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Teachers' Acceptance of Distant Learning the Post-COVID-19 Pandemic: A GETAMEL Point of View on an Integrated Fuzzy DEMATEL and BWM

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Teachers' Acceptance of Distant Learning the Post-COVID-19 Pandemic: A GETAMEL Point of View on an Integrated Fuzzy DEMATEL and BWM

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Abstract: Higher education institutions (HEIs) have shifted from traditional classrooms to online distance learning due to different lockdowns. This abrupt transition facilitates the continuation of the teaching and learning process among HEIs, notwithstanding the post-COVID-19 pandemic, at the very least, while posing issues regarding individual learners' values. This article is based on a recently published application of the VETA model, a recently enlarged variant of the widely used UTAUT2. Despite providing critical insights to academics on how to explain the success of online distance learning in terms of individual values through structural equation modeling, the findings may have a few limitations. Motivated by addressing these gaps, this work re-evaluates the nine constructs using fuzzy DEMATEL and BWM. The key findings established the categorical representation of constructs as well as their priority weights, which can provide critical insights into the evolving COVID-19 literature on education, especially informing the design of efforts and indicators to support e-learning strategies during the pandemic.

Keywords: e-learning; individual values; post-COVID-19 pandemic; fuzzy system theory; DEMATEL; BWM

1. Introduction

In controlling the transmission of COVID-19, distance education is deemed the immediate alternative to face-to-face classes in universities (Rizun & Strzelecki, 2020). Academics are currently coping with the usage of learning management systems and other digital platforms provided by their particular higher education institutions (HEIs), as well as the profusion of lectures, training, webinars, and tutorials required to use these technologies efficiently (Donitsa-Schmidt & Ramot, 2020). The transition from traditional to online education raises several critical concerns for HEIs (Sahu, 2020). Numerous attempts have been undertaken in the present literature to understand these growing difficulties better. For example, some realistic counsel has been provided to the government, higher education institutions, and instructors regarding how to manage the educational penalties of the pandemic (Daniel, 2020). Shahzad et al. (2020) established a framework for determining the success of e-learning portals by examining the effects of information quality, system quality, and service quality on user satisfaction and the effectiveness of the e-learning system employed. Mishra et al. (2020) highlighted faculty and student perceptions of the online teaching-learning process during the COVID-19 pandemic. They presented a roadmap for HEIs to transition to online (i.e., remote) education using their existing resources. Recent works in the literature have presented various areas involving strategies in online distance teaching amid the pandemic (Shahzad et al., 2020; Mishra et al., 2020; Bao, 2020), e-learning (Pham & Ho, 2020; Sukendro et al., 2020; Bryson &

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Andres, 2020),students' perceptions (Chandra, 2020; Aristovnik et al., 2020; Hebebci et al., 2020), challenges and opportunities (Donitsa-Schmidt & Ramot, 2020; Neuwirth et al., 2020; Adedoyin & Soykan, 2020; Brammer & Clark, 2020), responses (Azorin, 2020; Assunção & Gago, 2020; Quezada et al., 2020; Zhu & Liu, 2020; Izumi et al., 2020), digital readiness (Händel et al., 2020; Zalite & Zvirbule, 2020), online assessment (Josi et al., 2020; García-Peñalvo et al., 2020), and digital transformation (Iivari et al., 2020; Mhlanga & Moloi, 2020; Greenhow et al., 2020). This list is highly dynamic, reflecting the tremendous evolution of knowledge on the need to cultivate a positive outlook in numerous education sectors. Furthermore, this ever-increasing roster of research works in the literature also translate to the urgency and criticality of addressing pressing concerns the education sector amidst the pandemic.

In resource-scarce developing countries, HEIs have faced a variety of challenges exacerbated by insufficient technological infrastructure, insufficiency in pedagogy, and scarcity of resources, as well as factors of skills, culture, competencies, practices, individual values, and attitudes (Thomas, 2020; Teräs et al., 2020). For example, they lack the requisite expertise and technological infrastructure to enable online classes, which necessitate the development of lesson plans, instructional materials (e.g., audiovisual modules), and a technical support group (Bao, 2020). Educators are also apprehensive about a shortage of online teaching skills and expertise, poor internet speeds, inadequate WIFI coverage, the layout of the interface, the quality of content, system use and acceptance, and technological resources in distant places, to name a few (Shahzad et al., 2020; Azhari & Ming, 2015). Additionally, critical hurdles to remote education include local culture and customs, skills and abilities, and individual beliefs and attitudes (Vial, 2019). Therefore, understanding the determinants affecting remote education becomes critical in order to provide a more informed viewpoint on fine-tuning response actions in response to this abrupt transition (Rizun & Strzelecki, 2020). Therefore, it is critical for higher education institutions to continuously inspire academics (Panisoara et al., 2020).

The COVID-19 pandemic highlights abnormal conditions, and relatively few works examined the probable adoption of distance education during these challenging times (Mhlanga & Moloi, 2020). Notable works in the domain literature focus on the adoption of digital education technologies, including both cognitive and affective factors, in addressing the adverse impacts of the utilization of technology in the teaching-learning process on a never-before-seen scale. Recognizing that students and teachers alike are affected by the sudden shift in educational schemes amid the pandemic, some research works in the literature also focus on teachers' perspectives. For one, König et al. (2020) reported the contributory elements of teachers in adopting digital education technology during the COVID-19 pandemic, which includes information and communication technology tools, digital competence, and digital learning opportunities. Tandon (2020) also developed a theoretical model highlighting online teaching adoption factors during the crisis and associates the positive impact of performance expectancy as well as relative facilitating conditions towards behavioral intention and attitude. Tandon (2020) also demonstrated that effort expectancy has failed to motivate the adoption of online teaching and the significant relationship of social influence with behavioral intention but not with attitude. Similarly, Ho et al. (2020) proposed a research model that included five exogenous variables, including computer self-efficacy, interpersonal influence, external influence, system interactivity, and content feature that were integrated, as well as three endogenous variables, which included perceived ease of use, perceived usefulness, and attitude toward the use of an e-learning system, that was integrated, and that affected students' acceptance of e-learning during the pandemic.

