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Transformational Entrepreneurship and Digital Platforms: A Combination of ISM-MICMAC and Unsupervised Machine Learning Algorithms

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Abstract: For many years, entrepreneurs were considered the change agents of their societies. They use their initiative and innovative minds to solve problems and create value. In the aftermath of the digital transformation era, a new group of entrepreneurs have emerged who are called transformational entrepreneurs. They use various digital platforms to create value. Surprisingly, despite their importance, they have not been sufficiently investigated. Therefore, this research scrutinizes the elements affecting transformational entrepreneurship in digital platforms. To do so, the authors have considered a two-phase method. First, interpretive structural modeling (ISM) and Matrices d'Impacts Croises Multiplication Appliqué a Un Classement (MICMAC) are used to suggest a model. ISM is a qualitative method to reach a visualized hierarchical structure. Then, four unsupervised machine learning algorithms are used to ensure the accuracy of the proposed model. The findings reveal that transformational leadership could mediate the relationship between the entrepreneurial mindset and thinking and digital transformation, interdisciplinary approaches, value creation logic, and technology diffusion. The GMM in the full type, however, has the best accuracy among the various covariance types, with an accuracy of 0.895. From the practical point of view, this paper provides important insights for practitioners, entrepreneurs, and public actors to help them develop transformational entrepreneurship skills. The results could also serve as a guideline for companies regarding how to manage the consequences of a crisis such as a pandemic. The findings also provide significant insight for higher education policymakers.

Keywords: transformational entrepreneurship; digital platforms; ISM; MICMAC; unsupervised machine learning algorithms

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1. Introduction

Over the past decade or so, the appearance of multiple sets of new and influential digital technologies has transformed digital infrastructures and platforms [1,2]. Moreover, innovation and entrepreneurship activities have been significantly affected within organizations, and implications for far-reaching policies [3–5]. Many believe such a transformation was initiated after various waves of technologies emerged. In addition, digital platforms have become major playgrounds for these transformational entrepreneurs [6]. The COVID-19 epidemic has also led us to a more digital world. At the forefront of this,

there is online shopping. In reality, many believe that the COVID-19 disease has changed people's mindsets [7] and shopping ways forever [8]. Hence, businesses need to rethink their business strategies increasingly more.

To succeed in business and community practices, there must be higher levels of entrepreneurial activities to encourage action and increase social capital in society. Then, perhaps transformational entrepreneurship could be the key.

Transformational entrepreneurship is considered an alternate type of entrepreneurial activity because of its interdisciplinary nature and its focus in challenge-based entrepreneurship [9]. Transformational entrepreneurship refers to a capability and an intended action towards creating change in the life of an entrepreneur and organization which contributes to societal changes and is characterized by the emergence of a new qualitative dimension of possibilities [10]. A way to integrate sustainability practices, as well as focus on sustainable future trends, is provided by transformational entrepreneurship [11]. To manage the expectations and needs of the world's increasing population, digital transformation has gone from being a technological opportunity to a pure necessity [12]. This phenomenon has been speeded up by the COVID-19 pandemic [8]. The mentioned developments have created remarkable changes in several businesses, with digital transformation introducing novel mechanisms and procedures affecting the key structures of how a company carries out business [13].

The main benefit of digital platforms is in their ability to reduce transaction costs and make it easier to conduct transactions [14]. This means there can also be a reliance on customer forms of entrepreneurship on digital platforms that provide more user-focused innovation [15]. Digital platforms are a form of transformational entrepreneurship as they produce radical change in society [16]. The entrepreneur is supported by implementing digital platforms to create strategic choices, allowing the company to offer its services despite confronting challenges, including the store closures resulting from the pandemic [8]. Nowadays, the whole implication of traditional retail has been revised and is still going on, rationalizing it and merging it with a more Omni channel logic where digital platforms have an essential effect [17].

Because of societal evolution, technological enhancement, and globalization, entrepreneurial activity continues to evolve. Furthermore, the entrepreneurial behavior's nature continues to develop with the universal importance of social enterprise to support and maintain societies and the need for economically and environmentally continuous business behavior [18]. Transformational entrepreneurship (TE) is a notion that refers to the entrepreneurs' competence to meet universal challenges, including the economic crisis, to enhance society's well-being [17].

On the one hand, entrepreneurs use social media for various reasons that are essential to succeeding in their ventures. The connection and openness of social media overcome the difficulty or inability of entrepreneurs to identify and obtain expert views [19,20]. It is essential in the early stages of entrepreneurial ventures, where the need for support and information to start and run a business is vital to its durability. In addition, they use those platforms commonly to promote their services or products [21]. On the other hand, transformational entrepreneurship has increased with the availability of multiple business models. These business models make it easier for transformational entrepreneurs to take advantage of various potentials [22]. Ref. [18] suggests that transformational entrepreneurship is a useful way to bridge societal goals with entrepreneurial activities. This means transformational entrepreneurship is a distinct type of entrepreneurship due to its focus on social problems and often occurs through learning or education programs [16]. As said before, after the COVID-19 crisis, as there were stay-at-home restrictions and limited mobility options for consumers, there was a quick need to change existing business practices in order to survive the crisis. This problem was exacerbated by the international and domestic border shutdowns. As a consequence, the transformational entrepreneurs tended to focus on using digital platforms as a way to enable them to discuss business ideas. So, it is important to improve transformational entrepreneurship and find the

most influential factors to do so. Based on the abovementioned issues and the current scenario of the COVID-19 pandemic, this research aims to identify the factors affecting transformational entrepreneurship in digital platforms.

