameters, since some uncertainties are involved; hence, a fuzzy system should be applied [41].

However, in some situations, when the square sum of the B.D. and NBD is higher than one, Pythagorean fuzzy sets are not suitable, which motivated Senapati and Yager [42] to develop Fermatean fuzzy sets (FFSs) to handle the aforementioned limitation. More specifically, the cubic sum of the B.D. and NBD is less than or equal to one in FFSs, making FFSs more powerful in coping with complex MCDA issues more effectively. Recently, several scholars have shown interest in applying FFSs in various fields. For instance, Senapati and Yager [43] developed aggregation operators for FFSs and weighted product models (WPMs) for dealing with MCDA problems. Senapati and Yager [44] developed Fermatean fuzzy weighted averaging/geometric operators and applied them to solve an MCDA problem. Liu et al. [45] proposed a new distance measure and applied FF-TODIM (an acronym in Portuguese for Interactive Multi-Criteria Decision Making) and the FF-Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) to evaluate the performance of the proposed distance measure. Garg et al. [46] developed several aggregation operators for FFSs and employed them in facility selection during the COVID-19 pandemic. Aydemir and Yilmaz Gunduz [47] developed Dombi operators for FFSs and established the FF-TOPSIS to evaluate the performance of the proposed operators. Mishra and Rani [48] proposed FF-Weighted Aggregated Sum Product Assessment (WASPAS) and a new score function in order to deal with healthcare waste management problems. Mishra et al. [49] proposed the FF-Criteria Importance Through Intercriteria Correlation (CRITIC) with Evaluation Based on Distance from the Average Solution (EDAS) method

to select sustainable third-party reverse logistics providers by using a new generalized score function. Rani and Mishra [50] proposed the FF–Einstein aggregation-operator-based MULTIMOORA method in order to select electric vehicle charging stations.

All in all, the main contributions of the present paper are presented below.

1. To identify the challenges to the adoption of Industry 4.0 for a sustainable transformation through a literature review.
2. To propose a novel CRITIC-COPRAS framework of the identified challenges based on a Fermatean fuzzy environment to deal with the uncertainty in decision making.
3. To apply the proposed methodology to evaluate the progress of Lithuanian fintech companies in dealing with the identified challenges for a sustainable transformation.
4. To conduct comparative analyses to study the reliability and applicability of the proposed method compared to the other methods.

The present paper is organized as follows. Section 2 presents the challenges to the adoption of Industry 4.0 for a sustainable transformation in detail. The proposed methodology is presented in Section 3. Section 4 provides the research results. Section 5 presents comparative analyses. The results are discussed in Section 6, and finally, Section 7 presents a comprehensive conclusion to the research.

## 2. Challenges to the Adoption of Industry 4.0 for a Sustainable Digital Transformation

In this section, the challenges to the adoption of Industry 4.0 for a sustainable transformation are presented in detail. The identified challenges are classified into external and internal challenges. The external challenges comprise the lack of standards and regulations, governmental support, security, and privacy, the environmental side effects, lack of infrastructure, legal and contractual uncertainty, and difficulty in coordination and collaboration. The internal challenges comprise the lack of a skilled workforce, the competency of new business models, resistance to change, managerial support, lack of awareness of the advantages of I4.0, data management, and cost of implementation.

### 2.1. External Challenges

The external challenges are presented in detail in the following.

#### 2.1.1. Lack of Standards and Regulations ( $C_1$ )

Companies have various perceptions of engineering processes, software applications, and manufacturing operations, making partnership and interaction more complex [51]. Therefore, developing standards and regulations for connectivity throughout the entire value chain is crucial and enables companies to participate and interconnect autonomously [52]. On top of that, in Industry 4.0, systems should communicate freely through an intelligence mechanism; thus, it is necessary for companies to follow data-sharing protocols and global standards [53,54]. However, it is believed that there is a lack of standards and reference architecture due to the novelty of the concept of Industry 4.0 [55,56].

#### 2.1.2. Governmental Support ( $C_2$ )

It is possible to boost the digitalization process by creating and improving the infrastructure through governments. Therefore, governments should develop concrete policies for developing I.T. infrastructure, standards, and reference architecture and for handling regulatory compliance issues [28]. Governments should officially support the promotion of new technology through tax refund compliance, nationalized legislation, hardware infrastructure, industrial standards, and media publications [57–59]. In addition, governments could shape the discourse on Industry 4.0 and institutionalize its adoption by developing supportive policies in order to mitigate the adverse impacts of external challenges [60]

### 2.1.3. Privacy and Security (C<sub>3</sub>)

Data security and privacy risks could adversely affect the scalability of digital technologies [61]. Industry 4.0 copes with a considerable amount of data; thus, security is a significant concern in uncovering the true capability of Industry 4.0 [32]. Ervural and Ervural [62] mentioned that “it is vital to employ end-to-end encryption to avoid phishing, vulnerability, other attacks, enhancing cybersecurity and privacy.” Furthermore, Qin et al. [63] mentioned that cybersecurity risks related to authorization, verification, and access to systems, privacy, networks, and applications remain considerable challenges.

### 2.1.4. Environmental Side Effects (C<sub>4</sub>)

Moktadir et al. [64] mentioned that the massive automation of manufacturing in the implementation of Industry 4.0 might create severe environmental impacts, since the energy resource demands could be increased [65]. Industry 4.0 primarily aims to increase production and quality. Although the competitiveness and revenues of companies can increase, several negative impacts on the environment could happen as a result, such as the poor discharge of waste, air pollution, and the intensive utilization of raw materials, energy, and information [66].

### 2.1.5. Lack of Infrastructure (C<sub>5</sub>)

Collaboration requires proper management of the connections among different companies. In this vein, challenges related to the creation of value through collaboration require companies to provide an excellent infrastructure in order to facilitate data flow among companies [27]. Furthermore, sufficient resources and proper infrastructure are vital requirements for a transition to new business models that fit the novel digital technologies [67]. For instance, a lack of signal coverage and effective communication could be barriers to the implementation of Industry 4.0 [55,56].