COVID-19's dynamic literature in HEIs now includes critical elements for using e-learning platforms to facilitate distance education (Panisoara et al., 2020; Ho et al., 2020). Evidently, the work of Ho et al. (2020) examines the effect of fear in technology adoption on students and teachers. The fear associated with family lockdown situations, learning failure and losing social relationships significantly impacts perceived ease of use, perceived usefulness, and subjective norm Ho et al. (2020). Another work that highlights the motivation and continuance intention for digital education technology was reported by Ho et al. (2020), who proposed a model from the job demands-resources

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model, self-determination theory, and technology acceptance model (TAM) to explain the relationships of cognitive and affective constructs associated with continued exposure of teachers on digital platforms in the teaching-learning process. On the other side, Rizun & Strzelecki (2020) examined the effect of experience, enjoyment, computer phobia, and self-efficacy on students' acceptance of distant education. They employed a widely accepted version of the TAM for e-learning – the General Extended Technology Acceptance Model for E-Learning (GETAMEL), which Al-Maroof et al. (2020) had previously developed. GETAMEL offers a considerable advantage due to its rigorous theoretical approach to its development, mainly designed for e-learning platforms. Their work offers crucial insights into how important constructs explain students' acceptance of distance learning. However, while its focus lies on students' views, the perspectives of academics and teachers equally affected by the shift to distance education were not explored. Understanding these perspectives would provide insights into the other end of the teaching-learning continuum. In fact, it has been found in the literature that communication between students and teachers is key to a successful online class. Other than that, effective teaching distance learning is also needed to deliver learning to students.

Despite the recent work of Rizun & Strzeleck (2020), a few reservations could be observed. First, despite its popularity, structural equation modeling) (i.e., adopted by Rizun & Strzeleck, 2020), being used to establish causal relations among factors, often leads to some fallacies due to model modification (see Abdullah & Ward, 2016 for an in-depth discussion of the limitations of SEM). Specifically, Abdullah & Ward (2016) discussed that most models following a SEM framework were often modified for better fitness, given that most observations pertain to data inconsistency with the initially hypothesized model. Such limitations might result in model trimming via critical ratios or modification indices (Abdullah & Ward, 2016). In fact, Wei et al. (2010) provided some details exposing this kind of dilemma. It is observed that most initial models under consideration are rejected, which forces scholars to continuously modify and perform re-estimation measures with respect to the model until it fits the data.

On the other hand, Arbuckle & Wothke (1999) and Sellin (1990) criticized the practice of modifying models as relevant ratios and indices must not be treated as definitive guides. That is, without any theoretical support, Abdullah & Ward (2016) even further provided a list of fallacies that may affect the results and insights obtained from the model. Following throughout of view Jend & Tzeng (2012) also resonated with the fallacies of SEM. Second, most established models (e.g., TAM, Unified Theory of Acceptance and Use of Technology (UTAUT)) for evaluating technology systems (e.g., digital educational technologies) require that these samples completely understand these systems. Most investigations using the SEM framework involve many samples (Jeng & Tzeng, 2012). Such prerequisites are frequently not realized, resulting in empirical models that do not adequately analyze causal linkages using SEM (Jeng & Tzeng, 2012). Third, Hsieh et al. (2016), citing the decomposed theory of planned behavior (DTPB) as an example, asserted that the assumption of variable independence frequently leads to an inadequate depiction of connections. According to Hsieh et al. (2016), most models (e.g., DTPB) only evaluate the influence of variables, leaving the cause-and-effect relationships among variables out of the analysis. The model proposed by Rizun & Strzelecki (2020) may suffer from such a limitation. To initiate an argument, consider two constructs: technological pedagogical knowledge self-efficacy and continuance intention. In the hypothesized model of Rizun & Strzelecki (2020), the former has a significant positive effect on continuance intention. However, it is reasonably proper to put forward that, with the continuous intention of use and actual use of educational technologies, technological pedagogical knowledge would possibly gain additional momentum over time. This kind of feedback causal loop fails to be represented by Rizun & Strzelecki (2020). Finally, the identification of critical components for remote education was not investigated because the goal was to just simulate the acceptability of moving education to distance learning.

With the above reasons and research gaps, the fundamental departure of this study is to develop the methodological process of assessing the GETAMEL model proposed by Al-Maroof et al. (2020)

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and adopted recently by Rizun & Strzelecki (2020) utilizing an analytical method centered on expert opinion – the decision-making trial and evaluation laboratory (DEMATEL). DEMATEL was developed by the Geneva Research Centre of the Battelle Memorial Institute (Gabus & Fontela, 1972) to manage a complicated structure of elements connected by causal links, relying on graph theory and linear algebra principles for its usefulness (Gabus & Fontela, 1973). It focuses on (1) establishing causal relationships between network elements (e.g., constructs within a collection of constructs) and (2) categorizing these components according to their net cause and net influence. The DEMATEL is a practical and helpful tool for deriving a clear structural model from the structure of intricate causal connections between elements (Abdullah & Ward, 2016). DEMATEL has also been frequently used throughout the last few decades. The DEMATEL has a limited number of applications in education, including strategic management (Özdemir & Tüysüz, 2017), performance evaluation (Chen, 2012; Ranjan et al., 2015), and e-learning (Tzeng et al., 2007; Jeong & González-Gómez, 2020). Please keep in mind that this list is not exhaustive. Some COVID-19-related applications of the DEMATEL are already developed in the current literature, except for education (see Kashyap & Raghuvanshi, 2020; Dizbay & Öztürkoğlu, 2020; Maqbool & Khan, 2020; Altuntas & Gok, 2020; Ocampo & Yamagishi, 2020). On the basis of the arguments of Abdullah & Ward (2016) on the drawbacks of SEM in causal modeling, several modeling has been published on the use of the DEMATEL technique in the assessment of certain prominent models, including the TAM model (Chang & Chen, 2018; Chen, 2018; Nguyen et al., 2020), UTAUT (Jeng & Tzeng, 2012; Liao & Chen, 2020), DTPB (Lee et al., 2013; Hsieh et al., 2016; Sheng-Li et al., 2018), among others. A comprehensive assessment of the methodology and uses of the DEMATEL throughout the last decade was given by Sheng-Li et al. (2018) in their paper.

