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Evaluation of Artificial Intelligence Requirements in Aviation Industry using Fuzzy Cognitive Map Approach

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Abstract

In recent years, sudden developments have occurred in technology. The widespread use of digital technologies and digital transformation have created an environment that allows advanced technologies to be developed and accepted by both the public and the business world. One of today's shocking developments is the rise of artificial intelligence (AI) technology. AI brings with it many opportunities both socially and economically and it has an impact on almost many sectors. One of these sectors is the aviation industry. It is extremely important for the world economy and countries. Furthermore, it has a complex structure where large data sets and changing customer demands are abundant. The use of AI technologies in the aviation industry can provide many competitive advantages. For this reason, focusing on AI requirements is extremely critical. For this reason, this study aims to determine and analyze AI requirements. The identified requirements are analyzed in a case study in Turkey aviation industry. For this purpose, cognitive map (CM) approach is adopted in the study to analyze the requirements. Modeling and solving real-life problems are complex and involve human perception that creates uncertainty. To overcome this complexity and uncertainty, the classical CM method is applied in fuzzy environment.

Keywords
Artificial Intelligence, Artificial Intelligence Requirements, Aviation Industry, Digital Transformation, Fuzzy Cognitive Map

1. Introduction

Recently, the transformative power and potential of artificial intelligence (AI) have attracted the attention of business experts in various sectors. These experts are looking for ways to stay ahead of the curve by integrating AI into business operations (Broderick, 2021). While AI is used to improve decision-making processes and increase customer experience in many industrial fields, it also provides benefits in automating routine tasks (Broderick, 2021).

The aviation system has maintained its reputation as one of the most reliable forms of travel for decades. The autonomy that comes with the rise of AI technology and its integration into the aviation system in recent years requires the ability to be trusted by customers, employees, consumers and the public as a business or regulatory tool in the aviation ecosystem (CAA, 2024). The transformative power of AI, which is believed to usher in a new era in the aviation industry, has begun to show its impact in the sector (CAA, 2024). The aviation industry continues to evolve and adapt to new technologies. Increasing demand for global air travel and increasing passenger volumes are driving airports and airlines towards AI to transform the passenger experience (Singer, 2024). AI's ability to quickly and accurately process large amounts of data is proving its power in overcoming the unique challenges of air travel while providing an edge in improving efficiency, safety and customer experience (Sahota, 2024). For this reason, the importance of adopting AI is increasing to gain the power to compete in the sector and demonstrate better performance (Bojanki et al., 2023).

At this point, it is extremely critical to compete in the global market and business world where AI has begun to dominate, to ensure profitability and to ensure the trust of all stakeholders. For this reason, focusing on AI requirements can be a guide for companies. However, the concept of AI and the aviation industry are inherently complex. They have a complex and multifaceted structure in which many components are related to each other. For this reason, in this study, it is aimed to analyze the AI requirements based on the existence of a causal relationship.

In the literature, there are different analytical methods that consider the relationships between criteria such as the Analytical Network Process (ANP) (Saaty, 1996), the Decision-Making Trial and Evaluation Laboratory (DEMATEL) (Gabus and Fontela, 1972) and cognitive map (CM) approach (Tolman, 1948). However, technological advances and AI requirements have variability and dynamism. From this point of view, CM approach has been adopted in this study. On the other hand, dealing with the complexity of real-life problems involves human perception and the uncertainty. Therefore, the classical CM approach has been extended to fuzzy sets (Zadeh, 1965). The classical CM approach can only determine the presence of relationships between criteria and positivity or negativity of them. Besides, it does not consider dynamism. However, the fuzzy cognitive map (FCM) approach (Kosko, 1986) considers the determination of the weights of the relationships between the criteria Furthermore, FCM approach has a dynamical behavior. This allows scenario analysis for future situations. In this way, it can be observed how the network-like system is affected by the changes made. The FCM approach has been utilized in a case study conducted in Turkey aviation industry to check the validity of the determined criteria. After obtaining the importance degree of the AI requirements, the FCM-based model of these requirements has been visualized.

