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Fuzzy best-worst method for analysing the threats of AI in education

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Abstract: AI integration to support functional operations has been a growing interest in the literature owing to the numerous perceived and actual benefits. While this has been widely considered in several industries, integrating AI in education (AIEd) has been limited primarily due to diverse requirements in the educational platform. As such, it is difficult to pinpoint the threat that hampers such innovation. To provide an analytical framework to analyse the threats of applying AIEd, this paper employs the fuzzy best-worst method (BWM). To illustrate the framework, a case study in a state university in the Philippines is conducted. Interesting results revealed that the stakeholders prioritise threats related to the knowledge-based implementation of AI technologies, followed by threats related to the evaluation of the type of technologies available. Such results provide a guideline to stakeholders to address high-priority threats before integrating AIEd.

Keywords: artificial intelligence; education; fuzzy set theory; best-worst method; BWM.

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1 Introduction

Over the years, the global educational system has continuously searched for innovative ways to deliver learning most efficiently (Haleem et al., 2022). Recognising that there can be a number of educational reforms considered not only in curriculum design but also in technological enhancements, schools have remained eager to implement potentially useful innovations. With the rise of advanced technologies taking over other industries, such as finance and manufacturing, several improvements in operational efficiency, productivity, and resource savings have been observed (Kwangmuang et al., 2021). Following the success of implementing advanced technologies in other industries, the educational sector deemed it fitting to take advantage of such benefits brought about by artificial intelligence (AI). AI enables tasks to be performed by digital machines that follow intelligent beings' instinctive behaviours (Chiu, 2021; Chiu et al., 2022; Xia et al., 2022). Some key branches of AI include speech, big data analytics, algorithms, and other advanced computing tools. In general, AI has increasingly transformed the interaction, communication, learning, and working conditions of people who take advantage of such technology (Chiu, 2021; Chiu et al., 2022). In the specific context of education, a concept involving AI in education, also termed AIEd, emerged to aid in the administration, assessment, teaching, and learning of educators and students. Specifically, such roles of AIEd enhancement also influenced the outcomes of both educators-centred and student-centred education, covering efficiency at work, competence in teaching, attitude toward AIEd, engagement and motivation, performance, skills, and non-cognitive aspects (Chiu et al., 2023) (see Figure 1). Among the many functions of AIEd include intelligent tutor mechanisms, robotics, dashboards for learning analysis, bots, and automated evaluation of electronic documents (Chiu et al., 2023; Chen et al., 2020). With these supplementary functions, AIEd continues to provide a stimulating environment for educators and students by facilitating a more personalised experience in teaching and learning, including assessment and development of programs.

Since the inception of AIEd, several advances in the educational domain emerged. For one, AI, together with virtual reality (VR) and augmented reality (AR), was used in neurosurgery to simulate the process of removing brain tumours during surgery (Chassignol et al., 2018). On the other hand, ChatGPT and Twitter data in higher education were analysed and found to have significant affordances in perceived usefulness, ease of use, and analysis of public sentiments (Fuchs, 2023). In another case, AI is used in designing the learning tasks for K-12 education, including technical resources, tools, and other pedagogical approaches (Li et al., 2024). Among the many other implementations of AI in enhancing the educational system, it is clear that AI provides distinctive layers of effectiveness in instructional design by reflecting students' interests and facilitating the conditions of the educational environment in schools (Li et al., 2024). Aside from that, AIEd continues to aid in students' learning experience and assist in nurturing the teaching-learning point of education (Kumar et al., 2024).

Despite the promising edge of AIEd, not all schools are open to fully integrating AI into their current educational platform, considering this approach's intrinsic flaws and limitations. In fact, several works in the literature explored the challenges brought about by the implementation of AIEd and indeed confirmed that such issues need to be carefully accounted for prior to any AI integration. For example, Ouyang and Jiao (2021) emphasised that for AIEd to work, the design and operations should fit the values and interpretations of stakeholders, including students, such that AI models align with human