### 2.1.6. Legal and Contractual Uncertainty (C<sub>6</sub>)

Digitalization raises a legal challenge as competition grows. While employing a digital strategy, laws concerning liability for artificial intelligence, data protection, and standardization must be valued [68]. The security of online data transformation should be guaranteed in organizations where information and communications technology (ICT) is used. Virtual organizations do not officially exist without a legislative personality and cannot be considered officially independent units. These organizations' privacy regulations are not violated as long as the contracts are adhesive and valid [55].

### 2.1.7. Difficulty in Coordination and Collaboration (C<sub>7</sub>)

Transparent collaboration among network members is essential in perceiving the organizational policies in the adoption of Industry 4.0 for a sustainable transformation [69]. In this vein, high-performance hardware and software are needed in order to have a decent communication system among members, which would require data synchronization and standardized interfaces for achieving more reliable conjunction with manufacturers [70]. On top of that, Batista and Bourlakis [71] and Jia et al. [72] mentioned that it is crucial to have real-time and regular communication with other members by tracking organizational operations to abolish production delay.

## 2.2. Internal Challenges

The internal challenges are presented in detail in the following.

### 2.2.1. Lack of a Skilled Workforce (C<sub>8</sub>)

Gadre and Deoskar [32] mentioned that there is a lack of employees who are talented with respect to meeting the changes brought by current technological trends. New careers have emerged, leading companies to hire a new generation of tech-savvy workers. It is crucial to train and promote the current employees to boost their efficiency and quality,



since their competency sets are getting stale [64]. On top of that, the workforce should be trained to become familiar with adoption strategies for a sustainable transformation [73].

#### 2.2.2. New Business Models' Competency (C<sub>9</sub>)

Companies should compete in a dynamic and complex world, which requires a highly flexible and customized environment. In this vein, companies need to adopt new business models to deal with the current complexity stemming from new digital technologies [74]. A plethora of data are generated in manufacturing systems, leading companies to integrate multiple systems for handling the big data generated. The productivity of companies improves through big data analytics, and a concrete foundation could be provided for scheduling new projects through the prediction of new events by using big data analytics [75]. However, data scientists should develop suitable algorithms in order to adopt new business models, as only some events out of millions are advantageous [54].

#### 2.2.3. Resistance to Change (C<sub>10</sub>)

Industry 4.0 leads companies to change their culture and to enhance their flexibility in adopting new technologies for a sustainable transformation [32]. However, there is a lack of a backbone for initiating radical digitalization strategies [76]. On top of that, most industries are still unsure of and unfamiliar with Industry 4.0 because of their ignorance of its potential advantages; thus, many industries have shown resistance to the adoption of Industry 4.0 technologies [56,77].

#### 2.2.4. Managerial Support (C<sub>11</sub>)

The development of an influential Industry 4.0 concept, dedication, and managerial support are crucial for accepting the changes. Industry 4.0 looks for revolutionary transformations in processes and operations [78]; thus, the most relevant management practices should be implemented. Businesses should train their employees to improve their skills, develop companies' capabilities and knowledge management programs, and design innovative business models for sustainable transformation, while all these activities cannot be possible without dedication and managerial support [79]. Furthermore, a clear vision and mission concerning digital operations are required, since Industry 4.0 provides innovative methods for business operations, especially manufacturing, through the digital transformation. However, organizations fail to show their Industry 4.0 strategies due to their lack of managerial support [80].

#### 2.2.5. Lack of Awareness of the Advantages of I4.0 (C<sub>12</sub>)

There is a shallow awareness of what Industry 4.0 entails among scholars and practitioners [81]. Therefore, a highly organized and focal study is required to determine the advantages of the implications of Industry 4.0, while practitioners undoubtedly perceive the critical role of the adoption of Industry 4.0 in manufacturing processes [56].

However, scholars and practitioners are still unsure of the implications of Industry 4.0 for sustainable transformation [82]. On top of that, companies should understand the benefits of the adoption of Industry 4.0, though it benefits businesses without any doubt [56,83].

#### 2.2.6. Data Management (C<sub>13</sub>)

One of the essential needs for the adoption of Industry 4.0 is data management. In Industry 4.0, several machines, manufacturing systems, sensors, and facilities are interconnected to generate big data [84]. In other words, large amounts of real-time quality and production data are generated and analyzed by companies. As a result, it is necessary to make data readily accessible and available [85]. Furthermore, available and accessible big data could assist managers in using the innovations of Industry 4.0 for a sustainable transformation, while this could not happen without a more outstanding data quality [32].

### 2.2.7. Cost of Implementation ( $C_{14}$ )

Implementation cost is the investment expenditure required to develop Industry 4.0 technologies and infrastructures in organizations. However, financial constraints in developing and improving their machines, equipment, facilities, and innovative sustainable processes are significant challenges to the implementation of Industry 4.0 among companies [56,86]. On top of that, it is challenging to adopt Industry 4.0 in SMEs due to the lack of funds for proper technologies. Furthermore, emerging technologies, such as IoT, often threaten companies' investments because possible financial losses or a lack of recovery of funds could happen [87].

## 3. Methodology

The present study aims to propose a novel extended MCDA method in order to evaluate the performance of fintech companies with respect to the identified challenges to Industry 4.0 adoption for a sustainable digital transformation. To this end, firstly, the challenges were identified by reviewing the current literature. Afterward, the identified challenges were ranked using the FF-CRITIC method based on three decision experts' support. Next, the decision experts supported companies' performance in terms of the weighted challenges through the Fermatean fuzzy linguistic variables; then, the FF-COPRAS method was applied to evaluate and rank the fintech companies. The preliminaries of the Fermatean fuzzy sets and the steps of the proposed method are presented in the following.

