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PRIORITIZING CHALLENGES IN AI APPLICATIONS IN HEALTHCARE: MULTI-CRITERIA DECISION MAKING APPROACH

SAĞLIK SEKTÖRÜNDE YAPAY ZEKÂ UYGULAMALARINDA KARŞILAŞILAN ZORLUKLARIN ÖNCELİKLENDİRİLMESİ: ÇOK KRİTERLİ KARAR VERME YAKLAŞIMI

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ABSTRACT

Artificial Intelligence (AI) applications have become increasingly popular in recent years as technological capabilities have evolved. AI applications in healthcare are one of the areas that need to adapt quickly in order not to lose touch with the times. Focusing only on the opportunities that AI applications bring to healthcare can make this adaptation process problematic. Instead, it is important for the efficiency of the adaptation process to identify the challenges that may arise with AI applications in healthcare and prioritize these challenges. This study used the Analytical Hierarchy Process (AHP) method, which is the most widely used Multi-criteria Decision Making (MCDM) method. For the study, the opinions of 5 experts were obtained, 3 of whom are medical doctors and 2 are faculty members working on AI applications. The aim of the study is to provide guidance to policy makers and practitioners on the challenges they should focus on when adopting Artificial Intelligence in healthcare. The result of the study shows that the most important challenge is "Ethical Problems". Among the "Ethical Problems", the "Principle of Ethical Double Effect" is the most important with a value of 0,569.

ÖZET

Yapay Zekâ (AI) uygulamaları teknolojik imkanların gelişmesiyle son yıllarda giderek daha fazla popülerlik kazanmaktadır. Sağlıkta AI uygulamaları ise çağın gerisinde kalmamak adına hızla adapte olunması gereken alanlardan bir tanesi olmaktadır. Yalnızca sağlıkta AI uygulamalarıyla elde edilecek fırsatlara odaklanmak, bu adaptasyon sürecinde sorunlara yol açabilmektedir. Bunun yerine sağlıkta yapay zekâ uygulamalarında karşılaşılabilecek zorlukların tespiti ve bu zorlukların önceliklendirilmesi adaptasyon sürecinin verimliliği açısından önemli olmaktadır. Bu çalışmada en yaygın olarak kullanılan Çok Kriterli Karar Verme (ÇKKV) yöntemi olan Analitik Hiyerarşi Süreci (AHS) yöntemi kullanılmıştır. Çalışmada 3'ü tıp doktoru 2'si AI uygulamaları konusunda çalışmaları bulunan öğretim üyeleri olmak üzere 5 uzmanın görüşü alınmıştır. Çalışmanın amacı sağlıkta yapay zekâ uygulamaları sırasında karşılaşılan hangi zorluklara odaklanmaları gerektiği konusunda politika yapıcılara ve uygulayıcılara rehberlik etmektir. Çalışmanın sonucunda en önemli zorluğun "Etik Problemler" olduğu görülmektedir. "Etik Problemler "in içerisinde de en önemlisi 0,569 değeri ile "Etik Çift Etki Prensibi"'dir.

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Conceptual Framework

As technology has evolved, the definition of "Artificial Intelligence" in the literature has changed. In its most general definition, Artificial Intelligence is a general term for the technology used to develop machines that can exhibit human-like behaviors and movements without being assisted by living organisms. Artificial Intelligence (AI) is the ability of computers or computer-controlled robots to perform tasks generally associated with intelligent organisms. The term is often used to describe the development of systems equipped with human intellectual processes, such as reasoning, meaning acquisition, generalization, or learning from previous experience. The first research on Artificial Intelligence technology dates back to 1950. In the early 1950s, Alan Turing posed the question "Can Machines Think?". Computer scientist and cognitive scientist "John McCarthy" used the term "Artificial Intelligence" at the first Artificial Intelligence conference "Dartmouth Conference" in 1956.

Because Artificial Intelligence can identify meaningful relationships in raw data, it can be used to aid diagnosis, treatment, and prediction for many medical conditions. Artificial Intelligence has the potential to be used in almost all areas of medicine, including drug development, monitoring patients, and creating personalized treatment plans.

AI has many benefits, such as increasing efficiency and flexibility and lowering the cost of healthcare applications. It is common to look more at the positives when paradigm shifts occur. Focusing too much on the benefits that can be achieved when adopting new technological trends like AI overlooks the challenges that come with technological change. In addition to the opportunities, there are also several challenges that need to be considered by practitioners and policymakers when adopting AI applications in healthcare. Identifying these challenges, determining their importance, and prioritizing them will both facilitate the transition to AI applications in healthcare and lead to clearer opportunities.

