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Aircraft Acquisition Post-Pandemic: Human vs. AI Perspectives using Multi-Criteria Decision Methods

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ABSTRACT

In the post-pandemic era, Indonesia's commercial airlines are under increasing pressure to expand their fleets in response to a sharp rebound in passenger demand. While traditional aircraft acquisition decisions have relied heavily on expert judgment, recent advancements in artificial intelligence (AI) and decision support systems have introduced new possibilities for enhancing strategic evaluations. This study contributes to the growing body of research on AI-assisted decision-making by comparing human expert assessments with AI-generated recommendations in selecting new aircraft. Using a hybrid multi-criteria decision-making (MCDM) framework that integrates the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), we assess eight aircraft models across six key criteria: aircraft price, seating capacity, maximum take-off weight (MTOW), cargo capacity, range, and cost per available seat mile (CASM). Our findings reveal subtle differences in how humans and AI assign weights to each criterion. However, a Mann-Whitney U test ($p = 0.689$) confirms that these differences are not statistically significant. Notably, both approaches converge on the same optimal choice—the A321neo—highlighting the potential of AI to augment, rather than replace, human decision-making in complex procurement scenarios.

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1. INTRODUCTION

Aviation is one of many industries affected by the COVID-19 pandemic. This has been caused by regulations restricting air travel and public concerns about the possibility of contracting the COVID-19 virus while traveling by air. This has resulted in a decrease in the number of passengers, which has impacted the number of operating aircraft and the financial performance of airlines. Airlines must adjust their operations to maintain their financial performance and avoid deterioration [1].

The demand for air travel has increased significantly as the COVID-19 pandemic ends, with many regulations regarding air travel restrictions lifted. Due to the substantial reduction in aircraft operations in Indonesia compared to before the pandemic, airplane ticket prices have skyrocketed. To stabilize ticket prices and meet the demand for air travel, airlines, including low-cost carriers, need to expand their fleet size by acquiring additional aircraft [2], [3].

Determining the appropriate aircraft type for airline procurement is a complex process that must be divided into several steps. The first step is defining the criteria for selecting the correct aircraft type. Previous research by Ardil (2020) on the aircraft selection process identified criteria such as aircraft price, fuel efficiency per seat, range, number of seats, luggage volume, and Maximum Take-off Weight (MTOW) for selecting the right aircraft type [4]. Other research by Dožić et al. (2018) considers criteria including seat capacity, MTOW, range, purchasing cost, maintenance cost, cost per available seat mile (CASM), delivery time, payment conditions, fleet commonality, and comfort to determine the correct type of aircraft [5]. Additionally, research conducted by Kiraci & Bakir (2018) on the aircraft selection process applies criteria such as range, price, speed, seating capacity, fuel consumption, maximum payload, and the amount of greenhouse gas released to determine the correct aircraft type [6]. From these various studies, different conclusions emerge regarding the appropriate aircraft type for an airline due to differences in objectives, methodologies, criteria used, and available aircraft options.

The weight of each criterion will significantly influence the decision when determining the correct aircraft type. Therefore, assigning weight to each criterion is critical in selecting the appropriate aircraft type. One common method for determining the weight of each criterion is the analytical hierarchy process, in which the chosen expert completes the pairwise comparison questionnaire for each criterion [7], [8].

However, this method also has a limitation: the judgment made by a human expert is subjective, which may lead to bias if the expert has other interests [9]. With the current technology, humans can involve artificial intelligence in decision-making, such as multi-criteria decision-making. Artificial intelligence can be utilized to determine the weight of criteria and processes conducted in previous research by Svoboda & Lande (2024) [10]. Few studies have utilized this approach in the available literature on the use of artificial intelligence in decision-making. Research conducted by Dehghanimohammadabadi & Kabadayı (2024) uses artificial intelligence with the AHP framework to make a decision for supplier selection that uses three criteria and fifteen sub-criteria [11]. Other research conducted by H. Wang et al. (2025) uses artificial intelligence in a hybrid MCDM framework to assess the problem regarding supplier evaluation [12]. Furthermore, no prior research compares the results of human experts and artificial intelligence in decision-making processes, particularly in multi-criteria decision-making. Therefore, this research aims to fill this gap by comparing the results of human experts and artificial intelligence in selecting the appropriate type of aircraft.

