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Prioritizing Barriers and Strategies Mapping in Business Intelligence Projects Using Fuzzy AHP TOPSIS Framework in Developing Country

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Abstract

Business Intelligence (BI) is an essential technology in an increasingly competitive landscape since it helps make decisions more accurately. To achieve an effective BI implementation, the organization must formulate the right strategy to overcome its challenges. This research aimed to develop a framework to map barriers into strategies using qualitative and quantitative methods. The qualitative approach is driven by interviewing BI experts to validate the barriers and strategies previously obtained. Based on the interview, there are 19 barriers and 9 strategies that could be used. The quantitative approach compiles a priority list of the most significant barriers and the most effective strategies to overcome these barriers using fuzzy AHP TOPSIS, an MCDM method to eliminate inconsistencies during ranking. The results indicate that the lack of collaboration between the IT and BI departments, the BI implementation demands to be done quickly, and low data quality are the main barriers that hinder BI's success. This research also found that business people's involvement in a BI project is the best strategy to overcome the obstacles. The chances of a successful BI implementation will increase by having good cooperation between IT and business units within the company.

Keywords:

Business Intelligence;
BI Barriers;
BI Strategic;
BI Implementation;
MCDM;
Fuzzy AHP TOPSIS.

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1- Introduction

In today's increasingly competitive business environment, decision-making speed and accuracy are critical. Nowadays, the decision-making process is no longer relevant by relying only on intuition because the problems are becoming increasingly complex and complicated. It needs more reliable data analysis within the company [1, 2]. According to Dehghan et al. (2013) [3], data analysis in decision-making is one of the factors that can determine whether a company can survive in business competition. BI has become an essential competitive advantage for companies nowadays [2, 4].

According to Cognini et al. (2014) [5], BI can provide companies with information about the right people, the right time, and the right channels for their business interests. A survey conducted by Gartner (2015) [6] says that more than 75% of companies in the world are investing or planning to invest in BI. Companies using BI aim to increase customer experience, achieve higher marketing targets, reduce costs, and also improve business performance [7]. Because of BI's ability to support business, IT managers make BI project implementation a top priority nowadays [2].

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According to Kursan and Mihi (2010) [8], BI refers to various software solutions, including the technology and methodology needed to get the correct information to increase overall business performance in the market. In previous studies, BI has been proven to provide benefits by improving performance, providing learning data from the past, enhancing operational efficiency, and strengthening organizational intelligence [1, 9]. Because of all the benefits that BI has, it is expected that it will grow more quickly in the years to come.

Despite the advantages of BI, the development of BI projects cannot be separated from barriers. One barrier to developing a BI project is data quality. According to Williams and Williams (2007) [10], based on a survey of more than 250 executives, 40% said that their decisions were based on bad quality data. According to Kwak (2002) [11], there are ten other barriers in the development of BI projects: political, legal, cultural, technical, managerial, economic, environmental, social, corruption, and physical. This shows that there are many aspects that can irritate the success of BI project development. Besides, BI projects' development requires high costs because they need several resources, such as the procurement of data warehouses and data processing. According to a survey conducted by Stamford (2014) [12], companies could spend around $14.4 billion in 2013 on BI every year.

Many studies discussed BI, for example, research conducted by Ain et al. (2019) [4], examines BI adoption, utilization, and success. Research by Božič & Dimovski (2019) [1] explained about critical success factors of BI implementation. Studies by Llave (2017) and Tutunea (2015) [13, 14] discussed BI implementation and solutions. There are also some researches about BI project's barriers by Kwak (2002) [11], Mesároš et al. (2015) [15] and Williams (2011) [16]. The existing studies have discussed BI in the areas mentioned comprehensively. To the best of the authors' knowledge, research that maps the barriers of BI with their solutions has not been found.

There are a lot of barriers in BI project development. Those barriers have different impacts and frequency of appearances. Consequently, it is necessary to rank which barriers often occur, so the organization can focus on solving their significant barrier. Organizations also need to know what strategies are appropriate in overcoming these obstacles.

This study aims to map the barriers into the appropriate strategies that will later produce priority arrangements or ranking strategies. The mapping was carried out using one of the Multi-Criteria Decision Making (MCDM) methods, namely fuzzy AHP TOPSIS. Fuzzy AHP TOPSIS is a combination of 2 MCDM methods, fuzzy AHP and fuzzy TOPSIS. Both methods are commonly used in decision making by ranking alternatives or priorities and choosing the best one from a multi-criteria case that combines qualitative and quantitative factors [17-19]. Fuzzy AHP TOPSIS is used in this study because it can better overcome the expert's uncertainty and increase decision-making accuracy compared to the fuzzy AHP method alone [20]. In addition, Sun (2010) [21] argues that the method is the most accurate, effective, and systematic in helping the decision-making process. Besides, it makes the decision-maker understands the overall evaluation process easier. In Indonesia, research on Business Intelligence is still limited. Whereas, one of the factors that can affect the success of BI that needs to be investigated is the macro-environmental factor [22] which is strongly influenced by the conditions of a country. Business Intelligence is widely used in large companies in Indonesia since many large companies use electronic data. Based on the Ministry of Information and Technology, at least 500 companies already use data electronically in Indonesia [23]. The use of large-scale electronic data cannot be separated from business intelligence because BI is essential in processing, reporting, and seeking insights from the data. Based on World Bank data, Indonesia is in the fourth rank of the most populous country, with 54 percent of the population using the internet [24, 25]. Companies in Indonesia, especially B2C companies, usually work with a lot of data since many users use their applications, so the implementation of BI would become more challenging.

According to the United Nations, Indonesia is a developing country [26]. Despite that, the use of BI has begun to grow rapidly; for instance, the application of BI in various companies' lines has experienced a rapid increase of more than 200% in the last 12 years [27]. In this context, the implementation of BI in Indonesia becomes an interesting subject for study. Therefore, our research aims to explore barrier factors for BI implementation by interviewing experts who have experience in BI implementation. This research aims to fill the gap by contributing to the inhibiting factors and strategies for implementing BI in Indonesia. Hopefully, the results obtained from this research can be applied in Indonesia and generalized to other developing countries with the same characteristics.

2- Literature Review

2-1- Barriers and Strategies in BI Project Development

BI implementation brings many benefits to the organization. However, it cannot be denied that sometimes there are obstacles, problems, and risks in its implementation. Many factors can be barriers to BI implementation projects, including technology, people, processes, and management styles.

Research by Yeoh & Koronios (2010) [28], and Olszak & Ziemba (2012) [29] divided BI implementation barriers into three categories: organization, process, and technology. The organizational dimension is a dimension that describes the internal characteristics of a company. The elements consist of internal company, people, management support & sponsorship, clearly defined vision, and business case. Process dimensions describe the flow and all attributes involved in implementing a BI system until the end use of the cycle. This dimension includes business-centric, business-driven, approaches to system development, and change management. Meanwhile, the technology dimension is a dimension that relates to the system's technical ability in carrying out scalability and flexibility and is related to the quality and integrity of data, both technically and procedurally.