Healthcare institutions and healthcare professionals will need to adapt to the AI shift to avoid being behind the times. In addition, from a national perspective, awareness of the challenges and the ranking of the importance of these challenges that arise in AI applications in healthcare will provide a sustainable competitive advantage. Moreover, greater awareness of this information across the country is expected to promote and accelerate the successful application of AI. Therefore, the objective of this work is to prioritize the challenges that arise in AI applications in healthcare. The challenges that were used to conduct this empirical study were identified through literature review. From the review of literature, it was found that the challenges in AI applications in healthcare are identified as data problems, human problems and ethical problems (Sunarti et al., 2021; Vellido, 2019; Lee and Yoon, 2021; Briganti, Le, 2020; Verghese et al., 2018).

Data Problems

Data Bias: For an AI model to be valid and reliable, the dataset must be of the right quality. For example, a dataset consisting only of women or people over 50 years old may have low coverage, depending on the application domain. So, if the dataset is not of the right quality, the results will be biassed.

Insufficient Data: Big data is needed to run AI models. If a sufficiently large dataset is not available during the creation of a model or during the testing phase of the created model, it is not possible to obtain healthy results from the created model.

Interpretability: Interpreting the results obtained by using AI technology is not always easy. Developing human-machine interaction and strengthening the communication between these two actors requires a certain amount of training and time. Instead of conducting the human-machine relationship directly with medical professionals, data scientists should also be used.

Privacy and Anonymity: Healthcare data is some of the most private data. Due to this sensitive nature of healthcare data, accessing it without an individual's consent can lead to negative consequences. Accordingly, great attention should be paid to the confidentiality of healthcare data. There are trust issues with AI technology when it comes to protecting the anonymity and privacy of individuals, which is challenging.

Cybersecurity: Cybersecurity aims to protect against malicious attacks. AI applications also require a high level of cybersecurity with respect to sensitive healthcare data. Achieving this high level of cybersecurity is a challenge.

Human Factor Problems

The Need for Human Interaction: In fields such as healthcare, where empathy with people evokes a sense of trust, the need for human interaction is inevitable. This human cognitive threshold is a challenge for the adoption of AI technology in healthcare.

Training/Education Needs: Creating a well-trained workforce that can harmonise with the technology is an important issue for any new technology. Departments of medical engineering and biomedical engineering are being opened in some universities around the world to meet this need. In addition, some universities are adding new courses to the medical education curriculum to train a workforce that can harmonise with AI technologies. But all this means a transformation process that will take many years. Training the existing medical workforce is quite costly. In this regard, the need for training is a challenge for the use of AI technology in healthcare.

Loss of Managerial Control: There is a bureaucratic management system that has been embedded in the healthcare system for decades. This system, where medical experts are consulted and responsibilities are shared with practitioners, breaks down with the integration of AI technology, which can lead to a sense of loss of control.

Resistance to Change: The question of whether healthcare professionals will be replaced by AI evokes resistance to change. Although there are academic studies in the literature stating that AI technology will not replace medical staff, e.g. (Topol EJ., 2019), (5), there is a general prejudice about this situation. Accordingly, it is a challenge for medical professionals. This may lead them to slow down the adoption of AI technology.

Job Loss: While AI will not replace medical staff, it will indeed create systems to support healthcare decision-making that will reduce the number of healthcare workers needed to do the same job. As a result, it is normal for medical staff to be at risk of unemployment.

Ethical Problems

The Principle of Ethical Double Effect: Some inventions in the field of healthcare may harm humanity instead of having positive effects. In this regard, ethical values should always be observed. The ethical principle of double effect is important in the field of healthcare. The ambiguity about AI technology's adherence to this principle poses a challenge.

Ethical Problems Associated with Research and Biomedical Medicine: Ethical principles such as autonomy, utility, innocence, and justice must be respected by AI in healthcare applications. All applications to be performed with AI must also meet the criteria of consent, privacy and safety, voluntary participation and autonomous decision making.

Multi-criteria Decision Making (MCDM) and Analytic Hierarchy Process (AHP)

Multi-criteria Decision Making (MCDM) methods are used to optimize the decision problem under the influence of multiple decision criteria (Yu, 2013). Decisions are often not made based on a single criterion. The decision problem faced in daily life, as well as in academic or business life, is solved by considering more than one criterion (Ustinovichius et al., 2007). In decision-making problems, there may be conflicting goals. Also, the same decision problem may require maximizing some criteria and minimizing others (Kumar et al., 2017). MCDM is used to solve all these problems where other methods are inadequate (Zeleny, 2011). In an increasingly complex business world, it is obvious that decisions and projects must be based on professional and scientific data (Doğan and Derici, 2019).

In MCDM problems, decision makers make their decisions based on decision variables called "decision criteria". In MCDM problems, the objective may be to weight the decision criteria to be used in decision making, i.e., to determine their importance, as well as to select the optimal decision alternative (Vinogradova et al., 2017). Determining the importance of decision criteria in MCDM problems is a necessary step. In particular, MCDM provides a useful set of methods for decision makers and practitioners to determine which criteria are more important and should be prioritized (Triantaphyllou et al., 1998).