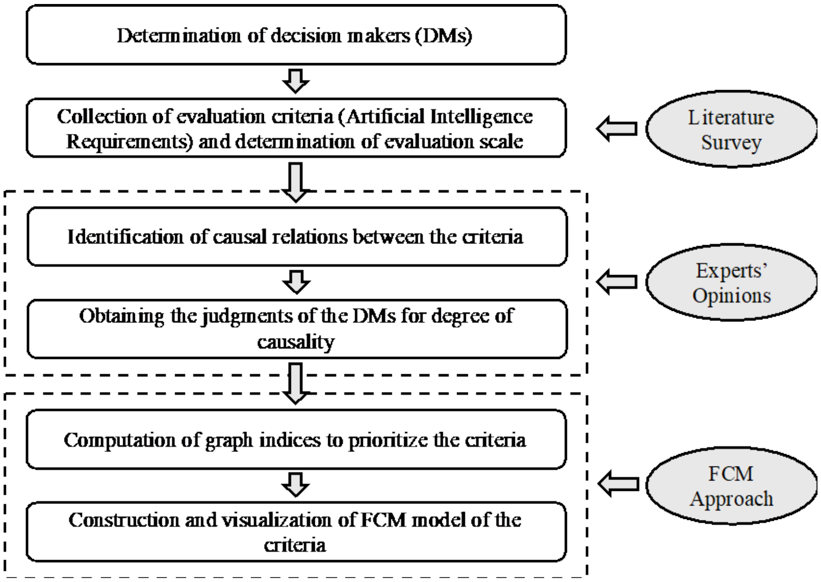

Figure 1. The followed steps in the study

The study consists of following sections: Section 2 introduces AI within the aviation industry context. Utilized methodology in the study is explained in Section 3. Details of the conducted case study are provided in Section 4. Section 5 discusses the obtained results before the study is concluded in Section 6. The followed steps in the study are shown in Figure 1.

2. Artificial Intelligence in Aviation Industry

There has been a sudden acceleration in technological developments in recent years. The rapid impact of digital technologies all over the world has initiated the era of digital transformation, which is very popular now. International Air Transportation Association (IATA) defines digital transformation as creating value by destroying old processes and rebuilding them by leveraging digital assets. Digital transformation involves both the implementation of new technologies and the transformation of business operations, and one of the ways to achieve digital transformation is through artificial intelligence (AI) (Dresner et al., 2020). There are different definitions of the AI in the literature. For example, Goudarzi et al. (2018) defines the AI as computer programs that can be embodied (e.g., robots) or disembodied (e.g., Google Now and Apple's Siri) and exhibit human-specific intelligence-based features such as learning, logical reasoning, decision-making, and problem solving. On the other hand, Dresner et al. (2020) defines the AI as the collection of technologies that allow machines to act, understand, detect, and learn either on their own or by augmenting human learning.

Goudarzi et al. (2018) indicated that nowadays, the World has been witnessing the 4th Generation of AI. They expressed the capabilities of 4th generation AI as “Analysis and Conclusion”, “Perceiving Outside World”, “Abstraction of Knowledge”, “Learning from Experience”. The new generation is different from the previous generations in terms of different ways:

1. It is capable of learning and abstracting knowledge without large amounts of training data,
2. It has ability to understand context,
3. It can go from one domain to another.

IATA evaluates AI as a comprehensive technology that enhances existing and new business capabilities for both airlines and other organizations across the aviation value chain (Goudarzi et al., 2018). Rishi Mehta, CEO of WAISL Ltd., states that AI is a tool to achieve certain business goals and should be seen as much more than a standalone technology. Emphasizing that operations can be improved, and passenger experience can be improved by incorporating AI technology into a broader strategy, Mehta underlines that AI technology must be used effectively to gain a competitive advantage (Bojanki et al., 2023). AI has the potential to change the rules of the game with the right collaborations, and it provides many advantages in the aviation industry, such as automatic planning, targeted advertising, customer feedback analysis, improved flight operations, personalized services and customer experience. Due to this fact, it is adopted by the best airlines around the world (Kumar, 2022). Kumar (2022) emphasizes that AI technologies will have far-reaching effects on the aviation industry. In that study, it is stated that AI technologies such as natural language processing, machine learning, robots and machine vision shape the future of the aviation industry. Within the scope of aviation, some of the future areas of use of AI systems, their potential features and capabilities are as follows (Goudarzi et al., 2018):

- Commercial decision-making,
- Safety and real-time monitoring,
- 24/7 AI services, baggage delivery,
- More comfortable flight experience,
- Enhanced value proposition,
- 100% up to date,
- Seamless airport security,
- Marketing and sales,
- Pricing strategies,
- Customer loyalty,
- Network optimization etc.

AI technology provides benefits in a wide range of areas, such as optimizing existing processes and/or systems, keeping the necessary ones, removing or invalidating the unnecessary ones. It is capable of being used individually or in combination in a wide variety of areas and situations within the aviation industry (Goudarzi et al., 2018). The benefits of AI for some areas of aviation industry can be summarized as follows (Dresner et al., 2020): Maintenance, repair and overhaul; Training; Cargo operations; Air traffic management; Flight safety; Revenue manegement; Customer service enhancement. On the other hand, development and implementation of standard practices, cost of implementation, human factors and risks regarding data privacy are evaluated as some major challenges (Dresner et al. 2020). Therefore, it is critical to consider the requirements of AI that may provide many benefits to companies in the aviation industry to focus on the potential areas and challenges. Identifying and analyzing AI requirements, understanding the system created by these requirements and determining their importance levels can be beneficial in creating a road map that can guide companies in the aviation industry in their AI-based transformation journeys.

The AI process needs considering a complex and multi-faceted system that requires considering many interrelated factors simultaneously. For this reason, the fuzzy cognitive map (FCM) method, which allows numerical analysis by taking this relationship into consideration, has been used in this study. Details regarding the FCM method are given in the following section.