The emergence of obstacles in the development of BI projects has encouraged other researchers to formulate strategies that can overcome them. These strategies are in the form of recommendations, best practices, and critical success factors. Based on the literature study results, the authors found various lists of obstacles and strategies derived from 11 previous studies, summarized in Tables 1 and 2. In this study, the barriers are grouped into 3 categories according to the research by Yeoh & Koronios (2010) [28], and Olszak & Ziemba (2012) [29], which are organizational, process, and technological aspects. In addition, the experts also validate the grouping process, so the result is more validated. Table 1 provides information about obstacles (group by three categories) and Table 2 provides strategies in developing BI projects.

Table 1. List of Obstacles in BI Project Development

Criteria	Code	Barriers	References
People/ Organization	HP1	Lack of competency in BI developers	Olszak & Ziemba (2012) and Fortune & White (2006) [29, 30]
	HP2	Lack of defining the purpose of using BI	Williams & Williams (2007), Williams (2011), Wise (2007), Dawson & Van Belle (2013) [10, 16, 31, 32]
	HP3	Bad relationships between companies and vendors	Olszak & Ziemba (2012) and Dawson & Van Belle (2013) [29, 32]
	HP4	Difficulty in learning about BI technology	Williams (2011), and Wise (2007), Dawson & Van Belle (2013), Eckerson (2002) [16, 31, 32, 33]
	HP5	Lack of support from top management financially	Mesároš et al. (2015), Olszak & Ziemba (2012), Fortune & White (2006), Dawson & Van Belle (2013), Eckerson (2002) [15, 29, 30, 32, 33]
	HP6	Less collaboration between IT/BI departments and businesses	Mesároš et al. (2015), Olszak & Ziemba (2012), Wise (2007) [15, 29, 31]
	HP7	Employees are not ready for change	Boyer et al. (2010) [34]
	HP8	Lack of best practice	Olszak & Ziemba (2012), Dawson & Van Belle (2013), Ali Khan et al. (2010) [29, 32, 35]
Business/ Process	HB1	There is no effective change management	Olszak & Ziemba (2012), Fortune & White (2006) [29, 30]
	HB2	Users are less able to define business problems	Olszak & Ziemba (2012) and Lennerholt et al. (2020) [29 , 36]
	HB3	End-users are not included in the BI project	Mesároš et al. (2015), Olszak & Ziemba (2012), and Dawson & Van Belle (2013) [15, 29, 32]
	HB4	BI implementation that demands to be done quickly	Retrieve from the interview with experts
Techno-logy	HT1	Improper use of technology	Olszak & Ziemba (2012) and Jalil & Hwang (2019) [29, 37]
	HT2	Problems of integration between BI and other related systems	Olszak & Ziemba (2012) [29]
	HT3	Poor data quality	Olszak & Ziemba (2012), Dawson & Van Belle (2013), Eckerson (2002), Ali Khan et al. (2010) [29, 32, 33, 35]
	HT4	The system is not user friendly	Olszak & Ziemba (2012), Dawson & Van Belle (2013) [29, 32]
	HT5	Complex BI technology	Olszak & Ziemba (2012), Eckerson (2002) [29, 33]
	HT6	Difficult to get data access	Retrieve from the interview with the experts
	HT7	Do not have adequate infrastructure	Retrieve from the interview with the experts

Table 2. Development Strategies

Code	Strategy	References
S1	Create a Business Intelligence Competency Center (BICC)	Dehghan et al. (2013), Olszak & Ziemba (2012), Boyer et al. (2010), [3, 29, 34]
S2	Conduct a clear assessment of the situation in the company	Boyer et al. (2010) [34]
S3	Make a clear priority list matrix	Boyer et al. (2010) [34]
S4	Standardize and consolidate systems	Boyer et al. (2010) [34]
S5	Engaging businesspeople in the BI project	Fortune & White (2006), Dawson & Van Belle (2013), Eckerson (2002), Boyer et al., (2010) [30, 32, 33, 34]
S6	Use technology that suits your needs	Fortune & White (2006), Eckerson (2002) and Jahantigh et al. (2019) [30, 33, 38]
S7	Create a community to promote BI	Williams (2011) [16]
S8	Provide training to BI developers regularly	Retrieve from the interview with the experts
S9	Make appropriate BI system design (design)	Retrieve from the interview with the experts

2-2- Fuzzy AHP TOPSIS

2-2-1- Fuzzy Set

Fuzzy-set logic is an advanced form of *Boolean logic* by Zadeh (1965) [39]. It was based on the mathematical theory of fuzzy sets, which is a form of generalization from classical theory. One of the advantages of fuzzy logic is the rules can be understood using human language [40]. According to Ordoobadi (2009) [41] fuzzy sets are used to represent the uncertainty of human thought into mathematical forms. Fuzzy sets are widely applied in determining managerial decisions that have a lot of uncertainty. According to Patil & Kant (2014) [42], in practice, fuzzy numbers and the value of Triangular Fuzzy Number (TFN) can be used to present linguistic values. A "~" sign is usually used to indicate fuzzy-set symbols.

The definition of a fuzzy set described by Patil & Kant (2014) [42] are as follows:

Definition 1 has been explained in the previous explanation that with μA (x) ∈ [0,1], where $\mu A\ (x)\ =1$ indicates that x as a whole is a member of $\tilde{A}$.

Definition 2 α-cut of fuzzy-set $\tilde{A}$ from the non-empty set of X can be defined as the following equation:

$$A\,\alpha\ =\ \{x \in X \mid \mu A\ (x)\ \geq\ \alpha\},\qquad where\ \alpha\ \in\ [0,1]$$

Suppose x = 3 with a value of α = 0.5, pieces α-cut at points 2 and 3 so that α0,5 = (2,3,4).

Definition 3 A fuzzy set $\tilde{A}$ of the non-empty set X reaches the highest membership level if the value is 1. max $\mu A\ (x)\ =\ 1$

Definition 4 A fuzzy N number is a fuzzy subset of non-empty sets.

Definition 5 A fuzzy-set A is convex if and only if an α-cut of A is convex set for each α at the interval in the following equation:

$$\mu A(X1 + (1-\lambda)X2) \geq min\ (\mu A\ (x1), \mu A\ (x2))\ \forall x \in [x1, x2] \text{ where is } lamda \in [0,1] \tag{1}$$

Definition 6 In the TFN, if the membership function is $\mu A\ (x)$ of fuzzy-sets $A\ =\ (l, m, u)$ in universe X with l, m, u are real numbers and $l\ \leq\ m\ \leq\ u$ is defined as follows:

In the fuzzy triplet or (l, m, u) with m is the main value, l is the lowest value and u the highest value. If the value (l, m, u) is (1, 3, 5) with $\tilde{3}$ as the main fuzzy value. While the reciprocal value is ($1u$, $1m$, $1l$).

Definition 7 Defining the confidence level interval α, the TFN can be defined using this equation:

$$\forall\alpha\ [0,1]\ M\alpha\ =\ [l\alpha, u\alpha]\ =\ [(m-l)\alpha\ +\ l, -(u-m)\alpha\ +\ u]$$

Definition 8 Suppose that a = (a1, a2, a3) and b = (b1, b2, b3) are two TFNs, so the distance between them can be obtained as Equation 2:

$$\mathrm{d_v}\ (\tilde{a},\tilde{b}) = \sqrt{\frac{1}{3}[(a1-b1)^2 + (a2-b2)^2 + (a3-b3)^2]} \tag{2}$$

2-2-2- Fuzzy AHP

Fuzzy AHP is a combination of Fuzzy and AHP methods. Thomas Saaty first introduced AHP in 1990. According to Saaty (1990) [43], AHP is an effective tool for complex decision making and can be aimed at decision-makers in making priorities and making the best decisions. AHP can help to capture the subjective and objective aspects of a decision by eliminating complex decisions into a series of pairwise comparisons. In addition, AHP is also a technique that can be used to check the consistency of a decision-making evaluation so that it can reduce the bias of the decision-making process [43].