The DEMATEL incorporates intrinsic ambiguity as an expert-oriented analytic tool, notably in the judgment elicitations of human experts inside its framework. Considering that the fuzzy set theory highlights cognitive uncertainty, various extensions of the traditional DEMATEL method have also been greatly employed. Some of its recent applications and extensions can be found in various areas such as third-party logistics (Govindan et al., 2016), waste recycling (Liu et al., 2020), remanufacturing (Xia et al., 2015), reverse logistics (Garg, 2020), sustainable supply chain (Luthra et al., 2018), and ICT adoption (Singh et al., 2019). Note again that this list is not intended to be comprehensive. While it can be found in the extant literature that DEMATEL and its extensions in fuzzy set theory have gained increased popularity, the tool falls short in providing priority weights to criteria. As is, the DEMATEL approach can only cluster criteria based on its characteristics as well as evaluate the inherent interrelationships among factors; the priority weights, however, can provide a more in-depth analysis for policymakers. Therefore, the DEMATEL approach can be used as an auxiliary tool to other multi-criteria decision-making (MCDM) approaches, which can satisfactorily evaluate criteria and generate priority weights. Among the developed MCDM tools that can function as desired, a recent one, the best-worst method (BWM) by Rezaei (2015), proves to be a viable tool to use. In fact, BWM can handle the inconsistency issue of analytical hierarchy process (AHP) (Rezaei, 2015) and obtain weights of criteria, among other advantages. Several applications of BWM have been found across various problem areas such as manufacturing setting (Sofuoğlu, 2020), healthcare (Ming et al., 2020), the energy sector (Kazemitash et al., 2021), and smart product service system (Chen & Ming, 2020).

1.1. Research Gap Analysis and Research Questions

With DEMATEL's efficacy in modeling causal links as well as the ability of BWM to evaluate criteria based on its representation in the decision process, this work advances the proposed model of Rizun & Strzelecki (2020) by offering a different methodological perspective, an expert-based analytic causal modeling approach based on fuzzy DEMATEL-BWM. In this work, the nine constructs identified Rizun & Strzelecki (2020) (i.e., obtained from the original GETAMEL) were adopted in constructing a structural model using fuzzy DEMATEL and BWM. In comparison to SEM, the proposed approach incorporates the following extensions: (1) it uncovers inherent causal

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relationships between constructs; (2) it considers indirect effects between constructs in addition to direct effects, thereby generating total relations; (3) it defines key constructs as inputs for decision-making; and (4) it contributes to the understanding of complex and interconnected problems, which is integral in an interdisciplinary approach. This paper is believed to advance the knowledge in managing educational technology amid the pandemic by proposing an integrated MCDM approach to analyze instructors' adoption of distance education.

In brief, this paper aims to advance the evaluation process of investigating technology acceptance of teachers under the GETAMEL & MCDM perspective in the context of education. Such a goal is believed to provide a significant contribution in the domain given the sophisticated synergy of the solution approaches involving fuzzy DEMATEL and BWM in analyzing the factors that affect technology acceptance among teachers. In order to fully achieve these objectives, the following research questions must be addressed at the end of the study:

- How does each construct under the GETAMEL framework affect each other in the context of technology acceptance among teachers??
- What is the priority ranking of these constructs in formulating initiatives and strategies geared towards the acceptance of technology among teachers?

The rest of this article will be structured as follows: The second section provides an overview of fuzzy set theory, DEMATEL, and BWM. Section 3 details the recommended methodology. Section 4 discusses the results and conclusions. Finally, section 5 concludes with a conclusion and discussion of future work.

2. Preliminaries

2.1. Fuzzy Set Theory

The notion of fuzzy set theory has been frequently employed in traditional MCDM approaches to include the vagueness of human perception in decision-making, especially when the constructs under consideration are subjective in the first place (Kuo, 2011). As a result, the subjective judgment of decision-makers during evaluation is captured more efficiently and develops better by utilizing this idea. For a complete description of fuzzy set theory, we suggest readers (Zadeh, 1965) original work. Nonetheless, the following are fuzzy set theory's core and useful notions.

We let X be a universal set, and A is a member of X. Assuming that A is a standard fuzzy set for which a membership function exists as i $\mu_A(x)$ and $\mu_A(x): X \to [0,1]$. Then, the set of a 2-tuple $A = \{x, \mu_A(x): x \in [0,1]$ is established as a fuzzy set where x is a member of A and $\mu_A(x)$ is the membership function of $x \in A$. Furthermore, the triangular fuzzy number $A = (l, m, u)$ is a triplet and the membership function of such triplet follows the expression in Equation (1):

$$\mu_A(x) = \begin{Bmatrix} 0 & x < l \\ (x-l)/(m-l) & l \le x \le m \\ (u-l)/(u-m) & m \le x \le u \\ 0 & x > u \end{Bmatrix} \quad (1)$$

Then, the universe of discourse, X, can be defined such that $l, m, r \in \mathbb{R}, \mu_A(x) \to [0,1]$.

2.2. DEMATEL

The DEMATEL approach, developed in the 1970s by the Geneva-based Battelle Memorial Institute for a Science and Human Affairs Program, is a graph theory-based tool that views a system as a graph, with elements or concepts and their causal relationships. It achieves two goals: (1) it identifies the overall causal links between elements based on direct and indirect relationships, and (2) it classifies these factors according to their characteristics as net cause or net effect. Specifically, the DEMATEL approach takes into account criteria that serve as both cause and effect. These DEMATEL objectives contribute to a better understanding of the features mentioned above or concepts, which are often interrelated in complex issues (Gabus, 1972; 1973).

The following steps summarize DEMATEL's computational algorithm. Take note that the notations used in this work are derived from those used by Ocampo & Yamagishi (2020).

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1. Create a system that involves a finite number of n elements. Let $p_1, p_2, \ldots, p_n$ represent these n elements.
2. Develop a direct-relation matrix. To do this, a pool of experts is tapped $H = 1,2,\ldots,\mathbb{N}$ where each expert elicits judgments on the influence of element p_i on element p_j, $i, j \in \{1, \ldots, n\}$. As such, a set of k direct-relation matrices $Z^k = \left(z_{ij}^k\right)_{n\times n}$, $k = 1,2,\ldots,H$ can be obtained. Here, z_{ij} represents causal influence, with a scale of 0 (no influence) to 4 (very high influence), representing strands of influences. The direct-relation matrix Z, $\forall Z^k, k = 1,2,\ldots,H$, is aggregated by any pre-defined aggregation method (e.g., arithmetic mean method).
3. Generate the normalized direct-relation matrix. Using Equation (2), this matrix is developed.