3. Method: Fuzzy Cognitive Map

Identification and analysis of AI requirements within the scope of the aviation industry is a strategic decision-making problem that includes many different criteria and decision-making processes. However, in some decision-making problems, using the assumption of independence between criteria is not appropriate for the nature of the problem. Therefore, utilization of relation-based methods may provide more reliable results. For this purpose, this study utilizes the FCM method to analyze the AI requirements.

FCMs are capable of modelling key events, concepts, and their cause-effect relationships in any scenario. One of the most important advantages of using FCM is its potential to be used as a prediction tool in decision support (Montibeller and Belton, 2006). The FCM method simulates the development of the system over time to predict the future behavior of the concepts that make up a system, based on the initial state represented by a set of values (Feyzioglu et al., 2007). These features make FCM an attractive tool for analyzing AI requirements in a dynamic and changing ecosystem such as the aviation industry. The academic literature shows that FCM has applicability in various areas for different purposes. Maden and Yücenur (2024) utilized the FCM method to evaluate sustainable metaverse characteristics. Maden and Alptekin (2023) selected procurement performance metrics using FCM method. Havle and Dursun (2022) evaluated digital transformation success factors in energy industry. Büyüközkan et al. (2019) used it to analyze the success factors for digital transformation in aviation industry. Dogu and Albayrak (2018) evaluated criteria for pricing decisions in strategic marketing management. Büyüközkan and Vardaloğlu (2012) analyzed success factors of CPFR in retail industry.

FCM is the fuzzy extension of CM approach, and it was proposed by Kosko (1986). It is used to deal with complex problems faced by individuals and organizations through structuring and analyzing (Kwahk and Kim, 1999). The model of causal relationships between variables of a system can be constructed by FCM and with its dynamical behavior (Papakostas, 2008). There are nodes representing the variables and directional arrows representing the causal relationships between variables (Soner et al., 2015) in the FCM concept. Let C_i indicate the nodes where $i = 1,2,3,\dots,N$. Here, N shows the total number of variables. Here, weighted arcs connect the nodes. Let w_{ij} be the weight of the arcs. Remember that the variable is not allowed to affect itself, and hence, all w_{ii} values are zero. The value range of the causal relations is [-1,1] and the following principles are preserved in this causality (Papageorgiou et al., 2009).

- $w_{ij} > 0$ indicates a causal increase: If C_i increases (decreases), then C_j increases (decreases),
- $w_{ij} < 0$ indicates a causal decrease: If C_i increase (decreases), then C_j decrease (increases),
- $w_{ij} = 0$ indicates no relationship.

The mathematical expression used in the analysis of FCMs is shown in Eq. (1).

$$A_i^{(t+1)} = f\left(A_i^{(t)} + \sum_{j=1, j\neq 1}^{n} A_j^{(t)} w_{ji}\right) \tag{1}$$

The value of the variable at step $(t+1)$ is $A_i^{(t+1)}$. Here, $f(x)$ indicates the threshold function that is shown in Eq. (2). The growth rate is set to -0.1 ($\alpha = -1$). $A_i^{(t)}$ represents the initial concept value at iteration t. Additionally, $A_j^{(t)}$ shows the concept value at iteration t (Büyüközkan et al., 2021).

$$f(x) = \frac{1}{1+e^{-\alpha x}} \tag{2}$$

The function of this function is used to reduce the variable value to a normalized range (Bueno and Salmeron, 2009) The implementation of the equation given above in accordance with the appropriate number of iterations will enable the observation of the long-term behavior of the system. The simulation can be repeated multiple times with different starting vectors, so that the effect of different initial states on the dynamic behavior of the system can be monitored. When the system examined shows the behaviors defined above, the simulation is terminated, and the outputs are interpreted according to the values obtained based on the last iteration (Soner et al., 2015).

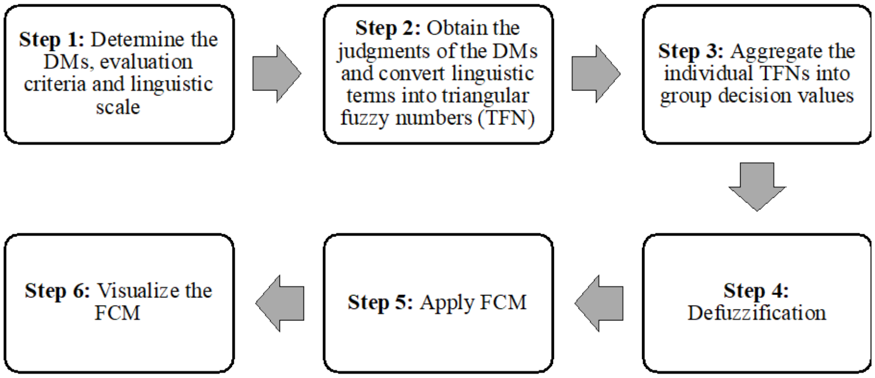

Figure 2. Computational steps of the FCM approach

Computational steps that are shown in Figure 2 of the utilized FCM approach can be given as follows (Büyüközkan et al., 2019; Büyüközkan et al., 2023):
Step 1. Determine the DMs, evaluation criteria and linguistic scale:

The decision-makers (DMs) who are industrial experts are selected based on their academic background, experiences, positions, willingness to help and information levels. Evaluation criteria are obtained through literature review and the opinions of the DMs. Linguistic terms (Büyüközkan and Vardaloğlu, 2012; Soner et al., 2015) given in Table 1 are used for the evaluation of the criteria.

