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Comparative study of AHP and Fuzzy AHP Decision-Making Methods in the Selection of Low-Code Platforms in Automotive Startup Company

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Abstract: During the "Tech Winter" that struck the tech industry in late 2022, startups faced significant budget cuts, necessitating high efficiency in software development. Automotive Startup Company serves as an exemplar, adopting a strategic approach to address this situation by integrating Low-Code Platforms (LCP) into their product development operations. This study aims to assess the effectiveness of various LCPs to find the most suitable platform for the company's specific needs. Employing the Analytic Hierarchy Process (AHP) and Fuzzy AHP methods, this research evaluates LCP alternatives based on the Low-Code Platform Attractiveness Measurement Model (LCPAMM) across five main criteria: Usability, Functional Suitability, Control, Maintainability, and Perceived Cost, gathering input from 18 experts consisted of software developers and management in IT department of Automotive Startup Company. The results reveal that OutSystems, scoring 0.478 in AHP and 0.475 in Fuzzy AHP, performs best across all criteria, followed by Mendix and Microsoft Power Apps. Furthermore, Fuzzy AHP proved advantageous in managing the ambiguities and uncertainties often present in subjective assessments. From this analysis, the study concludes that the utilization of LCPs can be a solution to enhance development efficiency and reduce operational costs. Moreover, the proper use of LCPs can potentially offer an alternative solution in the face of workforce reductions, allowing companies to remain competitive in a dynamic market.

Keywords: *Analytic Hierarchy Process, Fuzzy, Low-Code Platform, Multi-criteria decision-making, Startup*

1. Introduction

In the late 2022, there's a surge of laying off done by startup technology companies in Indonesia. This lay off affects the company ability in software developments, especially in internal affairs, since the number of professional developers laid off is significant. There are several solutions proposed to address this lack of manpower in this specific area, and of them is implementing Low-Code Platform (LCP).

In nations such as Indonesia, renowned for its thriving startup ecosystem, the tactile presence of the wave can be observed. Organizations, whether in their early stage or well-established, are actively studying Low-Code Platforms (LCP) as a means to foster innovation, enhance cost-efficiency, and maintain flexibility in a dynamic market environment. Nevertheless, the selection of a particular low-code platform is a complex process that is influenced by a multitude of criteria, encompassing aspects such as usability, suitability of features, cost, and maintainability.

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This research study aims to conduct a thorough investigation of the decision support to select low-code platform for specific automotive startup company, by incorporating well-established frameworks like the Low-Code Platform Attractiveness Measurement Model (LCPAMM)[1] and utilizing robust decision-making tools like the Analytic Hierarchy Process (AHP) and its' Fuzzy variant.

1.1. Low Code Platform (LCP)

An LCP refers to a platform utilized for the rapid development and deployment of customized applications. This is achieved by augmenting development abstraction and reducing—or perhaps eliminating—the coding process involved in application development[2].

In general, LCP are equipped with several tools that facilitate the management of application operations. These tools can be implemented using either straightforward scripting language or visual dialogues. The majority of frequently used actions can be found within function libraries, which can further enhance their functionality by integrating with external services through the utilization of Application Programming Interfaces (APIs). In the context of application deployment, it is important to note that various Low-Code Platform (LCP) employ distinct methodologies. However, it is universally acknowledged that all LCPs facilitate the deployment of applications to enable user accessibility. All apps naturally possess the capability to implement role-based settings and access restrictions, which govern the permissions granted to users when using the program [3].

The Utilization of LCP can lead to increased productivity by minimizing the need for doing common tasks of moderate complexity, such as Graphical User Interface (GUI) design, object relation mapping, model-view-controller (MVC) implementation, and deployment across several environments.

One potential drawback associated with the utilization of Low Code is the reliance on the service provider of the Low Code Platform (LCP). The application's potential for becoming unmaintainable may arise from its dependence on a service provider that discontinues its operations [3].

