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Constructing an Interpretive Structural Model to Unravel the Interconnected Drivers of Teaching Quality in Higher Education

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ABSTRACT

Identifying the primary factors of teaching quality remains a pivotal agenda for informed decision making, strategic planning, and resource allocation. This study builds upon ten key factors derived from previous research and recognizes the inherent complexity within their relationships. Emphasizing the necessity for a structured model, this work employs an interpretive structural modelling (ISM) approach and Matrice d'impacts croisés multiplication appliquée á un classment (MICMAC) analysis for constructing a hierarchical model that delineates the interrelationships among the factors influencing teaching quality. The findings indicate the substantial impact of intrinsic factors, particularly teachers' individual and psychological characteristics, on other factors. Additionally, our analysis highlights the critical role of student composition in enhancing overall teaching quality. These insights significantly contribute to the literature by offering valuable guidance to decision makers for maintaining teaching quality within higher education institutions.

KEYWORDS

Driving Factors, Higher Education Institutions, Interpretive Structural Modeling, MICMAC Analysis, Teaching Quality

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INTRODUCTION

As higher education institutions (HEIs) strive to provide a comprehensive learning environment, teaching effectiveness becomes critical in ensuring positive educational outcomes (Fauth et al., 2019). High-quality teaching in universities extends beyond the mere transmission of knowledge (Sun et al., 2017); it encompasses a range of pedagogical practices, instructional strategies, and support mechanisms that facilitate student engagement and thinking (Madani, 2019). By examining various dimensions of teaching quality, from teacher-centered factors to institutional support (Lim & Ho, 2022), researchers gain insights into the vital role universities play in nurturing the intellectual growth of students (Paul & Nayagam, 2018); these insights become critical in the design of effective measures for upholding teaching quality. Thus, HEIs need to push for an environment that promotes a learning mode that ensures lifelong education, guaranteeing their stability and relevance (Abbas, 2020).

Over the years, researchers and practitioners have long been challenged to list the most impactful driving factors behind high-quality instruction (Praetorius et al., 2018). With the same objective, several studies (e.g., Cho & Baek, 2019; Nalipay et al., 2023; Fan & Shum, 2023; Phung et al., 2024) have identified factors that significantly impact the teaching quality in HEIs. These factors include individual characteristics of the teachers (Cho & Baek, 2019), psychological characteristics (Nalipay et al., 2023), self-efficacy (Daumiller et al., 2021), teaching motivation (Siostrom et al., 2023), teaching experience (Podolsky et al., 2019; Graham et al., 2020), professional development (Vermunt et al., 2019; Darling-Hammond et al., 2017), student composition (Dietrich & Cohen, 2021), students' feedback (Lazarides & Buchholz, 2019), institutional culture (Lebelo, 2021), and institutional resources (Shattuck, 2014).

Although teaching quality is a popular domain in the literature, an in-depth holistic assessment of the factors that influence it remains a gap. Several teaching-quality frameworks proposed by various studies (e.g., Mamites et al., 2022; Cappella et al., 2016) differ in focus, level of abstraction, and subject-relatedness. Recently, Mamites et al. (2022) analyzed the causal relationship between the factors influencing teaching quality in public HEIs in the Philippines and identified the crucial factors between them. Using the neutrosophic decision-making trial and evaluation laboratory (DEMATEL), the study revealed that individual characteristics, psychological characteristics, and institutional culture are key factors in teaching quality, while institutional resources and student composition are minor factors. While DEMATEL models the causal relationships among these factors and eventually identifies the critical factors, a structured model representing a hierarchy that aids in better decision-making is a relevant gap in the domain literature.

To address the gap, this work utilizes a list of factors that significantly impact teaching quality identified through a literature survey. Due to the subjectivity of the identified driving factors and the notion that the evaluation of their relationships reflects an expert judgment, an interpretive structural modeling (ISM) approach and the matrice d'impacts croisés multiplication appliquée à un classement (MICMAC) analysis were adopted in this study (Warfield, 1974a). ISM works such that the complex relationships of the factors are characterized by an interaction map that presents a clearer understanding of the system's structure. With this, a useful guideline is provided for creating a graphical representation of the structure. In this study's context, the ISM application gives structural clarity to the set of factors affecting teaching quality. Consequently, it establishes a hierarchical order for characterization and prioritization, which could become inputs to planning, decision-making, and policymaking. The method is effective in existing or nonexistent connections between each pair of factors where the user or the decision-maker elicits his knowledge of the factors under consideration (Quiñones et al., 2020). Considering the factors and subjective characteristics, ISM-MICMAC examines the effect of these factors, including their transitive relations, and categorizes them based on their driving and dependence powers.

The use of the ISM has been demonstrated in various areas of applications such as big-data analytics (Gupta & Goyal, 2021), online shopping (Basar et al., 2021; Guerrero et al., 2023), social

commerce (Pijo et al., 2023), research productivity (Ocampo et al., 2022), additive manufacturing (Sonar et al., 2020), health-care systems (Kumar & Sharma, 2018), the mining industry (Khaba & Bhar, 2018), and university technology transfer (Quiñones et al., 2020), among others. The integrated ISM-MICMAC has also been applied in the education sector, brought about by the need to understand complex systems arising in teaching and learning, not to mention the greater scope of managing educational processes. In those applications, ISM-MICMAC is considered an effective tool in the identification of a structure within a system to extract more comprehensive information and a simplified view of such a system. In a recent study by Hota et al. (2023), ISM-MICMAC was used to model the challenges of online education in India due to the COVID-19 pandemic. In this study, an analysis of the driving and dependence powers of challenges permitted the decision-makers to develop a framework that can be used by policymakers and stakeholders in India's education sector. Hartanti et al. (2022) also used ISM-MICMAC to model the relationship of the eight identified lean wastes in higher education institutions. Through the development of the model, a more effective prioritization was developed in the formulation of a series of actions to eliminate the waste.

To demonstrate the ISM-MICMAC analysis in structuring the factors associated with teaching quality, a local case study was conducted in Philippine public universities. As such, a purposive survey of domain experts was facilitated to extract the relationships of the identified factors of teaching quality. In the Philippines, the K to 12 Basic Education Curriculum was launched in 2012, causing significant change that has encouraged Philippines HEIs to consistently pursue teaching-quality reforms (Roberto & Madrigal, 2018). The insights that can be crafted from a more structured hierarchical view of the factors would contribute to a better understanding of these factors and aid decision-makers in the development of more responsive initiatives to improve teaching quality.