$$G = \frac{z}{\max\limits_{1\le i\le n} \sum_{j=1}^{n} z_{ij}} \tag{2}$$

Calculate the total relation matrix T, which represents all the direct and indirect causal relationships among the system elements. The total relation matrix $T = \left(t_{ij}\right)_{n\times n}$ is computed using Equation (3).

$$T = G + G^2 + G^3 + \cdots = G(I - G)^{-1} \tag{3}$$

4. Calculate the vectors of prominence and relationship in the data. The prominence and relationship among factors are represented by $(D + R^T)$ vector which is composed of vectors D and R generated as shown in Equations (4) and (5).

$$D = \left(\sum_{j=1}^{n} t_{ij}\right)_{n\times 1} = (t_i)_{n\times 1} \tag{4}$$

$$R = \left(\sum_{i=1}^{n} t_{ij}\right)_{1\times n} = \left(t_j\right)_{1\times n} \tag{5}$$

Vector $(D + R^T)$, also known as the prominence vector, indicates how important each element is in relation to the other elements. A higher value of $(D + R^T)$ reflects stronger links between elements [77]. Additionally, the elements can be classified into two: being net effect (i.e., dispatchers) or net cause (i.e., receivers) group. The net effect group is represented by elements in the $(D - R^T)$ vector while the net cause group is represented by elements in the $(D + R^T)$ vector.

5. Create a map of prominence-relationships. This map depicts the elements $(D + R^T, D - R^T)$ mapping. Element t_{ij} denotes the directed relationships in the prominence-relation map. However, several of these total correlations are unimportant in principle and reality. To eliminate these trivial relations, a threshold value is chosen such that when t_{ij}, a directed edge is constructed in the prominence-relation map from element p_i to element p_j.

2.3. Best-Worst Method

Best-worst method (BWM), developed by Rezaei (2015), stems from the pairwise comparison among factors based on their interrelations. While carrying out an a_{ij} comparison, the decision-maker specifies both the direction of preference i over j and the strength of that preference i over j. In most cases, the decision-maker has no difficulty stating the desired outcome. Although articulation of one's preferences might be challenging, it is virtually always the root of inconsistency in a group.

This approach produces the weights from a pairwise comparison of the best and worst criteria/alternatives with the rest of the criteria/alternatives in the dataset. The use of a five-step process determined the weights. In addition, a consistency ratio is constructed in order to assess the dependability of the final findings. We used a sample of university students to demonstrate the applicability of our novel strategy by posing a real-world decision-making dilemma involving the selection of a mobile phone. A variety of assessment criteria were used to evaluate the outcomes between BWM and AHP, and it was found that BWM outperformed AHP in all of them. BWM has a number of distinguishing characteristics that make it a reliable and interesting approach.

The BWM method may be carried out as follows:

Step 1. Develop a list of choice criteria.

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The criteria $\{c_1, c_2, \dots, c_n\}$ that should be considered to arrive at a choice should be firstly identified in this phase.

Step 2. Identify the most desired and important criteria (i.e., best criterion) and the least desirable and important (i.e., worst criterion).

In this stage, the decision-maker determines which criteria are the best and which criteria are the worst in general. At this point, there is no comparison to be drawn.

Step 3. Identify the preference of the best criterion over all the other criteria using numerical scale of 1 (lowest) to 9 (highest).

The resulting Best-to-Others vector would be:

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}), \tag{6}$$

where a_{Bj} indicates the preference of the best criterion B for every criterion j. As such, $a_{BB} = 1$.

Step 4. Identify the preference of all the criteria over the worst criterion using numerical scale of 1 (lowest) to 9 (highest).

The resulting Others-to-Worst vector would be

$$A_W = (a_{1w}, a_{2w}, \dots, a_{nw})^T, \tag{7}$$

where a_{jw} indicates the preference of the criterion j for every worst criterion W. As such, $a_{ww} = 1$.

Step 5. Find the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$.

To compute the optimal weights for the criteria, consider that for each pair of ${}^{w_B}/_{w_j}$ and ${}^{w_j}/_{w_w}$, the relations as are expressed as follows ${}^{w_B}/_{w_j} = a_{Bj}$ and ${}^{w_j}/_{w_w} = a_{jw}$ where the maximum absolute differences $\left|{}^{w_B}/_{w_j} - a_{Bj}\right|$ and $\left|{}^{w_j}/_{w_w} - a_{jw}\right|$ for all j is minimized. In consideration to the non-negativity and sum condition for the weights, the following expression can be generated:

$$\min \max_j \left\{\left|{}^{w_B}/_{w_j} - a_{Bj}\right|, \left|{}^{w_j}/_{w_w} - a_{jw}\right|\right\} \tag{8}$$

subject to:

$$\sum_j w_j = 1$$

$w_j \geq 0$, for all j.

Hence, Equation (8) can be converted as in Equation (9):

$$\min \varepsilon \tag{9}$$

subject to:

$$\left|{}^{w_B}/_{w_j} - a_{Bj}\right| \leq \varepsilon, \text{ for all } j$$

$$\left|{}^{w_j}/_{w_w} - a_{jw}\right| \leq \varepsilon, \text{ for all } j$$

$$\sum_j w_j = 1$$

$w_j \geq 0$, for all j.

By solving the model, the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$.and ε^* are obtained.

2.4. The Synergy of Fuzzy-DEMATEL and BWM

The MCDM approaches introduced in this paper namely fuzzy DEMATEL and BWM proved to be outstanding approaches when implemented separately as can be noted in many problem applications in the literature even outside the education sector. Recognizing such capability of approaches, this paper takes advantage of the synergy of these tools to further the area of understanding the technology adoption behavior among teachers amidst the challenges brought by the pandemic. With fuzzy DEMATEL, the constructs under GETAMEL can be better understood based on its inherent characteristics and interrelationships. When constructs are viewed collectively according to how they affect other constructs, decision-makers can provide more directed policy strategies and initiatives to aid in the understanding of technology acceptance among teachers. Furthermore, by integrating the key results obtained from the fuzzy DEMATEL approach as inputs

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to the key outputs of BWM, constructs are not only limited to the identification of its characteristics and interrelationships but also includes the exposition of its priority ranking based on the importance of one construct with respect to another, and vice versa. Overall, the characterization of constructs as well as the identification of its priority ranking gives a full view to the decision-makers in considering key constructs that significantly affect the technology acceptance of teachers. Such results satisfactorily address the research problem previously noted in the paper; that is, to advance the process of evaluating the technology acceptance of teachers.