### 3.1. Preliminaries

**Definition 1.** [42,49] Assume that  $\Delta$  is a limited universe of discourse; thus, a Fermatean fuzzy set could be presented with Equation (1).

$$T = \{ \langle t_i, (b_T(t_i), n_T(t_i)) \rangle \mid t_i \in \Delta \} \quad (1)$$

where  $b_T : \Delta \rightarrow [0,1]$  shows the B.D. of an element  $t_i \in \Delta$  in an FFS, while  $n_T : \Delta \rightarrow [0,1]$  represents the NBD of an element  $t_i \in \Delta$  in an FFS. On top of that, the condition  $0 \leq (b_T(t_i))^3 + (n_T(t_i))^3 \leq 1$  must be satisfied for each  $t_i \in \Delta$ .

**Definition 2.** [42,49] Let  $\lambda = (b_\lambda, n_\lambda)$ ; then, the indeterminacy degree of the FFS is expressed using Equation (2).

$$\pi_\lambda = \sqrt[3]{1 - b_\lambda^3 - n_\lambda^3} \quad (2)$$

where  $b_\lambda$  and  $n_\lambda \in [0,1]$ , and  $0 \leq b_\lambda^3 + n_\lambda^3 \leq 1$ .

**Definition 3.** [42,49] Assume  $\lambda = (b_\lambda, n_\lambda)$  is an FFS; then, the score and accuracy functions of  $\lambda$  are calculated using Equations (3) and (4).

$$\wp_s(\lambda) = b_\lambda^3 - n_\lambda^3 \mid -1 \leq \wp_s(\lambda) \leq 1 \quad (3)$$

$$\wp_a(\lambda) = b_\lambda^3 + n_\lambda^3 \mid 0 \leq \wp_a(\lambda) \leq 1 \quad (4)$$

Furthermore, the following comparative schemes could be considered to rank  $\lambda_1 = (b_{\lambda_1}, n_{\lambda_1})$  and  $\lambda_2 = (b_{\lambda_2}, n_{\lambda_2})$  as two PFSs.

- (a) If  $\wp_s(\lambda_1) > \wp_s(\lambda_2)$ , then  $\lambda_1 > \lambda_2$ .
- (b) If  $\wp_s(\lambda_1) < \wp_s(\lambda_2)$ , then  $\lambda_1 < \lambda_2$ .
- (c) If  $\wp_s(\lambda_1) = \wp_s(\lambda_2)$ , then
  - I. If  $\wp_a(\lambda_1) > \wp_a(\lambda_2)$ , then  $\lambda_1 > \lambda_2$ .
  - II. If  $\wp_a(\lambda_1) < \wp_a(\lambda_2)$ , then  $\lambda_1 < \lambda_2$ .
  - III. If  $\wp_a(\lambda_1) = \wp_a(\lambda_2)$ , then  $\lambda_1 = \lambda_2$ .

**Definition 4.** [42,49] Assume that  $\lambda = (b_\lambda, n_\lambda)$ ,  $\lambda_1 = (b_{\lambda_1}, n_{\lambda_1})$ , and  $\lambda_2 = (b_{\lambda_2}, n_{\lambda_2})$  are three FFSs. Some operators for the FFSs are presented using Equations (5)–(11).

$$\lambda^c = (n_\lambda, b_\lambda) \quad (5)$$

$$\lambda_1 \cap \lambda_2 = (\min\{b_{\lambda_1}, b_{\lambda_2}\}, \max\{n_{\lambda_1}, n_{\lambda_2}\}) \quad (6)$$

$$\lambda_1 \cup \lambda_2 = (\max\{b_{\lambda_1}, b_{\lambda_2}\}, \min\{n_{\lambda_1}, n_{\lambda_2}\}) \quad (7)$$

$$\lambda_1 \oplus \lambda_2 = \left( \sqrt[3]{b_{\lambda_1}^3 + b_{\lambda_2}^3 - b_{\lambda_1}^3 b_{\lambda_2}^3}, n_{\lambda_1} n_{\lambda_2} \right) \quad (8)$$

$$\lambda_1 \otimes \lambda_2 = \left( b_{\lambda_1} b_{\lambda_2}, \sqrt[3]{n_{\lambda_1}^3 + n_{\lambda_2}^3 - n_{\lambda_1}^3 n_{\lambda_2}^3} \right) \quad (9)$$

$$l\lambda = \left( \sqrt[3]{1 - (1 - b_\lambda^3)^l}, (n_\lambda)^l \right), l > 0 \quad (10)$$

$$\lambda^l = \left( (b_\lambda)^l, \sqrt[3]{1 - (1 - n_\lambda^3)^l} \right), l > 0 \quad (11)$$

### 3.2. Proposed FF-CRITIC-COPRAS

In this section, the proposed methodology is presented step by step. The CRITIC method, which was proposed by Diakoulaki et al. [88], calculates the objective weights of identified challenges. Afterward, the COPRAS method, which was proposed by Zavadskas et al. [89], evaluates the performance of Lithuanian companies in terms of the ranked challenges based on decision experts' (DEs') support. On top of that, the decision experts support the alternatives through the linguistic variables presented in Table 1. It should be noted that fuzzy numbers were used to compare challenges and evaluate the companies in terms of the weighted challenges by using the operators that are presented in the following.