The low-code approach possesses inherent constraints, rendering it more appropriate for the development of non-complex programs that are specifically required by a single department within an organization. One of the applications of low code technology that involves citizen developers is the creation of data collection forms.

1.2. Citizen Developer

A citizen developer refers to a user at the business level who possesses the ability to design apps to facilitate their business operations, even without substantial expertise in programming and coding. This is made possible by utilizing Low Code or No Code Platform. The emergence of low code and no code platforms has given rise to the concept of a citizen developer. Individuals have the ability to develop and execute applications to facilitate their business or organization, even in the absence of a technical foundation in programming. This approach facilitates the empowerment of end-users and mitigates reliance on IT teams or professional developers. By utilizing low code or no code platform, individuals without formal programming backgrounds, known as citizen developers, are empowered to create basic business solutions or apps tailored to their own or their organization's requirements [4].

Nevertheless, it is important to guarantee the security, reliability, and manageability of the applications developed using low code and no code platforms, despite the fact that these platforms empower individuals without formal programming backgrounds. The significance of skilled developers remains crucial in sophisticated or important applications. However, the inclusion of citizen developers within organizations can effectively expedite the process of innovation and enable timely adaptation to evolving business requirements. Therefore, the inclusion of citizen developers and the utilization of low code or no code platforms can play a crucial role in an organization's plan for digital transformation.

2. Model and Methods

2.1. Low Code Platform Attractiveness Measurement Model (LCPAMM)

The Low Code Platform Attractiveness Measurement Model (LCPAMM) is a theoretical framework that exerts influence on the level of attractiveness of Low-Code Platforms (LCPs).

The concept of Low Code Platform Attractiveness (LCPA) refers to the perception among citizen developers that there is alignment between the offerings of a Low-Code Platform (LCP) and the requirements of end-users. The Low Code Platform Attractiveness (LCPA) is impacted by several key factors, including usability, functional appropriateness, maintainability, perceived cost affordability, and control[1].

The LCPAMM comprises a total of 5 criteria and 20 sub-criteria. In this research, we will use the 5 criteria defined in this model:

1. Usability (U)
2. Functional Suitability (FS)
3. Control (C)
4. Maintainability (M)
5. Perceived Cost Affordability (Co)

2.2. Analytic Hierarchy Process

The Analytical Hierarchy Process (AHP) enables decision-makers to effectively organize attributes in the context of multi-attribute situations. However, previous research has indicated that the Analytical Hierarchy Process (AHP) is limited in its ability to effectively address ambiguity and uncertainty during the comparison phase. Several implementations of Fuzzy Analytic Hierarchy Process (AHP) were created based on the aforementioned information[5].

There are three level of hierarchy in AHP: (1) The goal, which is the top-most of the hierarchy, (2) Criteria, which are listed under the goals. These criteria can have sub-criteria if needed, (3) alternatives, which is the option that need to be measured with respect to the criteria.

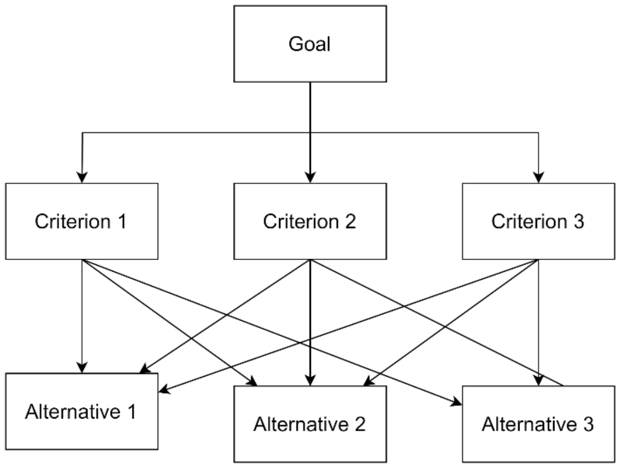

Fig 1. An example of hierarchy in AHP

Initially, the criteria to be evaluated are determined. For our study, these criteria are represented as $(C_1, C_2, \dots, C_5)$. And alternatives, which represented as (A_1, A_2, A_3).