2. METHODS

2.1 Definition of Methods

This research examines how human experts and artificial intelligence differ in selecting an aircraft by utilizing the AHP and TOPSIS methods, along with statistical tests to identify any statistically significant differences. The AHP method determines the weight of each criterion assessed by both human experts and artificial intelligence. The TOPSIS method identifies the most suitable type of aircraft based on those weights. Finally, the study compares the rankings produced by human experts and artificial intelligence after applying TOPSIS.

2.2 Data Collection

The first step is determining the criteria for selecting the appropriate aircraft type, specifically low-cost carrier aircraft operating in Indonesia. To achieve this, a literature review of the aircraft selection process from 2014 to 2024 is conducted, as shown in Table 1, and an interview is conducted with a human expert. The hierarchical structure of this research is illustrated in Figure 1, featuring six criteria and eight alternative types of aircraft. The next step involves five human experts filling out a pairwise comparison questionnaire for each criterion, with the qualifications for each human expert shown in Table 2. The same questionnaire is also administered to artificial intelligence (ChatGPT model o1) by transforming it into a prompt. Eight prompt combinations and two types of memory (with and without memory) are used to generate pairwise comparisons for each criterion:

1. zero shot + chain of thought
2. zero shot + tree of thought
3. one shot + chain of thought
4. one shot + tree of thought
5. zero shot + chain of thought + role-based
6. zero shot + tree of thought + role-based
7. one shot + chain of thought + role-based
8. one shot + tree of thought + role-based

This combination of prompting techniques follows H. Wang et al. (2025) research, which utilizes a mix of prompting methods, including zero-shot, one-shot, and chain of thought.

Besides the results of the questionnaire, the technical and economic data of the criteria for each type of aircraft are also gathered to rank of aircraft types using TOPSIS methods, which is shown in Table 3 [23], [24], [25].

Table 1. Literature review for aircraft selection process research paper 2014-2024

Authors	Criteria	Alternative	Methods Used
Dožić & Kalić (2014) [13]	Seat capacity, Price, Baggage capacity, MTOW, Payment conditions, CASM	ERJ 190, CRJ 700, CRJ 900, CRJ 1000, ATR 72–500, ATR 72–600, Q 400 NG	AHP
Dožić & Kalić (2015) [14]	Seat capacity, Price, MTOW, Baggage per passenger, CASM	ATR 72-500, ATR 72-600, E 190, Q400, CRJ 700, CRJ 900, CRJ 1000, A319, A320, A321, A319neo, A320neo, A321neo, B737-700, B737-800, B737-900ER	ESM, Regression, Fuzzy logic
Bruno et al. (2015) [15]	CASM, Aircraft price, Speed, Autonomy, Seat comfort, Cabin luggage compartment size, Environmental pollution, Noise	Bombardier CRJ1000, Sukhoi SSJ100, Embraer ERJ190	AHP, Fuzzy Set Theory
Dožić et al. (2018) [16]	Seat capacity, MTOW, Range, Purchasing costs, Maintenance costs, CASM, Delivery time, Payment conditions, Fleet commonality, Comfort	ATR72-500, ATR72-600, ERJ 190, Q400 NG, CRJ 700, CRJ 900, CRJ 1000	Fuzzy AHP
Kiraci & Bakir (2018) [6]	Range, Price, Speed, Seating capacity, Fuel consumption, Maximum payload	A320, A321, B737–800, B737-900 ER	AHP, CORPRAS, MOORA
Dožić & Kalić (2018) [5]	Seat Capacity, Price, Baggage capacity, MTOW, Payment conditions, CASM	ERJ 190, CRJ 700, CRJ 900, CRJ 1000, ATR 72–500, ATR 72–600, Q 400 NG	AHP, FAHP, Even Swaps method
Ilgin (2019) [17]	Price, Fuel consumption, Range, Number of seats, Luggage volume	A319 neo, A320 neo, A321 neo, B737 max 7, B737 max 8, B737 max 9	Linear Physical Programming-LPP, TOPSIS
Ardil (2019)[18]	Price of aircraft, Fuel efficiency per seat, Aircraft range, Aircraft seat capacity, MTOW, Maximum payload	A320neo, A321neo, B737 max 8, B737 max 9	Multiple Criteria Utility Theory, Maximal Regret Minimization Theory
Kiracı & Akan (2020) [19]	Range, Fuel consumption per seat mile, Speed, Useful life of the aircraft, Landing and take-Off distance, MTOW, Aircraft seat capacity, Maintenance cost, Salvage cost, Operating cost, Price of aircraft, Pollution, Noise	A320neo, A321neo, B737 max 8, B737 max 9	IT2FAHP, IT2FTOPSIS
Ardil (2020) [4]	Aircraft price, Aircraft fuel consumption, Aircraft fuel efficiency per seat, Aircraft range, Aircraft number of seats, Aircraft luggage volume, MTOW	A319neo, A320neo, A321neo, B737 max 7, B737 max 8, B 737 max 9	PARIS, TOPSIS
Ardil (2022) [20]	Price, Fuel consumption, Range, Number of seats, Luggage Volume, MTOW	A319neo, A320neo, A321neo, B737 max 7, B737 max 8, B 737 max 9	Entropic Weight Method, Preference Optimization Programming, TOPSIS
Ardil (2023) [21]	Flight range, Number of seats, MTOW, Luggage volume, Fuel consumption, Purchase cost	A319neo, A320neo, A321neo, B737 max 7, B737 max 8, B 737 max 9	Reference Linear Combination (RLC)
Bağcı & Kartal (2024) [22]	Purchase cost, Fuel capacity, Maximum seat capacity, Range, MTOW, Cargo capacity	A319neo, A320neo, A321neo, B737 max 7, B737 max 8, B737 max 9	SWARA, COPRAS