values while maintaining its learner-centred cause. Such a line of argument falls squarely into the idealism presented by Chassignol et al. (2018), highlighting that students have different learning paces, thus forging the need for a more well-fitted learning experience (Newton, 2016). By personalising the experience of students, the unique needs of students will be met by designing educational content with respect to their pace and knowledge level (APLU, 2017). In fact, personalisation of the learning experience is believed to be most beneficial for exceptional learners (i.e., learners with disabilities) (El Nagggar et al., 2024). Aside from challenges on the side of the students, Zhang and Aslan (2021) also highlighted other challenges in implementing AIEd, such as costs and expandability, ethical considerations, privacy issues, lack of guidelines, and limitations on the expertise of educators in AI. When these challenges are put in place in the decision-making, stakeholders of various disciplines and perspectives will be able to collaborate effectively in terms of the development, research, implementation, and evaluation of AIEd. Furthermore, Abulibdeh et al. (2024) also pointed out the specifics of the ethical dimensions, among others, in integrating AIEd for sustainable development. It was emphasised that the extant literature only emphasises the aspects involving the technicalities and pedagogy of AIEd and less on its ethical dimensions which also play an important role in the eventual development of an effective AIEd. As a whole, a standout work in the body of knowledge by Chiu et al. (2023) comprehensively pointed out an in-depth discussion of possible future research directions involving AIEd. Here, major challenges that emerged in the review include insufficient resources for more flexible learning, determining the most suitable data for AI predictive models, insufficient link between AI technologies and teaching functions, insufficient capability of AI technologies to be used in interdisciplinary programs, increasing inequity among students due to an apparent digital divide, teachers' lack of knowledge in the use of AI technologies, unfavourable attitudes of students and teachers towards AI technologies, insufficient socio-emotional research on AIEd, insufficient perspectives of AIEd research, and ineffective methods of evaluating AIEd. The study emphasised that these challenges can pave the way for future research directions to better understand the incorporation of AIEd.

A common theme of all works in the literature involving AIEd challenges and opportunities provides a comprehensive overview across all perspectives and concerns. As of date, these works are descriptive and do not provide additional insights on the priority of challenges which is a significant part of the decision-making process involving the integration of AI into education. Although characterising the challenges in the literature based on comprehensive works prior is a good starting point for understanding the context of AIEd, there is a need to explicitly uncover the nature of these challenges in order to generate a design fit for the eventual implementation of AIEd. Analysing these challenges at a deeper level can ensure proper strategic plans aligned to the core capabilities and essential threats perceived by decision-makers, affecting educators, students, and school administrators. Following these arguments, the multicriteria decision-making (MCDM) approach is deemed a suitable tool to analyse the challenges in AIEd. Generally, MCDM approaches are designed to analyse the relationships among factors and further rank the alternatives based on such factors (Bongo et al., 2018). In the context of AIEd challenges, these challenges can be treated as factors that further influence the decision to integrate AI into education. Several MCDM approaches have been presented in the literature to aid in the analysis and understanding of the constructs