Then, pairwise matrices are established to capture the relative importance of one criterion over another, and of one alternative over another with respect to a criterion. The matrix—denoted as C—has dimension of $(n \times n)$, where (n) signifies the amount of criterion. Each element, (C_{ij}), represents the relative importance of criteria (i) over (j).

From this pairwise matrix, the weight of each criterion is calculated through normalization process. We do this by calculate the sum of values within column (i) and then divide each element of C_{ij} with the summed value. The matrix with new value—denoted as X—will then get each of their row (j) average computed. The result is the weight of the criterion (W).

$$C_{ij} = \sum_{i=1}^{n} C_{ij} \tag{1}$$

$$X_{ij} = \frac{C_{ij}}{\sum_{i-1}^{n} C_{ij}} \tag{2}$$

$$W_{ij} = \frac{\sum_{j=1}^{n} X_{ij}}{n} \tag{3}$$

From the weight result, The Consistency Ratio of the matrix can be computed. First, calculate the Consistency Vector (Cv) from the (W).

$$\begin{bmatrix} Cv_{11} \\ Cv_{21} \\ Cv_{31} \end{bmatrix} = \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix} \times \begin{bmatrix} W_{11} \\ W_{21} \\ W_{31} \end{bmatrix}$$

$$Cv_{ij} = \frac{1}{W_{ij}} \times [C_{ij}W_{11} + C_{ij}W_{21} + C_{ij}W_{31}] \tag{4}$$

Then the eigenvalue (λ) can be computed by calculating the average from the (Cv).

$$\lambda = \sum_{i=1}^{n} Cv_{ij} \tag{5}$$

Finding (λ) enable the calculation of Consistency Index (CI), which expressed as

$$CI = \frac{\lambda - n}{n-1} \tag{6}$$

Based on CI, we are finally computing the Consistency Ratio (CR), which expressed as

$$CR = \frac{CI}{RI} \tag{7}$$

The *RI* is Random Inconsistency Indices, which value can be found at Saaty work on AHP[5], [6]. The detail can be found at Table 1.

Table 1. Random Inconsistency Indices (RI) for *n* 1–10

N	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

2.3. Fuzzy Analytic Hierarchy Process (F-AHP)

The problem-solving in this research is done by breaking the problem into smaller, more comprehensible parts. The primary objective of the research is clearly visible and is divided into criteria that need to be achieved. Goal alternatives are hierarchical structured, making them easy to understand and facilitating decision-making. The hierarchical structure of this research is shown below:

Fuzzy AHP is used in this research to determine the priority weights of each variable and sub-variable, or in this case, each criterion and sub-criteria. It will consider the subjective opinions of respondents using a fuzzy scale, which considers the possibility of a value lying between two distinct values[7].

In the process of multi-criteria decision-making, the Fuzzy Analytical Hierarchy Process (Fuzzy AHP) provides a robust framework, allowing for the incorporation of subjective and imprecise information through the use of Triangular Fuzzy Numbers (TFNs) [7].

The process of Fuzzy AHP in the establishment of matrix is not different than AHP. The key difference is what value is stored within the matrix. In AHP, we represent the relative importance of criteria (i) over (j) using single number within the scale that we choose. Whereas in Fuzzy AHP, we are using a TFN, denoted as $(\left(l_{ij}, m_{ij}, u_{ij}\right))$.