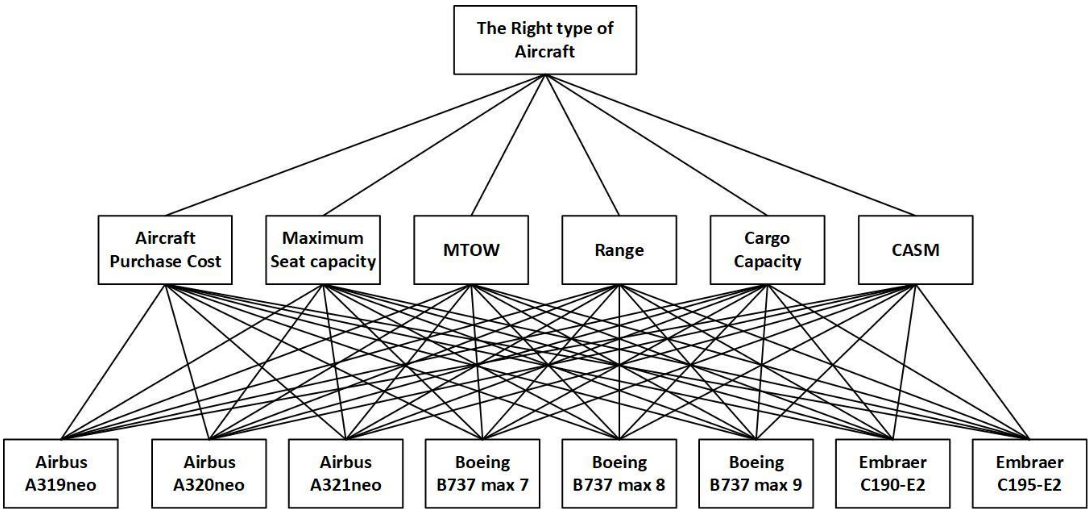

Figure 1. Aircraft selection process hierarchy structure

Table 2. Detail Qualification of Human Expert

Human expert	Role	Education	Work Experience
Human expert 1	Vice president of engineering services in MRO	Bachelor's degree in mechanical engineering	31 Years in aircraft engineering
Human expert 2	Vice president of business support in airline	Master's degree in industrial engineering	14 years (9 years in airline procurement and supply chain)
Human expert 3	Aviation consultant (previously CEO of engineering in airline)	Master's degree on Airline management	30 years (15 years in airline operation)
Human expert 4	Manager of Airworthiness in MRO	Doctoral degree in aerospace engineering	15 years (10 years in aircraft engineering)
Human expert 5	Aviation consultant (previously CEO of aircraft manufacturer)	Master's degree in management	42 years (25 years in aircraft manufacturer)

Table 3. Multi-response value for each criterion for all alternative aircraft types