3. Proposed Procedure: Application of Fuzzy-DEMATEL and BWM for Teachers' Acceptance to Distance Education Amidst the COVID-19 Pandemic

In this section, the proposed approach for modeling teachers' acceptance to distance education is described. With the implementation of this proposed approach, the research questions specified in Section can be satisfactorily addressed:

Step 1: Identify models' constituent constructs.

[1] suggested the components that best represent the desire to deploy distant learning during the post-COVID-19 pandemic. In summary, Table 1 lists the nine structures, together with their accompanying short definitions and the codes for brevity of presentation.

Table 1. Constructs of the GETAMEL for shifting to distance education.

Code	Construct	Description	References
PU	Perceived usefulness	the degree to which a user of a given system believes it will enhance his or her job or academic performance compared to alternative means of completing user's tasks.	(Liu & Lin, 2006; Abdullah & Ward, 2016)
PEOU	Perceived ease of use	the degree to which a person, using any system, believes that this usage would be effortless	(Aguilera-Hermida et al., 2021)
ATU	Attitude toward using technology	the degree of the evaluative affect of the individual in using the technology	(Fishben & Ajzen, 1975; Davis, 1985)
ITU	Intention to use	the subjective probability of the individual will use the technology	(Fishben & Ajzen, 1975; Davis, 1985)
AU	Actual use	the act of applying the technology	(Aguilera-Hermida et al., 2021)
XP	Experience	the total number and variety of computer abilities that a person has learned throughout time	(Abdullah & Ward, 2016)
ENJ	Enjoyment	the degree to which the process of applying a system is regarded as pleasant, regardless of results	(Abdullah & Ward, 2016)
CA	Computer anxiety	the elicitation of uncomfortable or emotional responses when executing any task on a computer	(Schlebusch, 2018)
SE	Computer self-efficacy	a user's belief in his or her competence to perform a specific activity using a computer	(Rizun & Strzelecki, 2020)

Step 2: Create the initial direct-relation matrices represented by linguistic variables.

In this particular step, a case study in educational institutions at the Philippines is carried out to demonstrate the applicability of the proposed approach to assess the acceptance of teachers to distance education amidst the pandemic. Here, six academics with considerable expertise and training in using digital educational technology elicit opinions about the contextual linkages between conceptions. Three of them have doctoral degrees, while one is presently seeking one. They are all employed at academic institutions holding positions ranging from Assistant Professor to Professor. Academic jobs need an average of 13.8 years of experience and 9.3 years in supervisory and administrative roles. Since the COVID-19 epidemic began, these academics have been working from home, using online learning and flexible learning methods. Additionally, they do research in a variety

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of fields (e.g., education, technology management, business management, information and communication technology, management science, and tourism), having published between ten and one hundred Scopus-indexed articles.

Take note that this study adopts Yin's (1994) perspective on analytic generalization. Analytic generalization, as defined by Yin (1994) is a strategy for defending, disputing, extending, refining, or expanding theoretical propositions, in contrast to the widely held notion of statistical generalization, which broadly describes the population from a well-defined randomly generated sample. Due to the fact that it addresses theoretical premises, it permits the generalizability of this work's conclusions from a theoretical standpoint (Medalla et al., 2020). According to analytic generalization, a small group of decision-makers (in this case, five experts) is adequate to produce critical insights about the use of digital education technologies because of their high alignment to purposive sampling as the predominant data gathering strategy. It is important to note that although all academics may not always accept the conclusions, they do lead to a greater theoretical grasp of the subject. Medalla et al. (2020), Ancheta Jr. et al. (2018), Bongo et al. (2018b), Bongo & Ocampo (2018), Ocampo et al. (2018b), Ocampo et al. (2020), among others, have used DEMATEL-based methods in their research. Using the assessment scale (i.e., in linguistic variables) indicated in Table 2, the members of this expert group were invited to create an initial direct-relation matrices on their own time. In other words, a pen-and-paper type of questionnaire is distributed to these academics for further evaluation. The goal of this questionnaire is to extract the influence of one construct to another. For instance, a sample initial direct-relation matrix is presented in Table 3. Note that the intersection between PU (row-wise) and PEOU (column-wise) has a rating of VHI. This implies that the academic who evaluated this believes that perceived usefulness (PU) has very high influence to perceived ease of use (PEOU). The same way can be interpreted for the rest of the matrix elements in the table.

Table 2. The grey linguistic rating scale.

Linguistic variables	The equivalent fuzzy number
No influence (NI)	(0, 0.1, 0.3)
Low influence (LI)	(0.1, 0.3, 0.5)
Medium influence (MI)	(0.3, 0.5, 0.7)
High influence (HI)	(0.5, 0.7, 0.9)
Very high influence (VHI)	(0.7, 0.9, 1.0)

Table 3. Sample initial direct-relation matrix in linguistic variables accomplished by one academic.

	PU	PEOU	ATU	ITU	AU	XP	ENJ	CA	SE
PU	NI	VHI	HI	HI	VHI	HI	VHI	NI	HI
PEOU	HI	NI	VHI	NI	NI	HI	VHI	VHI	HI
ATU	HI	HI	NI	VHI	HI	HI	VHI	VHI	VHI
ITU	HI	HI	VHI	NI	HI	HI	HI	VHI	NI
AU	VHI	NI	VHI	HI	NI	HI	HI	HI	HI
XP	VHI	HI	VHI	HI	HI	NI	VHI	HI	VHI
ENJ	HI	VHI	VHI	HI	HI	VHI	NI	HI	VHI
CA	HI	HI	VHI	HI	VHI	HI	VHI	NI	VHI
SE	HI	HI	HI	HI	VHI	VHI	HI	VHI	NI

Step 3: Generate the initial fuzzy direct-relation matrices.

The fuzzy initial direct-relation matrix shown in Table 3 is converted to its corresponding fuzzy numbers shown in Table 2. The results of this conversion is shown in Table 4.

Step 4: Aggregate the initial fuzzy direct-relation matrices.

In this step, the initial fuzzy direct-relation matrix elements are aggregated by Equation (10) as used by Bongo & Ocampo (2016). Here, the $\tilde{\boldsymbol{w}}_j$ notation represents the aggregated matrix element with respect to $\boldsymbol{k}$ decision-makers. Table 5 shows the aggregated direct-relation matrix.

$$\tilde{\boldsymbol{w}}_j = \frac{1}{k}(\tilde{\boldsymbol{w}}_j^1 + \tilde{\boldsymbol{w}}_j^2 + \cdots + \tilde{\boldsymbol{w}}_j^k) \quad (10)$$

Step 5: Obtain the initial direct-relation matrix with crisp elements.