LITERATURE REVIEW

Teaching quality in HEIs is influenced by various factors, each playing a significant role in shaping the overall effectiveness of university teaching and promoting a positive learning environment. These factors can be categorized into three: intrinsic factors, growth-fostering factors, and contextual factors. Considering these factors is crucial for understanding the multifaceted nature of teaching quality to design effective strategies to enhance it.

Intrinsic Factors

Intrinsic factors in teaching quality are inherent to the teachers and directly influence their teaching effectiveness. These factors are crucial in evaluating teaching quality, as they form the teachers' individual interpretations and conceptions of teaching and how they use both their subjective and objective assessment of problems in the learning environment (Dunkin, 2002). The three highly relevant intrinsic factors are individual characteristics, psychological characteristics, and self-efficacy of teachers. These factors are deeply rooted within the teacher's attributes, beliefs, and capabilities, shaping their instructional practices and overall performance.

Individual characteristics of teachers encompass demographic factors such as gender, age, and marital status (Reid, 2010). Numerous studies have provided empirical evidence that supports the influence of these individual characteristics on teaching quality. They suggest that gender differences can influence student–teacher relationships. Additionally, older teachers tend to exhibit higher work-commitment levels than younger teachers. Alongside demographic characteristics, intellectual capacity, class management, and effective communication of teachers are essential components of quality teaching (Ting, 2000).

On the other hand, the psychological characteristics of teachers refer to conscientiousness and emotional stability, which have been found to impact teaching quality significantly. While earlier studies showed minimal evidence of a direct association between personality traits and teaching performance, recent findings have revealed a strong link between certain psychological traits and

teaching quality. These traits, which are relatively stable and may have a neuropsychological basis, play a vital role in shaping teachers' instructional practices, passion, commitment, and teaching behaviors (Judge & Hurst, 2008; Klassen & Tze, 2014). Curci et al. (2014) revealed that teachers with higher emotional intelligence exhibited greater effectiveness in managing classroom behavior. This, in turn, facilitated the development of positive student–teacher relationships and ultimately enhanced overall learning outcomes (Curci et al., 2014).

In addition to individual and psychological characteristics, self-efficacy plays a vital role in teaching quality. Self-efficacy was introduced by Bandura (1977) as a socio-affective concept that refers to individuals' perceptions and beliefs about their ability to achieve a specific level of performance. It also encompasses their demonstration of coping mechanisms when faced with challenges and difficulties and their ability to direct their actions. It was found that teachers with high levels of self-efficacy are more likely to be effective teachers because they are more open to new teaching methods, set themselves more challenging goals, exhibit a higher level of planning and organization, direct their efforts at solving problems, seek assistance, and adjust their teaching strategies when faced with difficulties (Barni et al., 2019). High self-efficacy is also associated with increased effort, engagement in informal learning activities, persistence, and reduced stress (Alibakhshi et al., 2020). They exhibit effective instructional practices, a passion for teaching, and a commitment to student success. While the relationship between self-efficacy and teaching quality is still being explored, empirical evidence suggests that self-efficacy interventions and training can positively influence teaching quality (Holzberger et al., 2013).

Growth-Fostering Factors

The next category of these factors is growth-fostering factors, which include teaching motivation, professional development of the teachers, and students' feedback. They are termed growth-fostering because they create and facilitate conditions directly contributing to the teachers' personal and professional growth. Teaching motivation influences a teacher's instructional behaviors and practices. Hein et al. (2012) found a positive relationship between teaching motivation and teaching characteristics, such as autonomy support. Teaching motivation influences instructional behaviors, practices, and teacher competence (Zee & Koomen, 2016). High motivation leads to increased effort, goal setting, persistence, attention to instruction, and engagement in professional-development activities (Kunter & Holzberger, 2014; Ross & Bruce, 2007; Klassen et al., 2011). Understanding the relationship between teaching motivation and teaching quality has implications for teacher training and professional development (Praetorius et al., 2017).

Furthermore, professional development is crucial for improving teaching quality. It pertains to structured professional learning that changes teaching practices and enhances student learning outcomes (Darling-Hammond et al., 2017). Expanding teachers' knowledge and skills is necessary for effective teaching (Mizell, 2010). A study reported by Gore et al. (2017) suggests that professional training and development contribute to improving teaching quality. Moreover, students' feedback also enhances teaching quality. According to Flodén's (2017) study, students' feedback can be categorized into two groups based on how university teachers perceive them. Feedback that teachers positively perceive can influence their teaching. In contrast, negatively perceived feedback may trigger negative emotions, leading teachers to make unwarranted changes to their instructional methods. However, this scenario is largely contingent upon the professional pride and integrity of the teachers, who have the potential to utilize such feedback constructively. Feedback provided by students drives improvement-oriented actions from teachers (Bijlsma et al., 2019). Positive relationships between student feedback and teaching quality have been established in previous studies (Gaertner & Brunner, 2018; Hammonds et al., 2017).

Contextual Factors

The last category of these factors that influence teaching quality is the contextual factors, which refers to the broader circumstances, conditions, and external elements surrounding the teaching and learning environment. These factors include teaching experience, institutional culture and resources, and student composition. Contextual factors provide the backdrop and context for teaching and learning. They influence the educational experience, but their impact is more indirect and external, affecting the conditions and environment in which growth-fostering factors can operate. A fundamental contextual factor that plays a significant role in determining teaching quality is teaching experience. Teaching experience is considered a factor influencing teaching quality. Podolsky et al. (2019) demonstrated the positive association between teaching experience and effective student learning. Collaborative environments that support teachers' ongoing growth are essential for fostering effective teaching (Podolsky et al., 2019).

Another contextual factor that influences teaching quality is institutional factors, subdivided into institutional culture and institutional resources. Institutional culture refers to the university's established patterns, values, beliefs, and ideologies (Kezar & Eckel, 2002). A positive institutional culture, focusing on teaching-centered and learning-centered policies, improves teacher–student interactions and enhances teaching quality (Cox et al., 2011). Institutional resources, including curriculum materials and teacher collaboration, influence teaching quality (Hill et al., 2015; Ronfeldt et al., 2015). As suggested by Ho and Peng (2016), resource integrations of HEIs proved to be a relevant factor in their overall performance as learning centers.