Table 1. Determined evaluation scale (Soner et al., 2015; Büyüközkan et al., 2023)

Linguistic terms	**Membership functions**
Positively very strong (PVS)	(1.00, 1.00, 0.75)
Positively strong (PS)	(1.00, 0.75, 0.50)
Positively medium (PM)	(0.75, 0.50, 0.25)
Positively weak (PW)	(0.50, 0.25, 0.00)
Zero (Z)	(0.25, 0.00, -0.25)
Negatively weak (NW)	(0.00, -0.25, -0.50)
Negatively medium (NM)	(-0.25, -0.50, -0.75)
Negatively strong (NS)	(-0.50, -0.75, -1.00)
Negatively very strong (NVS)	(-0.75, -1.00, -1.00)

Step 2. Obtain the judgments of the DMs and convert linguistic term into triangular fuzzy numbers (TFN):

Relations between the criteria are evaluated by the DMs using Table 1. Let n denotes the number of DMs. Hence n number of evaluation matrices are obtained. Linguistic terms are transformed into triangular fuzzy numbers (TFN) given in Table 1.

Step 3. Aggregate the individual TFNs into group decision values:

An evaluation matrix is constructed based on a DM. During this step, individual evaluation matrices are integrated to obtain fuzzy group-decision matrix using arithmetic mean (Maden and Yücenur, 2024).

Step 4. Defuzzification:
Combined evaluations of the DMs are converted to crisp (normal) numbers. Assume that $\widetilde{w}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is the aggregated fuzzy weight between criteria C_i and C_j where l_{ij} indicates the lower value of the TFN, m_{ij}shows the middle value and finally, u_{ij} u_{ij} represents the upper value. Center of gravity (COG) method which was developed by

Chou and Chang (2008) is used for the defuzzification process. Here w_i indicates defuzzified group decision weight.

$$w_i = \frac{l_i + m_i + u_i}{3} \tag{2}$$

Step 5. Apply FCM:

The concept values, their initial states and values at different iterations (until reaches equilibrium) are computed using Eq. (1) and Eq. (2) at this step.

Step 6. Visualize the FCM:

The FCM model of the evaluation criteria is constructed based on the computed concept values and weights of the links.

4. Case Study

AI provides advantages regarding customer touch-point enablers, operational enablement, support and management capabilities, advanced business intelligence, ground handling operations (Goudarzi et al., 2018). It is of critical importance to research AI requirements to benefit from these advantages, gain competitive power and ensure profitability. Therefore, a case study is conducted in Turkey aviation industry to identify analyze the AI requirements and validate the utilized FCM method. For this purpose, the computational steps of the FCM method given in Section 3 are applied. The details of the applied steps are given as follows:

Step 1. Determination of the DMs, evaluation criteria and linguistic scale:

Let $\boldsymbol{DMs} = (\boldsymbol{DM_1}, \boldsymbol{DM_2}, \boldsymbol{DM_3}, \boldsymbol{DM_4})$ be the set of four decision-makers (DMs) who are industrial experts in the aviation industry are selected based on their academic background, experiences, positions, willingness to help and information levels. Each has knowledge about rising technologies, AI technology and information technologies. Due to privacy and confidentiality concerns, further information cannot be provided. The evaluation criteria (AI requirements) that are shown in Table 2 are collected through the literature survey and opinions of the DMs. The linguistic scale that is given in Table 1 is selected as the evaluation scale.

Table 2. The AI requirements obtained through literature survey opinion of the DMs.

AI Requirements (AIRs)	Sources
AI Strategy (R_1)	MOSTI (2021); Insider Intelligence and eMarketer (2022).
AI Trustworthiness (R_2)	EASA (2020).
Privacy (R_3)	Büyüközkan et al. (2020); EASA (2020).
Transparency (R_4)	EASA (2020); MOSTI (2021); CAA (2024).
Trust (R_5)	CAA (2024).
High Data Quality (R_6)	Havle et al. (2023).
Education and Change Management (R_7)	Havle et al. (2023); Bilan (2024).
Interoperability (R_8)	Büyüközkan et al. (2020); Büyüközkan et al. (2021); Havle et al. (2023).
Infrastructure and Usability (R_9)	Bilan (2024).
Security and Robustness (R_{10})	EASA (2020); MOSTI (2021); CAA (2024).

Step 2. Evaluation of the DMs and conversion of linguistic terms into triangular fuzzy numbers (TFN):

The DMs evaluated the influential relationships among the AI requirements using the linguistic terms given in Table 1. Only the evaluation matrix of DM_4 is presented in Table 3 to illustrate the evaluation process due to page limitation.