**Table 1.** The linguistic terms and FFNs.

Linguistic Terms	FFNs
Extremely High (EH)	(0.9, 0.1)
Very High (VH)	(0.8, 0.1)
High (H)	(0.7, 0.2)
Medium-High (MH)	(0.6, 0.3)
Medium (M)	(0.5, 0.4)
Medium-Low (ML)	(0.4, 0.5)
Low (L)	(0.25, 0.6)
Very Low (VL)	(0.1, 0.75)
Extremely Low (EL)	(0.1, 0.9)

#### Step 1. Construction of the decision matrix.

Assume that  $\{O_1, O_2, \dots, O_m\}$  is a set of companies,  $\{C_1, C_2, \dots, C_n\}$  is a set of challenges, and  $\{E_1, E_2, \dots, E_p\}$  is a group of DEs who support each company  $O_i$  with respect to a challenge  $C_j$  using Fermatean fuzzy linguistic variables. The decision matrix (N) is expressed by  $N = (g_{ij}^k)$ , for  $i = 1, \dots, m; j = 1, \dots, n$ , while  $g_{ij}^k$  presents the given support to the company (i) with respect to the challenge (j) by the kth DE.

#### Step 2. Calculation of the decision experts' significance degrees.



Suppose that the significant degrees of the DEs are presented using FFNs; then, suppose that  $\omega_k = (b_k, n_k)$  is the significance degree of the  $k$ th DE. The formula for calculating the  $k$ th DE's weight is presented using Equation (12).

$$\omega_k = \frac{\left( b_k^3 + \pi_k^3 \times \left( \frac{b_k^3}{b_k^3 + n_k^3} \right) \right)}{\sum_{k=1}^p \left( b_k^3 + \pi_k^3 \times \left( \frac{b_k^3}{b_k^3 + n_k^3} \right) \right)}, K = 1, \dots, p; \omega_k \geq 0, \sum_1^p \omega_k = 1. \tag{12}$$

Step 3. Aggregated FF-decision matrix.

In this step, the individual decision-making matrices must be aggregated using the Fermatean fuzzy weighted averaging (FFWA) operator presented in Equation (13). Let  $\mathbb{Z} = (z_{ij})_{m \times n}$  be the aggregated FF-decision matrix, where

$$z_{ij} = \left( \sqrt[3]{1 - \prod_{k=1}^r \left( 1 - (b_{ij}^k)^3 \right)^{\omega_k}}, \prod_{k=1}^r (n_{ij}^k)^{\omega_k} \right) \tag{13}$$

Step 4. Determination of the challenges' weights using CRITIC.

The challenges are ranked using CRITIC. The steps of CRITIC are presented in the following [49,90].

Step 4.1. Construction of the score matrix.

The first step of CRITIC is constructing the score matrix  $\Xi = (k_{ij})_{m \times n}$  by using Equation (14) [48].

$$k_{ij} = \frac{1}{2} \left[ \left( b_j^3 - n_j^3 - \ln(1 + \pi_j^3) \right) + 1 \right], \text{ for } i = 1, \dots, m \tag{14}$$

Step 4.2. Normalization of the score matrix.

Equation (15) is used to construct the normalized score matrix  $\tilde{\Xi} = (\tilde{k}_{ij})_{m \times n}$ .

$$\tilde{k}_{ij} = \begin{cases} \frac{k_{ij} - k_j^-}{k_j^+ - k_j^-}, & j \in N_b \\ \frac{k_j^+ - k_{ij}}{k_j^+ - k_j^-}, & j \in N_n \end{cases} \tag{15}$$

where  $k_j^- = \min_i k_{ij}$  and  $k_j^+ = \max_i k_{ij}$ .

Step 4.3. Calculating the standard deviation of the challenges.

Equation (16) is used to calculate the standard deviation of the challenges.

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^m (\tilde{k}_{ij} - \bar{k}_j)^2}{m}} \tag{16}$$

where  $\bar{k}_j = \sum_{i=1}^m \frac{\tilde{k}_{ij}}{m}$ ,

Step 4.4. Calculating the correlation between challenges.

Equation (17) is used to calculate the correlation between challenges.

$$r_{jt} = \frac{\sum_{i=1}^m (\tilde{k}_{ij} - \bar{k}_j) (\tilde{k}_{it} - \bar{k}_t)}{\sqrt{\sum_{i=1}^m (\tilde{k}_{ij} - \bar{k}_j)^2 \sum_{i=1}^m (\tilde{k}_{it} - \bar{k}_t)^2}} \tag{17}$$

Step 4.5. Calculation of the information quantity.

In this step, the information quantity of each challenge is calculated with Equation (18).

$$v_j = \sigma_j \left( \sum_{t=1}^n (1 - r_{jt}) \right) \quad (18)$$

Step 4.6. Calculation of the weight.

In the last step, the weight of each challenge is calculated with Equation (19).

$$\omega_j = \frac{v_j}{\sum_{i=1}^m v_j} \quad (19)$$

Step 5. Summation of the challenges' values.

As mentioned, the COPRAS method is used to evaluate the alternatives with respect to the weighted challenges. To this end, firstly, the values of the challenges are summed using Equation (20) for benefit challenges and Equation (21) for cost challenges.

$$\alpha_i = \left( \sqrt[3]{1 - \prod_{j=1}^n (1 - (b_{ij})^3)^{\omega_j}}, \prod_{j=1}^n (n_{ij})^{\omega_j} \right), \text{ for beneficial challenges} \quad (20)$$

$$\beta_i = \left( \sqrt[3]{1 - \prod_{j=1}^n (1 - (b_{ij})^3)^{\omega_j}}, \prod_{j=1}^n (n_{ij})^{\omega_j} \right), \text{ for non - beneficial challenges} \quad (21)$$

Step 6. Calculating the degree of the challenges.

The degree of the challenges is calculated using Equation (22).

$$C_i = S(\alpha_i) + \frac{\sum_{i=1}^m S(\beta_i)}{S(\beta_i) \sum_{i=1}^m \frac{1}{S(\beta_i)}} \quad (22)$$

where  $S(\alpha_i)$  and  $S(\beta_i)$  are the score functions of the benefit and cost challenges, which are calculated using Equation (14).

Step 7. Estimation of the utility degree.