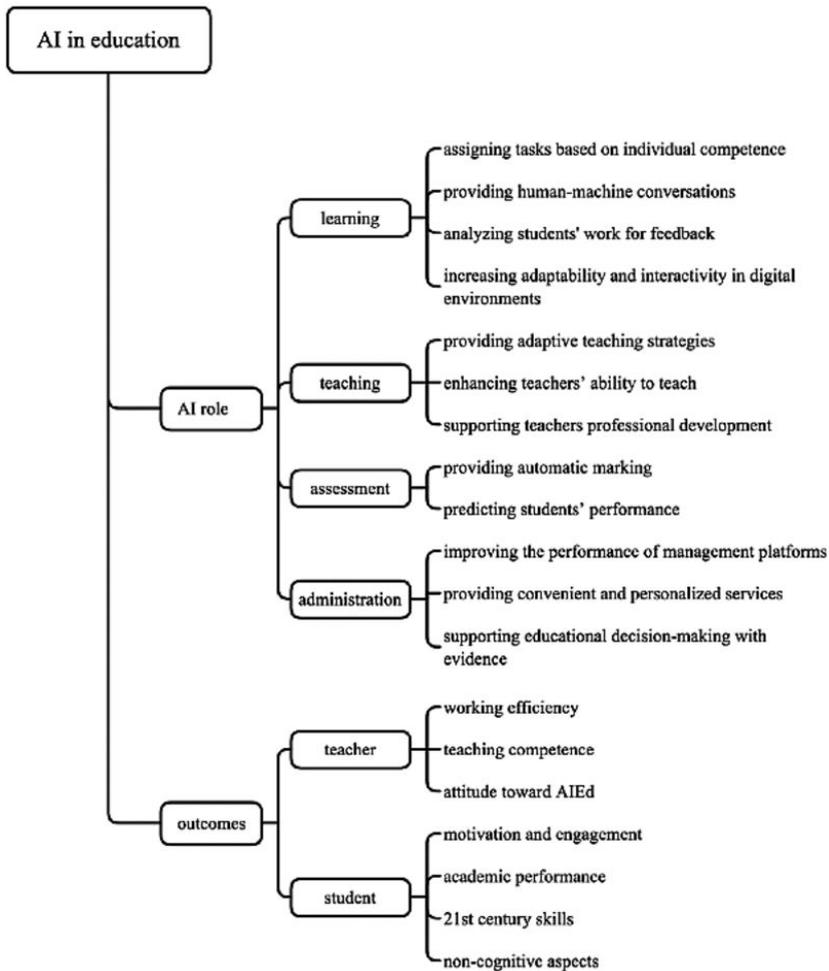
involved in the process of decision-making. Such approaches include *Matriced' Impacts Croise's Multiplication Appliquee a UN Classement* (MICMAC), decision-making trial and evaluation laboratory (DEMATEL), analytic network process (ANP), analytic hierarchy process (AHP), best-worst method (BWM), interpretive structural modelling (ISM), with further combinations of each other and extensions including fuzzy set theory. DEMATEL is developed to distinguish the inherent nature of criteria according to causal and effect clusters (Gabus and Fontela, 1972). In some cases, understanding whether a factor causes or is an effect of another provides valuable insights to decision-makers in formulating strategies that will address such factors. Unlike DEMATEL, AHP and its later extension, ANP, is designed to quantify how much more a factor dominates others based on a certain attribute (Saaty, 1996, 1980). Using ratio scales to evaluate discrete and continuous pairwise comparisons of factors, a priority vector can be generated to aid in the analysis. Furthermore, implementing AHP or ANP requires factors to have an established hierarchy or network of relationships; otherwise, it may not clearly represent the approach used. From the computational flow of AHP and ANP, BWM also considers pairwise comparison among factors but provides a prior phase of identifying the best and worst factors (Rezaei, 2015). The best factor is evaluated with respect to other factors, while all the different factors is evaluated with respect to the worst factor. ISM, coupled with MICMAC analysis, analyses the mutual influences among factors including its driving and dependence powers (Warfield, 1974). The main advantage of ISM-MICMAC is its capability to handle direct and indirect relations among factors (Valan et al., 2020).

Relying on the capabilities of each MCDM approach, several works in the literature have applied such approaches across various domains. To name a few, Ozegin et al. (2024) developed an AHP and GIS-based tool to evaluate the vulnerability of groundwater. Bongo and Seva (2023) evaluated the factors involved in measuring the performance of air traffic controllers by taking advantage of the clustering capabilities of fuzzy DEMATEL and the ranking capabilities of fuzzy BWM. On the other hand, Del Pilar et al. (2019) explored the critical failure factors of microbusinesses using ISM-MICMAC analysis. Among the domains explored in the literature which uses MCDM approaches, the following domains have been extensively covered: manufacturing (Dohale et al., 2024; Soltani et al., 2023; Kumar et al., 2023; Zeng et al., 2022; Chand et al., 2020), supply chain (Wang et al., 2024; Singh et al., 2023; Liu et al., 2023; Magableh and Mistarihi, 2022; Badulescu et al., 2022), logistics (Nila and Roy, 2023; Görçün et al., 2023; Krstić et al., 2022; Kilic et al., 2023; Alazzawi and Zak, 2020; Ocampo et al., 2020), air transportation system (Raad and Rajendran, 2024; Dugger et al., 2022; Bhadra and Dhar, 2022; Montlaur et al., 2023; Liu et al., 2024; Bongo and Ocampo, 2016), healthcare (Krishankumar et al., 2024; Salehi et al., 2023; Erol et al., 2023; Wahab et al., 2023; Stević et al., 2020), construction (Chingo et al., 2020), and environmental considerations (Bagheri et al., 2022).

Despite the many applications of MCDM tools in various fields, there are currently no works involving AIED due to the field's infancy. Therefore, a significant research gap in the literature points towards a more systematic way of understanding the dynamics of challenges and other concerns revolving around the implementation of AIED. Given such a need, this paper investigates the challenges of AIED using fuzzy BWM. It has been presented earlier how each MCDM approach works and drawing along such functions, BWM provides a better means of analysing the factors, or in this case, the challenges, based on its fuzzy priority weights (Guo and Zhao, 2017). Furthermore, exploring the inherent best and worst challenges can also aid the decision-makers in formulating

solutions fit to the eventual incorporation of AI in educational design. To illustrate this goal, a case study in a state university in the Philippines is conducted. For ease of discussion, the challenges in AIED are used interchangeably with threats in AIED.