Table 3. Relation matrix by DM_4

DM_4	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
R_1	Z	PM	PM	Z	PM	Z	Z	Z	Z	PS
R_2	PM	Z	PM	PS	PS	PM	PS	Z	Z	PM
R_3	PM	PM	Z	PM	PS	PM	PM	Z	Z	PM
R_4	Z	PS	PM	Z	PS	PS	PS	Z	Z	PS
R_5	PM	PS	PS	PS	Z	PS	PM	Z	Z	PS
R_6	Z	PM	PM	PS	PS	Z	PM	Z	Z	PS
R_7	Z	PS	Z	PS	Z	Z	Z	Z	Z	PS
R_8	Z	Z	Z	Z	Z	Z	Z	Z	Z	PS
R_9	Z	Z	Z	Z	Z	Z	Z	Z	Z	PS
R_{10}	PM	PM	PM	PM	PM	PM	PM	PM	PS	Z

Step 3. Aggregation of the individual TFNs into group decision values:

Individual evaluation matrices are integrated to obtain fuzzy group-decision matrix using arithmetic mean.

Step 4. Defuzzification:

Combined evaluations of the DMs that are in the fuzzy group-decision matrix are converted to crisp (normal) numbers using Eq. (2). The defuzzied values are shown in Table 4.

Table 4. Defuzzied aggregated group decision values

Defuzzied Values	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
R_1	0.000	0.563	0.563	0.250	0.563	0.250	0.250	0.250	0.250	0.875
R_2	0.563	0.000	0.500	0.750	0.750	0.500	0.750	0.000	0.000	0.563
R_3	0.563	0.500	0.000	0.500	0.750	0.500	0.500	0.000	0.000	0.563
R_4	0.250	0.750	0.500	0.000	0.792	0.750	0.750	0.000	0.000	0.875
R_5	0.563	0.750	0.750	0.792	0.000	0.750	0.500	0.000	0.000	0.875
R_6	0.250	0.500	0.500	0.750	0.750	0.000	0.500	0.000	0.000	0.750
R_7	0.250	0.750	0.250	0.750	0.250	0.250	0.000	0.000	0.000	0.750
R_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.750
R_9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.750
R_{10}	0.563	0.563	0.563	0.667	0.667	0.563	0.563	0.563	0.792	0.000

Step 5. Apply FCM:

For this purpose, Eq. (1) and Eq. (2) are employed. Table 5 shows the computational results at each iteration until system reaches equilibrium (at iteration #9). This steady state (***) of the system gives the initial concept values.

Table 5. Computed iterations and steady state of the system

Growth Rate	Iterations									
-0.1	It. #0	It. #1	It. #2	It. #3	It. #4	It. #5	It. #6	It. #7	It. #8	It. #9***
R_1	1.00000	0.40131	0.46274	0.45497	0.45596	0.45583	0.45585	0.45585	0.45585	0.45585
R_2	1.00000	0.36877	0.45030	0.43971	0.44107	0.44089	0.44091	0.44091	0.44091	0.44091
R_3	1.00000	0.38639	0.45709	0.44802	0.44918	0.44903	0.44905	0.44905	0.44905	0.44905
R_4	1.00000	0.36683	0.44982	0.43890	0.44030	0.44012	0.44014	0.44014	0.44014	0.44014
R_5	1.00000	0.36538	0.44906	0.43814	0.43954	0.43936	0.43938	0.43938	0.43938	0.43938
R_6	1.00000	0.38788	0.45790	0.44881	0.44997	0.44983	0.44984	0.44984	0.44984	0.44984
R_7	1.00000	0.38196	0.45559	0.44601	0.44724	0.44708	0.44710	0.44710	0.44710	0.44710
R_8	1.00000	0.45481	0.48169	0.47909	0.47939	0.47935	0.47936	0.47936	0.47936	0.47936
R_9	1.00000	0.44913	0.48003	0.47670	0.47709	0.47704	0.47705	0.47705	0.47705	0.47705
R_{10}	1.00000	0.31540	0.42587	0.41256	0.41422	0.41401	0.41404	0.41403	0.41404	0.41404

Step 6. Visualize the FCM:

The FCM model of the evaluation criteria is constructed based on the computed concept values and weights of the links. The model that is presented in Figure 3 is constructed using SocNetV (https://socnetv.org/).