From this pairwise comparison matrix, the fuzzy geometric mean for each criterion is computed. For a given criterion (i), the geometric mean is expressed as:

$$[GM_i = \left(\sqrt[n]{\prod_{j=1}^{n} l_{ij}}, \sqrt[n]{\prod_{j=1}^{n} m_{ij}}, \sqrt[n]{\prod_{j=1}^{n} u_{ij}}\right)] \tag{8}$$

Subsequently, the fuzzy weights, (W_i), for each criterion are derived from the geometric means [8]. The weight of criterion (i) is calculated as:

$$[W_i = \left(\frac{GM_{i_l}}{\sum_{j=1}^{n} GM_{j_l}}, \frac{GM_{i_m}}{\sum_{j=1}^{n} GM_{j_m}}, \frac{GM_{i_u}}{\sum_{j=1}^{n} GM_{j_u}}\right)] \quad (9)$$

To further refine the results, first we calculate averaged weights, (M_i), and then normalized weights, (N_i). The averaged weight (M_i) for each criterion is calculated by:

$$[M_i = \frac{l_i + m_i + u_i}{3}] \quad (10)$$

While the normalized weights (N_i) are derived as:

$$[N_i = \frac{M_i}{\sum_{j=1}^{n} M_j}] \quad (11)$$

As a concluding step, the Consistency Ratio (CR) can be utilized to assess the reliability of the pairwise comparison matrix. An acceptable threshold for CR, typically set at 0.1, ensures that the provided judgments are consistent [9].

3. Application in Decision Support in Automotive Startup Company

3.1. Hierarchical Structure

The Fuzzy Analytical Hierarchy is implemented into the automotive startup company that sells and leases cars both used and new by connecting several stakeholders together, such as seller, buyer, agent, inspector, and financing agents. In order to keep the business confidential, the name of the company is preserved.

In this research, there are 5 criteria and 3 alternatives:

1. Criteria

a. Usability (U)

b. Functional Suitability (FS)

c. Control (C)

d. Maintainability (M)

e. Perceived Cost Affordability (Co)

2. Alternatives

   a. Outsystem (A1)

   b. Mendix (A2)

   c. Microsoft Power Apps (A3)

The hierarchical structure of criteria and alternatives above compared to the goal is presented in Fig 2.

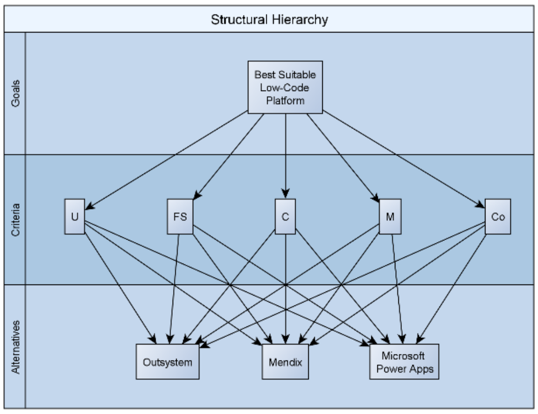

Fig 2. Structural Hierarchy and alternatives

4. Data Collection

4.1. Respondent's Profile

The questionnaire was completed by 18 experts and all are belonging to the various technology department employees of automotive startup company. The result was 18 matrices of pairwise criteria comparison and 18 sets of pairwise alternative comparison with respect to criteria matrices.

4.2. Scaling

The scale used in this implantation for both AHP is the 9-level scaling taken from The Fundamental Scale of Absolute Numbers by Saaty[5], [6]. The detail of this scale is shown in Table 3.

Table 3. Importance Scale for AHP

Saaty Scale	Definition
1	Equally Important
3	Weakly Important
5	Fairly Important
7	Strongly Important
9	Absolutely Important
2 4 6 8	Value between important scale.

The scale used in Fuzzy AHP implementation is similar to the one used in AHP implementation; however, each scale is converted into Triangular Fuzzy Number (TFN). This also hold true to the data collected, thus converting respondents' responses to TFN to follow the scale.

Table 4. Triangular Fuzzy Number conversion of Saaty Scale[10].