Figure 1 The roles and outcomes of using AIED



Source: Adapted from Chiu et al. (2023)

2 Methodology

2.1 Fuzzy set theory

In the typical form of MCDM approaches, assessing the factors relies heavily on numerical scale ratings, which have been relatively critiqued in the literature due to their inability to handle subjective judgements. In order to overcome such limitations, the original formation of MCDM approaches has been prominently transformed into its fuzzy

counterpart, which incorporates vagueness in decision-making (Kuo and Lin, 2002). In the context of AI education, several criteria cannot be directly quantified (e.g., lack of knowledge); therefore, the use of fuzzy set theory perfectly aids in the evaluation of such criteria. The work of Zadeh (1965) provides an in-depth discussion of the foundations of fuzzy set theory.

In the formulation of fuzzy set theory, suppose that Y is a universe with $A \subseteq Y$. Set A is expressed as a fuzzy set if \exists it is a member of $\mu_A(y)$ such that $\mu_A(y): Y \rightarrow [0, 1]$. Considering a 2-tuple set, $A = \{y, \mu_A(y): y \in Y, \mu_A(y) \in Y \rightarrow [0, 1]\}$ is a set of fuzzy numbers such that $y \in A$ and $\mu_A(y)$ is a member of $y \in A$. Specifically, a triangular fuzzy number is composed of a 3-tuple $\tilde{A} = (l, m, r)$ and a function $\mu_A(y)$ can be defined as in the following [see equation (1)]:

$$\mu_A(y) = \begin{cases} 0 & y < l \\ (y-l)/(m-l) & l \leq y < m \\ (r-l)/(r-m) & m \leq y \leq r \\ 0 & y > r \end{cases} \quad (1)$$

where l, m, r are any real numbers $l, m, r \in R, \mu_A(y) \rightarrow [0, 1]$ and Y is the universal set.

2.2 Best-worst method

In the recent developments of the MCDM domain, Rezaei (2015) developed the BWB to generate the priority weights of criteria by selecting the best and worst criterion. While most MCDM approaches rely on pairwise comparisons, such as AHP and ANP, which are in danger of committing inconsistencies in the assessment, BWB performs reference comparisons instead. Specifically, the best criterion is evaluated with respect to the others and the other criteria are evaluated with the worst criterion. Such way of reference comparisons eliminate the issues of consistency and provide a more accurate and easy way of the decision-making process. While BWB is relatively new, it has been transformed into its fuzzy counterpart developed by Guo and Zhao (2017) and has addressed several realistic cases in the literature.

2.3 Research procedure

To carry out the analysis of AIED threats under fuzzy BWB, the following steps are considered:

Step 1 Identify the best and worst threat among a set of decision criteria representing AIED.

The first step involves selecting the best and worst threats in AIED (see Table 1). The best threat is termed as c_B while the worst threat as c_W .

Step 2 Conduct fuzzy pairwise comparisons for the best threat.

The selected best threat is evaluated with respect to the remaining threats in terms of preference, denoted as \tilde{a}_{ij} , with i as the best threat while j is the others. In order to carry out the pairwise comparison, linguistic scales listed in Table 2 are used with the fuzzy best-to-others vector represented as \tilde{A}_B , as expressed in equation (2):

$$\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \dots, \tilde{a}_{Bn}) \quad (2)$$