However, according to Kahraman et al. (2003) [44], AHP is still not good enough in representing human judgment in the decision-making process. So that some researchers make a combination of AHP methods with fuzzy logic aimed at increasing uncertainty and various subjective problems related to the process of giving values/weights in overcoming the different perspective of linguistic variables from each expert. Kahraman et al. (2003) [44] overcomes the uncertainty of AHP by using fuzzy logic, which usually uses a Triangular Fuzzy Number (TFN) scale. Research by Patil & Kant (2014), Chen et al. (2015) and Baylan (2020) [42, 45, 46] describe the steps used to implement fuzzy AHP.

Step 1: Develop a hierarchical structure that is a combination of all factors and subfactors on existing problems.

Step 2: Determine the Expert for decision making. According to Chen et al. (2015) [45], to support a more objective decision, the background of each expert should be given more attention. The expert must have a lot of experience with the topic of the research proposed. Every expert is required to provide judgments based on their experience and expertise.

Step 3: Determine linguistic variables and scale of fuzzy conversion. Each expert will assign a value to each factor compared. This comparison can be made with a questionnaire. Triangular Fuzzy Number (TFN) is used to represent variable linguistics in pairwise comparison matrices (see Table 3).

Table 3. Triangular Fuzzy Number (TFN)

Intensity	Fuzzy Number	Linguistic Variable	TFN
1	$\tilde{1}$	Equally	(1,1,3)
3	$\tilde{3}$	Weakly/moderately	(1,3,5)
5	$\tilde{5}$	Strongly	(3,5,7)
7	$\tilde{7}$	Very strongly	(5,7,9)
9	$\tilde{9}$	Extremely	(7,9,11)

Step 4: Make a paired comparison matrix. Experts are asked to fill in a paired comparison matrix that compares categories based on a predetermined scale. The value of a compared category will be the opposite in the other categories compared. Then, each scale given by the expert is converted to the appropriate TFN value as shown in Equation 3 [45]:

$$\widetilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ 1/\tilde{a}_{12} & 1 & \cdots & \tilde{a}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ 1/\tilde{a}_{1n} & 1/\tilde{a}_{2n} & \cdots & 1 \end{bmatrix} \tag{3}$$

Step 5: Combining each matrix into a representative matrix. Merging matrices into a representative matrix can be done using Equations 4 to 6. The variable k shows the number of experts or shows the number of matrices, $A_k = \{a_{ijk}\}$, where $a_{ijk} = (l_{ijk}, m_{ijk}, u_{ijk})$ represents the relationship between elements i to j that has been entered by expert *k.*

$$l_{ij} = \min(l_{ijk}) \tag{4}$$

$$m_{ij} = \sqrt[k]{\prod_{k=1}^{k} m_{ijk}} \tag{5}$$

$$u_{ij} = \max(u_{ijk}) \tag{6}$$

Step 6: Change the pairwise comparison fuzzy matrix into a pairwise comparison crisp matrix. In making a fuzzy matrix change into a crisp matrix several additional variables are needed such as α and μ. The value of α represents the expert's level of confidence in his choice in making a decision. After selecting an α value, the value can be entered into a paired fuzzy comparison matrix and then selected for the μ value:

$$\widetilde{Ax} = \begin{bmatrix} 1 & \widetilde{a_{12}} & \cdots & \widetilde{a_{1n}} \\ \widetilde{a_{21}} & 1 & \cdots & \widetilde{a_{2n}} \\ \cdots & \cdots & \cdots & \cdots \\ \widetilde{a_{n1}} & \widetilde{a_{n2}} & \cdots & 1 \end{bmatrix} \tag{7}$$

The value of μ represents the level of expert satisfaction with the matrix. The greater the value of μ indicates the higher level of optimism of the expert. After determining the two variables, a calculation can be made to convert the fuzzy matrix into a crisp matrix pairwise comparison using the formula as shown in Equation 8:

$$\left(a_{ij}^{\alpha}\right)^{\lambda} = \left[\lambda \,.\, l_{ij}^{\alpha} + (1-\lambda) u_{ij}^{\alpha}\right] \tag{8}$$

Step 7: Look for Consistency Index (CI) and Consistency Ratio (CR) from the paired comparison matrix. CR is needed to ascertain whether the overall matrix has a consistent value. This step aims to control the results of the fuzzy AHP method. The steps taken to check this consistency begin with finding the maximum eigenvalue (λmax) of the crisp matrix. The maximum eigenvalue (λmax) can be searched using Equation 9:

$$Aw = \lambda\, max.w \tag{9}$$

After obtaining the maximum eigenvalue of the crisp matrix, CR and CI values can be calculated using Equations 10 and 11.

$$CI = \frac{\lambda\max - n}{n-1} \tag{10}$$

$$CR = \frac{CI}{RI(n)} \tag{11}$$

CI is a consistency index, n is the number of dimensions of the matrix, and *Ri* is the random index whose value depends on the number of dimensions of the matrix used, these values can be seen in Table 4. CR and CI values are between 0 to 1. CR which is equal to or smaller than 0.1 then the matrix can be declared consistent. If it is not consistent, it is necessary to do a data retrieval or repeat the process of comparing the criteria by the expert.

Table 4. Random Index

N	3	4	5	6	7	8	9
Ri(n)	0.58	0.9	1.12	1.24	1.32	1.41	1.45

Step 8: Weigh each criterion. This weighting can be done by normalizing each column and row in each matrix. The equation used in normalization can be seen in equation:

$$W_j = \frac{W_j}{\sum_{i=1}^{n} W_i} \tag{12}$$

where *Wj* is weight, criteria *j* and *n* are the total numbers of criteria.

2-3-3- Fuzzy TOPSIS

Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is one of the Multiple Criteria Decision Making (MCDM) methods developed by [47]. According to [20] MCDM is usually used to make decisions by finding the best choices from all available alternatives. In the classic MCDM method, including TOPSIS, the rating and weight of the criteria must be known with certainty [47]. The data used in TOPSIS depends on real-life situations according to the perceptions of each expert. It implies that the preferences cannot be estimated with an exact number. The expert judgment also cannot be compared one to another. So, from this TOPSIS deficiency, according to [48], a combined fuzzy TOPSIS method was formed which was expected to be able to overcome the uncertainty of the assessment given by the expert.

Patil & Kant (2014) [42] describes the stages of applying the fuzzy TOPSIS method as follows:

Step 1: Collect data. Data needed to be used in the fuzzy TOPSIS process is the value of all criteria, sub criteria, and alternatives to the problem.

Step 2: Determine the value of the linguistic variable and change it to the value of the Fuzzy Number (TFN). The linguistic variable used by Patil & Kant (2014) [42] in determining the strategy is the TFN. After being determined, it can be done to change the scale value given by the expert to the value of TFN and its reciprocal TFN.