Saaty Scale	Definition	Fuzzy Triangular
1	Equally Important	(1, 1, 1)
3	Weakly Important	(2, 3, 4)
5	Fairly Important	(4, 5, 6)
7	Strongly Important	(6, 7, 8)
9	Absolutely Important	(9, 9, 9)
2	Value between important scale.	(1, 2, 3)
4		(3, 4, 5)
6		(5, 6, 7)
8		(7, 8, 9)

4.3. Pairwise Comparison Table

The pairwise comparison table created for criteria and for alternatives with respect to criteria. There is total of 6 pairwise comparison matrix for each of 18 respondents. The example of this table is shown at Table 5.

The result of pairwise comparison table is then converted to matrix. The matrix of AHP consists of one value for each criterion comparison, while Fuzzy AHP matrix consists of three triangular values for each criterion comparison. Table 6 is the example of criteria comparison matrix and table 7 is the example of alternative comparison matrix with respect to criteria U.

Table 6. The example of criteria pairwise comparison matrix.

	U	FS	C	M	CO
U	1				
FS		1			
C			1		
M				1	
CO					1

Table 7. The example of alternative pairwise comparison matrix

	A1	A2	A3
A1	1		
A2		1	
A3			1

5. AHP Implementation

5.1. Criteria Weight Calculation

The consolidated result of AHP implementation on criteria pairwise comparison is shown in table 6. Based on the result, each criterion's weight is calculated.

Table 5. The example of Pairwise Comparison Table of Criteria

Criterion A	A. Imp. (9,9,9)	S. Imp. (6,7,8)	F. Imp. (4,5,6)	W. Imp. (2,3,4)	Eq. Imp. (1,1,1)	W. Imp. (2,3,4)	F. Imp. (4,5,6)	S. Imp. (6,7,8)	A. Imp. (9,9,9)	Criterion B
Usability										Feature Suitability
Usability										Control
Usability										Maintainability
Usability										Cost
Feature Suitability										Control
Feature Suitability										Maintainability
Feature Suitability										Cost
Control										Maintainability
Control										Cost
Maintainability										Cost

Table 8. Matrix *C* of the consolidated criteria pairwise comparison

C	U	FS	C	M	CO
U	1.000	0.646	1.827	0.787	0.618
FS	1.549	1.000	1.415	1.088	2.058
C	0.547	0.707	1.000	0.289	1.187
M	1.271	0.919	3.460	1.000	1.169
CO	1.617	0.486	0.843	0.855	1.000
∑	5.984	3.757	8.544	4.020	6.032

Based on table 8, the result is then calculated into *X* matrix. From matrix *C* and *X*, we can calculate the eigenvector and normalize them to get the Weight (*W*). Using (1), (2) and (3), we got the result at table 9.

Table 9. Matrix *X* and the calculation (5) and (6) result *(W)*.

X	U	FS	C	M	CO	Total	W
U	0.167	0.172	0.214	0.196	0.103	0.851	**0.170**
FS	0.259	0.266	0.166	0.271	0.341	1.302	**0.260**
C	0.091	0.188	0.117	0.072	0.197	0.665	**0.133**
M	0.212	0.245	0.405	0.249	0.194	1.304	**0.261**
CO	0.270	0.129	0.099	0.213	0.166	0.877	**0.175**

Equation (4) through (7) can be used to determine the consistency of the matrix. This to ensure that the matrix is usable and consistent so the result are matters.

This case study using RI = 1.12. And the result of (8) is 0.07. Thus, using (9), the result of CR is determined to be 0.0662695, which is < 0.1. Thus, the consistency of the matrix is determined, and the result from AHP processing can be accepted.

Then we can rank the priority of each criterion based on *W*. From table 9 we got that M (Maintainability) rank first. Followed by FS (Functional Suitability), and then Co (Perceived Cost Affordability), U (Usability), and the last rank is C (Control).

5.2. Alternative Weight Calculation and Final Ranking

All the matrices of alternative pairwise comparison with respect to criteria also have their weight calculated using (2) and (3). After that, it is calculated again with respect to criteria's weight. The result of this calculation is shown at table 10.