In relation to the research gap, it can be said that exploring the factors affecting transformational entrepreneurship is an important topic that has not been addressed much, and in most of the past research, the factors affecting transformational entrepreneurship in the digital platform have been examined individually; but in this study, the effect of these factors is checked at the same time. Thus, the authors have used two primary methods in this study. First, the ISM-MICMAC method was used to propose the model. Then, four unsupervised machine learning algorithms were considered, which helped us compare the results more precisely.

The paper is structured as follows. First, after the Section 1, the extant literature is reviewed. Then, the applications of the machine learning algorithms are discussed. The research method is explained afterwards, and the findings are proposed accordingly. Finally, the paper concludes with some remarks and directions for future research.

2. Literature Review

Transformational entrepreneurship was considered when the cooperation and interaction of individuals, institutions, and communities were required in order to take advantage of existing opportunities and achieve a broader scale of progress [18,23]. It helps to improve the well-being of society by exerting an impact on the political, economic, social, and cultural aspects (multidimensional impact) and also on people, organizations, communities, and society (multilevel) [24]. In other words, transformational entrepreneurship creates entrepreneurial activities, bringing major transformations in industry and markets, and cultural and social life [25]. As a result of its interdisciplinary essence and focus on challenge-based entrepreneurship, transformational entrepreneurship is regarded as an alternative type of entrepreneurial activity. To explain the main alterations in society under the influence of entrepreneurial activities and create competitiveness and market performance, the term transformational entrepreneurship has become popular in academic society [11,26].

Transformational entrepreneurs are much rarer in an economy and are more difficult for investors and policymakers to identify. They build bigger businesses that will grow if they are in the right conditions. In addition, because these entrepreneurs create jobs for others through their expansion processes, they can be considered the real engines of growth in an economy [23]. Ref. [25] recommends that transformational entrepreneurship has a substantial long-term socioeconomic effect. Ref. [27] adds that transformational entrepreneurship is an essential social form of entrepreneurship that goes beyond cultural barriers. Ref. [28] and Turner [29] recognize that the features commonly related to transformational entrepreneurship are building a strong team and possessing a futuristic and disruptive dream. Moreover, according to Roth and DiBella [30], the five competencies needed for enabling transformational change are (i) innovation, (ii) enterprise awareness (e.g., industry knowledge), (iii) seeking growth and leadership, (iv) balancing employee well-being, and (v) management interrelationships of organizational change. On the other hand, ref. [21] state that entrepreneurs' acceptance and use of social media have been affected by many factors broadly classified under technical, organizational, personal, and environmental factors.

This section is an explanation of the factors confirmed by experts using the Delphi method and these factors were identified as effective factors on transformational entrepreneurship. There are definitely other factors that influence transformational entrepreneurship, which the research cannot investigate; but as far as possible, based on a systematic review and existing references, the important factors have been identified in this study. In the next sections, the authors provide relevant explanations and research related to some factors affecting transformational entrepreneurship in digital platforms.

2.1. Digital Transformation

Digital platforms have been replicated as innovation engines for other companies to build diversified products and services in different fields, ranging from video games, PCs, and smartphones to newer websites set up by YouTube, Twitter, Facebook, and many others [31,32]. Digital transformation has evolved from a technological opportunity to a mere necessity to manage the expectations and needs of the world's increasing population [12]. These technologies are altering small, medium, and large firms [33]. They transform people's daily work, behavior, and abilities [34,35]. Every dimension of the work organization is influenced by this change [36,37]. Previous research has indicated how digital technologies foster novel modes of entrepreneurial innovation and initiative that transcend traditional industrial/sectoral boundaries, ecosystems, encompass networks, and communities, integrate and initiate non-digital and digital assets, and speed up the evolution and scaling of modern investments [32,38–45].

2.2. Transformational Leadership

Leaders must create the required situations to encourage their subordinates' behaviors and attitudes, resulting in collective entrepreneurship [46]. Transformational leaders desire to demonstrate entrepreneurial strategies based on high foresight and innovation [47]. Franco and Matos [48] emphasize that transformational directors are so active that they start activities and strive to achieve the development and performance of the group and the organization. Researchers have argued that directorship is a key element of corporate governance, a vital model for the development of corporate entrepreneurship, and a practical matter [49–52]. Ref. [53] shows that transformational leadership positively influences corporate entrepreneurship and its aspects—new business investment, innovation, predictability, self-renewal, and risk taking—both directly and through absorption potential. The capacity of transformational leadership to impact corporate entrepreneurship through absorption capacity added other interesting alternatives. Boukamcha [54] emphasizes the relatively relevant relationship of transformational leadership elements in setting up corporate entrepreneurship patterns.

2.3. Interdisciplinary Approach

The interdisciplinary (also called cross-disciplinary) approaches to entrepreneurship have gained interest among entrepreneurship scholars. They are brimming with examples of the application of various methods to entrepreneurship [55]. According to Oganisjana et al. [56], using an interdisciplinary approach can facilitate the development of entrepreneurial culture. Transformational entrepreneurship is a multifaceted phenomenon which is investigated through various lenses. However, such an approach is loosely explored due to the newness of the phenomenon in question. Its nature is entangled with "anthropology, economics, sociology and regional planning" [11]. Some scholars believe that an interdisciplinary approach could increase the level of transformational entrepreneurship, as it requires various tools, techniques, and perspectives, ranging from those used in traditional business models to digital platforms [16,57].