Alternative	Criterion					
Aircraft	Purchase cost (million $)	Maximum seat (pax)	MTOW (kg)	Range (km)	Cargo Capacity (m^3)	CASM($)
A319neo	101.5	160	75500	6850	27.0	0.08085
A320neo	110.6	194	79000	6300	37.0	0.07188
A321neo	129.5	244	97000	7400	51.0	0.06674
B737-max 7	96.0	172	80000	7040	32.3	0.08500
B737-max 8	117.1	210	82600	6480	44.0	0.07111
B737-max 9	124.1	220	88300	6110	51.3	0.68780
E190-E2	64.6	114	56400	5278	21.3	0.08308
E195-E2	72.8	146	62000	4815	25.4	0.06962

2.3 Data Analysis

After collecting the results from the pairwise comparison of each criterion using artificial intelligence, five prompt combinations are randomly selected using simple random sampling without replacement method to represent five artificial intelligence "experts". This approach is used to equal the number of human expert participants in this research, that are five human experts, and this procedure follows Dehghanimohammadabadi & Kabadayı (2024), who use artificial intelligence as expert judgments, with each result standing for one expert, after which the AHP method is employed to calculate the weight of each criterion [11]. Subsequently, the results from both the artificial intelligence and human experts are calculated separately to determine the weight of each criterion. As a result, there are two weighting values: the weight of each criterion assessed by artificial intelligence and the weight of each criterion evaluated by a human expert.

Using the weights from the previous process, the rankings for each aircraft type are calculated using the TOPSIS method. Consequently, there are two types of aircraft rankings: one based on weights determined by artificial intelligence and the other based on weights evaluated by a human expert. We then compare artificial intelligence- and human-expert rankings to see whether they differ in overall ordering and logical reasoning when evaluating each criterion. Finally, we do the Mann-Whitney U test to see whether any weight differences are statistically significant. This approach aligns with Dash (2016) research that uses weight values from AHP calculations as input to determine whether a statistically significant differences indicated by the Mann-Whitney U test [26].

3. RESULTS AND DISCUSSION

3.1 Aircraft Criteria Weight

Five of the eight types of prompt combinations have been randomly selected to represent the artificial intelligence expert. These combinations are presented in Table 4, each corresponding to a distinct expert judgment. Subsequently, the AHP method is utilized for pairwise comparisons using artificial intelligence to determine the weight of each criterion, as illustrated in Table 5. The same AHP method will be applied to evaluate the pairwise comparison results by a human expert, as shown in Table 6.

Table 4. Prompt combination that represents an artificial intelligence expert

Artificial Intelligence Expert	Prompting Technique Combination
Generate Result 1	One shot + chain of thought + role-based
Generate Result 2	Zero shot + chain of thought
Generate Result 3	One shot + chain of thought
Generate Result 4	One Shot + tree of thought + role-based
Generate Result 5	Zero shot + tree of thought

Table 5. The weight of criterion judged by artificial intelligence

Criteria	Purchase cost	Maximum seat	MTOW	Range	Cargo Capacity	CASM	Priority Vector
Purchase cost	1.000	0.392	3.000	5.000	4.169	0.384	0.182
Maximum seat	2.551	1.000	3.064	5.348	6.346	0.530	0.279
MTOW	0.333	0.326	1.000	1.933	1.380	0.200	0.076
Range	0.200	0.187	0.517	1.000	0.425	0.175	0.043
Cargo Capacity	0.240	0.158	0.725	2.352	1.000	0.229	0.064
CASM	2.605	1.889	5.000	5.720	4.359	1.000	0.357

Table 6. The weight of the criterion judged by human expert

Criteria	Purchase cost	Maximum seat	MTOW	Range	Cargo Capacity	CASM	Priority Vector
Purchase cost	1.000	1.122	2.631	2.862	1.783	1.000	0.195
Maximum seat	0.891	1.000	2.491	2.491	1.939	0.891	0.168
MTOW	0.380	0.401	1.000	1.516	1.052	0.380	0.085
Range	0.349	0.401	0.660	1.000	0.824	0.349	0.069
Cargo Capacity	0.561	0.516	0.951	1.213	1.000	0.561	0.101
CASM	1.864	3.728	4.856	5.008	2.551	1.864	0.382