Table 10. Result of AHP implementation

Criteria	*W*	A1	A2	A3
U	0.170	0.480	0.271	0.249
FS	0.260	0.484	0.307	0.209
C	0.133	0.493	0.209	0.298
M	0.261	0.466	0.288	0.246
Co	0.175	0.474	0.210	0.316
Final Score		**0.478**	**0.266**	**0.256**
Alternative Rank		**1**	**2**	**3**

The result is different to the scoring calculation, where A1 (Outsystems) is the first, rather than third. Meanwhile A3 (Microsoft Power Apps) is the third rank, instead of first. A2 is still in the same place, which is second place.

6. Fuzzy AHP Implementation

6.1. Criteria Weight Calculation

The consolidated result of Fuzzy AHP implementation on criteria pairwise comparison is shown in table 11. Based on the result, we can use (8) to get the *GM* of each criterion.

Table 11. Matrix consolidation *C* of criteria pairwise comparison

C	U	FS	C	M	CO
U	(1.000, 1.000, 1.000)	(0.553, 0.646, 0.755)	(1.524, 1.791, 2.078)	(0.645, 0.757, 0.885)	(0.543, 0.618, 0.711)
FS	(1.324, 1.549, 1.810)	(1.000, 1.000, 1.000)	(1.176, 1.415, 1.663)	(0.902, 1.047, 1.210)	(1.761, 2.058, 2.379)
C	(0.481, 0.558, 0.656)	(0.601, 0.707, 0.850)	(1.000, 1.000, 1.000)	(0.249, 0.289, 0.335)	(1.28, 1.484, 1.708)
M	(1.129, 1.321, 1.55)	(0.827, 0.955, 1.108)	(2.986, 3.460, 4.016)	(1.000, 1.000, 1.000)	(1.018, 1.169, 1.334)
CO	(1.407, 1.617, 1.841)	(0.42, 0.486, 0.568)	(0.585, 0.674, 0.781)	(0.75, 0.855, 0.982)	(1.000, 1.000, 1.000)

Then we calculate the geometric means of the matrix *C* on table 11 using (10). The result is table GM_i as shown in table 12. This table has TFN value, instead of single value like eigenvector of AHP.

Table 12. Geometric Mean of Matrix *C.*

CRI		GM_i	
U	0.783	0.885	0.998
FS	1.048	1.187	1.347
C	0.598	0.695	0.812
M	1.232	1.385	1.559
CO	0.764	0.853	0.957

GM_i then calculated into fuzzy weight (W_i) using (9). The result of this weight calculation is presented in table 13.

Table 13. Fuzzy Weight (W_i) of Criteria

CRI		W_i	
U	0.138	0.177	0.225
FS	0.184	0.237	0.304
C	0.105	0.139	0.184
M	0.217	0.277	0.352
CO	0.134	0.171	0.216

These fuzzy weights are still on triangular value. We need to normalize them so that they are in singular value that we can rank. For this process we calculate the average (M_i) using (10) and then normalize them to get N_i using (11).

Table 14. Average (M_i) and normalized weight (N_i) of criteria

CRI	M_i	N_i	Rangking
U	0.180	**0.176**	**3**
FS	0.242	**0.237**	**2**
C	0.143	**0.140**	**5**
M	0.282	**0.276**	**1**
CO	0.174	**0.170**	**4**
TOTAL	1.021		

Table 14 shown that in Fuzzy AHP, the first rank is M (Maintainability), followed by FS (Functional Suitability) at rank 2, then U (Usability) at rank 3. Co (Cost) and Control (C) are at rank 4 and rank 5 respectively.

6.2. Alternative Weight Calculation and Final Ranking

We do the same for every alternative matrix with respect to criteria. The example of alternative Weight calculation for criteria FS (Functional Suitability) is shown at table 15.