Student composition also influences teaching quality. Valiandes (2015) argued that teachers must design their instructional strategies to address the diverse needs of their students. Fauth et al. (2021) emphasized that the quality of teaching received by students depends on the class composition. Student composition can comprise sociocultural background (Ready & Wright, 2011), student achievement, cognitive abilities (Nikolaeva & Synekop, 2020), or motivational composition (Fauth et al., 2021).

In summary, various factors, including individual characteristics, psychological traits, self-efficacy, teaching motivation, teaching experience, professional development, student composition, students' feedback, institutional culture, and institutional resources, all contribute to teaching quality. Nevertheless, these factors have inherently intertwined relationships, which would impact their roles in teaching quality. Setting aside these relationships may be counterintuitive and may result in a constricted view of how they promote teaching quality in a comprehensive manner. These interconnected factors should be considered to promote effective teaching practices and improve student outcomes. In addition, such interconnectedness among factors leads to greater complexity that influences decision-makers in the design of response strategies. Thus, a structured model becomes beneficial to handle this complexity and provides decision-makers a better guide in promoting teaching quality.

PRELIMINARIES

Interpretive Structural Modeling

Interpretive structural modeling is an interactive, computer-assisted learning process in which a complex system is structured into several subsystems or elements through the collaborative efforts of domain experts, resulting in a multilevel structural model (Matawale et al., 2013). Its primary objective is to comprehend intricate situations and subsequently devise effective strategies for resolving underlying issues (Warfield, 1974a, 1974b, 1976). By modeling existing or absent relationships between factors, ISM transforms vague and loosely articulated systems and mental models into well-defined structures serving various purposes. It is interpretive, as it often seeks the judgment of experts on how the components are related to each other (Sharma & Bhat, 2014).

ISM finds extensive applications in innovation and technology management. For instance, it has been used to model barriers in the implementation of green and traditional technology transfer (Khan et al., 2017), explore antecedents of innovation through big open linked data (Dwivedi et al., 2019), identify critical success factors for cloud-computing adoption (Raut et al., 2017), analyze practices of agile supply chain (Rahimi et al., 2020), investigate barriers in green textile supply-chain management (Majumdar & Sinha, 2019), examine root barriers in developing renewable energy resources (Rezaee et al., 2019), and explore barriers in transitioning toward off-site construction (Gan et al., 2018). Note that this list is not exhaustive; other ISM applications exist in various fields.

The required computational steps of the ISM are as follows:

Step 1: Create a comprehensive list of system components with similar characteristics (e.g., factors, barriers, and practices, among others) under consideration. This list should be derived from a thorough literature review, expert focus-group discussions, or a combination of both methods. Here, we denote components to represent factors affecting teaching quality.

Step 2: After compiling the list of components from Step 1, experts establish contextual relationships among these components based on their knowledge and experience. To evaluate these relationships, a self-structural interaction matrix (SSIM) is created for each expert. The SSIM helps analyze and incorporate the perspectives of experts regarding the interrelationships among the identified factors. Four symbols are used to denote the orientation of the contextual relationships between factors i and j: (1) **V** denotes that factor i will augment factor j; (2) **A** denotes that factor i will be augmented by factor *j*; (3) **X** denotes factors i and j will help augment each other; and (4) **O** denotes that factors i and j are unrelated.

Step 3: An initial reachability matrix is constructed for each SSIM of an expert by substituting the symbols of **V**, **A**, **X**, and **O** into a binary matrix of 1 and 0, where 1 signifies that a relationship exists between the factors affecting teaching quality and 0 indicates that the contextual relationship between the factors does not exist. The procedure follows the following guidelines:

(1) If the (i,j) entry in the SSIM is **V**, then the (i,j) entry in the reachability matrix is 1 and the (j,i) entry is 0.
(2) If the (i,j) entry in the SSIM is **A**, then the (i,j) entry in the reachability matrix is 0 and the (j,i) entry is 1.
(3) If the (i,j) entry in the SSIM is **X**, then the entry for both (i,j) and (j,i) is 1.
(4) If the (i,j) entry in the SSIM is **O**, then the entry for both (i,j) and (j,i) is 0.

Step 4: The individual initial reachability matrices from experts are combined using a specified aggregation method. The aggregation method is designed to integrate experts' judgments into a single aggregate initial reachability matrix, mimicking a group decision. However, if the judgments in the SSIM are elicited through a focus-group discussion, this step may not be necessary.

Step 5: An initial reachability matrix *M* is generated by adding the previously generated matrix, D, from Step 4 with an identity matrix *I,* as shown in Eq. (1). The final reachability matrix, denoted as *M**, is computed by applying Boolean multiplication and addition operators, as indicated in Eq. (2). This process allows us to determine the values of the matrix *M** based on the specified operations. The final reachability matrix is calculated from the transitive closure of the initial reachability matrix. This process involves incorporating the transitive relationships among the relevant factors. By integrating these relationships, the method ensures a comprehensive and interconnected analysis of the factors under consideration. The transitivity check for all relations establishes the transitive closure. In the context of ISM, the transitive closure of a binary relation R on a set $\mathcal{U}$ is referred to as the final reachability matrix. It is the smallest relation on $\mathcal{U}$ that encompasses R while maintaining transitivity. Eq. (2) is utilized to obtain the final reachability matrix.

$$M = D + I \tag{1}$$

$$M^* = M^k = M^{k+1},\ k > 1 \tag{2}$$

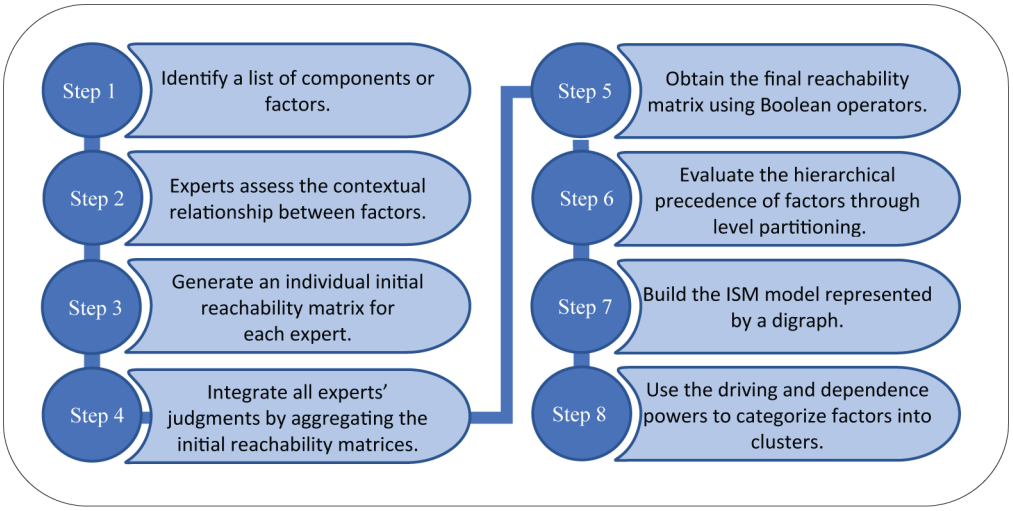
Step 6: The final reachability matrix, once obtained, is used for the hierarchical organization of factors through level partitioning. This process facilitates the straightforward construction of the digraph from the matrix M^*, as Pfohl et al. (2011) described. By implementing this step, it becomes possible to ascertain the precedence of certain factors over others, providing valuable insights into their interrelationships and dependencies within the system.