Step 3: Calculates aggregate fuzzy values and combines fuzzy matrices into representative matrices. All fuzzy matrices that have been changed can be merged into m x n matrices where m is all alternatives and n is all existing criteria. The modified fuzzy value has 3 values according to the TFN value in stage 2 so that it has the form $\tilde{x}k$ = (ak, bk, ck), where k = 1, 2, ... k or the number of matrices/experts and the aggregate fuzzy value becomes $\tilde{x}$ = (a, b, c). The values of a, b, c can be searched successively with the following equation:

$$a = {}^{\min}_{\mathrm{k}}\{a_k\} \tag{13}$$

$$b = \frac{1}{k}\sum_{k=1}^{k} b_k \tag{14}$$

$$c = {}^{\max}_{\mathrm{k}}\{c_k\} \tag{15}$$

Merging matrices can be done by becoming the following matrix:

$$\tilde{R} = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{x}_{m1} & \cdots & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{16}$$

Value i = 1, 2, ..., m and j = 1, 2, ..., n

Step 4: Perform normalization of fuzzy matrices. The raw data on the matrix is changed by normalizing using a linear scale. Normalization aims so that one criterion can be compared with the other. Suppose a fuzzy matrix $\tilde{R}$ that has been processed in stage 2 before can be normalized with the formula:

$\tilde{R} = [rij]\ m \times n$

value of i = 1,2, ... m and j = 1,2, ... n. So:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) \tag{17}$$

The variable $cj*$ is the maximum value of cij (profit criteria)

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) \tag{18}$$

The variable $a_j^-$is the minimum value of aij (cost criteria)

Step 5: Forms a normalized weighted matrix. The weighted normalization matrix ($\tilde{V}$) is formed by multiplying the weight of each criterion (wj) and the corresponding normalization matrix

$$\tilde{V} = [\tilde{v}ij] \times n \tag{19}$$

where i = 1, 2, ..., m and j = 1, 2, ..., n and $vij = rij$ (.) wj

Step 6: Determining Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS). Furthermore, we can find FPIS and FNIS values using Equations 20 and 21:

$$d_i^+ = \sum_{j=1}^{n} dv(\tilde{v}_{ij}, \tilde{v}_j^*) \tag{20}$$

$$d_i^- = \sum_{j=1}^{n} dv(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{21}$$

Step 7: Perform calculations from each alternative of FPIS and FNIS values. CCi coefficient represents the distance of FPIS (A*) and FNIS (A-). Can be calculated using the formula:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{22}$$

Step 8: Perform alternative ratings. Ranking can be seen from the coefficient (CCi) from the highest to the lowest value. The highest CCi value represents the most important alternative.

3- Research Methods

In this study, the authors used a type of qualitative and quantitative research. The qualitative approach is conducted by interviewing BI experts to validate the list of barriers and strategies obtained from the literature study. The quantitative approach is used to compile a priority list of the most significant obstacles to BI's success and the most effective strategies to overcome these barriers using fuzzy AHP TOPSIS. This quantitative method starts with filling out the questionnaire.

The list of barriers and strategies has been collected through the literature study and validated by several experts through interviews. There are nine experts involved to validate, add and subtract, the list of obstacles and strategies. The experts consist of people who have handled BI projects both at a company that uses BI and a vendor company that serves BI manufacturing in other companies. Experts consist of; CEO, data analyst, data scientist, database, data warehouse staff, and Business Intelligence Competency Center (BICC) staff.

This study uses a methodology as shown in Figure 1, which is adapted from [49]. The methodology consists of 3 stages: identification and formation of hierarchies of barriers and strategies, use of fuzzy AHP, and use of fuzzy TOPSIS, described in Figure 1.

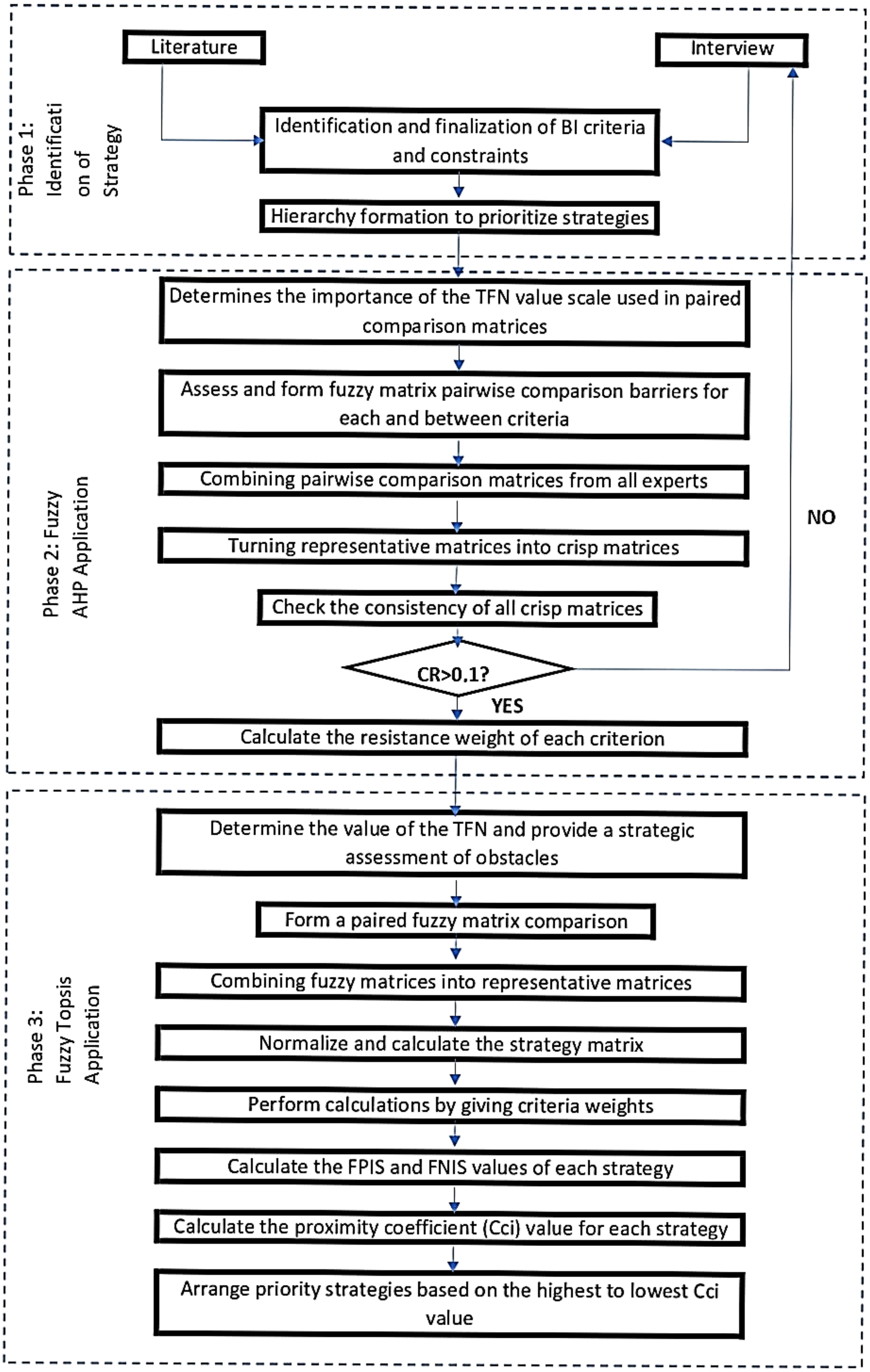

Figure 1. Flowchart of the research methodology

In step 1 the author identified the BI project obstacles and strategies. Identification is made through literature studies and expert interviews. After getting the list of obstacles and strategies, a hierarchy of 4 levels is formed. The first level is the purpose of using the fuzzy AHP TOPSIS method. The second level is the barrier category. The third level is the list of barriers from each category in the second level. And the last, the fourth level, is the strategy used to overcome the obstacles from the third level. The hierarchy can be seen in Figure 2.