5. Results and Discussion

The initial concept values and their ranked order are shown in Table 6. Based on this, the results are visualized through a graph given in Figure 4 to show the importance degrees of the AI requirements in the system. Concept values of the

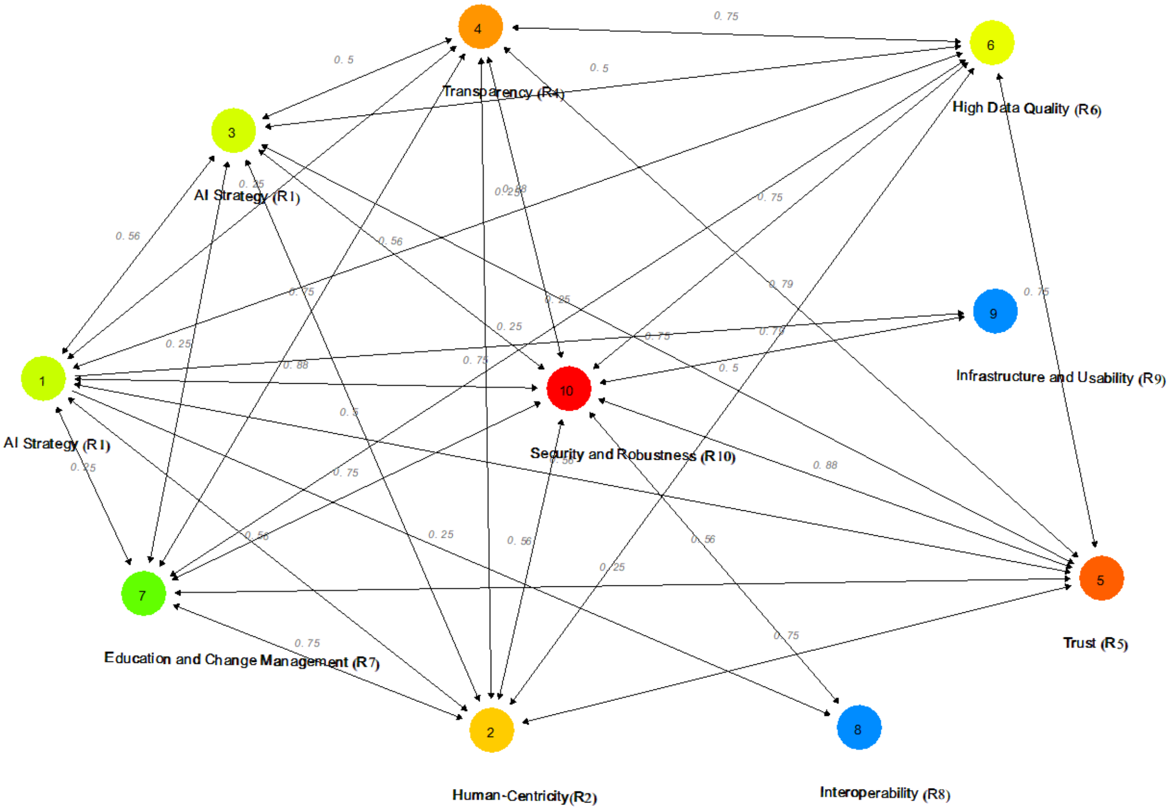

Figure 3. The FCM model of AI requirements in the aviation industry

reveals that the most significant first three requirements are “Interoperability (R_8)”, “Infrastructure and Usability (R_9)”, and “AI Strategy (R_1)”. The companies in Turkey aviation industry should consider rearranging their strategies by involving AI technologies to provide usable and interoperable systems based on appropriate infrastructure. The structure of the model illustrates how an AI included ecosystem is interrelated. Focusing only single factor would not be sufficient to elevate the whole system. To gain profitability, trust, customer loyalty and competitive advantages, the companies in the aviation ecosystem should consider all possible factors. The result of the study shows that the most significant requirements have less direct connection. However, indirect impacts of other requirements on them makes these requirements central players of the whole system.

Table 6. Importance degree and ranked order of AI requirements

AIRs	Concept Values	Rank
AI Strategy (R_1)	0.45585	**3**
Human-Centricity(R_2)	0.44091	**7**
Privacy (R_3)	0.44905	**5**
Transparency (R_4)	0.44014	**8**
Trust (R_5)	0.43938	**9**
High Data Quality (R_6)	0.44984	**4**
Education and Change Management (R_7)	0.44710	**6**
Interoperability (R_8)	0.47936	**1**
Infrastructure and Usability (R_9)	0.47705	**2**
Security and Robustness (R_{10})	0.41404	**10**