Step 7: The final reachability matrix M^* is utilized to build the ISM model, where a directed edge from i to j indicates a contextual relationship existing between them. This structure forms a digraph, which is then transformed into the ISM model by representing the vertices with the factors that influence teaching quality. The resulting ISM model visually portrays the contextual relationships, including causal connections, among these factors, clearly representing their impact on teaching quality.

Step 8: The MICMAC analysis is employed to assess the driving and dependence power of factors influencing teaching quality. Based on this analysis, the factors can be categorized into four clusters: (1) autonomous factors with weak driving and dependence power, showing limited interaction with the system and minimal impact on others; (2) dependent factors with weak driving power but strong dependence, making them highly sensitive to changes and serving as indicators of system changes; (3) linkage factors with strong driving and dependence power, acting as intermediate factors between the driving and dependent clusters; and (4) independent factors with strong driving power but weak dependence, displaying significant influence on the system without being significantly affected by other factors. These clusters provide valuable insights into the dynamics and interactions among the factors affecting teaching quality.

Fig. 1 presents the algorithm to summarize the application of the ISM-MICMAC approach.

Figure 1. Algorithm of the Interpretive Structural Modeling Approach



Problem Statement

Given n factors affecting teaching quality, for each $i, j \in \{1,\ldots,n\}$, there exists a relation R, describing iRj, where R assumes one of the following: **V**, **A**, **X**, and **O**. The problem can be formally presented in two parts:

1. Construct an interpretive structural model in a hierarchical form that best describes a more structured representation of the relationships, including those transitive ones, existing between the n factors of teaching quality.
2. Resulting from the relationships described in the n teaching quality factors, determine which belong to autonomous, dependent, linkage, and independent clusters of factors.

METHODOLOGY

Case-Study Background

In the 2022 global talent ranking by the Institute for Management Development (IMD), the Philippines landed the 54th spot. For the 2022 rankings, IMD observed that global economies are reassessing the balance they make when cultivating domestic and international talent in a bid to compensate for skilled labor losses as a result of travel constraints and lockdowns during the pandemic. An important factor considered in this ranking is the readiness factor, which measures the quality of the skills and competencies available in a country's talent pool. Furthermore, the readiness factor is directly related to the education sector, which has received insufficient focus. The Philippines struggled in the 2023 World University Rankings, with only 4 out of 669 institutions making the list. In response, the Commission on Higher Education (CHED), a policymaking body for Philippine higher education, mandated HEIs to adopt competency-based standards and outcome-driven systems to enhance educational quality. Although the Philippines has a policy thrust to invest heavily in education, it has been underinvesting in the sector for the past years relative to its neighboring economies in the region. To address this issue, the government has considered increasing educational investments in the upcoming years. Several stakeholders have supported the creation of policies that aim to expand access and improve the quality of education to alleviate the problem. A good number of the policies would initiate structural changes in basic and higher education and intensify partnerships with the private sector and industry. However, these changes are lagging, and reforms have not yet reached maturity.

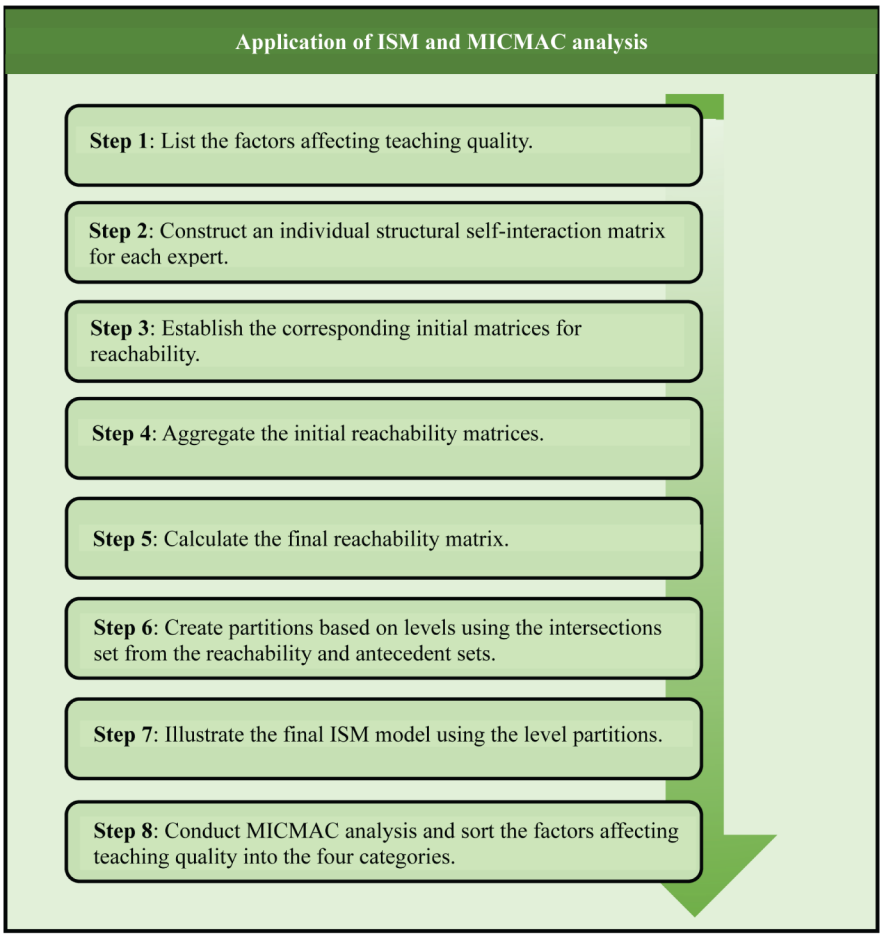
While increased spending for education is desirable, resource allocation becomes increasingly relevant, and teacher quality is the single most important in-school factor that influences learning, as espoused in the domain literature. As such, investments in the professional development of teachers should also be made, especially using the results of assessments such as the National Achievement Test, Programs for International Students Assessment, and The Trends in International Mathematics and Science study. Further, the country should seriously consider leveraging innovative technology solutions, such as high-touch, high-tech education, to improve learning, as the Pew Research Center (2018) suggested. Meanwhile, the government focuses on improving teaching quality, aligning with the K–12 curriculum changes. HEIs became adaptive with their curricula to address these shifts (Commission on Higher Education, 2012). Nevertheless, the comprehensive overhaul of the educational system poses salient challenges. HEIs faced readiness issues during the K–12 program implementation, including requalification of educators, curriculum realignment, and workforce management (Acosta & Acosta, 2017), negatively affecting education quality. The impact of these reforms is evident in the performance of Filipino students, particularly in certain K–12 tracks, where Almerino et al. (2020) noted below-average achievement, implying their unpreparedness for higher education. Additionally, the Fourth Industrial Revolution brought further challenges. HEIs embraced technology-based approaches known as Education 4.0, requiring curriculum and pedagogical