The findings reveal that the assessment weights assigned by artificial intelligence are 35.7% for CASM, 27.9% for maximum seat capacity, 18.2% for purchase cost, 7.6% for MTOW, 6.4% for cargo capacity, and 4.3% for range, resulting in a consistency ratio of 0.037. In comparison, the weights determined by human experts are 38.2% for CASM, 19.5% for purchase cost, 16.8% for maximum seat capacity, 10.1% for cargo capacity, 8.5% for MTOW, and 6.9% for range, yielding a consistency ratio of 0.017. Across both evaluations, CASM remains the most significant criterion. This aligns with the assertion by Chiambaretto & Combe (2023) that low-cost carriers prioritize cost efficiency, which in this study is reflected in the importance of the CASM criterion. Furthermore, the research demonstrates that CASM is an indicator of operational performance through economic metrics [27].

3.2 Aircraft Alternative Ranking

Following the assessment of the importance of each criterion identified by both AI and human experts, the TOPSIS method is used to rank various aircraft types based on the multi-response values presented in Table 3. The weighted multi-response values for all aircraft types are detailed in Table 7 for AI evaluations and in Table 8 for assessments conducted by human experts.

Following the calculations, the A321neo emerges as the most suitable aircraft, with the B737 Max 9, B737 Max 8, A320neo, E195-E2, B737 Max 7, A319neo, and E190-E2 ranked in that order, as assessed by artificial intelligence. In evaluations from human experts, the A321neo also ranks first, followed by the B737 Max 9, B737 Max 8, E195-E2, A320neo, E190-E2, B737 Max 7, and A319neo, as displayed in Table 10. Regardless of the evaluation method—artificial intelligence or human expertise—the A321neo consistently stands out as the optimal choice. This conclusion is supported by research conducted by Ilgin (2019), Kiracı & Akan (2020), and Ardıl (2020), confirming that the A321neo is superior to other options. Additionally, in a study by Guntut & Gokdalay (2023), the A321neo is recognized as the best aircraft for low-cost carriers, owing to its technical, economic, and environmental benefits. economic, and environmental benefits.[28].

Table 7. Multiple response values after being weighted by the AHP calculation are judged by artificial intelligence.

Alternatives	Purchase cost	Maximum seat	MTOW	Range	Cargo Capacity	CASM
	min	max	max	max	max	min
A319neo	0.0626	0.0843	0.0257	0.0159	0.0163	0.1361
A320neo	0.0682	0.1023	0.0269	0.0147	0.0223	0.1210
A321neo	0.0798	0.1286	0.0330	0.0172	0.0308	0.1124
B737 max 7	0.0592	0.0907	0.0272	0.0164	0.0195	0.1431
B737 max 8	0.0722	0.1107	0.0281	0.0151	0.0266	0.1197
B737 max 9	0.0765	0.1160	0.0301	0.0142	0.0310	0.1158
E190-E2	0.0398	0.0601	0.0192	0.0112	0.0129	0.1399
E195-E2	0.0449	0.0770	0.0211	0.0149	0.0153	0.1172

Table 8. Multiple response values after being weighted by the AHP calculation are judged by a human expert

Alternatives	Purchase cost	Maximum seat	MTOW	Range	Cargo Capacity	CASM
	min	max	max	max	max	min
A319neo	0.0669	0.0508	0.0290	0.0259	0.0255	0.1458
A320neo	0.0729	0.0616	0.0304	0.0239	0.0349	0.1297
A321neo	0.0854	0.0774	0.0373	0.0280	0.0481	0.1204
B737 max 7	0.0633	0.0546	0.0307	0.0267	0.0305	0.1533
B737 max 8	0.0772	0.0666	0.0317	0.0245	0.0415	0.1283
B737 max 9	0.0818	0.0698	0.0339	0.0231	0.0484	0.1241
E190-E2	0.0426	0.0362	0.0217	0.0182	0.0201	0.1499
E195-E2	0.0480	0.0463	0.0238	0.0242	0.0240	0.1256

3.3 Comparison between Artificial Intelligence and Human Expert in Aircraft Selection Process

Table 9 displays the discrepancies in evaluations between artificial intelligence and human experts for each selection criterion. The comparison of AI and human expert assessments during aircraft selection shows both convergence and divergence on key decision-making criteria. Both groups recognized Cost per Available Seat Mile (CASM) as the most crucial element, an anticipated result due to its significant effect on operational efficiency and profitability, particularly for budget-conscious airlines in the post-pandemic era. This agreement underscores CASM's importance as a commonly prioritized metric in fleet acquisition strategies.