2.4. Entrepreneurial Mindset and Thinking

Developing entrepreneurial thinking has been on the agenda of EU policymakers and is a concern for educators. Traditional approaches to entrepreneurship education fail to resolve the ambiguities of the entrepreneurial procedure [58]. The entrepreneurial mindset is "the capability to quickly sense, act, and mobilize, even under unclear situations" [59]. The necessity for an entrepreneurial mindset is particularly evident in the present business environment to maintain competitiveness. Individuals must learn traditional management principles, be innovative and creative, and quickly understand, act, and mobilize. Therefore, the entrepreneurial mindset can be perceived as a special mental status of an individual, which is oriented towards entrepreneurial activities and results, often in search of opportunities with rare and uncontrolled resources [60]. As stated by Senges [61], in-

dividuals with an entrepreneurial mindset are passionately searching for novel chances and easy actions to utilize these chances. Ref. [62] mentions that entrepreneurial people recognize opportunities, take risks, seize opportunities, and finally feel satisfaction. Studies suggest that developing an entrepreneurship mindset influences transformational entrepreneurship [58,60,63]. Innovation thinking in the transformation mechanism allows the organization to welcome open innovation in the procedures and methods of creativity. To achieve this goal, it has been argued that organizations must have the ability to actively merge external innovations into the value network and converge internal innovations with ecosystem motivations [64,65]. Ref. [66] states that organizations should develop innovative thinking abilities from the onset of the digital transformation journey. Ref. [67] shows that innovation results in high impact, which can probably contribute to socioeconomic development and transformational entrepreneurship.

2.5. Value Creation Logic

Value creation is a set of actions increasing the value of a company's services and goods. The more value creation, the more effective the entrepreneurship [68]. Transformations of digital platforms promote value creation. The highest stages of entrepreneurship are found in communities with digital profits and the highest value creation. The application of digital technology results in increased consumption, employment, and reduced costs, encouraging entrepreneurs to broaden their attempts and create new entrepreneurs [68]. Many researchers have concentrated on the correlation between these two elements [69–74].

2.6. Technology Diffusion

Sustainable growth, in the long run, demands adopting new technologies. The significance of modern technologies arises from the reality that they are spread across different applications and users and in various geographical areas. Hence, disseminating technological advances between manufacturers within a country and across international borders is as vital as innovation for long-term growth [75]. Technology diffusion is the dynamic result of adoption. It characterizes technology accumulation across its adopters. Additionally, it can result from individual adoption decisions [76]. As Dosi and Nelson [77] pointed out, the main forces driving technology dissemination are the spread of information/knowledge and profit expectations, while development/acceptance costs and uncertainty about new technologies present barriers to dissemination. According to Shafigullina et al. [78], the entrepreneurs' work is influenced by digital technologies' diffusion since they are enablers of new working ways [79] and are due to any changes in entrepreneurs' work context [80].

The identified factors are summarized in Table 1.

Table 1. Identified factors based on literature review.

	Factors	Key References
F1	Digital transformation	Konopik et al. [66]; Jafari-Sadeghi et al. [42]; Corvello et al. [81]; Von Briel et al. [41]
F2	Transformational leadership	Konopik et al. [66]; Shafique and Kalyar [53]; Boukamcha [54]
F3	Interdisciplinary approach	Oganisjana et al. [56]
F4	Entrepreneurial mindset and thinking	Kooskora [60]; Slettl [58]; Stolze et al. [63] Konopik et al. [66]; Xu and Maas [67]
F5	Value creation logic	Galindo-Martín et al. [68]; Hitt et al. [72]; Mishra [73]
F6	Technology diffusion	Shafigullina et al. [78]; Miller and Garnsey [82]

3. Applications of Machine Learning

One type of artificial intelligence called machine learning, in which computers can improve and adapt their processes without explicit human planning, is especially useful

for people who sell products or services online. Implementing new and advanced machine learning approaches enables the organization to achieve greater benefits by accurately predicting customer demand, understanding interaction, and cross-selling products [83].

Machine learning assists users to benefit more from the search experience and can accurately identify the products or services they are looking for. As machine learning becomes more strategically involved in the search process, search results become more meaningful and instead of what the buyer has just typed in the search bar, it matches what they need [84]. On the other hand, machine learning uses more accurate and personal data such as the buyer's specific shopping habits, the colors or appearance they prefer, and the budget type they might have to play with. Such a solution can prioritize product recommendations in terms of their revenue generation or sales increase [85]. Machine learning is about to become a great asset for e-commerce companies looking to automate many of their most intensive and cost-effective manual processes to gain meaningful insights from their customers and, most significantly, clicks, purchases, repeat visits, and positive ratings [86].

Thus, machine learning approaches create better customer involvement, support in analyzing the buyer behavior, and track the products from the vendors to reaching the customers' hands [87]. Commonly, three types of machine learning algorithms exist that can be used based on the task and learning environment: (i) the supervised machine learning algorithm, (ii) the unsupervised machine learning algorithm, and (iii) the reinforcement machine learning algorithm [83,88].

4. Materials and Methods

4.1. Data Collection and Delphi Technique

The Delphi technique includes the following steps: (i) identifying an expert group, (ii) determining the individuals' willingness to serve in a group, (iii) collecting individual input about a particular subject and then collecting them in main statements, (iv) analyzing group data, (v) collecting information about a new questionnaire and sending it to each panel member for a survey, analyzing new data, and restoring distribution of responses to members of the panel, (vi) requesting that each member check the data and appraise their position according to group responses, and (vii) evaluating input and sharing minority supporting statements with the panel [89].

The data were collected by sending emails to experts in the study area. In fact, first, a list of experts was prepared. In the next step, a secondary list was prepared according to who was available and more chances to respond. Finally, it was decided to send the emails in several stages (10 emails in every step), and after receiving feedback in each stage, the next emails were sent. Despite the efforts and accuracy of the authors, the data collection phase took more than three months (February 2022 to May 2022) to collect 84 sets of data. The inclusion criteria included at least 10 years of study or work experience in digital platforms and entrepreneurship. According to the group counseling and literature based on the Delphi technique, 6 main criteria were determined (Table 1).