The utility degree of the alternatives is determined using Equation (23). The highest utility degree indicates the best alternative.

$$U_i = \frac{C_i}{C_{max}} * 100 \text{ for } i = 1, \dots, m \quad (23)$$

#### 4. Results

As mentioned above, the present study aims to evaluate the performance of five Lithuanian fintech companies in terms of the fourteen identified challenges to a sustainable digital transformation. To this end, three DEs supported the companies' performance with respect to the identified challenges using linguistic variables in Table 1. On top of that, we assume that the importance of the DEs is  $\{(0.8, 0.45, 0.67); (0.75, 0.55, 0.74); (0.8, 0.5, 0.71)\}$ . In the first step, the decision-making matrix should be created, which is shown in Table 2.

**Table 2.** Decision-making matrix.

		O1	O2	O3	O4	O5
C1	DE1	EH	MH	L	ML	H
	DE2	H	MH	L	ML	H
	DE3	H	H	VL	ML	MH
C2	DE1	H	L	H	M	M
	DE2	H	ML	MH	ML	M
	DE3	MH	L	H	ML	MH
C3	DE1	VH	H	EH	L	ML
	DE2	MH	MH	MH	L	ML
	DE3	H	MH	VH	L	ML
C4	DE1	M	M	L	VL	M
	DE2	MH	MH	M	L	M
	DE3	MH	M	ML	VL	M
C5	DE1	VH	L	ML	ML	ML
	DE2	M	L	ML	ML	L
	DE3	M	L	M	M	ML
C6	DE1	MH	ML	L	M	ML
	DE2	MH	ML	M	M	ML
	DE3	MH	M	L	ML	ML
C7	DE1	VL	VL	ML	M	M
	DE2	L	EL	ML	MH	MH
	DE3	L	VL	ML	H	MH
C8	DE1	VL	ML	L	H	MH
	DE2	M	ML	L	H	H
	DE3	L	L	L	H	MH
C9	DE1	M	H	EH	ML	MH
	DE2	ML	MH	VH	ML	MH
	DE3	ML	M	H	ML	MH
C10	DE1	VL	ML	ML	H	ML
	DE2	VL	M	ML	MH	ML
	DE3	L	MH	L	MH	ML
C11	DE1	L	ML	MH	M	ML
	DE2	L	ML	MH	MH	M
	DE3	ML	ML	M	ML	ML
C12	DE1	H	MH	M	ML	M
	DE2	H	H	M	ML	MH
	DE3	MH	VH	M	M	M
C13	DE1	ML	ML	MH	H	ML
	DE2	M	H	MH	MH	ML
	DE3	ML	MH	EH	H	M
C14	DE1	ML	VL	ML	ML	H
	DE2	ML	VL	M	VL	MH
	DE3	ML	EL	ML	L	H

After calculating the importance of the DEs, the aggregated decision-making matrix should be created, which is shown in Table 3

**Table 3.** Aggregated decision-making matrix.

	O1	O2	O3	O4	O5
C1	$\lambda\{0.8\ 0.16\ 0.78\}$	$\lambda\{0.64\ 0.26\ 0.90\}$	$\lambda\{0.22\ 0.65\ 0.89\}$	$\lambda\{0.40\ 0.50\ 0.93\}$	$\lambda\{0.67\ 0.23\ 0.88\}$
C2	$\lambda\{0.67\ 0.23\ 0.88\}$	$\lambda\{0.31\ 0.57\ 0.92\}$	$\lambda\{0.67\ 0.23\ 0.88\}$	$\lambda\{0.44\ 0.46\ 0.93\}$	$\lambda\{0.54\ 0.36\ 0.93\}$
C3	$\lambda\{0.72\ 0.18\ 0.85\}$	$\lambda\{0.64\ 0.26\ 0.90\}$	$\lambda\{0.81\ 0.14\ 0.77\}$	$\lambda\{0.25\ 0.60\ 0.92\}$	$\lambda\{0.40\ 0.50\ 0.93\}$
C4	$\lambda\{0.57\ 0.33\ 0.92\}$	$\lambda\{0.54\ 0.37\ 0.93\}$	$\lambda\{0.41\ 0.50\ 0.93\}$	$\lambda\{0.18\ 0.70\ 0.87\}$	$\lambda\{0.50\ 0.40\ 0.93\}$
C5	$\lambda\{0.66\ 0.25\ 0.89\}$	$\lambda\{0.25\ 0.60\ 0.92\}$	$\lambda\{0.44\ 0.46\ 0.93\}$	$\lambda\{0.44\ 0.46\ 0.93\}$	$\lambda\{0.37\ 0.53\ 0.93\}$
C6	$\lambda\{0.60\ 0.30\ 0.91\}$	$\lambda\{0.44\ 0.46\ 0.93\}$	$\lambda\{0.37\ 0.53\ 0.93\}$	$\lambda\{0.47\ 0.43\ 0.93\}$	$\lambda\{0.40\ 0.50\ 0.93\}$
C7	$\lambda\{0.22\ 0.65\ 0.90\}$	$\lambda\{0.10\ 0.79\ 0.79\}$	$\lambda\{0.40\ 0.50\ 0.93\}$	$\lambda\{0.62\ 0.29\ 0.90\}$	$\lambda\{0.57\ 0.33\ 0.92\}$
C8	$\lambda\{0.66\ 0.57\ 0.92\}$	$\lambda\{0.36\ 0.53\ 0.93\}$	$\lambda\{0.25\ 0.60\ 0.92\}$	$\lambda\{0.70\ 0.20\ 0.87\}$	$\lambda\{0.64\ 0.26\ 0.90\}$
C9	$\lambda\{0.44\ 0.46\ 0.93\}$	$\lambda\{0.61\ 0.29\ 0.91\}$	$\lambda\{0.82\ 0.13\ 0.76\}$	$\lambda\{0.40\ 0.50\ 0.93\}$	$\lambda\{0.60\ 0.30\ 0.91\}$
C10	$\lambda\{0.18\ 0.69\ 0.87\}$	$\lambda\{0.52\ 0.39\ 0.93\}$	$\lambda\{0.36\ 0.53\ 0.93\}$	$\lambda\{0.64\ 0.26\ 0.90\}$	$\lambda\{0.40\ 0.50\ 0.93\}$
C11	$\lambda\{0.32\ 0.56\ 0.92\}$	$\lambda\{0.40\ 0.50\ 0.93\}$	$\lambda\{0.57\ 0.33\ 0.92\}$	$\lambda\{0.51\ 0.40\ 0.93\}$	$\lambda\{0.44\ 0.47\ 0.93\}$
C12	$\lambda\{0.67\ 0.23\ 0.88\}$	$\lambda\{0.72\ 0.18\ 0.85\}$	$\lambda\{0.50\ 0.40\ 0.93\}$	$\lambda\{0.44\ 0.46\ 0.93\}$	$\lambda\{0.54\ 0.37\ 0.93\}$
C13	$\lambda\{0.44\ 0.47\ 0.93\}$	$\lambda\{0.60\ 0.31\ 0.91\}$	$\lambda\{0.77\ 0.20\ 0.81\}$	$\lambda\{0.67\ 0.23\ 0.88\}$	$\lambda\{0.44\ 0.46\ 0.93\}$
C14	$\lambda\{0.40\ 0.50\ 0.93\}$	$\lambda\{0.10\ 0.80\ 0.79\}$	$\lambda\{0.44\ 0.47\ 0.93\}$	$\lambda\{0.30\ 0.61\ 0.91\}$	$\lambda\{0.67\ 0.23\ 0.88\}$