adjustments (Costan et al., 2021). Technological competitiveness is essential to thrive in Education 4.0 (Costan et al., 2021). Regrettably, the Philippines largely lags in this aspect, especially in its public universities. Beyond these transitions, the Philippines has long struggled with its poor global reputation in education quality (Ortiga, 2018). Government efforts to provide and improve education for the public exist (Haque & Kohda, 2018); however, the complexity of the educational system, involving various stakeholders, has led to some oversight in pedagogical aspects. Consequently, strategic investments are imperative for meaningful improvements in the Philippine education landscape.

Application of the Interpretive Structural Modeling and MICMAC Analysis

It is important to emphasize that the factors of teaching quality are characterized by complex interactions, with difficulty in determining the boundaries outlining each factor and the magnitude of such interactions. Thus, a thorough understanding of these complexities may steer decision-makers as to how a factor plays a role in another factor. Likewise, these complexities could reveal important characteristics of these factors. To satisfy these objectives, an ISM approach is adopted in this work. Fig. 2 shows the framework that provides the steps for adopting ISM and MICMAC analysis in determining the inherent characteristics of factors affecting teaching quality and identifying those priority factors.

Figure 2. The Proposed Methodological Framework



Step 1: List the factors affecting teaching quality. The list was obtained from the previous work of Mamites et al. (2022), which was derived through an extensive literature review of the factors that could affect teaching quality. The references for each factor were updated in this study. The list of these factors is shown in Table 1.

Step 2: Construct an individual structural self-interaction matrix (SSIM) for each expert. Twenty-four experts were gathered to obtain judgments on the contextual relationships among factors affecting teaching quality. Table 2 shows the profile of the experts, their assigned codes (e.g., R1, …, R24), and their corresponding weights, which reflect their relative importance in the overall group decision. Out of 24 experts, 12 possessed doctorate degrees, 10 possessed master's degrees, 1 had a bachelor's degree, and 1 preferred anonymity. They have been in academia for a median of eight years, with 16 holding several leadership positions. A corresponding SSIM was constructed for each expert, with entries labeled as **V**, **A**, **X**, and **O**, as discussed above.

Step 3: Establish the corresponding initial matrices for reachability. For each SSIM, an initial reachability matrix is constructed by substituting **V**, **A**, **X**, and **O** with its corresponding binary value. The process is explained in detail above.

Step 4: Aggregate the initial reachability matrices. In this study, as a component of the aggregation method, experts are assigned weights based on several criteria, including their years of experience in academia, the duration of their supervisory or managerial roles, the length of their academic tenure, affiliations, and current job titles. These weights are shown in Table 2. The emphasis is placed primarily on the number of years in academia, with decreasing consideration given to subsequent factors in the list. The aggregation process adds the product

Table 1. The Final List of Factors Affecting Teaching Quality

Code	Factor	Description	References
IC	Individual characteristics	Linked to the attributes of individual teachers, encompassing age, sex, and role.	Feldman (2007); Cho and Baek (2019)
PC	Psychological characteristics	An enduring and fairly consistent quality or collection of qualities potentially rooted in neuropsychological factors.	Klassen and Tze (2014)
SE	Self-efficacy	Confidence in the ability to effectively pursue desired objectives through chosen actions.	Klassen and Tze (2014); Holzberger et al. (2013)
TM	Teaching motivation	Support, drive, and flexible qualities teachers exhibit in performing their profession.	Zee and Koomen (2016); Praetorius et al. (2017)
TE	Teaching experience	The duration of time the teacher has engaged in their professional practice.	Podolsky et al. (2019); Graham et al. (2020)
PD	Professional development	An organized program of professional development is provided by the institution, leading to modifications in teaching methodologies.	Gore et al. (2017); Darling-Hammond et al. (2017)
SC	Student composition	The social, mental, and drive-related traits of the students within a sociocultural context.	Fauth et al. (2021); Rjosk et al. (2015)
SF	Students' feedback	The evaluation and appraisal of teaching excellence by students.	Bijlsma et al. (2019); Gaertner & Brunner (2018); Hammonds et al. (2017)
IS	Institutional culture	Ingrained patterns, actions, commonly held principles, convictions, and ideologies.	Kezar and Eckel (2002); Kustra et al. (2014)
IR	Institutional resources	Educational materials, curriculum content, and additional resources provided by the educational institution.	Hill and Charalambous (2012); Hill et al. (2015)