Nonetheless, differences emerge in the second-tier preferences. The AI model placed greater emphasis on maximizing seating capacity, as it could enhance break-even performance during high-demand situations. Conversely, human experts focused on purchase cost, indicating a risk-averse strategy tied to managing capital expenditure and market unpredictability. This disparity implies that the AI leans towards long-term operational efficiency, while human experts are more wary of risks associated with initial investments and variable load factors.

Further differences emerged in how cargo capacity was valued. Human experts assigned it greater importance, acknowledging the increasing role of auxiliary revenue streams in airline business models. In contrast, the AI system minimized this factor, possibly due to a more limited optimization focus on passenger metrics. This underscores a limitation of AI when domain-specific strategic nuances are not adequately represented in the model.

Interestingly, both AI and human experts assigned moderate to low importance to criteria like MTOW and range. This could result from the study's emphasis on narrow-body aircraft typically utilized for domestic or regional flights in Indonesia, where extended range or payload capacities are not as crucial.

Table 9. Comparison of weight for each criterion judged by artificial intelligence and human experts.

Criteria	Artificial Intelligence		Human Expert	
	Priority Vector	Ranking	Priority Vector	Ranking
Purchase cost	18.19%	3	19.46%	2
Maximum seat	27.85%	2	16.77%	3
MTOW	7.56%	4	8.54%	5
Range	4.26%	6	6.92%	6
Cargo Capacity	6.45%	5	10.08%	4
CASM	35.69%	1	38.23%	1

Table 10. Comparison of aircraft type ranking for this context of research that judges by artificial intelligence and a human expert.

Alternatives	Artificial Intelligence		Human Expert	
	Preferences	Ranking	Preferences	Ranking
A319neo	0.356	7	0.352	8
A320neo	0.552	4	0.514	5
A321neo	0.663	1	0.594	1
B737 max 7	0.417	6	0.402	7
B737 max 8	0.605	3	0.552	3
B737 max 9	0.627	2	0.573	2
E190-E2	0.341	8	0.413	6
E195-E2	0.457	5	0.531	4

The Mann-Whitney U test revealed no statistically significant difference ($p = 0.689$) between the two priority vector sets, as shown in figure 2; however, the practical implications of these differences are noteworthy. Statistical similarity does not equate to functional equivalence. The congruence in top rankings suggests that AI systems can produce outcomes similar to human decision-making. Yet, the differences in intermediate rankings highlight potential for hybrid approaches, combining AI's rapid, data-driven evaluations with human judgment to enhance decisions within operational contexts.

Additionally, when the research examines the rankings of the most appropriate aircraft according to artificial intelligence and human experts, the top three ranks are the same for both evaluations. However, starting from rank 4, distinctions arise between the assessments made by artificial intelligence and those determined by human experts, as illustrated in Table 10. In this case, we chose only one specific aircraft type, adhering to the low-cost airline's operational guidelines stipulating the use of a single aircraft type for greater efficiency. The alignment between artificial intelligence and human experts' conclusions concerning the optimal aircraft for this situation demonstrates that artificial intelligence can significantly support human experts in selecting the right aircraft type.

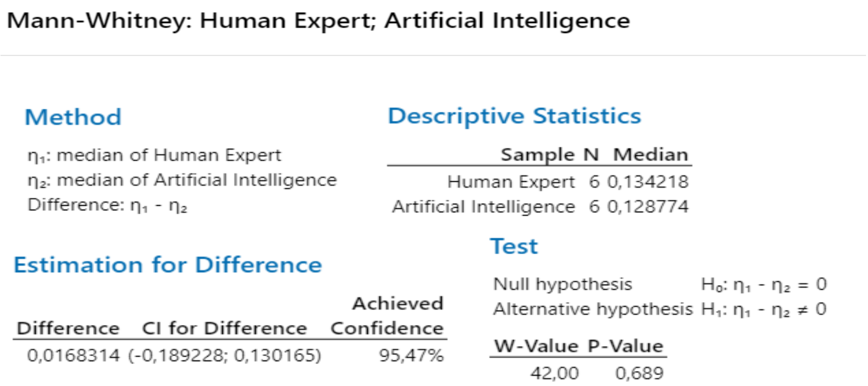

Figure 2. Result for test of comparison of weight for each criterion that is judged by artificial intelligence and human expert using Mann-Whitney U test.