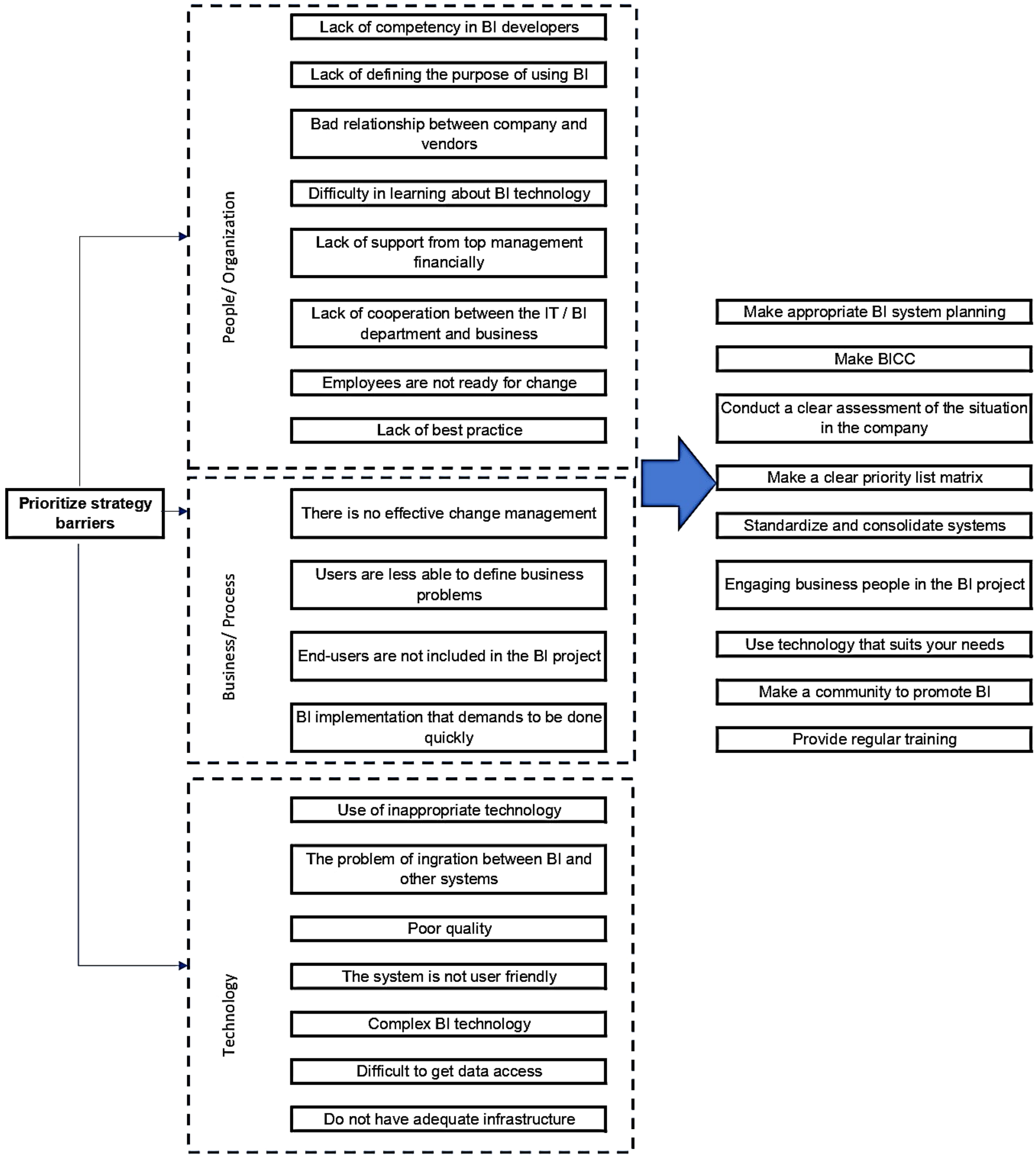

Figure 2. **Fuzzy AHP-TOPSIS Framework for Developing Barriers to Priorities and BI Project Development Strategies**

In step 2, the use of fuzzy AHP is weighted from the obstacles in each category using fuzzy. Respondents were asked to assess the barriers of each category that had been compiled. This assessment is done by giving weight to each obstacle compared. These obstacles are compared based on respondents' assessment on which obstacles are more important to solve than other obstacles. The weight used is the weight of fuzzy values. The weight will later be converted to a scale value, using a triangular fuzzy conversion scale conversion.

In step 3, the use of fuzzy TOPSIS will be sequenced or prioritized by BI strategy. This arrangement is done by calculating the weight of obstacles that can be solved by each existing strategy. This calculation uses fuzzy values as in stage 2. Then we calculate the weight of the strategy so that we get the highest value strategy that represents that the strategy can solve the obstacles that most influence BI's success.

4- Results

4-1- Fuzzy AHP (FAHP)

The FAHP stage consists of changing the matrix given by experts to a pairwise comparison matrix, converting the pairwise comparison matrix into a fuzzy matrix, combining all fuzzy matrices per criterion into a representative matrix, checking matrix consistency, and calculating the weight of criteria and sub-criteria.

Stage 1: Changing the Matrix Value into a Pairwise Comparison Matrix. The experts were asked to provide an assessment of each obstacle that had been compared through a questionnaire. The questionnaire was given by e-mail to each expert and returned via e-mail as well, but some were provided directly. The value given is still single, so it needs to be changed to a pairwise comparison matrix. Each expert was asked to fill in 5 matrixes consisting of people/organization barriers matrix, business/process barriers matrix, technological barriers matrix, comparison between criteria matrix, and comparison between obstacle and strategy matrix.

Stage 2: Changing Pairwise Comparison Matrix into Fuzzy Matrix. The pairwise comparison matrix that has been formed in the previous stage is converted to a fuzzy scale following the TFN value. Table 5 shows the result of the transformation from a pairwise comparison matrix into a fuzzy matrix.

Table 5. **Fuzzy Matrix Obstacles Process/Business Criteria One Expert**

	HB1			**HB2**			**HB3**			**HB4**		
HB1	1.00	1.00	1.00	5.00	7.00	9.00	5.00	7.00	9.00	0.20	0.33	1.00
HB2	0.11	0.14	0.20	1.00	1.00	1.00	5.00	7.00	9.00	5.00	7.00	9.00
HB3	0.11	0.14	0.20	0.11	0.14	0.20	1.00	1.00	1.00	0.20	0.33	1.00
HB4	1.00	3.00	5.00	0.11	1.02	11.00	0.11	1.24	11.00	1.00	1.00	1.00

Stage 3: Merging Fuzzy Barriers Matrix from Experts to Representative Matrix. The representative matrix formed is a combination of 7 fuzzy matrices that are different according to the number of experts filling. This representative matrix is formed using geometric mean. Some representative matrices formed later can be seen in Table 6.