Table 1 Threats of AIEd

| <i>Threat</i> | <i>Description</i> |
|--|---|
| Insufficient resources for more flexible learning | This threat pertains to the methods of teaching as well as the resources used in learning that are homogeneous and do not provide personalised experience (Cao et al., 2021; Fernández-Batanero et al., 2022). |
| Determining the most suitable data for AI predictive models | The data involving student performance used in classical models do not necessarily render the most fit for implementing AIEd (Sharma et al., 2019; Rasheed, 2023; Olawumi and Oladapo, 2025). |
| Insufficient link between AI technologies and teaching functions | The available technologies involving AI and learning models are not sufficiently understood by the users regarding its implementation (Chiu et al., 2023; Stolpe and Hallström, 2024; Tan et al., 2025). |
| Insufficient capability of AI technologies to be used in interdisciplinary programs. | AI technologies deemed fit for other student learning may not necessarily be applicable across all learning environments (Nicolae and Nicolae, 2018; Bates et al., 2020). |
| Increasing inequity among students due to an apparent digital divide. | AI technologies are found to be underdeveloped in the context of student learning and engagement, as well as the pedagogical knowledge among educators (Luckin, 2017). |
| Teachers' lack of knowledge in the use of AI technologies. | Due to the hardcore technicalities underneath the application of AI in the educational platform, the main functions of learning, teaching, assessment, and administration cannot be fully realised without proper knowledge of how AI works or how it can be applied appropriately (Chiu et al., 2023). |
| Unfavourable attitudes of students and teachers toward AI technologies. | Using AI technologies also brings about negative emotions to students and educators, especially how AI might outperform or displace the future workforce and foster weak self-efficacy among educators (Wang et al., 2020). |
| Insufficient socio-emotional research on AIEd. | The socio-emotional outcomes of AI implementation have not yet been widely investigated, thus leading to risks in ethical issues related to its use (Banerjee et al., 2021). |
| Insufficient perspectives of AIEd research | With the strong engineering and technical background of AIEd, by far, in the literature, the educational research perspective lacks the directions necessary for the active engagement of educators, students, and researchers of the field (Holstein et al., 2019). |
| Ineffective methods of evaluating AIEd | Poorly structured data and evaluation of AI technologies involving big data are apparent and pose a threat to the eventual implementation of AI (Renz and Hilbig, 2020). |

Source: Adapted from Chiu et al. (2023)

Step 3 Conduct fuzzy pairwise comparisons for the worst threat.

The selected worst threat is evaluated with respect to the remaining threats in terms of preference. Here, the other threats are compared to the worst threat in terms of preference, represented by \tilde{a}_{jW} , where j refers to the other threats and W refers to the worst threat. The same linguistic scales shown in Table 2 are used to obtain the fuzzy best-to-others vectors in equation (3).

$$\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \dots, \tilde{a}_{nW}) \quad (3)$$

Table 2 Linguistic scales for the evaluation of decision criteria

| Linguistic term | Membership function |
|---------------------------|---------------------|
| Equally important (EI) | (1, 1, 1) |
| Weakly important (WI) | (2/3, 1, 3/2) |
| Fairly important (FI) | (3/2, 2, 5/2) |
| Very important (VI) | (5/2, 3, 7/2) |
| Absolutely important (AI) | (7/2, 4, 9/2) |

Source: Adapted from Bongo and Seva (2023)

Step 4 Run the model and solve for the optimal solution.

The optimal fuzzy weight $(\tilde{w}_1^*, \tilde{w}_2^*, \dots, \tilde{w}_n^*)$ for each threat is treated for each fuzzy pair $\tilde{w}_B / \tilde{w}_j$ and $\tilde{w}_j / \tilde{w}_W$ having $\tilde{w}_B / \tilde{w}_j = \tilde{a}_{Bj}$ and $\tilde{w}_j / \tilde{w}_W = \tilde{a}_{jW}$. For these conditions to be met across all instances of j , solving for the minimised maximum absolute gaps $\left| \frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{a}_{Bj} \right|$ and $\left| \frac{\tilde{w}_j}{\tilde{w}_W} - \tilde{a}_{jW} \right|$ for all j is necessary. While the classical BWM makes use of crisp numbers, the weights of each threat are expressed as $\tilde{w}_j = (l_j^w, m_j^w, u_j^w)$. Furthermore, graded mean integration representation (GMIR) is employed to convert the fuzzy numbers into its crisp counterpart [see equation (4)] where $\tilde{a}_i = (l_i, m_i, u_i)$ and the GMIR $R(\tilde{a}_i)$. To compute the optimal solution, (i.e., criteria weights) and the optimal value of $\tilde{\zeta}$ specifically expressed as $\tilde{\zeta}^*$, equation is used such that $l^{\tilde{\zeta}} \leq m^{\tilde{\zeta}} \leq u^{\tilde{\zeta}}$ and $\tilde{\zeta}^* = (k^*, k^*, k^*)$, $k^* \leq l^{\tilde{\zeta}}$:

$$R(\tilde{a}_i) = \frac{l_i + 4m_i + u_i}{6} \quad (4)$$

$$\min \tilde{\zeta}^*$$

subject to:

$$\left\{ \begin{array}{l} \left| \frac{l_B^w, m_B^w, u_B^w}{l_j^w, m_j^w, u_j^w} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \leq (k^*, k^*, k^*) \\ \left| \frac{l_j^w, m_j^w, u_j^w}{l_{jW}^w, m_{jW}^w, u_{jW}^w} - (l_{jW}, m_{jW}, u_{jW}) \right| \leq (k^*, k^*, k^*) \\ \sum_{j=1}^n R(\tilde{w}_j) = 1 \\ l_j^w \leq m_j^w \leq u_j^w \\ l_j^w \geq 0 \\ j = 1, 2, \dots, n \end{array} \right. \quad (5)$$

To ensure that the fuzzy comparisons among threats are fully consistent, $\tilde{a}_{Bj} \times \tilde{a}_{jW} = \tilde{a}_{BW}$ must be ensured. Therefore, the consistency index (CI) specified for the fuzzy BWM approach (see Table 3) further dictates the value of CR [see equation (6)].

$$CR = \frac{\tilde{\zeta}^*}{CI} \quad (6)$$

Table 3 Value of consistency index (CI) for every fuzzy rating between the best and worst criterion

| a_{BW} | <i>EI</i> | <i>WI</i> | <i>FI</i> | <i>VI</i> | <i>AI</i> |
|---------------------------|-----------|-----------|-----------|-----------|-----------|
| Consistency index ζ | 3.00 | 3.80 | 5.29 | 6.69 | 8.04 |

Source: Gou and Zhao (2017)

A CR value approaching zero indicates a high consistency of evaluation made by the experts.

3 Results and discussion

3.1 Case study

Cebu Technological University (CTU) is one of the biggest state universities in Cebu City, Cebu, Philippines. As of date, the university strives to deliver quality education to the increasing number of students per year. One of the strategies considered by the administrators is the possibility of embedding AI into the educational design of supplementary technologies employed in the university. In fact, the College of Education has largely put forward initiatives to innovate their instruction delivery by integrating technological advancements into its programs. Considering that CTU is a state university that only relies on government funds for expansions in their technological capabilities, not to mention the lack of human resources and skills to implement AIEd, it becomes a challenge for the university to fully embrace the potential benefits of AI application. Therefore, an important step for administrators is to conduct a more stringent analysis of the threats of AIEd. When the threats associated with beginning AI implementation in the College of Education as a pilot testbed are thoroughly analysed, this can serve as a springboard for the university to fully embrace AIEd across all its colleges.

Along these lines, this paper focuses on assessing AI's threats in education through a fuzzy BWM approach. The threats considered are as follows: insufficient resources for more flexible learning (T1), determining the most suitable data for AI predictive models (T2), insufficient link between AI technologies and teaching functions (T3), insufficient capability of AI technologies to be used in interdisciplinary programs (T4), increasing inequity among students due to an apparent digital divide (T5), teachers' lack of knowledge in the use of AI technologies (T6), unfavourable attitudes of students and teachers towards AI technologies (T7), insufficient socio-emotional research on AIEd (T8), insufficient perspectives of AIEd research (T9), and ineffective methods of evaluating AIEd (T10). Following the fuzzy BWM approach, the decision-makers in the College of Education elicit their judgment on the importance of the threats in analysing the integration of AIEd. The evaluation processes started by selecting the best and worst

threats to be considered in the decision-making process. Then, the subsequent steps of the fuzzy BWM approach utilised the linguistic scales shown in Table 2 from ‘Equal importance’ to ‘absolutely importance’ in order to assess the importance of the best threat to others and the other threats to the worst threat. A sample evaluation of best-to-others and others-to-worst made by expert 1 is shown in Table 4 and Table 5, respectively. These linguistic scales are then converted to its corresponding fuzzy numbers.