4. CONCLUSION

This study demonstrates that an artificial intelligence-enhanced decision-making framework, which integrates AHP and TOPSIS across six criteria—purchase cost, maximum seat capacity, MTOW, range, cargo capacity, and CASM—yields result comparable to those from human experts for eight aircraft models in Indonesia's post-pandemic commercial aviation sector. Although AI and human assessments produce slightly different priority scores, particularly for maximum seat capacity, purchase cost, and cargo capacity, these differences are not statistically significant (Mann-Whitney U test, $p = 0.689$). Both methods identify the Airbus A321neo as the top choice. This research adds to the ongoing discourse on AI-human collaboration in decision-making by showing how AI systems, paired with strong MCDM techniques, can reflect human judgments and offer scalable insights for the aviation industry. Future investigations could build on this work by integrating dynamic factors such as market fluctuations, anticipated maintenance costs, or environmental performance, further enhancing AI's role in sustainable and adaptable fleet management.

REFERENCE

[1] M. Kalić, D. Babić, S. Dožić, J. Kuljanin, and N. Mijović, "Impact of Covid-19 on The Aviation Industry: An Overview of Global and Some Local Effects," *Anali Pravnog Fakulteta u Beogradu*, vol. 70, no. 4, pp. 1079–1127, 2022. http://dx.doi.org/10.51204/Anali_PFBU_22405A

[2] H. Fathurahman, M. A. Berawi, I. Sulistyarini, A. Kusuma, Y. Nasution, and Komarudin, "Post COVID-19 Recovery Models and Strategies for Aviation in Indonesia," *International Journal of Technology*, vol. 11, no. 6, pp. 1265–1274, 2020. http://dx.doi.org/10.14716/ijtech.v11i6.4455

[3] L. Garrow and V. Lurkin, "How COVID-19 is impacting and reshaping the airline industry," *Journal of Revenue and Pricing Management*, vol. 20, no. 1, pp. 3–9, Feb. 2021. http://dx.doi.org/10.1057/s41272-020-00271-1

[4] C. Ardil, "Aircraft Selection Process Using Preference Analysis for Reference Ideal Solution (PARIS)," *International Journal of Aerospace and Mechanical Engineering*, vol. 14, no. 3, pp. 80–90, 2020.

[5] S. Dožić and M. Kalić, "Aircraft type selection problem: Application of different MCDM methods," *Advances in Intelligent Systems and Computing*, vol. 572, pp. 156–175, 2018. http://dx.doi.org/10.1007/978-3-319-57105-8_7

[6] K. Kiracı and M. Bakır, "Using the Multi Criteria Decision Making Methods in Aircraft Selection Problems and an Application," *Journal of Transportation and Logistics*, pp. 13–24, Apr. 2018. http://dx.doi.org/10.26650/JTL.2018.03.01.02

[7] B. Ayan, S. Abacıoğlu, and M. P. Basilio, "A Comprehensive Review of the Novel Weighting Methods for Multi-Criteria Decision-Making," *Information*, vol. 14, no. 5, May 01, 2023. http://dx.doi.org/10.3390/info14050285

[8] T. L. Saaty and J. M. Katz, "How to make a decision: The Analytic Hierarchy Process," 1990.

[9] N. Munier and E. Hontoria, *Uses and Limitations of the AHP Method*, in *Management for Professionals*, Cham: Springer International Publishing, 2021. http://dx.doi.org/10.1007/978-3-030-60392-2

[10] I. Svoboda and D. Lande, "Enhancing Multi-Criteria Decision Analysis with AI: Integrating Analytic Hierarchy Process and GPT-4 for Automated Decision Support," 2024. http://dx.doi.org/10.48550/arxiv.2402.07404

[11] M. Dehghanimohammadabadi and N. Kabadayı, "The Ai-Driven Decision-Making (Aidm) Framework: Integrating Ahp and Chatgpt-4 for Supplier Selection," 2024. http://dx.doi.org/10.2139/ssrn.4997750