The aggregated initial direct-relation matrix is converted to its crisp counterpart by applying a defuzzification method as shown in Equation (11). Table 6 shows the resulting matrix.

$$d(\tilde{A},0) = \frac{l+2m+u}{4} \tag{11}$$

Table 4. Sample initial direct-relation matrix in fuzzy numbers.

		PU			PEOU			ATU		ITU	AU	XP		ENJ			CA			SE			PU	
PU	0.0	0.1	0.3	0.7	0.9	1.0	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1.0	0.5	0.7	0.9	0.7	0.9	1.0	0.0	0.1	0.3
PEOU	0.5	0.7	0.9	0.0	0.1	0.3	0.7	0.9	1.0	0.0	0.1	0.3	0.0	0.1	0.3	0.5	0.7	0.9	0.7	0.9	1.0	0.7	0.9	1.0
ATU	0.5	0.7	0.9	0.5	0.7	0.9	0.0	0.1	0.3	0.7	0.9	1.0	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1.0	0.7	0.9	1.0
ITU	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1.0	0.0	0.1	0.3	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1.0
AU	0.7	0.9	1.0	0.0	0.1	0.3	0.7	0.9	1.0	0.5	0.7	0.9	0.0	0.1	0.3	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9
XP	0.7	0.9	1.0	0.5	0.7	0.9	0.7	0.9	1.0	0.5	0.7	0.9	0.5	0.7	0.9	0.0	0.1	0.3	0.7	0.9	1.0	0.5	0.7	0.9
ENJ	0.5	0.7	0.9	0.7	0.9	1.0	0.7	0.9	1.0	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1.0	0.0	0.1	0.3	0.5	0.7	0.9
CA	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1.0	0.5	0.7	0.9	0.7	0.9	1.0	0.5	0.7	0.9	0.7	0.9	1.0	0.0	0.1	0.3
SE	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1.0	0.7	0.9	1.0	0.5	0.7	0.9	0.7	0.9	1.0

Table 5. Aggregated direct-relation matrix.

		PU			PEOU			ATU		ITU	AU	XP		ENJ			CA			SE			PU			PEOU	
PU	0.00	0.10	0.30	0.00	0.34	0.59	0.00	0.47	0.72	0.00	0.22	0.47	0.00	0.36	0.60	0.00	0.44	0.69	0.47	0.68	0.85	0.00	0.14	0.36	0.37	0.57	0.77
PEOU	0.00	0.32	0.58	0.00	0.10	0.30	0.00	0.50	0.74	0.00	0.22	0.47	0.00	0.15	0.37	0.00	0.47	0.72	0.00	0.47	0.70	0.00	0.49	0.72	0.45	0.65	0.86
ATU	0.45	0.65	0.86	0.00	0.47	0.72	0.00	0.10	0.30	0.00	0.34	0.59	0.00	0.22	0.47	0.00	0.32	0.58	0.00	0.50	0.74	0.00	0.49	0.72	0.00	0.32	0.56
ITU	0.00	0.47	0.72	0.00	0.47	0.72	0.00	0.34	0.59	0.00	0.10	0.30	0.00	0.32	0.58	0.00	0.47	0.72	0.00	0.47	0.72	0.00	0.55	0.77	0.00	0.22	0.47
AU	0.00	0.52	0.75	0.00	0.22	0.47	0.00	0.52	0.75	0.00	0.50	0.74	0.00	0.10	0.30	0.00	0.47	0.72	0.00	0.47	0.72	0.00	0.32	0.58	0.00	0.44	0.69
XP	0.00	0.50	0.74	0.00	0.47	0.72	0.00	0.23	0.48	0.00	0.32	0.58	0.00	0.47	0.72	0.00	0.10	0.30	0.00	0.50	0.74	0.00	0.47	0.72	0.00	0.34	0.59
ENJ	0.00	0.30	0.55	0.00	0.47	0.70	0.00	0.47	0.70	0.00	0.32	0.58	0.00	0.32	0.58	0.00	0.47	0.70	0.00	0.10	0.30	0.00	0.47	0.72	0.48	0.69	0.87
CA	0.00	0.50	0.74	0.00	0.50	0.74	0.00	0.47	0.70	0.00	0.22	0.47	0.53	0.74	0.92	0.00	0.47	0.72	0.00	0.52	0.75	0.00	0.10	0.30	0.00	0.23	0.48
SE	0.00	0.22	0.47	0.00	0.47	0.72	0.00	0.32	0.58	0.00	0.34	0.59	0.00	0.34	0.59	0.00	0.34	0.59	0.00	0.34	0.59	0.00	0.52	0.75	0.00	0.10	0.30

Table 6. The aggregated direct-relation matrix crisp values.

	PU	PEOU	ATU	ITU	AU	XP	ENJ	CA	SE
PU	0.13	0.32	0.42	0.23	0.33	0.39	0.67	0.16	0.57
PEOU	0.31	0.13	0.43	0.23	0.17	0.42	0.41	0.42	0.65
ATU	0.65	0.42	0.13	0.32	0.23	0.31	0.43	0.42	0.30
ITU	0.42	0.42	0.32	0.13	0.31	0.42	0.42	0.47	0.23
AU	0.45	0.23	0.45	0.43	0.13	0.42	0.42	0.31	0.39
XP	0.43	0.42	0.23	0.31	0.42	0.13	0.43	0.42	0.32
ENJ	0.29	0.41	0.41	0.31	0.31	0.41	0.13	0.42	0.68
CA	0.43	0.43	0.41	0.23	0.73	0.42	0.45	0.13	0.23
SE	0.23	0.42	0.31	0.32	0.32	0.32	0.32	0.45	0.13

Step 6: Normalize direct-influence matrix

This step follows the definition $\boldsymbol{X} = \boldsymbol{vG}$ where $\boldsymbol{X}$ represents the normalized direct-influence matrix with components $\boldsymbol{v} = \boldsymbol{min}_{ij}\left\{\frac{1}{\max\limits_{i} \sum_{j=1}^{n} g_c^{ij}}, \frac{1}{\max\limits_{j} \sum_{i=1}^{n} g_c^{ij}}\right\}$ for every $\boldsymbol{ij}$ is a member of $\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{n}$

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and $\boldsymbol{G}$ as the crisp aggregated direct-influence matrix (see Table 6). The normalized direct-influence matrix is presented in Table 7.