Table 4 Best-to-others fuzzy reference comparisons (sample evaluation by expert 1)

| <i>Threat</i> | <i>T1</i> | <i>T2</i> | <i>T3</i> | <i>T4</i> | <i>T5</i> | <i>T6</i> | <i>T7</i> | <i>T8</i> | <i>T9</i> | <i>T10</i> |
|---------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|------------|
| T7 | EI | EI | EI | EI | EI | VI | VI | EI | FI | VI |

Table 5 Others-to-best fuzzy reference comparisons

| <i>Threat</i> | <i>T1</i> |
|---------------|-----------|
| T1 | VI |
| T2 | VI |
| T3 | VI |
| T4 | VI |
| T5 | EI |
| T6 | EI |
| T7 | EI |
| T8 | EI |
| T9 | VI |
| T10 | VI |

Table 6 Fuzzy optimal weights

| <i>Criteria</i> | <i>l</i> | <i>m</i> | <i>u</i> |
|-----------------|----------|----------|----------|
| T1 | 0.0682 | 0.1365 | 0.1365 |
| T2 | 0.0770 | 0.1365 | 0.1365 |
| T3 | 0.0770 | 0.1365 | 0.1365 |
| T4 | 0.0770 | 0.1365 | 0.1365 |
| T5 | 0.4550 | 0.4550 | 0.4550 |
| T6 | 0.2730 | 0.2730 | 0.2730 |
| T7 | 0.0770 | 0.1365 | 0.1365 |
| T8 | 0.4550 | 0.4550 | 0.4550 |
| T9 | 0.0682 | 0.1365 | 0.1365 |
| T10 | 0.0682 | 0.1364 | 0.1364 |

Taking into account that the judgements in Tables 4 and 5 are in linguistic scales, these are now converted into fuzzy numbers, which are shown in Table 2. Here, these fuzzy numbers are used to solve the fuzzy optimal weights as shown in equation (5). Table 6 presents the fuzzy optimal weights as well as its corresponding crisp optimal weights in Table 7. After processing the individual judgements of experts, these are now summarised and aggregated in Tables 8 and 9. Furthermore, the average CR of 0.2779

generated from Table 10 also shows that the responses elicited by the experts are consistent.

Table 7 Crisp optimal weights

| <i>Criteria</i> | <i>Weights</i> |
|-----------------|----------------|
| T1 | 0.1251 |
| T2 | 0.1266 |
| T3 | 0.1266 |
| T4 | 0.1266 |
| T5 | 0.4550 |
| T6 | 0.2730 |
| T7 | 0.1266 |
| T8 | 0.4550 |
| T9 | 0.1251 |
| T10 | 0.1250 |

Table 8 Summary of weights per threat

| <i>Threat</i> | <i>Expert 1</i> | <i>Expert 2</i> | <i>Expert 3</i> | <i>Expert 4</i> | <i>Expert 5</i> |
|---------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| T1 | 0.1251 | 0.0650 | 0.0925 | 0.1533 | 0.1523 |
| T2 | 0.1266 | 0.1068 | 0.1001 | 0.1846 | 0.0980 |
| T3 | 0.1266 | 0.1068 | 0.1001 | 0.4381 | 0.0980 |
| T4 | 0.1266 | 0.1094 | 0.1037 | 0.3870 | 0.0980 |
| T5 | 0.4550 | 0.0321 | 0.1028 | 0.4381 | 0.0634 |
| T6 | 0.2730 | 0.1068 | 0.1001 | 0.4381 | 0.0980 |
| T7 | 0.1266 | 0.1094 | 0.1001 | 0.1634 | 0.0980 |
| T8 | 0.4550 | 0.1068 | 0.1001 | 0.1533 | 0.0980 |
| T9 | 0.1251 | 0.1068 | 0.1001 | 0.4381 | 0.0980 |
| T10 | 0.1250 | 0.1502 | 0.1001 | 0.1312 | 0.0980 |

Table 9 Aggregated weights of criteria

| <i>Criteria</i> | <i>Aggregated</i> |
|-----------------|-------------------|
| T1 | 0.1176 |
| T2 | 0.1232 |
| T3 | 0.1739 |
| T4 | 0.1649 |
| T5 | 0.2183 |
| T6 | 0.2032 |
| T7 | 0.1195 |
| T8 | 0.1826 |
| T9 | 0.1736 |
| T10 | 0.1209 |

Table 10 Consistency ratio of each decision-maker's evaluation

| <i>Expert</i> | <i>Best-worst</i> | <i>Rating</i> | <i>CI</i> | $\tilde{\xi}^*$ | <i>CR</i> |
|---------------|-------------------|---------------|-----------|-----------------|-----------|
| 1 | T7-T1 | EI | 3.00 | 2.0000 | 0.6667 |
| 2 | T10-T5 | AI | 8.04 | 1.6716 | 0.2079 |
| 3 | T5-T7 | EI | 3.00 | 0.1616 | 0.0539 |
| 4 | T5-T4 | FI | 5.29 | 2.000 | 0.3781 |
| 5 | T1-T5 | FI | 5.29 | 0.4384 | 0.0829 |