The experts were identified by examining the available resumes on social media and Google scholar. Several experts were also identified based on previous collaborations with researchers and universities. The experts' contact information, including email and telephone numbers, was identified, and their willingness to respond to the questionnaire was questioned. In some cases, depending on the importance and background of the person in question, the expert was asked to answer questions via Skype.

Coefficient of variation (COV) changes were applied to study the indicator's stability to ensure the Delphi technique consensus in this study. The mean COV in the first study was 0.19, which dropped to 0.17 in the second, thus showing an acceptable consensus [90]. To ensure validity, the inter-class correlation (ICC) coefficient value was consistently confirmed [91–93]. The questionnaire was to be evaluated by experts using the "average measurement of each factor". The ICC coefficient was assessed using these scores. The absolute agreement coefficient's value at 95% confidence intervals was also confirmed.

4.2. Interpretive Structural Modeling

Warfield's [94] approach toward ISM was followed to reach a visualized hierarchical structure. It is a collaborative learning process in which a number of closely related and dissimilar elements are combined into a model and widely applied from various management viewpoints [95,96]. It manages decision making by analyzing and resolving complex problems, such as those in entrepreneurship and digital marketing. This study follows the steps in the process suggested by Singh and Kant [97] and Dhir and Dhir [98].

4.3. Supervised Machine Learning Algorithms

A supervised learning algorithm is a data-based algorithm that does not use tags. The major task of this algorithm is to group, cluster, or organize large volumes of data so that a human (or other intelligent algorithms) can understand it [99]. This specification of unsupervised learning algorithms alone can enhance productivity for industries and businesses across the spectrum. Supervised machine learning also includes algorithms; the most important of these algorithms are [83] (i) support vector machines are a group of techniques for regression, classification, and outlier detection, (ii) Gaussian processes are a generic technique designed to solve probabilistic classification and regression problems, (iii) Naive Bayes are a group of algorithms based on applying Bayes' theorem, (iv) nearest neighbors offers functionality for unsupervised and supervised neighbors-based learning methods, and (v) decision trees are a non-parametric method used for regression and classification.

4.4. Unsupervised Machine Learning Algorithms

An unsupervised learning algorithm is a task-oriented algorithm. It is one of the most broadly used categories of machine learning since it is simple and easy to implement [88,100,101]. There are different unsupervised algorithms such as k-means, affinity propagation, DBSCAN, and BIRCH. The main advantage of ML and algorithms are the following: (i) they are efficient and simple predictive data analysis tools, (ii) they are available to everyone and applicable in different contexts, (iii) they are built on SciPy, matplotlib, and NumPy, and (iv) they are open source and commercially usable (BSD license).

5. Data Analysis and Findings

5.1. Building Adjacency Matrix or SSIM

An adjacency matrix is produced using the input of 84 experts to display the contextual connections between six parameters (Table 2). The contextual association between the components needs to be made and the advice based on the judgement of the experts needs to be given before the ISM technique can be used. We were able to ascertain the contextual links among the six criteria stated by the experts through structured interviews, which is a less biased method. The interviewer did not specifically identify the interviewee as she asked about the pair-wise comparison of the two criteria. What relationship, for example, exists between F1 and F2? The interviewee selected a symbol from the list of V, A, X, and O, as given in the table following this order where the relationships between the variables are as follows: (i) V: F1 variable i influences F2 variable j, (ii) A: F2 variable j influences F1 variable I, (iii) X: both variables i and j are connected, and (iv) O: both variables i and j are unrelated.

Table 2. Structural self-interaction matrix.

	F6	**F5**	**F4**	**F3**	**F2**	**F1**
F1	A	V	A	X	A	
F2	O	V	A	V		
F3	A	V	A			
F4	V	V				
F5	V					
F6						

Notes: Most direct effects were found between F5 (value creation logic) and other factors.

5.2. Initial Reachability Matrix (IRM)

According to SSIM, the reachability matrix must be developed. The SSIM must be converted into the reachability matrix for this purpose by turning symbols into 1s or 0s (Table 3). This conversion adheres to a few guidelines that have been outlined in earlier research (e.g., [102,103]).

Table 3. Initial reachability matrix.

	F1	F2	F3	F4	F5	F6
F1	0	0	1	0	1	0
F2	1	0	1	0	1	0
F3	1	0	0	0	1	0
F4	1	1	1	0	1	1
F5	0	0	0	0	0	1
F6	1	0	1	0	0	0

5.3. Final Reachability Matrix (FRM)

Using the MATLAB software, the transitivity rule research and power iteration analysis were carried out. Some IRM cells have their data filled by inference. The FRM is therefore built around the pair-wise comparison entries as well as a few inferred entries. The authors utilized the transitivity idea to fill in the gaps and inference. Any entry 1 * is a representation of incorporating transitivity.

$$R_f = R_j^K = R_j^{K+1}, K > 1 \quad (1)$$

where R_f is the FRM, and R_i is the IRM.

The FRM can be used to determine the variables' reachability and antecedent sets (Table 4). The total number of variables (including itself) that any variable may have an impact on is reflected in its driving force. Its reliance is the totality of the factors (including itself) that potentially have an effect on the variable.

Table 4. Final reachability matrix.

	F1	F2	F3	F4	F5	F6	Driving Power
F1	1 *	0	1	0	1	1 *	4
F2	1	1 *	1	0	1	1 *	5
F3	1	0	1 *	0	1	1 *	4
F4	1	1	1	1 *	1	1	6
F5	1 *	0	1 *	0	1 *	1	4
F6	1	0	1	0	1 *	1 *	4
Dependence power	6	2	6	1	6	6	

Notes: During the checking of transitivity, * indicates the values which are changed from "0" to "1" and shown with 1 *, power = k = 3.