Table 6. **Representative Matrix of Obstacles to Process/Business Criteria**

	HB1			**HB2**			**HB3**			**HB4**		
HB1	1.00	1.00	1.00	5.00	7.00	9.00	5.00	7.00	9.00	0.20	0.33	1.00
HB2	0.11	0.14	0.20	1.00	1.00	1.00	5.00	7.00	9,00	5.00	7.00	9.00
HB3	0.11	0.14	0.20	0.11	0.14	0.20	1.00	1.00	1.00	0.20	0.33	1.00
HB4	1.00	3.00	5.00	0.11	1.02	11.00	0.11	1.24	11.00	1.00	1.00	1.00

Stage 4: Checking Matrix' Consistency. Consistency checking aims to see the consistency of values in a matrix that has been combined (a representative matrix). The mechanism taken is to look for consistency values or Consistency Ratio (CR). CR values that are below or equal to 0.1 mean that the matrix is consistent. While if the CR values above 0.1, it is recommended to check the value of the pairwise comparison matrix or repeat the data collection stages.

Searching for CR values can be done by following several stages. The first stage is to convert a fuzzy representative matrix into a crisp matrix. This equation requires several variables such as preference value (α) and risk tolerance (λ). The author uses a value of 0.9 on each of these variables. Some of the resulting crisp matrices can be seen in Table 7.

Table 7. **Crisp Matrix Barriers to Process/Business Criteria**

	HB1	HB2	HB3	HB4
HB1	1.00	0.76	0.69	0.40
HB2	1.34	1.00	0.72	0.98
HB3	1.49	1.42	1.00	0.82
HB4	2.81	1.03	1.24	1.00

After calculating the crisp matrix, CR and CI values were calculated. The result is that the people/organization criteria barrier matrix was 0.05847, the process/business criteria barrier matrix was 0.041889, the technological criteria barrier matrix was 0.05, and the comparison matrix between criteria is 0.011207. The consistency value of all matrices is below 0.1 so that all matrices are declared consistent processed to the next stage.

Stage 5: Calculation of Weight of Criteria and Ranking of Obstacles. Then the weighting of each criterion is carried out. This calculation is done by looking for the weight values of each representative matrix. Calculation of weights can be seen as follows:

Weight of the people/organization category: 0.438

The weight of the process/business category: 0.356

Weight of technology category: 0.219

After the weight of each category is obtained, the final weight of each obstacle will be obtained. The subcategory/obstacle final weight is obtained by multiplying the category's weight and the subcategory's weights. Subcategories/barriers with the highest weight are the factors that get the main ranking or become the most important barriers. The weight and ranking of each barrier can be seen in Table 8.

Table 8. **Category and Subcategory Barrier Weight**

Category	Weight Category	Barriers code	Weight barriers	Final weight
People/ Organization	0.438	HP1	0.08	0.034
		HP2	0.18	0.078
		HP3	0.08	0.035
		HP4	0.10	0.042
		HP5	0.17	0.076
		HP6	0.19	0.082
		HP7	0.17	0.072
		HP8	0.07	0.028
Business/Process	0.356	HB1	0.15	0.052
		HB2	0.21	0.074
		HB3	0.24	0.087
		HB4	0.31	0.112
Technology	0.219	HT1	0.18	0.039
		HT2	0.11	0.024
		HT3	0.21	0.047
		HT4	0.11	0.023
		HT5	0.11	0.024
		HT6	0.15	0.033
		HT7	0.13	0.028

4-2- Fuzzy TOPSIS

Fuzzy TOPSIS is used to rank strategies in overcoming all obstacles in the criteria using the weights of each obstacle. This method requires the value generated in the previous method or FAHP.

Step 1: Turning Values from Expert into Fuzzy Strategy Matrix. The value given by the expert is changed into the TFN scale, which can be seen in Table 9.

Table 9. **Fuzzy Strategy Matrix toward Barriers in Process/Business Criteria from One Expert**

	HB1			HB2			HB3			HB4		
S1	5	7	9	3	5	7	3	5	7	3	5	7
S2	3	5	7	3	5	7	5	7	9	3	5	7
S3	1	3	5	7	9	11	7	9	11	3	5	7
S4	3	5	7	5	7	9	3	5	7	3	5	7
S5	5	7	9	5	7	9	5	7	9	3	5	7
S6	3	5	7	3	5	7	1	3	5	7	9	11
S7	7	9	11	3	5	7	7	9	11	5	7	9
S8	3	5	7	3	5	7	3	5	7	5	7	9
S9	7	9	11	7	9	11	7	9	11	5	7	9

Step 2: Combining Fuzzy Strategy Matrix into Representative Matrix. The fuzzy strategy from all experts is combined into a representative matrix using the existing equations as shown in Table 10.

Table 10. Strategy Representative Matrix for Barriers in Process/Business Criteria

	H2			HB3			HB4			H2		
1.00	3.66	9.00	1.00	3.66	11.00	1.00	4.81	11.00	1.00	3.66	9.00	1.00
1.00	5.64	11.00	1.00	4.09	11.00	1.00	3.06	11.00	1.00	5.64	11.00	1.00
1.00	3.36	11.00	1.00	3.39	11.00	1.00	4.29	11.00	1.00	3.36	11.00	1.00
1.00	2.56	9.00	1.00	2.01	9.00	1.00	4.63	11.00	1.00	2.56	9.00	1,00
1.00	6.86	11.00	1.00	6.49	11.00	1.00	3.69	11.00	1,00	6.86	11.00	1.00
1.00	2.40	9.00	1.00	2.73	11.00	1.00	4.85	11.00	1.00	2.40	9.00	1.00
1.00	2.47	7.00	1.00	3.39	11.00	1.00	3.00	11.00	1.00	2,47	7.00	1.00
1.00	2.56	9.00	1.00	2.14	9.00	1.00	5.04	11.00	1.00	2.56	9.00	1.00
1.00	4.06	11.00	1.00	4.06	11.00	1.00	3.95	11.00	1.00	4.06	11.00	1.00

Step 3: Matrix Normalization. Normalization consists of 2 stages. The first stage is done by finding the minimum value of each obstacle divided by the first value of the fuzzy obstacle. The second stage is multiplication between each row value and fuzzy column strategy and the weight value of each corresponding criterion. The results of the normalization of the first stage can be seen in Table 11.

Table 11. Normalization Strategy Matrix for Obstacles to Process/Business Criteria

	HB1			HB2			HB3			HB4		
S1	0.11	0.40	1.00	0.11	0.27	1.00	0.09	0.27	1.00	0.09	0.21	1.00
S2	0.09	0.24	1.00	0.09	0.18	1.00	0.09	0.24	1.00	0.09	0.33	1.00
S3	0.09	0.29	1.00	0.09	0.30	1.00	0.09	0.30	1.00	0.09	0.23	1.00
S4	0.14	0.41	1.00	0.11	0.39	1.00	0.11	0.50	1.00	0.09	0.23	1.00
S5	0.09	0.40	1.00	0.09	0.15	1.00	0.09	0.15	1.00	0.09	0.27	1.00
S6	0.14	0.38	1.00	0.11	0.42	1.00	0.09	0.37	1.00	0.09	0.21	1.00
S7	0.09	0.27	1.00	0.14	0.41	1.00	0.09	0.29	1.00	0.09	0.33	1.00
S8	0.09	0.43	1.00	0.11	0.39	1.00	0.11	0.47	1.00	0.09	0.20	1.00
S9	0.09	0.29	1.00	0.09	0.25	1.00	0.09	0.25	1.00	0.09	0.25	1.00

Step 4: Determining the Value of Fuzzy Ideal Solution (FPIS) and Fuzzy Negative Solution (FNIS). At this stage, the value that will be searched is d_i^+ and d_i^- toward the normalization matrix that has been obtained at the previous stage. The FPIS and FNIS matrices of each obstacle strategy can be seen in Tables 12 and 13. The combined FPIS and FNIS value matrices can be seen in Table 14.