Table 15. Alternative FS (Functional Suitability) Weight calculation

ALT		GM_i			W_i		M_i	N_i
A1	1.414	1.545	1.676	0.406	0.485	0.577	0.489	**0.484**
A2	0.888	0.975	1.078	0.255	0.306	0.371	0.311	**0.307**
A3	0.604	0.664	0.729	0.173	0.208	0.251	0.211	**0.209**

The final result of Fuzzy AHP, based on Table 12 and N_i of all alternative comparison pairwise matrices are then combined to get the alternative priority with respect to all criteria. The result is shown at table 16.

Table 16. Result of alternative priority with respect to all criteria.

Criteria	W	A1	A2	A3
U	0.176	0.466	0.283	0.251
FS	0.237	0.484	0.307	0.209
C	0.140	0.492	0.213	0.294
M	0.276	0.464	0.289	0.247
Co	0.170	0.477	0.229	0.294
Final Score		**0.475**	**0.272**	**0.253**
Alternative Rank		**1**	**2**	**3**

The result of Fuzzy-AHP is that the A1 get the first rank with 0.475. A2 get the second place with 0.272 and A3 is at last priority rank with 0.253.

7. Comparison Between Methods

At Table 17, the result from all methods (Scoring, AHP, and Fuzzy AHP) are merged into one table for comparison.

Table 17. Comparison of results between methods

Low-Code Platform	Scoring	AHP		Fuzzy-AHP	
	Rank	Weight	Rank	Weight	Rank
A1	3	0.478	1	0.475	1
A2	2	0.266	2	0.272	2
A3	1	0.256	3	0.253	3

Based on comparison at Table 17, we found that the rank is different when AHP and Fuzzy-AHP is implemented compared to Scoring method that is previously used at the company. Using scoring, the result goes to A3, while only have 3 criteria: Feature, maintainability, and cost.

After implementing LCPAMM as criteria and count the result using AHP and Fuzzy-AHP—thus, including other criteria to the process—the rank flipped. In AHP and Fuzzy-AHP, the rank is the same. However, the weight value is different. Alternatives A1 and A3 has higher weight value in AHP, while A2 has higher value in Fuzzy-AHP.

To get into this, we can see the comparison of criteria weight priority result of AHP and Fuzzy AHP on table 18.

Table 18. Comparison of criteria weight priority of AHP and Fuzzy-AHP

Criteria	AHP		Fuzzy-AHP	
	Weight	*Rank*	*Weight*	*Rank*
U	0.170	4	0.171	4
FS	0.260	2	0.259	2
C	0.133	5	0.132	5
M	0.261	1	0.264	1
Co	0.175	3	0.174	3

As shown at table 18, the rank between the two methods is the same. However, the Weight value is different. For example, the difference in weight between M (Maintainability) and FS (Functional Suitability) in AHP is very close with only 0.001 difference. This is not the case in Fuzzy AHP where the difference is 0.005. This could mean that Fuzzy AHP has more precise result so that the difference between ranks is shown clearly.

8. Conclusion

In this case study, we found that the result of AHP and Fuzzy-AHP is the same rank-wise, but has different in weight for each criterion and alternative with respect to criteria. A1 (Outsystems) is the first rank on both AHP and Fuzzy-AHP, thus, it is the first priority to reach the goal of "Best Suitable Low-Code Platform" to be implemented on Automotive Startup Company.

The calculation result will be different if the dataset is changed. Thus, this method is suitable to be used by other company with similar needs, since the respondents or experts of the company might have different needs compared to Automotive Startup Company.

The result is different from previous method used at the company to select vendor or tools (scoring method), which with the method, A3 (Microsoft Power Apps) is selected, whereas in AHP and Fuzzy-AHP, A3 is the lowest priority for the goal of the hierarchy. Since the previous method lacks criteria and might suffer from bias at assessment, we can say that the result of AHP and Fuzzy AHP in this case study is an enhancement of previous scoring method's result and therefore it is recommended to implement the result based on the ranks of this study.

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