5.4. Level Partitions

The accessibility set consists of the primary component as well as the additional components that could facilitate success. The preceding set, however, comprises both the component and any additional components that might aid in achieving it. The intersection of these sets is then calculated for each factor. In the ISM hierarchy, factors with identical access and intersection sets are at the top. We cannot accomplish any element above the top-level element of the hierarchy. The high-level element can be identified and then distinguished from the rest. The next step is to repeat the process to identify the elements at the next level. This is carried out repeatedly until each element's surface is identified (Table 5). The tables show three levels for the ISM model. The top-level elements of the ISM model used in this work are F1, F3, F5, and F6 (Figure 1).

Table 5. Level partitioning factors.

Factors	Reachability set	Antecedent set	Intersection set	Level
First Iteration				
F1	1, 3, 5, 6	1, 2, 3, 4, 5, 6	1, 3, 5, 6	1
F2	1, 2, 3, 5, 6	2, 4	2	
F3	1, 3, 5, 6	1, 2, 3, 4, 5, 6	1, 3, 5, 6	1
F4	1, 2, 3, 4, 5, 6	4	4	
F5	1, 3, 5, 6	1, 2, 3, 4, 5, 6	1, 3, 5, 6	1
F6	1, 3, 5, 6	1, 2, 3, 4, 5, 6	1, 3, 5, 6	1
Second Iteration				
F2	2	2, 4	2	2
F4	2, 4	4	4	
Third Iteration				
F4	4	4	4	3

Note: Calculated by Matlab software (R2022a).

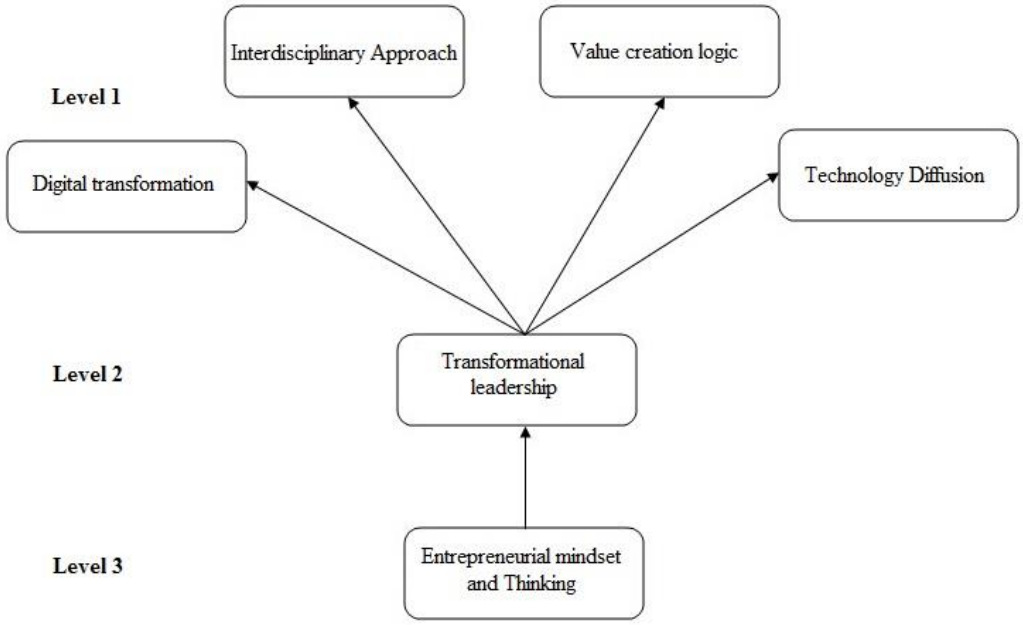

Figure 1. ISM model.

5.5. MICMAC Analysis

"Digital transformation", "interdisciplinary approach", "value creation logic", and "technology diffusion" are all at level I, according to Table 6. These might therefore be placed at the model's apex. Figure 1 makes it possible to recognize the variables, their relationships, and the hierarchical level of each variable. According to Figure 1, the linking factors are the fundamental building blocks of the model, making them the main driving force behind the other variables investigated in this study. The MICMAC approach is used to look at how the effects are dispersed "through reaction loops and paths for developing hierarchies for members of a set of elements" [104]. Each factor has been divided into groups based on their dependencies and motivating factors (Table 5). In MICMAC, there are four different categories of factors: autonomous, dependent, linked, and independent. Transformational leadership is the most crucial strategic variable in comparison to other factors, as shown in Figure 2 by letter "F2". In this study, there are two segments: segment I, which is autonomous, and segment II, which is dependent. There is no autonomous component in this situation, segment III linkage (F1, F3, F5, and F6), and segment IV linkage (F1, F3, F5, and F6). There are two independent components in this segment, namely F2 and F4.

Table 6. Level partitioning factors.

No	Algorithms	Model Parameters	Sample Size	Best Accuracy
1	Affinity propagation	model = affinity propagation (preference = 300, random state = 0)	84	0.858
2	Gaussian mixtures	model = Gaussian mixture (covariance_type = [“full”, “tied”, “diag”, “spherical”], n_components = 4, random_state = 30)	84	0.895
3	Mean shift	model = mean shift (bandwidth = [1, 11])	84	0.776
4	Spectral clustering	Model = spectral_clustering(graph, n_clusters = 4, eigen_solver = “arpack”)	84	0.801