Table 12. Value Matrix d_i^+ Strategy for Process/Business Barriers

d*	HB1	HB2	HB3	HB4
S1	0.03276	0.04487	0.05238	0.06639
S2	0.03120	0.04389	0.05202	0.06837
S3	0.03158	0.04507	0.05268	0.06674
S4	0.03291	0.04645	0.05653	0.06650
S5	0.03266	0.04367	0.05114	0.06734
S6	0.03267	0.04688	0.05380	0.06637
S7	0.03143	0.04685	0.05268	0.06849
S8	0.03302	0.04645	0.05584	0.06627
S9	0.03158	0.04450	0.05205	0.06705

Table 13. Matrix d_i^- Strategy for Process/Business Barriers

d-	HB1	HB2	HB3	HB4
S1	0.97378	0.96603	0.96097	0.95253
S2	0.97703	0.96897	0.96182	0.94800
S3	0.97617	0.96593	0.96032	0.95157
S4	0.97315	0.96308	0.95374	0.95221
S5	0,97420	0.96977	0.96449	0.95012
S6	0.97354	0.96242	0.95823	0.95259
S7	0.97649	0.96190	0.96033	0.94775
S8	0.97366	0.96308	0.95466	0.95288
S9	0.97617	0.96722	0.96175	0.95078

Table 14. Combined Value Matrix d_i^- and d_i^+ from Every Solution

	d*	d-
S1	0.59947	18.55600
S2	0.59931	18.55602
S3	0.61026	18.53359
S4	0.61298	18.52828
S5	0.57186	18.56879
S6	0.59322	18.54535
S7	0.60871	18.53604
S8	0.58111	18.55283
S9	0.60235	18.54800

Step 5: Calculating Strategy Values Based on FPIS and FNIS Values. After obtaining FPIS and FNIS values from each strategy, the value of CC_i is obtained. The higher value of CC_i the higher the level of importance of a strategy. For obtaining CC_i use $\frac{d_i^-}{d_i^- + d_i^+}$ formula. The results are shown in the next stage.

Step 6: Ranking of Strategies. Based on FPIS and FNIS values calculations, the proximity coefficient value (CCi) is obtained and priority is arranged based on the highest to the lowest CCi value. A list of priority/ranking strategies generated in this phase can be seen in Table 15.

Table 15. Strategy Ranking

	Strategy	CC_i	Ranking
S1	Make *Business Intelligence Competency Center* (BICC)	0.92010	4
S2	Conduct a clear assessment of the situation in the company	0.92010	5
S3	Make a clear priority list matrix	0.91865	8
S4	Standardize and consolidate systems	0.91847	9
S5	**Engaging businesspeople in the BI project**	**0.92341**	**1**
S6	Use technology that suits your needs	0.92094	3
S7	Create a community to promote BI	0.91881	7
S8	Provide training to BI developers regularly	0.92229	2
S9	Make appropriate BI system design (design)	0.91972	6

5- Discussion and Implications

After all steps are carried out, priority constraints and strategies are obtained according to their weight. Overall, it can be seen in Figures 3 to 5, the most significant barriers in each category are the lack of collaboration between IT/BI department, a BI implementation that demands to be done quickly and a low data quality. The most influential barrier in people/organizations category is the lack of collaboration between IT/BI departments and businesses. Lennerholt et al. [36] also reviews his research on these barriers. Lennerholt et al. [36], companies must pay attention to cooperative relations between business and IT departments because both roles are critical in the success of the BI project. The role of business people as users and owners of business processes and IT people as information providers make both parties play a big role in BI implementation success. Consequently, companies that implement BI projects need to consider the potential obstacles that might arise between these parties.