Table 7. Normalized direct-influence matrix G.

	PU	PEOU	ATU	ITU	AU	XP	ENJ	CA	SE
PU	0.00	0.09	0.11	0.06	0.09	0.11	0.18	0.04	0.16
PEOU	0.08	0.00	0.12	0.06	0.05	0.11	0.11	0.12	0.18
ATU	0.18	0.11	0.00	0.09	0.06	0.08	0.12	0.12	0.08
ITU	0.11	0.11	0.09	0.00	0.08	0.11	0.11	0.13	0.06
AU	0.12	0.06	0.12	0.12	0.00	0.11	0.11	0.08	0.11
XP	0.12	0.11	0.06	0.08	0.11	0.00	0.12	0.11	0.09
ENJ	0.08	0.11	0.11	0.08	0.08	0.11	0.00	0.11	0.19
CA	0.12	0.12	0.11	0.06	0.20	0.11	0.12	0.00	0.06
SE	0.06	0.11	0.08	0.09	0.09	0.09	0.09	0.12	0.00

Step 7: Obtain the total influential matrix.

The total influential matrix is computed using Equation (3). This matrix is shown in Table 8 as follows.

Table 8. Total influential matrix.

	PU	PEOU	ATU	ITU	AU	XP	ENJ	CA	SE
PU	0.48	0.55	0.56	0.42	0.51	0.56	0.69	0.51	0.66
PEOU	0.55	0.46	0.55	0.42	0.47	0.56	0.62	0.57	0.67
ATU	0.64	0.57	0.46	0.45	0.49	0.55	0.65	0.57	0.61
ITU	0.58	0.56	0.53	0.36	0.50	0.57	0.63	0.57	0.57
AU	0.60	0.53	0.57	0.48	0.43	0.58	0.64	0.55	0.62
XP	0.57	0.56	0.51	0.43	0.52	0.46	0.63	0.56	0.59
ENJ	0.57	0.59	0.57	0.46	0.53	0.59	0.55	0.59	0.70
CA	0.63	0.61	0.60	0.46	0.64	0.61	0.69	0.50	0.63
SE	0.48	0.52	0.48	0.40	0.46	0.50	0.55	0.52	0.46

Step 8: Categorize the constructs according to net effect or net cause characteristics.

Following Equation (4) and Equation (5), the $\boldsymbol{r}+\boldsymbol{s}$ and $\boldsymbol{r}-\boldsymbol{s}$ vectors are computed and shown in Table 9. This table also specifies the inherent characteristic of constructs being causal or effect. A negative $\boldsymbol{r}-\boldsymbol{s}$ value classifies a construct as an effect variable while a positive $\boldsymbol{r}-\boldsymbol{s}$ value classifies a construct as a causal variable. This step is one of the key functions that DEMATEL serve; being able to distinguish the inherent characteristics of constructs under evaluation.

Table 9. Relations among constructs.

	$\boldsymbol{r}$	$\boldsymbol{s}$	$\boldsymbol{r}+\boldsymbol{s}$	$\boldsymbol{r}-\boldsymbol{s}$	**class**
PU	4.94	5.10	10.04	-0.16	effect
PEOU	4.88	4.95	9.82	-0.07	effect
ATU	4.99	4.82	9.81	0.16	causal
ITU	4.87	3.88	8.74	0.99	causal
AU	4.99	4.56	9.55	0.43	causal
XP	4.84	4.98	9.82	-0.14	effect
ENJ	5.15	5.64	10.79	-0.50	effect
CA	5.37	4.94	10.32	0.43	causal
SE	4.37	5.51	9.88	-1.14	effect

Step 9: Select the best and worst construct.

To proceed with the proposed approach, the BWM is deployed. Similar to the fuzzy DEMATEL method, a paper-and-pen survey questionnaire is distributed to the experts for evaluation. This step

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involves the selection of a best construct and a worst construct that can be used to analze the acceptance of teachers in distance learning amidst the pandemic. It is found, by rule of majority, that the best and worst construct is computer anxiety (CA) and intention to use (ITU), respectively.

Step 10: Evaluate the best and worst constructs to and from the others.

In this step, the best-to-others vector is generated by using Equation (6). As a result, a sample evaluation is presented in Table 10. For example, in Table 10, the results of the evaluation can be interpreted in this manner: since this table shows the best-to-others vector, the best construct, CA, is evaluated against other constructs. It can be noted that the intersection between CA and ENJ is rated 3. This implies that computer anxiety (CA) preferred over enjoyment (ENJ) by a rating of 3 (i.e., on a scale of 1-9, where 1 is the lowest and 9 is the highest). On the other hand, the others-to-worst vector is generated by using Equation (7). Correspondingly, a sample evaluation is shown in Table 11. Similar to best-to-others vector, others-to-worst vector in Table 11 can be interpreted in the following manner: for example, XP is rated 2 against ITU. This implies that experience is preferred over the worst criterion, intention to use, by a rating of 2 (i.e., on a scale of 1-9, where 1 is the lowest and 9 is the highest)s.

Table 10. Sample best to others rating.

	PU	PEOU	ATU	ITU	AU	XP	ENJ	SE
CA	6	6	8	3	4	8	3	9

Table 11. Sample other-to-worst rating.

	ITU
PU	4
PEOU	3
ATU	3
AU	3
XP	2
ENJ	2
CA	2
SE	2

Step 11: Obtain the priority weights of constructs.

In this step, Equation (9) is used. A sample weights of constructs is shown in Table 12. A higher weight represents higher preference according to experts. The weights generated from each expert perspective is then arithmetically aggregated by solving for the grand mean as in Table 13.

Table 12. Sample weights of criteria.

	Weights
PU	0.1034
PEOU	0.1034
ATU	0.0776
ITU	0.2069
AU	0.1552
XP	0.0776
ENJ	0.2069
CA	0.0690
SE	0.1034

Table 13. Aggregated weights of criteria.