Next, the score matrix should be constructed and normalized. The normalized score matrix is shown in Table 4. In addition, the SD, information quantity, and challenges' weights are shown in Table 4.

**Table 4.** CRITIC results.

	O1	O2	O3	O4	O5	$\sigma_j$	$\nu_j$	$\omega_j$	Rank
C1	0.00	0.45	1.00	0.84	0.38	0.432	0.112	0.055	12
C2	0.98	0.00	1.00	0.24	0.51	0.444	0.168	0.082	3
C3	0.71	0.51	1.00	0.00	0.13	0.382	0.128	0.063	10
C4	0.00	0.13	0.54	1.00	0.26	0.317	0.155	0.076	8
C5	0.00	1.00	0.68	0.68	0.84	0.516	0.163	0.080	4
C6	0.00	0.76	1.00	0.64	0.90	0.532	0.138	0.068	9
C7	0.82	1.00	0.56	0.00	0.15	0.410	0.186	0.091	1
C8	0.90	0.87	1.00	0.00	0.23	0.487	0.161	0.079	7
C9	0.05	0.36	1.00	0.00	0.33	0.289	0.110	0.054	13
C10	1.00	0.39	0.73	0.00	0.66	0.452	0.173	0.085	2
C11	0.00	0.24	1.00	0.70	0.38	0.377	0.106	0.052	14
C12	0.24	0.00	0.84	1.00	0.74	0.457	0.162	0.080	6
C13	0.00	0.36	1.00	0.61	0.01	0.325	0.112	0.055	11
C14	0.63	1.00	0.57	0.77	0.00	0.480	0.163	0.080	5

After calculating the weights of the challenges, the FF-COPRAS method is applied to evaluate the companies' performance with respect to the weighted challenges. The FF-COPRAS results are shown in Table 5, wherein  $S(\alpha_i)$  and  $S(\beta_i)$  are the score functions of the benefit and cost challenges,  $C_i$  is the degree of the challenges, and  $U_i$  is the utility degree of the challenges.

**Table 5.** FF-COPRAS results and the companies' ranks.

Companies	$S(\alpha_i)$	$S(\beta_i)$	$C_i$	$U_i$ %	Rank
O1	0.128	0.220	0.285	58.72	3
O2	0.105	0.176	0.302	62.32	2
O3	0.223	0.132	0.485	100	1
O4	0.087	0.200	0.260	53.58	4
O5	0.091	0.218	0.249	51.41	5

According to Table 5, the companies' order with respect to the fourteen identified challenges to the adoption of Industry 4.0 is  $O_3 > O_2 > O_1 > O_4 > O_5$ . Therefore, company three is the best.

### 5. Comparative Analysis

A comparative analysis was performed in this section to compare the proposed method’s results with those of other FF-MCDA methods. To this end, FF-TOPSIS and FF-WPM, which were proposed by Senapati and Yager [42] and Senapati and Yager [43], were employed to rank the companies in terms of the identified challenges. The proposed framework’s irreplaceable merits and efficiency were investigated by comparing the results of FF-TOPSIS and FF-WPM and those of the proposed method.

#### 5.1. FF-TOPSIS

Steps 1–4. The same as in FF-CRITIC-COPRAS.

Step 5. Estimating the Fermatean fuzzy positive and negative ideal solutions.

The positive and negative ideal solutions are shown in Table 6.

**Table 6.** Positive and negative ideal solutions.

	S <sup>+</sup>	S <sup>-</sup>
C1	λ{0.22 0.65 0.89}	λ{0.8 0.16 0.78}
C2	λ{0.67 0.23 0.88}	λ{0.31 0.57 0.92}
C3	λ{0.81 0.14 0.77}	λ{0.25 0.60 0.92}
C4	λ{0.18 0.70 0.87}	λ{0.18 0.70 0.87}
C5	λ{0.25 0.60 0.92}	λ{0.66 0.25 0.89}
C6	λ{0.37 0.53 0.93}	λ{0.60 0.30 0.91}
C7	λ{0.10 0.79 0.79}	λ{0.62 0.29 0.90}
C8	λ{0.25 0.60 0.92}	λ{0.70 0.20 0.87}
C9	λ{0.82 0.13 0.76}	λ{0.40 0.50 0.93}
C10	λ{0.18 0.69 0.87}	λ{0.64 0.26 0.90}
C11	λ{0.57 0.33 0.92}	λ{0.32 0.56 0.92}
C12	λ{0.44 0.46 0.93}	λ{0.72 0.18 0.85}
C13	λ{0.77 0.20 0.81}	λ{0.44 0.47 0.93}
C14	λ{0.10 0.80 0.79}	λ{0.67 0.23 0.88}

Step 6. Calculating the relative closeness.