[12] H. Wang, F. Zhang, and C. Mu, "One for All: A General Framework of LLMs-based Multi-Criteria Decision Making on Human Expert Level," Feb. 2025. http://dx.doi.org/10.2139/ssrn.4997750

[13] S. Dožić and M. Kalić, "An AHP approach to aircraft selection process," in *Transportation Research Procedia*, Elsevier, 2014, pp. 165–174. http://dx.doi.org/10.1016/j.trpro.2014.10.102

[14] S. Dožić and M. Kalić, "Three-stage airline fleet planning model," *J Air Transp Manag*, vol. 46, pp. 30–39, Jul. 2015. http://dx.doi.org/10.1016/j.jairtraman.2015.03.011

[15] G. Bruno, E. Esposito, and A. Genovese, "A model for aircraft evaluation to support strategic decisions," *Expert Syst Appl*, vol. 42, no. 13, pp. 5580–5590, Aug. 2015. http://dx.doi.org/10.1016/j.eswa.2015.02.054

[16] S. Dožić, T. Lutovac, and M. Kalić, "Fuzzy AHP approach to passenger aircraft type selection," *J Air Transp Manag*, vol. 68, pp. 165–175, May 2018. http://dx.doi.org/10.1016/j.jairtraman.2017.08.003

[17] M. A. Ilgin, "Aircraft Selection Using Linear Physical Programming," *Journal of Aeronautics and Space Technologies*, vol. 12, no. 2, pp. 121–128, 2019.

[18] C. Ardil, "Aircraft Selection Using Multiple Criteria Decision Making Analysis Method with Different Data Normalization Techniques," *International Journal of Industrial and Systems Engineering*, vol. 13, no. 12, pp. 744–756, 2019.

[19] K. Kiracı and E. Akan, "Aircraft selection by applying AHP and TOPSIS in interval type-2 fuzzy sets," *J Air Transp Manag*, vol. 89, Oct. 2020 http://dx.doi.org/10.1016/j.jairtraman.2020.101924

[20] C. Ardil, "Aircraft Selection Using Preference Optimization Programming (POP)," *International Journal of Aerospace and Mechanical Engineering*, vol. 16, no. 11, pp. 286–291, 2022.

[21] C. Ardil, "Aircraft Selection Process Using Reference Linear Combination in Multiple Criteria Decision Making Analysis," *International Journal of Aerospace and Mechanical Engineering*, vol. 17, no. 4, pp. 146–155, 2023.

[22] B. Bağcı and M. Kartal, "A combined multi criteria model for aircraft selection problem in airlines," *J Air Transp Manag*, vol. 116, Apr. 2024. http://dx.doi.org/10.1016/j.jairtraman.2024.102566

[23] C. Ardil, "Aircraft Selection Using Multiple Criteria Decision Making Analysis Method with Different Data Normalization Techniques," *World Academy of Science, Engineering and Technology International Journal of Industrial and Systems Engineering*, vol. 13, no. 12, pp. 744–756, 2019.

[24] V. Bhaskara, "ANALYSIS: A320neo vs. 737 MAX: Airbus is Leading (Slightly)-Part II," 2016. Accessed: Oct. 24, 2024. [Online]. Available: https://web.archive.org/web/20160206082857/http://airwaysnews.com/blog/2016/02/05/a320neo-vs-737-max-pt-ii/

[25] AirInsight, "Embraer E-Jets E2 A Program Review," 2016.

[26] M. Dash, "Banking Performance Measurement for Indian Banks using AHP and Topsis," *The International Journal of Banking and Finance*, vol. 12, no. 2, pp. 63–76, 2016.

[27] P. Chiambaretto and E. Combe, "Business model hybridization but heterogeneous economic performance: Insights from low-cost and legacy carriers in Europe," *Transp Policy (Oxf)*, vol. 136, pp. 83–97, Jun. 2023. http://dx.doi.org/10.1016/j.tranpol.2023.03.016

[28] C. Güntut and M. Gökdalay, "Aircraft Selection Decision Support Model for Fleet Planning of the Low Cost Airlines," *Eskişehir Osmangazi Üniversitesi İktisadi ve İdari Bilimler Dergisi*, vol. 18, no. 2, pp. 460–478, Aug. 2023. http://dx.doi.org/10.17153/oguiibf.1253980