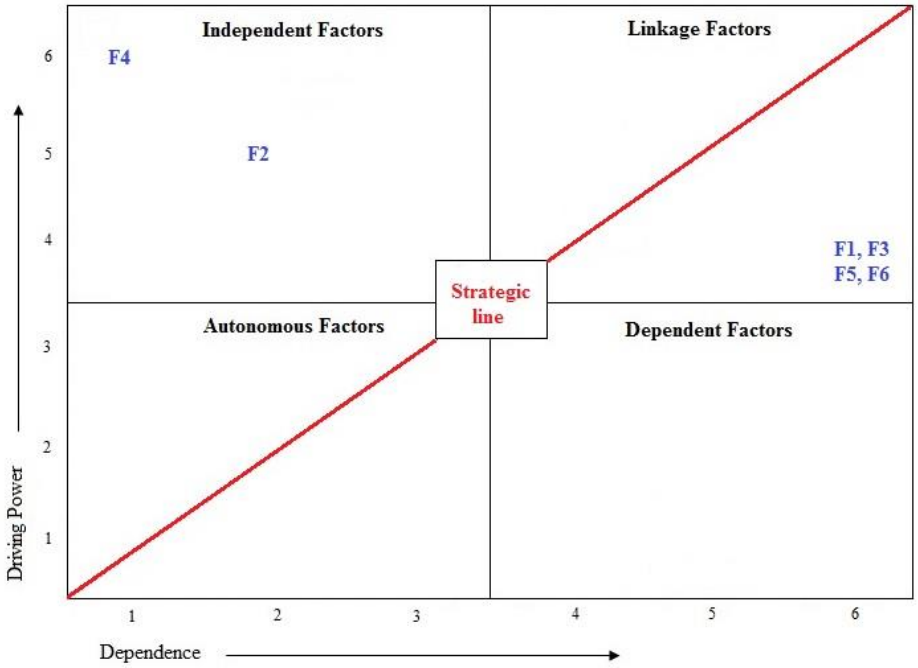

Figure 2. MICMAC analysis.

5.6. Application of Unsupervised ML

In this section, we use four distinctive algorithms (mean shift, spectral clustering, affinity propagation, Gaussian mixtures regarding authors’ experience) appropriate to the characteristics of the current study and the small size of the sample of experts to check the accuracy of the proposed ISM model. This section examines the characteristics of responsive experts regarding their demographic characteristics. In fact, we want to know that responsive experts fall into several clusters according to characteristics such as experience in entrepreneurship and digital platforms. Another important goal is to check the accuracy of the algorithms used, in which we try to compare four different algorithms under different conditions.

Based on scikit-learn documentation, affinity propagation was the first algorithm to be tested. In this algorithm, some clusters are generated by sending messages between pairs of samples until convergence is ensured. A dataset is then explained by a few exemplars recognized as the most representative. The messages sent between pairs demonstrate the appropriateness for one sample to be the exemplar of the other, which is updated in reaction to the values from other pairs. This updating happens iteratively until convergence, at which point the final exemplars are selected, and therefore the ultimate clustering is offered. Figure 3 is shown based on the affinity propagation algorithm (before and after the run).

Based on the results of this algorithm and the placement of experts in four different groups, the accuracy of the model in the best case is 0.858.

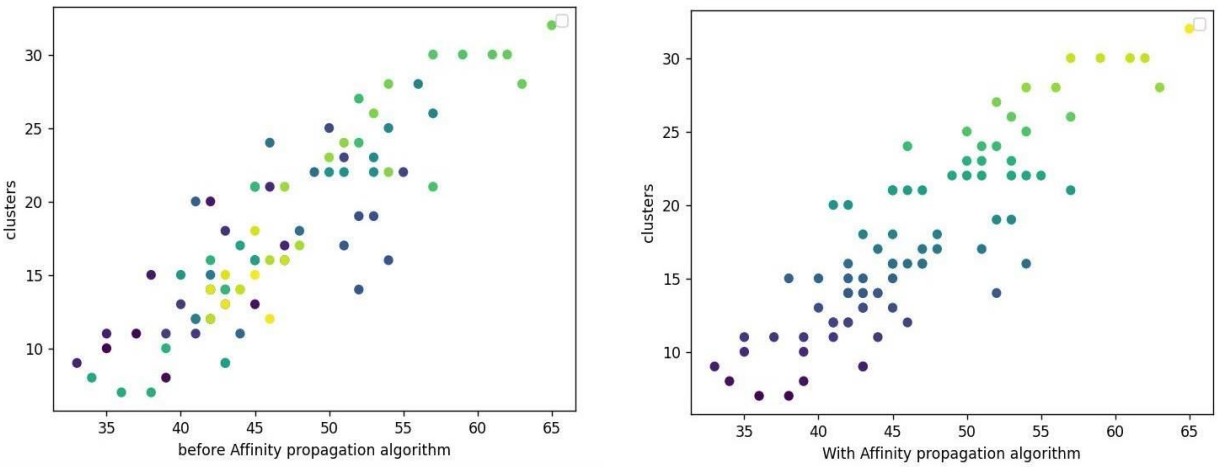

Figure 3. Output of affinity propagation algorithm (Matplotlib library with VS Code).

Regarding to scikit-learn documentation, The Gaussian mixtures model is the second algorithm to be evaluated. It is a probabilistic model that considers all the data points created from a combination of a limited number of Gaussian distributions, including unknown parameters. Such mixture models can be considered a technique to generalize k-means clustering to incorporate information related to the covariance structure of the data and the centers of the latent Gaussians. This model was investigated in four different covariance types (full, diag, tied, and spherical), and the results (Figure 4) indicate an accuracy of 0.895 (train data) in the full type as the best accuracy in different covariance types.