	Weights	Rank
PU	0.0948	5
PEOU	0.2334	1
ATU	0.0869	9

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ITU	0.1386	3
AU	0.1151	4
XP	0.0944	7
ENJ	0.1459	2
CA	0.0908	8
SE	0.0948	6

4. Discussion

The findings indicate that attitudes toward using (ATU), actual use (AU), intention to use (ITU), and computer anxiety (CA) are all members of the net cause group, implying that they are regarded as the primary motivating constructs in the acceptance of distance education by the teachers who participated. In order to successfully conduct the teaching-learning process using online platforms, it is necessary to first get their approval. Those constructions in the net cause group have a greater influential impact (D) than those in the influenced impact group (R). The perceived usefulness (PU), perceived ease of use (PEOU), experience (XP), computer self-efficacy (SE), and pleasure (ENJ) variables, on the other hand, are included in the net impact set of variables. They are perceived to be influenced by PU, PEOU, ITU, XP, and CA in reference to its $(D - R^T)$ values being negative. Such negative value implies that these constructs' influential impact (D) is lower than their influenced impact (R). These findings are almost straightforward in a practical sense as PU, PEOU, XP, SE, ENJ are resulting constructs with ATU, AU, ITU, CA for obvious reasons.

Ultimately identifying the critical constructs must simultaneously consider both $(D + R^T)$ and $(D - R^T)$ vectors. Thus, universities and stakeholders must concentrate their resources on investing in initiatives to increase teachers' self-efficacy toward using necessary platforms for distance education. Interest in seminars, training and workshops may be facilitated to improve the SE of academics.

With respect to the results of BWM, it can be seen that PEOU has the highest weight ranking first priority, followed by ENJ, ITU, AU, PU, SE, XP, and ATU. Therefore, the decision-makers must carefully consider the priority order among these constructs to allocate resources for policy implementation and corresponding improvements in any respect. Recognizing that the resources, not only in human but also in other aspects such as finances, are rather limited, it is essential to pinpoint crucial constructs relative to strategy formulation on teachers' acceptance in online distance learning.

5. Conclusions

As the suspension of physical lessons in schools remains a critical strategy for reducing even after the case of COVID-19 pandemic, institutions are required to immediately and massively move the teaching-learning process to digital platforms. Exacerbated by a lack of technical infrastructure, academic incompetence, and resource scarcity, particularly in developing economies, this abrupt shift creates a stressful environment for academics carrying out their teaching responsibilities, let alone their other roles in their respective organizations. The existing body of knowledge is rapidly catching up with reports on the numerous areas of schooling even after the pandemic period. A significant theme focuses on teachers' acceptance of distance education. Rizun & Strzelecki (2020)'s significant contribution, which proposes a model based on nine components, serves as the impetus for this effort. Despite providing critical insights into the problem domain, Rizun & Strzelecki's (2020) analysis using SEM has several drawbacks, including the following: (1) potential fallacies introduced by model modifications, (2) large sample size and technical knowledge requirements, (3) assumption of variable independence, and (4) classification of priority decision-making constructs.

This article addresses these shortcomings by utilizing a fuzzy-DEMATEL technique to model the components (or factors) underlying teachers' adoption of online education in the aftermath of the COVID-19 pandemic. The present study examines the causal links between the nine Rizun and Strzelecki constructs (2020) were evaluated. Results indicate that ATU, AU, ITU, and CA affect the

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following constructs on PU, PEOU, XP, SE, and ENJ. Finally, based on BWM, PEOU is the most crucial constructs in resource allocation decisions and policy formulations in furthering the shift to distance education amidst the pandemic. These findings were not explored by Rizun & Strzelecki (2020). Following the development of these insights, this study demonstrates that fuzzy-DEMATEL has significant promise for modeling studies in education, which are currently underrepresented in the domain literature.

The main takeaways of implementing the proposed fuzzy DEMATEL and BWM under a GETAMEL point of view lies on three folds: First, this paper has objectively showed how the factors involved in the acceptance of e-learning contribute to the eventual decision-making process of policymakers in academic institutions. Without an objective manner of exploring the interrelationships as well as the ranking of priorities among factors, it will be difficult to develop means and strategies to increase the acceptability of new modes of education, especially in unprecedented and unpredictable scenarios such as the pandemic. Thus, this paper clearly puts into practice the conceptual relations extracted from the analysis. Second, being able to identify the causal and effect factors affecting the acceptance of e-learning using fuzzy DEMATEL has paved the way for policymakers to invest scarce resources into select and significant factors at a time without having to utilize and focus on all seemingly important factors extraneously. Lastly, the fuzzy BWM has fulfilled the goal of the paper to objectively prioritize the factors based on their relative impact on other factors involved in the decision-making. When factors are being ranked by importance and relevance, policymakers can strategize on how the developments can be made to improve e-learning acceptance in academic institutions, not to mention the savings in other resources that may limit the decision-making and implementation process.

Overall, these findings have uniquely paved the way for the factors to be better managed in a way that policymakers no longer have to invest in each one of these to progress with the adoption of e-learning as the need arises. Previous research works were limited to the statistical relations among factors that affect the general adoption of technology in the area of distance learning. Such results may prove inadequate and difficult to comprehend at the level of the decision-makers in the actual field of education. For instance, while SEM may have been widely used to explore the relationships among factors, such an approach is unable to distinguish the inherent characteristics of the factors, that is, one being a cause or an effect of another. Other than that, statistical models such as SEM does not have the ability to consider the ranking of priorities of factors which could be a major point of argument for policymakers in establishing resolutions. Overcoming these limitations and incorporating fuzzy set theory, this paper can extract the subjective judgment of decision-makers and translate it into a more meaningful array of information regarding the overall e-learning adoption spectrum.

Nonetheless, the outcomes of this study must be interpreted cautiously. To begin, the scarcity of experts may serve as a springboard for future research. With a larger pool of experts, future research may examine the same model in conjunction with the proposed approach (i.e., grey-DEMATEL) to assess the findings' validity. Second, the proposed technique might be incorporated into any expanded model, as it captures several critical characteristics relating to instructors' acceptance of distant education. Thirdly, additional DEMATEL extensions could be investigated as a methodological extension for further analysis of any acceptance model. Fourth, other modeling tools could also be utilized to analyze Rizun & Strzelecki (2020)'s postulated model. Fourth, future study may include a solution to the resulting construct priority problem and the use of multi-attribute decision-making methodologies. Lastly, the scope of the technology acceptance framework can be further expanded to include the point of view of other entities in the education sector such as the students and administrators, to name a few.

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