In this step, the relative closeness to the Fermatean fuzzy ideal solutions is calculated using Equation (24).

$$R(K_i) = \frac{Y_i^-}{Y_i^- + Y_i^+} \text{ for } i = 1, \dots, m$$

where

$$Y_i^- = dis(S^-, z_{ij}) = \omega_j \sqrt{\frac{1}{2} \left[ \left( (b_{ij})^3 - (b_j^-)^3 \right)^2 + \left( (n_{ij})^3 - (n_j^-)^3 \right)^2 + \left( (\pi_{ij})^3 - (\pi_j^-)^3 \right)^2 \right]} \tag{24}$$

$$Y_i^+ = dis(S^+, z_{ij}) = \omega_j \sqrt{\frac{1}{2} \left[ \left( (b_{ij})^3 - (b_j^+)^3 \right)^2 + \left( (n_{ij})^3 - (n_j^+)^3 \right)^2 + \left( (\pi_{ij})^3 - (\pi_j^+)^3 \right)^2 \right]}$$

The calculated relative closeness and the final ranks of the companies are shown in Table 7.

**Table 7.** FF-TOPSIS results.

Companies	Y <sub>i</sub> <sup>+</sup>	Y <sub>i</sub> <sup>-</sup>	R(K <sub>i</sub> )	Rank
O1	0.20	0.13	0.39	3
O2	0.15	0.17	0.53	2
O3	0.10	0.24	0.70	1
O4	0.21	0.13	0.38	4
O5	0.23	0.11	0.32	5



According to FF-TOPSIS, the order of preference of the companies with respect to the identified challenges to the adoption of Industry 4.0 for a sustainable digital transformation is  $O_3 > O_2 > O_1 > O_4 > O_5$ , which is in line with the results of FF-CRITIC-COPRAS.

## 5.2. FF-WPM

Steps 1–4. The same as in FF-CRITIC-COPRAS.

Step 5. Normalization of the decision-making matrix.

In this step, the decision-making matrix is normalized using Equation (25).

$$\mathbb{N} = (\eta_{ij})_{m \times n} = \begin{cases} (b_{ij}, n_{ij}) & \text{for benefit challenges} \\ (n_{ij}, b_{ij}) & \text{for cost challenges} \end{cases} \quad (25)$$

Step 6. Calculation of the total relative significance.

The total relative significance of a company  $O_i$  is calculated using Equation (26), and then the score values of the relative importance degrees of the companies can be calculated. The best company has the highest score value for the relative importance degree. Table 8 shows the results of FF-WPM.

$$\delta(O_i) = \bigoplus_{j=1}^q \omega_j \cdot \eta_{ij} \text{ for } i = 1, \dots, m \quad (26)$$

**Table 8.** FF-WPM results.

Companies	$\delta(O_i)$	$S(\delta_i)$	Rank
O1	$\lambda\{0.42 \ 0.53 \ 0.92\}$	0.175	3
O2	$\lambda\{0.46 \ 0.48 \ 0.92\}$	0.202	2
O3	$\lambda\{0.56 \ 0.36 \ 0.92\}$	0.279	1
O4	$\lambda\{0.41 \ 0.51 \ 0.93\}$	0.172	4
O5	$\lambda\{0.39 \ 0.52 \ 0.93\}$	0.166	5

According to FF-WPM, the order of preference of the companies with respect to the identified challenges to the adoption of Industry 4.0 for a sustainable digital transformation is  $O_3 > O_2 > O_1 > O_4 > O_5$ , which is in line with the results of FF-CRITIC-COPRAS. The companies' rankings according to the three methods is presented in Table 9.

**Table 9.** Results of the comparative analysis.

Companies	Methods			Rank
	FF-COPRAS	FF-TOPSIS	FF-WPM	
	$C_i$	$S(\delta_i)$	$R(K_i)$	
O1	0.285	0.175	0.39	3
O2	0.302	0.202	0.53	2
O3	0.485	0.279	0.70	1
O4	0.260	0.172	0.38	4
O5	0.249	0.166	0.32	5

According to Table 9, the results of the three methods are the same, and company three is the best based on its performance with respect to the identified challenges to the adoption of Industry 4.0 for a sustainable digital transformation. Therefore, the proposed method was found to be efficacious in solving the MCDA issues with conflicting criteria. The primary advantages of the proposed FF-COPRAS method are presented in the following.

- Fermatean fuzzy numbers were employed to deal with uncertainty and ambiguity in MCDA issues. Although Kumar, Singh, and Dwivedi [27] applied conventional

fuzzy sets, we applied the specific case of Fermatean fuzzy sets. In addition, the indeterminacy degree was considered in all steps of the proposed method, which enhanced the method's accuracy; thus, the proposed method can deal with complex MCDA issues more appropriately.

- The CRITIC method was applied to calculate the objective weights in order to avoid subjectivity and to combine the challenges' conflicts and the individual intensities of the contrasts. In contrast, Senapati and Yager [42] and Senapati and Yager [43] selected the weights of the criteria randomly; thus, the proposed method can produce more accurate results than those of other methods.
- The proposed method can deal with MCDA problems with Fermatean fuzzy sets; however, it is suitable for tackling MCDA problems with fuzzy sets, intuitionistic fuzzy sets, and Pythagorean fuzzy sets. On top of that, FF-COPRAS is easy to apply and less time-consuming than FF-TOPSIS.