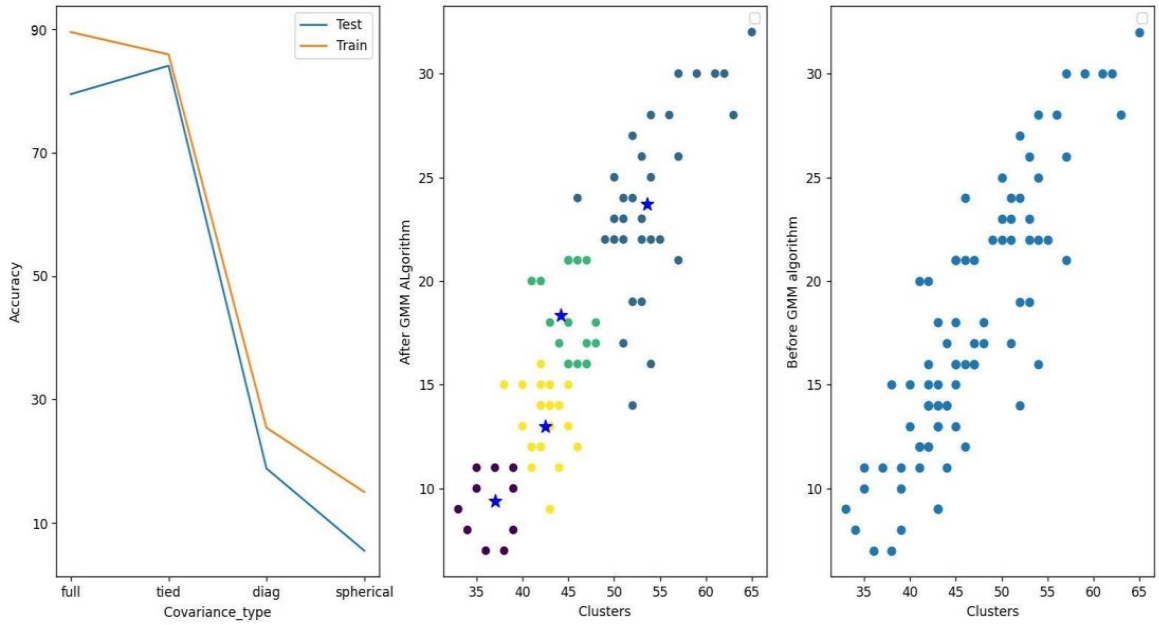

Figure 4. Output of Gaussian mixture algorithm (Matplotlib library with VS Code).

Scikit-learn documentation explained that mean-shift clustering, as a centroid-based algorithm, attempts to discover blobs in a smooth density of samples. It is an algorithm (based on the region of interest and center of mass), which works by updating candidates for centroids to be the mean of the points within a given region. To create the ultimate centroids, one could filter them at a post-processing level. According to Figure 5, this

algorithm, in the best case and considering four different clusters, offers an accuracy of 0.776, which is lower than other algorithms.

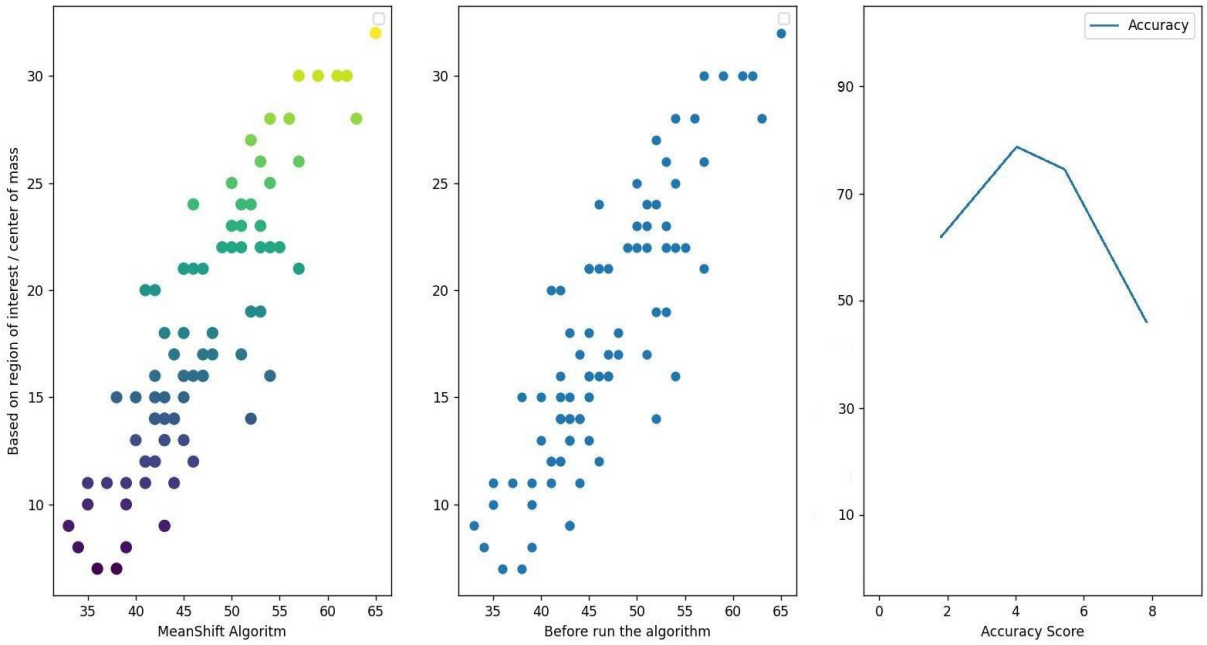

Figure 5. Output of mean-shift algorithm (Matplotlib library with VS Code).

Regarding scikit-learn documentation, spectral clustering carries out a low-dimension embedding of the affinity matrix between samples, followed by clustering, e.g., by k-means, of the elements of the eigenvectors in the low dimensional space. This criterion is especially interesting when working on images, where graph vertices are pixels, and weights of the edges of the similarity graph are computed using a function of a gradient of the image. The spectral clustering algorithm has been evaluated in this research. The results indicate the 0.801 accuracies of this algorithm, which is presented based on four clusters, as shown in Figure 6.