Table 2. Profile of the Experts and Their Corresponding Weights

Expert	Educational Background	Current Position	Number of Years in Academe	Number of Years Holding Supervisory or Managerial Positions	Number of Years Holding Academic Positions	Assigned Weight
R1	Doctor of Development Education	Assistant Professor	6	5	5	0.0450
R2	Doctor of Development Education	Instructor	12	0	12	0.0700
R3	Bachelor of Pre-Elementary Education	Instructor	4	0	4	0.0200
R4	Doctor of Development Education	Instructor	4	0	4	0.0200
R5	Doctor of Development Education	Assistant Professor	22	5	22	0.0700
R6	Doctor of Development Education	Instructor	10	4	10	0.0700
R7	*	*	*	*	*	0.0175
R8	Master of Arts in Teaching Special Education	Assistant Professor	24	2	1	0.0700
R9	Doctor of Business Administration	Director	8	5	8	0.0450
R10	Master of Arts in Education	Instructor	9	1	3	0.0450
R11	Master of Arts in Special Education	Instructor	9	0	0	0.0400
R12	Doctor of Education in Educational Management	Assistant Professor	14	9	9	0.0700
R13	Master of Arts in Vocational Education	Instructor	4	0	0	0.0175
R14	Doctor of Philosophy in Technology Management	MIS Coordinator	5	0	0	0.0175
R15	Master of Arts in Education	Instructor	4	0	0	0.0175
R16	Doctor of Philosophy in Education, Major in Research and Evaluation	Instructor	35	17	9	0.0700
R17	Doctor of Development Education	Instructor	19	0	0	0.0700
R18	Master of Arts in Special Education	Instructor	3	0	0	0.0175
R19	Doctor of Philosophy	Associate Professor	5	4	4	0.0400
R20	Doctor of Development Education	Supervisor	9	9	0	0.0450
R21	Master of Arts in Education	Instructor	1	0	0	0.0175
R22	Master of Science in Business Administration	Department Chair	23	5	5	0.0700
R23	Master of Arts in Education, Major in Guidance and Counseling	Instructor	4	0	4	0.0175
R24	Master of Arts in Education, Major in Guidance and Counseling	Instructor	4	0	4	0.0175

*The expert prefers to remain anonymous.

of each expert's assigned weights and the binary values in the initial reachability matrices. Then, each value in the matrix representing the presence or absence of a contextual relationship between two factors is compared to a threshold value of $\alpha = 0.875$. Values greater than α are given a binary value of 1 in the aggregate initial reachability matrix, implying that the two factors under consideration possess a contextual relationship. Otherwise, if the value is less than α, the corresponding value in the aggregate initial reachability matrix is 0. Table 3 presents the aggregate initial reachability matrix.

Step 5: Calculate the final reachability matrix. By utilizing Eqs. (1) and (2), the final reachability matrix *M** was calculated based on the aggregate initial reachability matrix *M*. Table 4 presents matrix *M**, as well as the driving and dependence powers of each factor.

Table 3. Aggregate Initial Reachability Matrix

Factor	IC	PC	SE	TM	TE	PD	SC	SF	IS	IR
IC	1	1	1	1	0	1	0	1	0	0
PC	0	1	1	1	0	1	0	1	0	0
SE	0	0	1	0	0	0	0	0	0	0
TM	0	0	0	1	0	1	0	0	0	0
TE	0	0	1	0	1	1	0	0	0	0
PD	0	0	0	0	0	1	0	0	0	0
SC	0	0	0	1	0	0	1	1	0	0
SF	0	0	0	1	0	0	0	1	0	0
IS	0	0	0	1	0	0	0	0	1	0
IR	0	0	1	0	0	0	0	0	0	1

Table 4. Final Reachability Matrix

Factor	IC	PC	SE	TM	TE	PD	SC	SF	IC	IR	Driving power
IC	1	1	1	1	0	1	0	1	0	0	6
PC	0	1	1	1	0	1	0	1	0	0	5
SE	0	0	1	0	0	0	0	0	0	0	1
TM	0	0	0	1	0	1	0	0	0	0	2
TE	0	0	1	0	1	1	0	0	0	0	3
PD	0	0	0	0	0	1	0	0	0	0	1
SC	0	0	0	1	0	1*	1	1	0	0	4
SF	0	0	0	1	0	1*	0	1	0	0	3
IS	0	0	0	1	0	1*	0	0	1	0	3
IR	0	0	1	0	0	0	0	0	0	1	2
Dependence Power	1	2	5	6	1	8	1	4	1	1	

Note: an asterisk denotes a transitive relationship.

Step 6: Create partitions based on levels. This process facilitates a direct formation of the directed graph using the final reachability matrix *M** (Pfohl et al., 2011). This stage enables the identification of factors that take priority over other factors. The final reachability matrix provides the reachability sets $\left(\boldsymbol{R}_i\right)$ and the antecedent sets $\left(\boldsymbol{A}_i\right)$ $\forall i$. The intersection sets $\boldsymbol{R}_i \cap \boldsymbol{A}_i$ can be generated from these sets. The reachability set $\left(\boldsymbol{R}_i\right)$ incorporates the factor i and other factors that i can reach. On the other hand, the antecedent set $\left(\boldsymbol{A}_i\right)$ includes the factor i and other factors that can reach i. Level I contains the factors with $\boldsymbol{R}_i = \boldsymbol{R}_i \cap \boldsymbol{A}_i$. After categorizing the factors belonging to Level I, these factors will be excluded from the list and the same process is applied to the remaining list of factors. This process is repeated until all the factors are categorized to a level. The purpose of level partitioning is to build the ISM. Table 5 presents the level partitions.

Step 7: Illustrate the final interpretive structural model. The level partitions in the previous step and the matrix *M** without the transitive relationships from the initial digraph form the basis for illustrating the final ISM. Fig. 3 shows the final ISM.

Step 8: Conduct the MICMAC analysis. The categorization of the factors affecting teaching quality is presented in Table 6. According to the MICMAC analysis, these factors are sorted into four categories: AUTONOMOUS, DEPENDENT, LINKAGE, and INDEPENDENT factors. Fig. 4 shows the MICMAC analysis representing the category where each factor appropriately belongs.

RESULTS AND DISCUSSION

The integration of the ISM and MICMAC analysis provides a comprehensive understanding of the driving and dependence power within a complex system of teaching quality factors. By identifying key factors while understanding their interdependencies and classifying them based on their influence, decision-makers can design more tailored fit strategies to make more informed and effective decisions (Quiñones et al., 2020), especially in crafting intervention initiatives to improve teaching quality.