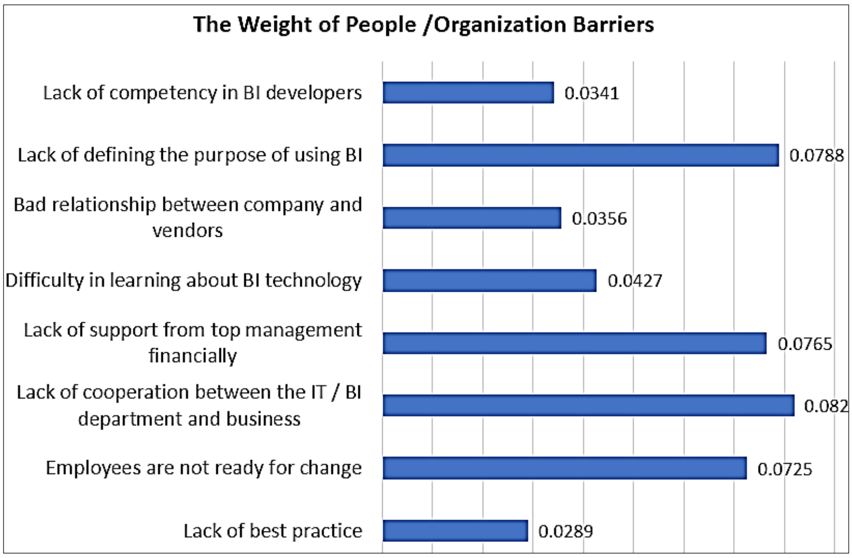

Figure 3. **Weight of Barriers in People/Organization Criteria**

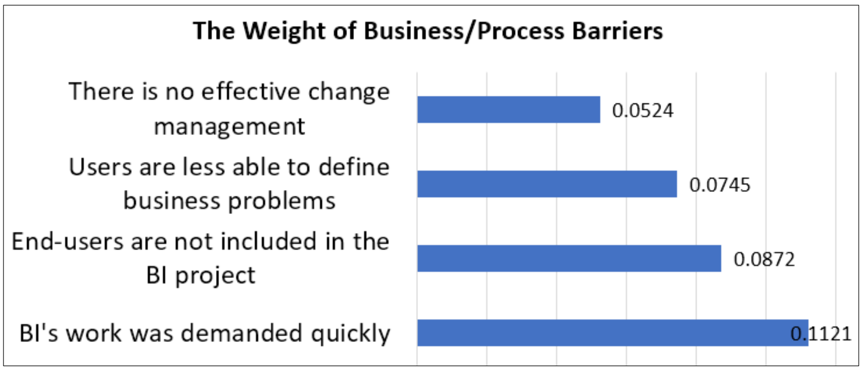

Figure 4. **Weight of Barriers in Business/Process Criteria**

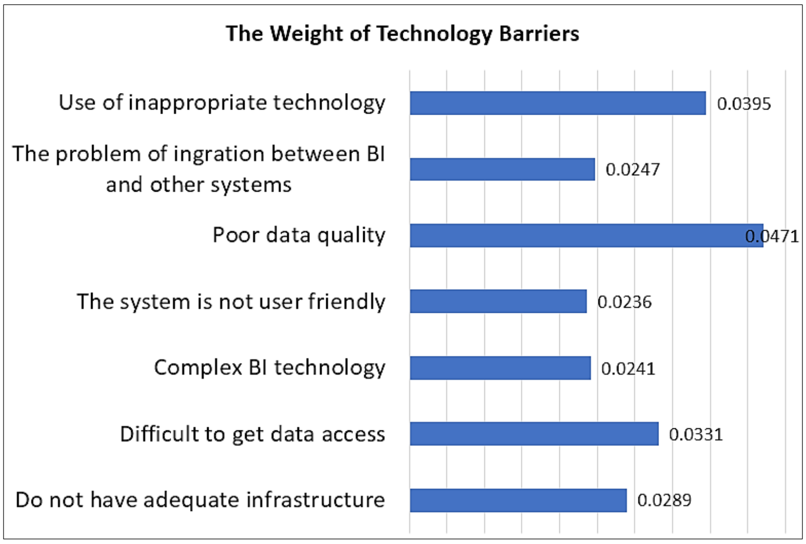

Figure 5. **Weight of Barriers in Technology Criteria**

Whereas in the process/business category barriers, the most significant obstacle in process/business category is BI's rapid prosecution. This obstacle was first proposed by one of the experts and then approved by all experts. Also, according to Eckerson (2005) [50], swift BI processing time is often an obstacle that makes a BI project report work fail. It is often found that BI reports that businesspeople requests cannot be used in decision making because of the rapid changes in data and market conditions. This obstacle is very influential in decision making at the operational level. Companies must be aware of these obstacles and take steps such as increasing the responsiveness and ability of employees in this field to change.

On technological criteria, the most significant obstacle is poor data quality. This finding is suitable with [33] study that said data quality was the most decisive obstacle to BI's success among 7 other obstacles in the BI usage phase. Another result regarding data quality, Dawson (2013) [32] found that data quality is the most popular obstacle compared to 23 other obstacles. This result also. These results are in accordance with research conducted by Passlick (2020) [51] which it is said that data quality is the crucial factor in BI success. This implies that the company needs to pay more attention to data quality from the beginning of pre-processing data to support BI project success.

The strategy with the highest-ranking to overcome the various obstacles in this study is to involve business people in the BI project. The second most significant strategy is providing training to BI developers regularly and using technology that suits their needs, as shown in Figure 6.

Figure 6. **Strategy Ranking**

The importance of involving businesspeople in every BI project undertaken is also emphasized by Dawson (2013) [32]. The reason to involve business people is that business people know more about the problems and conditions that exist in the company. Research conducted by Dawson (2013) [32] puts the involvement of businesspeople in BI projects into the most widely recognized strategy of success by 26 respondents consisting of BI managers, BI professionals, project managers, and IT staff.

Based on the results of this study, there are three categories of obstacles that need to be considered: organization/people, process/business, and technology. In the category of organization/people, companies should pay attention to the relationship between the IT/BI department as the party that implements BI technically and the business department as the party interested in the BI report. Both of the roles are vital in the success of the BI project. This implies that companies need to encourage cooperation between the two parties. According to Nidhra et al. [52], one solution that can be done is scheduling weekly meetings for relevant departments to discuss BI. One of the other activities that companies can do to bring both departments closer is holding gatherings between these parties, both formal and informal, so they have a more robust relationship.

In the process/business category, companies need to pay attention to BI's relatively fast life cycle because these obstacles can make a BI project's work fail. It is often found that BI reports that businesspeople request cannot be used in decision making because of the rapid changes in data and market conditions. This obstacle is very influential in decision making at the operational level. Companies must be aware of these obstacles and take steps such as increasing the responsiveness and ability of employees in this field to change. In addition, the company can also make quick updates related to data that is needed in decision making.

In the technology category, companies need to pay attention to the quality of data that will be used in decision making. The company can regulate and supervise the operational data process so that the data being used for BI needs can be of higher quality. According to Scannapieco (2006) [53], the process of improving data quality can be done in several ways, namely by establishing steering committees for data quality, setting rules and responsibilities in data input, choosing the right tools, and establishing data standardization. Companies also need to do some training, set up schedules for data cleansing on a large scale, prioritize data, and make in-house programs if they need to.

From the results of this research, it is known that the most effective strategy based on this research is to involve businesspeople in the BI project. The company should encourage businesspeople to always be involved in every BI project and encourage them to do so they can increase the chances of successful BI project implementation in the company. Good cooperation between the two departments can also be encouraged by the heads of each department. Leaders in each department need to have good leadership skills so that they can motivate employees to work together between the two departments. According to the results of the Nidhra et al. [52] study, the success of the BI project will be very dependent on how well the leaders of the company are doing.

This research has succeeded in formulating major obstacles for the BI project and strategies to overcome them. For academic implications, this research also succeeded in finding new obstacles that did not exist in previous research. However, this research has a limitation in that it has not followed up on the strategy that was given to the company. For future research, it would be interesting to systematically evaluate the BI implementation's success by seeing the report output, cooperation, and support of the project [54]. Future research can also examine BI's success by involving moderating factors both at the individual level (such as age, gender, and position in the organization) as well as moderation within the company (such as size of the company, organizational culture).

6- Conclusions

This study aims to determine the priority of obstacles and the right strategy to overcome these obstacles in the development of BI projects using fuzzy AHP TOPSIS. In addition, it also analyzes the priorities of obstacles and strategies that influence the development of the BI project. The conclusions from this study are:

- Based on the literature study, the author obtained the following obstacles and strategies: 17 obstacles and 7 strategies. Through the interview process and expert validation, there are 3 additional obstacles and 2 strategies. After being revalidated by the experts, 19 obstacles and 9 strategies were used in this research.
- After that, the application of fuzzy AHP TOPSIS is carried out. Fuzzy AHP is used to find barrier weights, which will then be used as input from fuzzy TOPSIS. From the results of fuzzy AHP TOPSIS, each category and strategy's ranking were obtained. The most influential barrier in the business/process category is BI projects that require a short period of time to be completed, so companies must take steps such as increasing the responsiveness and ability of employees in this field to minimize project failure. While the best strategy to implement is that the company must involve businesspeople in every BI project.

This study also found new factors that cause the failure of the BI project, such as: BI implementation that demands to be done quickly, difficult to get data access, and lack of adequate infrastructure. These factors were obtained from the interviews and agreed upon by all the experts. This study was done in Indonesia, and the factors from the interview have not yet been confirmed as to whether they only appear in developing countries or whether they can arise in developed countries. Research that uses two countries with different characteristics will be an interesting topic for future work.

7- Declarations

7-1- Author Contributions

Conceptualization, R.A., A.N.H., and I.C.H.; methodology, R.A., A.N.H., and I.C.H.; software, R.A., I.C.H. and A.N.H.; validation, R.A., I.C.H., and A.N.H.; resources, R.A., I.C.H., A.N.H., N.F.A.B., and K.P.; data curation, R.A. and A.N.H.; writing—original draft preparation, R.A., I.C.H., and A.N.H.; writing—review and editing, I.C.H; visualization, I.C.H. and R.A.; supervision, A.N.H. and K.P.; project administration, I.C.H., and N.F.A.B.; funding acquisition, A.N.H., and I.C.H. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

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7-5- Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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