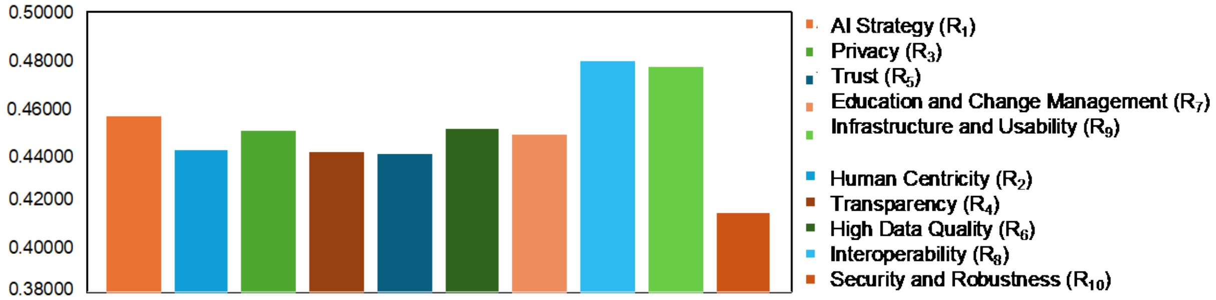

Figure 4. Comparison of the computed concept values

6. Conclusion and Perspective

The aviation industry is, by its nature, a very large, complex and multifaceted system formed by the combination of many subsystems. The most important part that ensures that each component is tightly connected is undoubtedly technology. For this reason, a dynamic transformation process that requires the widespread use of high technology and its constant updating and renewal is the most important requirement. In recent years, the spread of digital technologies and their integration into the aviation ecosystem has made this situation much more critical. The aviation industry is one of the most important industrial areas of both the world and the countries. Considering the economic returns of the aviation industry, the effects of digital transformation caused by technological developments on this structure have become one of the issues that need to be focused on. In addition to all these, digital transformation has paved the way for the adaptation of AI technology to this sector. The existence of strategic road maps that consider certain criteria for the implementation of AI technologies in the sector in a way that will provide competitiveness, profitability, safety and improved customer experience is one of the most important needs of aviation companies. From this point of view, this study aims to identify and analyze critical AI requirements for the aviation industry. For this purpose, the requirements for AI are collected through a literature survey and opinions of DMs who are experts from the aviation industry. The identified AI requirements are analyzed in a case study conducted in Turkey aviation industry. The FCM method is employed for the analysis of the determined requirements to verify the validity of the study. Results of the study shows that the AI concept in the aviation industry has a complex structure that consists of multiple causal relationships and the FCM method for this problem is a useful method. In addition, due to its very new place in aviation industry, AI concept creates uncertainty. It is seen that the used fuzzy sets can deal with this problem.

In future studies, the number of the criteria in the system can be increased. A model concerning the AI requirements can be proposed. Fuzzy extensions can be employed. Scenario and sensitivity analyses can be conducted. A further comparative analyses can be performed. The problem can be modeled and solved by adopting the multi-criteria decision-making approach.

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References

Bilan, M., How Generative AI Revolutionize the Aviation and Airlines Industry. Generative AI in Aviation and Airlines Industry: Real-Life Examples, Master of Code Global. https://masterofcode.com/blog/generative-ai-chatbots-for-airline-and-airport-industry , April 16, 2024.

Bojanki, R., Subramani, K. and Kumar, D., Decision making framework to identify successful AI investments for airports. Part 2, Capturing value: AI investment strategy. https://waisl.in/wp-content/themes/twentytwentythree/assets/images/profile-picture/Part2_WhitePaper.pdf, 2023.

Broderick, D., 5 Tips for Choosing AI-Powered Contract Review Software. Artificial Lawyer, Legal Tech & AI News and Views, October 26. (by Dan Broderick, CEO of BlackBoiler). https://www.artificiallawyer.com/2021/10/26/5-tips-for-choosing-ai-powered-contract-review-software/?trk=article-ssr-frontend-pulse_little-text-block, 2021.

Bueno S. and Salmeron, J.L., Benchmarking Main Activation Functions in Fuzzy Cognitive Maps. Expert Systems with Applications, 36, 5221-5229, 2009.

Büyüközkan, G. and Vardaloğlu, Z., Analyzing of CPFR success factors using fuzzy cognitive maps in retail industry. Expert Systems with Applications, 39(12), 10438-10455, 2012.

Büyüközkan, G., Feyzioğlu, O. and Havle, C.A., Analyzing success factors of digital transformation in aviation industry using fuzzy cognitive map approach. In 2019 3rd International Conference on Data Science and Business Analytics (ICDSBA) (pp. 124-128). IEEE, 2019.

Büyüközkan, G., Feyzioğlu, O., and Havle, C.A., Evaluation of Digital Transformation Success Factors in Air Cargo Industry using IFCM Approach. Proceedings of the 8th North American International Conference on Industrial Engineering and Operations Management, Houston, Texas, USA, June 13-16, 2023

Büyüközkan, G., Havle, C. A., & Feyzioğlu, O., A new digital service quality model and its strategic analysis in aviation industry using interval-valued intuitionistic fuzzy AHP. Journal of Air Transport Management, 86, 101817, 2020.

Büyüközkan, G., Havle, C. A., & Feyzioğlu, O., Digital competency evaluation of low-cost airlines using an integrated IVIF AHP and IVIF VIKOR methodology. Journal of Air Transport Management, 91, 101998, 2021.

Büyüközkan, G., Havle, C. A., and Feyzioğlu, O., Intuitionistic fuzzy cognitive map-based analysis of supply chain risks. In IFIP International Conference on Advances in Production Management Systems (pp. 634-643). Cham: Springer International Publishing, 2021.

CAA, CAA's Strategy for AI. Building Trust in AI5 Principles for AI and Autonomy, CAP2970, February. https://www.caa.co.uk/publication/download/21120, 2024.

Chou, S.W. and Chang, Y.C., The implementation factors that influence the ERP (enterprise resource planning) benefits. Decision support systems, 46(1), 149-157, 2008.