## 6. Discussion

Industry 4.0 can be considered the primary remedy for the environmental problems caused by traditional industrial activities, such as air and water pollution and soil erosion. However, there are several challenges to the adoption of Industry 4.0 in order to achieve sustainability through a digital transformation. Moktadir, Ali, Kusi-Sarpong, and Shaikh [64] concluded that "lack of infrastructure" is the main challenge to the adoption of Industry 4.0 out of the challenges identified in the Bangladeshi leather industry. In contrast, the results of the present study indicated that "difficulty in coordination and collaboration" is the most critical challenge in the adoption of Industry 4.0 out of the fourteen challenges identified in fintech companies in Lithuania, while "lack of infrastructure" ranked fourth. On top of that, the present study identified external and internal challenges to the adoption of Industry 4.0 and proposed an evaluation framework for analyzing the performance of fintech companies in terms of the identified challenges. In contrast, Chauhan, Singh, and Luthra [28] only identified the challenges without any rankings, and no framework for evaluation was proposed. Companies must deal with the challenges before incorporating intelligent production systems into their operations; thus, an evaluation framework could assist companies by leading them towards a fundamental digital transformation in order to achieve sustainability.

In addition, Kamble, Gunasekaran, and Sharma [55] concluded that "lack of clarity towards digitalization benefits" and "cost of implementation" have a minor impact on companies that are moving towards digitalization. In contrast, the present study showed that the "lack of awareness of the advantages of I4.0" and "cost of implementation" ranked fifth and sixth, respectively, out of the fourteen challenges identified. However, Kamble, Gunasekaran, and Sharma [55] and Chauhan, Singh, and Luthra [28] concluded that the adoption of Industry 4.0 by a company is related to potentialities such as resistance to change, lack of standards and regulations, and privacy, which is in line with the results of the present study. Furthermore, Lin, Lee, Lau, and Yang [59] confirmed that technological incentives have a critical role in the adoption of Industry 4.0, and Lin, Lee, Lau, and Yang [59] and Osakwe et al. [91] confirmed that the most significant influence driving the adoption of technologies is perceived advantage, which is inconsistent with the results of the present research. Moreover, Yadav, Luthra, Jakhar, Mangla, and Rai [56] confirmed that the high cost of implementation and lack of resources are significant economic challenges, and poor management and policy conflict are the most significant managerial challenges. The lack of standards and regulations has the most significant role in industrial adoption from the suppliers' perspective; however, all of these results are inconsistent with the results of the present study. In contrast, the present study compares all of these challenges to find the most important ones.

## 7. Conclusions

Industry 4.0 brings an entirely new perspective through new collaborative manufacturing technologies in order to simultaneously enhance outputs and decrease resource utilization. According to the current literature, many organizations and companies have identified and validated the constraints of the adoption of Industry 4.0. In addition, several studies have been conducted to investigate the challenges and barriers to the adoption of Industry 4.0 for a digital transformation toward sustainability as the European Commission [1] urges the delivery of the European Green Deal by “rethinking policies for clean energy supply across the economy, industry, production, and consumption, large-scale infrastructure, transport, food and agriculture, construction, taxation, and social benefits”.

In this vein, the present study first identified the challenges to the adoption of Industry 4.0 for a sustainable digital transformation. Afterward, a novel MCDA framework named FF-CRITIC-COPRAS was proposed to rank the identified challenges and evaluate the performance of fintech companies in Lithuania. The results indicated that coordination and collaboration were the most significant challenge to the adoption of Industry 4.0 out of the fourteen identified challenges, followed by resistance to change and governmental support. Furthermore, the results confirm that the proposed model has enough proficiency and superiority over the other models; the order of the companies in all methods was  $O_3 > O_2 > O_1 > O_4 > O_5$ , but the proposed method was more comprehensive and accurate, as it works with Fermatean fuzzy sets, which are an extension of conventional fuzzy sets, intuitionistic fuzzy sets, and Pythagorean fuzzy sets. Therefore, the proposed method can deal with problems with various types of fuzzy sets, and it avoids subjectivity by employing the CRITIC method. In addition, the proposed method is easier to apply than other methods, such as FF-TOPSIS.

As mentioned above, the challenges to the adoption of Industry 4.0 for a sustainable digital transformation were identified, which could be one of the main contributions of the present research. In addition, a novel evaluation model was proposed to assist policymakers in evaluating companies with respect to the challenges of Industry 4.0 adoption. Moreover, the applicability of the proposed method was evaluated by applying the proposed method to evaluate fintech companies in Lithuania with respect to the challenges, and comparative studies were conducted to show the superiority and efficiency of the proposed method. According to the results, the proposed method is suitable for dealing with multi-criteria evaluation problems in which several alternatives should be evaluated in terms of several criteria under uncertainty.

It is difficult to coordinate and collaborate with other network members due to a lack of infrastructure, such as the required hardware and software, standards and regulations, etc. Thus, it can be said that the challenges have interconnected relationships; however, the present framework assumed that the challenges are independent, which might be considered as a limitation of this research. Moreover, the fuzzy system’s complex operations make calculations time-consuming. In addition, data collection was time-consuming, since the decision experts were unfamiliar with the fuzzy linguistic variables and how they could support companies through linguistic variables that dealt with the identified challenges.

It is recommended for future scholars to apply methodologies in which independent factors are not necessary, such as system dynamics [92,93]. The extension of other MCDA approaches, such as WASPAS, CoCoSo, or MULTIMOORA, with Fermatean fuzzy sets for the development of evaluation frameworks in various fields and the application of the SWARA method to calculate the subjective weights of challenges could be some recommendations for future research.

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