Table 5. Final Leveling of Factors Affecting Teaching Quality

Factor	R_i	A_i	$R_i \cap A_i$	Level
IC	IC, PC, SE, TM, PD, SF	IC	I	V
PC	PC, SE, TM, PD, SF	IC, PC	PC	IV
SE	SE	IC, PC, SE, TE, IR	SE	I
TM	TM, PD	IC, PC, TM, SC, SF, IS	TM	II
TE	SE, TE, PD	TE	TE	II
PD	PD	IC, PC, TM, TE, PD, SC, SF, IS	PD	I
SC	TM, PD, SC, SF	SC	SC	IV
SF	TM, PD, SF	IC, PC, SC, SF	SF	III
IS	TM, PD, IS	IS	IS	III
IR	SE, IR	IR	IR	II

Figure 3. The Final Interpretive Structural Model

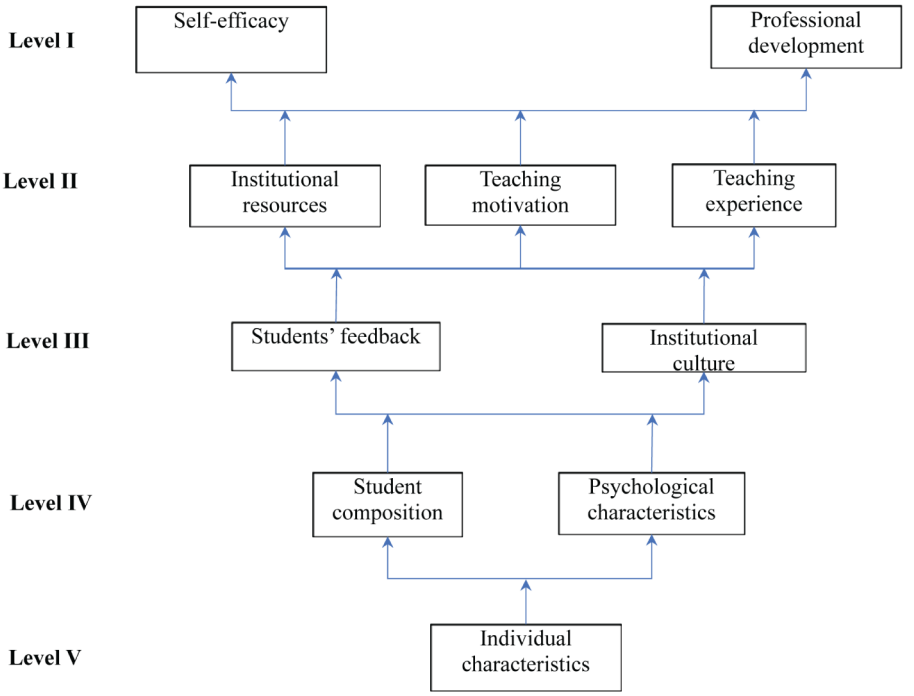
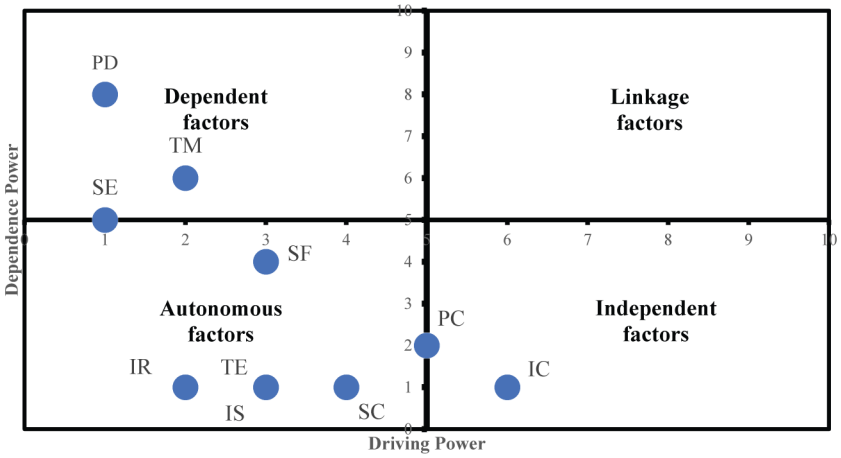


Table 6. Categorizing the Factors Affecting Teaching Quality

Factor	Driving Power	Dependence Power	Category
Individual characteristics	6	1	INDEPENDENT
Psychological characteristics	5	2	INDEPENDENT
Self-efficacy	1	5	DEPENDENT
Teaching motivation	2	6	DEPENDENT
Teaching experience	3	1	AUTONOMOUS
Professional development	1	8	DEPENDENT
Student composition	4	1	AUTONOMOUS
Students' feedback	3	4	AUTONOMOUS
Institutional culture	3	1	AUTONOMOUS
Institutional resources	2	1	AUTONOMOUS

Policymakers in HEIs would greatly benefit from understanding the general structure of the factors that affect teaching quality while considering their interdependencies to inform prioritization decisions (Mamites et al., 2022). This work identified a list of ten factors influencing teaching quality in institutions through a literature review and then categorized them using ISM-MICMAC analysis. With the list of factors, the analysis was implemented with the steps provided under Methodology. After the expert group provided the SSIMs, each was transformed into initial reachability matrices, followed by a defined procedure that appropriately aggregates the scores in a single matrix, capturing

Figure 4. The MICMAC Analysis



the knowledge and experience of the experts on teaching quality in a manner that represents a group decision. With the aggregate initial reachability matrix, the final reachability matrix, which encompasses the indirect relationships of the driving factors, was obtained to contain transitive relationships. The hierarchical ordering of the driving factors, which makes the construction of the digraph more interpretive, is presented in Table 5. On the other hand, the contextual relationships of the factors are portrayed in the final interpretive structural model, presented in Fig. 3.

By understanding the hierarchical structure of factors, decision-makers can develop strategies that address the most influential factors first. This approach enables better resource allocation and targeted interventions for those influential factors. In particular, individual characteristics and psychological characteristics, both intrinsic factors, emerge on the bottom level of the hierarchy, demonstrating their influence on other factors of teaching quality. These findings suggest that the intrinsic characteristics of teachers are pivotal in maintaining the teaching quality in HEIs, espousing the role of demographic factors and the emotional intelligence of teachers previously identified in the literature. Thus, HEIs need to establish a rigorous personnel selection process that places more emphasis on criteria such as intellectual capacity, the capability to manage classes effectively, and the ability to carry out effective communication. Such a selection process must also evaluate the psychological capacity of the teachers, highlighting those with higher emotional intelligence who can better show empathy to students regarding their needs (Curci et al., 2014).