3.2 *Managerial implications*

The fuzzy BWM ultimately provides key results in terms of the ranking of threats based on the evaluation made with respect to the threats. To summarise the optimal weights from the fuzzy BWM, Table 11 lists the threats in order of priority. It is worth noting that the first five ranking threats pertain to lack of knowledge in integrating AI into the educational platform. For the first ranking threat, since AI technologies are underdeveloped, it is unclear for the users especially the students and educators how to implement the AI models in terms of learning, engagement, and pedagogical knowledge. Such a top-ranking threat further supports the second rank in terms of insufficient knowledge of the use of AI technologies, lack of education research on the ethical side of the implementation, and the education perspectives in AI research. These results reveal that it is crucial for university decision-makers to understand the technology fully before its full-blown implementation (Casquejo et al., 2020). Without a proper background on how AI technologies will be integrated into the teaching and learning platform, it is difficult to comprehensively encompass the functional capabilities of the technologies as well as its critical low points.

Table 11 Ranking of threats

| <i>Rank</i> | <i>Threat</i> |
|-------------|--|
| 1 | Increasing inequity among students due to an apparent digital divide (T5) |
| 2 | Teachers' lack of knowledge in the use of AI technologies (T6) |
| 3 | Insufficient socio-emotional research on AIEd (T8) |
| 4 | Insufficient link between AI technologies and teaching functions (T3) |
| 5 | Insufficient perspectives of AIEd research (T9) |
| 6 | Insufficient capability of AI technologies to be used in interdisciplinary programs (T4) |
| 7 | Determining the most suitable data for AI predictive models (T2) |
| 8 | Ineffective methods of evaluating AIEd (T10) |
| 9 | Unfavourable attitudes of students and teachers towards AI technologies (T7) |
| 10 | Insufficient resources for more flexible learning (T1) |

It is also notable to mention that threats ranking sixth to eighth cover the evaluation of AI and have already worked past the knowledge-based level of the decision-makers. Here, the concern is more on selecting the most appropriate AI technology for learning, data for predictive models, and evaluation methods of AIEd. At this stage of the integration, the results pointed out that key experts are less concerned about AI's specific technologies and evaluation methods than having full knowledge about the technology itself. This can

be due to the fact that these threats, (i.e., T4, T2, and T10) already assume a working background in AIEd research. Considering that the university tapped as the case study is still in its infancy stage regarding technology adoption and AI integration, the results clearly reflected the most crucial concern of fully understanding the system before evaluating its overall performance.

4 Conclusions

AI technologies and models are a relatively growing topic of interest in the literature given the potential benefits that they provide in various service and manufacturing applications. With the benefits also come challenges that threaten other sectors' ability to fully immerse themselves in such innovative steps. In the education sector, the integration of AI has been widely studied, but most works focus only on descriptive analysis with respect to future research directions on AIEd opportunities and challenges. No in-depth analysis of the threats has been made in the literature, which can potentially pave the way for key stakeholders to consider future AIEd implementations. Therefore, this work investigated the threats in AIEd through the lens of the fuzzy BWM. This research direction provides the major contribution of this paper to the literature. In order to demonstrate the applicability of the tool, a case study in a state university in the Philippines is performed. Interestingly, the results mimicked the major threat faced by state universities in a developing country, pointing towards fully understanding the technology being considered for integration before anything else. Recognising that state universities in developing countries are limited with resources, financially, manpower-wise, and knowledge-wise, it is imperative to address threats that touch on knowledge-based concerns rather than focus on choosing which appropriate AI technology and model to integrate, thereby increasing its overall efficiency (Abing et al., 2018).

This paper can be further extended to address some of its limitations in the list of alternative AI technologies considered and the threats of AIEd. For one, alternative AI technologies and models can be evaluated side-by-side with the threats to understand how the selection process is carried out. In this way, the threats will serve as a starting point for analysing available technologies. Furthermore, opportunities in AIEd can also be looked into and analysed according to its characteristics and priority weights. For another, other analytic tools can also be explored such as optimisation modelling in order to ensure maximum efficiency of an AI technology being integrated into the educational sector.

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