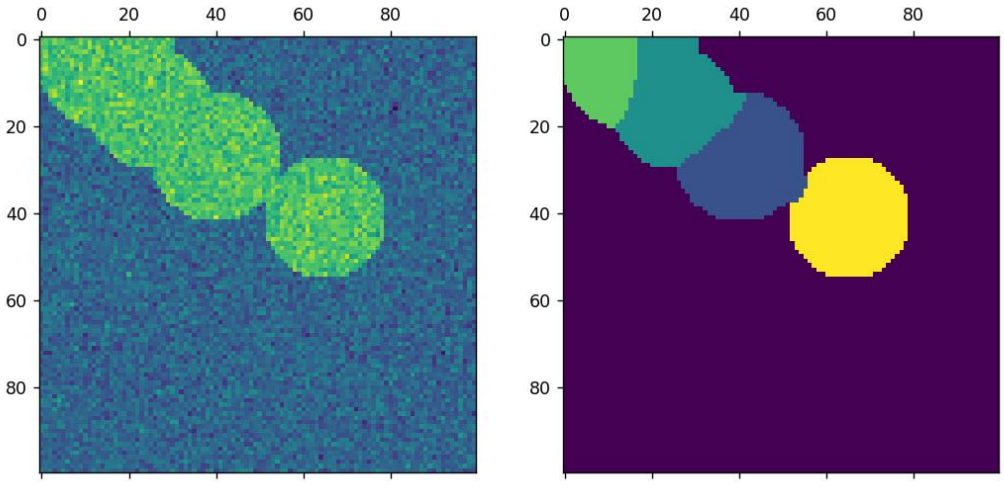

Figure 6. Output of spectral clustering algorithm (Matplotlib library with VS Code).

The outcomes of the four algorithms that were examined are compiled in Table 6. The GMM algorithm has a higher accuracy than other algorithms, despite the fact that all algorithms in general have an accuracy higher than 0.80. The affinity propagation algorithm's accuracy, however, is also crucial and has demonstrated to be of acceptable accuracy.

6. Discussion

In the first phase, we reached two key findings. First, based on the results (Figure 1), entrepreneurial mindset and thinking is the most independent variable which could facilitate the initiation and improvement of transformational leadership. This is consistent with [105] finding that the effectiveness of transformational leadership within an organization increases with the presence of entrepreneurially minded employees. Moreover, transformational leadership could mediate the relationship between entrepreneurial mindset and thinking and the other four elements [58], namely digital transformation (e.g., [12,17,34–37]), interdisciplinary approach [11,16,55,57], value creation logic [68–71], and technology diffusion [76,79,80]. Secondly, we have determined the most strategic element in terms of its high importance and low performance (Figure 2), by investigating which one is closer to the strategic red line. Thus, it was revealed that transformational leadership was the most strategic element in times of the COVID-19 crisis, which could improve the transformational entrepreneurship level. This finding is implicitly mentioned in some studies, such as Benna [106] and Gunawan et al. [107]. The result of the research of [108] also shows that transformational leaders play a critical role in fighting the COVID-19 pandemic by encouraging employees to be innovative and creative, undertaking active actions, and strengthening employee engagement through internal communication and ensuring the organization's sustainability.

In the second phase, we took advantage of unsupervised machine learning algorithms for clustering purposes in the realm of transformational entrepreneurship. It is noteworthy that this research is unique in terms of using such algorithms in entrepreneurship research [109]. According to Table 2, we determined the most relevant and applicable algorithms and used them to explore the accuracy of the proposed model according to the experts' views. Therefore, mean-shift, spectral clustering, affinity propagation, and Gaussian mixtures were used accordingly. We highlighted the most accurate models in Table 6. All the models revealed that the used model was accurate. These algorithms are marginally used in the transformational entrepreneurship literature [99,110,111]. Then, if future researchers investigate larger samples, the supervised machine learning algorithms might be used for prediction purposes. Big data and relevant analytical tools and platforms could be used to explore various dimensions of transformational entrepreneurship [16,112].

7. Conclusions

In the current dynamic environment and with the changes that are constantly happening in businesses, it is necessary to constantly change and innovate to survive. Leaders must understand how transformational entrepreneurs will be able to overcome obstacles in implementing change and try to develop it. Based on the findings of this study, among the factors affecting transformational entrepreneurship that were examined in this study, transformational leadership is the most influential variable for improving transformational entrepreneurship. Thus, it is suggested that business can successfully develop transformational entrepreneurship in their work in digital platforms in times of crisis by leaders with transformational behavior and positive attitudes toward the change. In organizations, ongoing professional development opportunities on dimensions of leadership should be provided for leaders to increase their levels of proficiency in transformational entrepreneurship in digital platforms.

From the practical point of view, this paper provides important insights for practitioners, entrepreneurs, and public actors to help them develop transformational entrepreneurship. The results could also serve as a guideline for companies regarding how to manage the consequences of a crisis such as a pandemic. The findings have also provided significant insight for higher education policymakers. It is therefore hoped that higher education policymakers will realize the importance of transformational leadership for transformational entrepreneurs in managing crises.

It is advised that future researchers use different unsupervised algorithms depending on the goal of the study. In addition, supervised algorithms in longitudinal studies

can be used in various studies based on predicting entrepreneurial performance. While using multi-criteria decision-making techniques, the ISM-MICMAC model described in the present study can be prioritized based on weight (MCDM). It is advised that future researchers examine the weight of variables in the MCDM approach using the Python pyAHP library. The current study has undoubtedly encountered some restrictions. One of the issues with data collection has been finding experts in the context of the COVID-19 outbreak.

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