Aside from these intrinsic characteristics, Fig. 3 also reveals that student composition is an influential factor in teaching quality. Thus, entrance examinations must clearly articulate the characteristics of students in a given academic program. For instance, the highly diverse cognitive abilities of students in a STEM program may yield difficulty for teachers in designing common instructional strategies. This would impact teaching quality, as teachers need to spend more time with those at the lower end of the range while keeping the interests high for those at the higher end.

The ISM-MICMAC analysis, where the driving and dependence powers are used to assign the factors into four clusters, is presented in Fig. 4. On the bottom right of Fig. 4, the first cluster encompasses the independent or extreme driving factors characterized by their strong driving power but weak dependence power. These factors would influence or affect the other factors, as the factors lying in this quadrant are considered the drivers or predictors of the outcomes in the system and are used to assess their impact on the remaining factors. Results from this study reveal that the bottom-right cluster of independent factors encloses only two factors: individual and psychological characteristics. This means that potential shortcomings in teaching quality are more likely to be associated with the

behavior of these characteristics and that the same factors are the most sensitive and vulnerable when external changes (e.g., policy shifts and adjustments with learning strategies) happen. To highlight, individual characteristics generated the highest driving power of 6 and the lowest dependence power of 1. This coincides with the notion of Toropova et al. (2019) that individual characteristics of teachers have a significant influence on the quality of teaching. Furthermore, factors from the dependent cluster will most likely refer to the individual characteristics of teachers in making an impact on teaching quality.

On the other hand, three dependent factors affect teaching quality. The self-efficacy, teaching motivation, and professional development factors have the least driving powers and the highest dependence powers. The strongest dependence among all the factors analyzed is taken by professional development, with a dependence power of 8. This result supports the review reported by Fletcher-Wood and Zuccollo (2020), which provided evidence that the costs of prioritizing the professional development of teachers do not heavily outweigh the benefits it provides to the students. Not far are the self-efficacy and teaching motivation factors, with dependence power of at least 5 and weak driving power of not more than 2. This observation implies that the factors classified in this cluster are most likely to be influenced or impacted by other variables in the system, mostly those of independent factors, as discussed above. Consequently, the same factors are most likely to be considered as the outcome or result of the interactions between independent factors. Moreover, the low driving power these factors possess implies that decision-makers put less emphasis on these factors to improve teaching quality.

Next, the autonomous factors, which are also considered standalone factors, are identified to be not driven by the system's other factors. From the results, five factors—institutional culture, institutional resources, teaching experience, student composition, and students' feedback—belong to the autonomous cluster. These factors have weak driving and dependence power; thus, they are relatively disconnected from the system. As the institutional culture and resources belong to this cluster, it supports the notion that both have less influence on the quality of teaching. While autonomous factors may have an impact on other factors, they do not have much influence on the performance of teaching quality, as they may have only a few relationships with other factors, and these connections are considerably weak.

In the context of MICMAC analysis, linkage factors are considered unstable, and stakeholders and decision-makers must oversee these factors. The absence of linkage factors, as depicted in the driver-dependence diagram (see Fig. 4), means no factors connect independent and dependent factors. Since no factors lie in this cluster in the system, there are no strong contextual relationships between factors, and no bridge is established between different factors that affect teaching quality. On the other hand, some factors are found in the dependence and driving power axes, including self-efficacy and psychological characteristics, lying between the autonomous-dependent and autonomous-independent clusters, respectively. The high dependence power of self-efficacy positions it into the independent cluster, and psychological characteristics, with its high driving power, makes it one of the dependent factors.

CONCLUSION AND FUTURE WORK

Maintaining teaching quality in the education sector holds a pivotal role in nurturing students' potential. The compilation of factors influencing teaching quality was proposed in a previous study (Mamites et al., 2022); however, a need for a structured model to represent the hierarchy from the complex relationships existing among these factors is an essential gap in the domain literature. Establishing the hierarchy provides a simplified view of the system of factors, leading to identifying factors requiring more attention. This identification of pertinent factors is critical, as they act as pivotal concepts for informed policy formulation. The hierarchical arrangement or classification of these factors plays an essential role, aiding policymakers in channeling resources toward the most pressing factors. The

ISM methodology substantially contributes to achieving this objective, as it evaluates the order and interdependence of linkages between different factors.

Given the findings suggesting the relevance of individual and psychological characteristics of teachers as critical to teaching quality, HEIs may employ better strategies in hiring teachers with a better fit to the students' needs and achieve greater teaching outcomes. Teachers' personality traits, as found in this work to be better drivers of enhanced teaching quality, can be one of the main interests of universities when evaluating potential candidates, with less priority on the cluster of factors that do not provide them with effective delivery of teaching. In addition, the interpretive structural model generated by the ISM-MICMAC analysis emphasizes the role of student composition as pivotal to teaching quality. Thus, HEIs must maintain rigorous qualifications for students enrolling in a program, eventually resulting in a homogeneous cohort. Although this notion is widely discussed in the literature, its presence in practice deserves more attention, especially in the case environment (i.e., the Philippines). Failing to achieve a cohort with a homogeneous background compels teachers to spend more time designing a teaching strategy that balances the disparity of the characteristics in the cohort. The findings presented in this study make a substantial contribution to the existing literature by offering valuable insights to enhance the quality of teaching and its underlying factors. Moreover, these outcomes hold practical significance for policymakers and stakeholders within the education sector. These insights guide decision-making and aid in strategically allocating resources by identifying the factors warranting the highest priority. This strategic allocation, in turn, facilitates the optimal utilization of resources for enhanced teaching quality.

While the methodological approach employed in this study has yielded valuable policy insights, it is also important to acknowledge its limitations. The subjectivity of the study findings arises from the notion that responses were elicited subjectively, resulting in a lack of empirical analysis regarding cause-and-effect relationships among factors. Furthermore, the study's single-case focus introduces potential bias due to the influence of case-specific conditions. It is important to note that the findings may not be universally applicable, given that the experts were exclusively from the Philippines. This suggests the likelihood of variations under different conditions. For future directions, incorporating statistical analysis to validate the identified structural relationships could enhance the robustness of the study findings. Achieving a more comprehensive understanding of teaching quality and its factors warrants spatial and longitudinal research. Employing other methods like fuzzy cognitive mapping could illuminate the dynamic nature of factors affecting teaching quality. Additionally, since the study's findings lack insights into long-term feedback relationships among factors, a system dynamics approach could better illustrate simultaneous impacts resulting from changes in a single factor.

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