Dogu, E. and Albayrak, Y.E., Criteria evaluation for pricing decisions in strategic marketing management using an intuitionistic cognitive map approach. Soft computing, 22(15), 4989-5005, 2018.

Dresner, M., Deillon, R., Flouris, T., Guedes Dias, J. and Papatheodorou, A., Digitalization, AI in aviation and the human factor. HERMES Air Transport Organization, Committee Report, https://hermes.aero/wp-content/uploads/2020/05/R20-R.pdf, (2020).

EASA, Artificial intelligence roadmap, A human-centric approach to AI in aviation. European Union Aviation Safety Agency https://www.easa.europa.eu/en/document-library/general-publications/easa-artificial-intelligence-roadmap-10 , February, 2020.

Feyzioglu, O., Buyukozkan, G. and Ersoy, M.S., Supply chain risk analysis with fuzzy cognitive maps. In 2007 IEEE international conference on industrial engineering and engineering management (pp. 1447-1451). IEEE, December 2007.

Gabus, A. and Fontela, E., World problems, an invitation to further thought within the framework of DEMATEL. Switzerland, Geneva: Battelle Geneva Research Centre. 1972.

Goudarzi, H., Hourcade, C., McEwan, D., Léopold, E., Mulder, H., Suidan, J., Antonio Rodriguez, J., Ivan Martin, J., Reda, M. Cicetti, M., Eagles, R., Roetger, T., AI in aviation exploring the fundamentals, threats and opportunities of artificial intelligence (AI) in the aviation industry. International Air Transport Association (IATA) White Paper, June, 2018.

Havle, B.B. and Dursun, M., Digital Transformation Success Factors Evaluation in Energy Industry. In Intelligent Systems in Digital Transformation: Theory and Applications (pp. 151-175). Cham: Springer International Publishing, 2022.

Havle, C. A., Kilic, S., & Ucler, C., Modernizing data and cloud practices: A review and model proposal for future studies. In 2023 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) (pp. 1-7). IEEE, 2023.

Insider Intelligence and eMarketer, AI in Customer Experience. How AI Is Improving the Ways Companies Reach Consumers. Acxiom. https://marketing.acxiom.com/rs/982-LRE-196/images/eMarketer_AI_in_Customer_Experience_Report.pdf, 2022.

Kosko, B., Fuzzy cognitive maps, International Journal of Man-Machine Studies 24(1), 65–75, 1986.

Kumar, M., Optimized application of artificial intelligence (AI) in aviation market. International Journal of Recent Research Aspects, 9(4), 2022.

Kwahk, K.Y. and Kim, Y.G. Supporting Business Process Redesign Using Cognitive Maps. Decision Support Systems ,25, 2, 155-178, 1999.

Maden, A. and Alptekin, S.E., Procurement Performance Metric Selection Using SCOR Modelling and Scenario-Based Fuzzy Cognitive Map. In International Conference on Intelligent and Fuzzy Systems (pp. 465-471). Cham: Springer Nature Switzerland, August 2023.

Maden, A. and Yücenur, G.N., Evaluation of sustainable metaverse characteristics using scenario-based fuzzy cognitive map. Computers in Human Behavior, 152, 108090, 2024.

Montibeller, G. and Belton, V., Causal maps and the evaluation of decision options—a review. Journal of the Operational Research Society, 57(7), 779-791, 2006.

MOSTI, Malaysia National Artifical Intelligence Roadmap 2021-2025 (AI-RMAP). Published by: Ministry of Science, Technology & Innovation (MOSTI). https://airmap.my/wp-content/uploads/2022/08/AIR-Map-Playbook-final-s.pdf , 2021.

Papageorgiou, E.I., Markinos, A. and Gemptos, T., Application of Fuzzy Cognitive Maps for Cotton Yield Management in Precision Farming. Expert Systems with Applications, 36, 12399–12413, 2009.

Papakostas, G.A., Boutalis, Y.S., Koulouriotis, D.E. and Mertzios, B.G., Fuzzy Cognitive Maps for Pattern Recognition Applications. Int. J. of Pattern Recog. and Artificial Intelligence, 22(8), 1461–1486, 2008.

Saaty, T.L.,The analytic network process. Pittsburgh: RWS Publications, 1996.

Sahota, N., Navigation the skies with AI: How airlines are transforming air travel, Forbes. https://www.forbes.com/sites/neilsahota/2024/03/29/navigating-the-skies-with-ai-how-airlines-are-transforming-air-travel/?sh=16b5e1a21b9c , March 29, 2024.

Singer, D., The future of air travel: How AI will reimagine airports. The Airline Passenger Experience Association (APEX), https://apex.aero/articles/ai-sxsw/, March 14, 2024.

Soner, O., Asan, U. and Celik, M., Use of HFACS–FCM in fire prevention modelling on board ships. Safety Science, 77, 25-41, 2015.

Tolman, E.C., Cognitive maps in rats and men. Psychological review, 55(4), 189, 1948.

Zadeh, L.A., Fuzzy sets. Information and control, 8(3), 338-353, 1965.

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