The Analytic Hierarchy Process (AHP) method, which is easy to implement for the solution of the MCDM problems, is widely used (Ersoy and Doğan, 2020). AHP was first discussed in the work of Myres and Alpert in 1968. Later, in 1977, it was developed by Professor Thomas Lorie Saaty and started to be used in solving decision problems (13). In solving decision problems, the lack of adoption of complex abstract modeling approaches has led to the development of a mathematically simpler method that is easier to understand and apply. Finally, in the early 1970s, Saaty developed the AHP method, one of the modern decision support methods. AHP is a method that can be applied to many problems. One of the most common applications of the method is to decision problems where there are many decision criteria. AHP can be used to weight and rank the decision criteria appropriately (Saaty, 1980). The decisions to be made involve many subjective criteria that need to be explained as well as the objective criteria. To realize this, the measurement of the subjective data along with the measurement of the objective data should provide the decision maker with the optimal solution to the decision problem to be solved. AHP is a theory of pairwise comparison based on the priority ratings of expert opinions. In this theory, subjective criteria and objective criteria can be evaluated together in the same decision problem. This evaluation is done depending on which criterion the decision maker evaluates as more dominant than the other when comparing between the given measurements (Saaty, 2008). By reducing complex decisions to a series of pairwise comparisons and synthesizing their results, the AHP helps to capture the subjective and objective aspects of the decision (Triantaphyllou et al., 1998). In addition, the AHP contains a useful technique for checking the consistency of the decision maker's judgments, thereby reducing bias in the decision-making process (Saaty, 1980).

One of the most critical stages of the decision-making process is the selection and ranking of criteria that are important to the decision problem (Kumar and Parimala, 2020). In AHP, these criteria are arranged in a hierarchical structure. In this context, AHP identifies the priorities among the criteria and helps in decision making. (Shapira and Goldenberg, 2005) Based on pairwise comparison, AHP combines both the importance of the criteria and the preference distances of the alternatives into a single overall score for ranking the alternatives (Ngai, 2003).

AHP uses a 9-point scale developed by Saaty. This scale is used to determine the significance of the numbers. The numbers also indicate the ratio of the benchmarks being compared. Studies have shown that approximately 7±2 states of the human brain can be assessed in short-term memory in this way. Based on this experience, Saaty and many AHP practitioners estimate that the 1 to 9 scale is appropriate for understanding people's preferences (Saaty, 1986).

Table 1. Pairwise Comparison Scale of The AHP Method (Saaty, 1986)

Values	Definition
1	Equally important
3	Moderately important to one over the other
5	Very important
7	Significantly very important
9	Extremely important
2,4,6,8	Consensus values

According to AHP, the structure of a multi-criteria decision problem is modeled as shown in Figure 1:

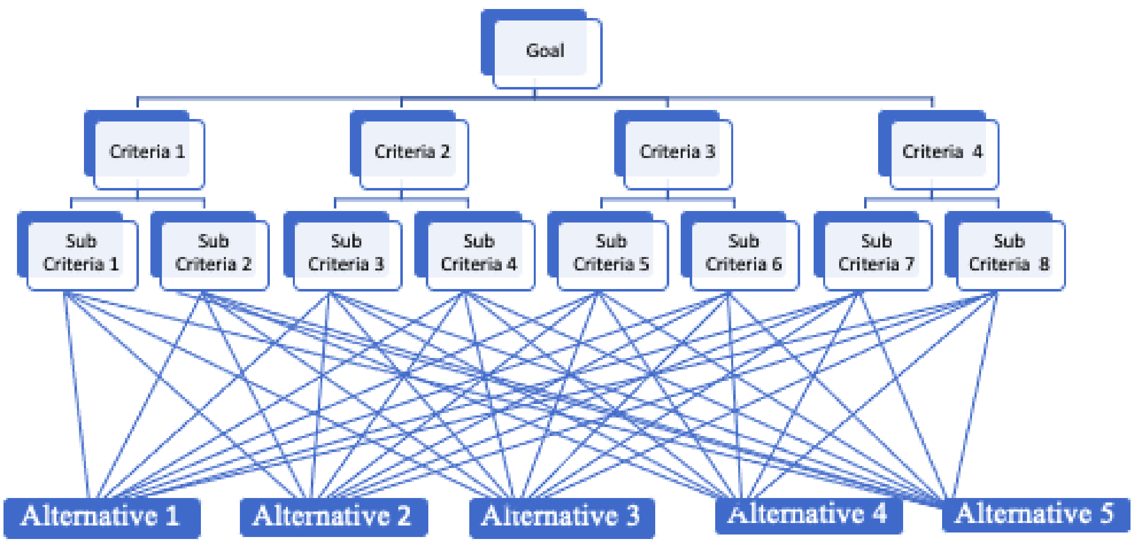

Figure 1. General Hierarchical Structure Of The AHP Method

The application steps of the AHP method are as follows:

Step 1 - Hierarchical Structure: For the purpose of making a decision, a decision hierarchy is created from top to bottom. At the middle level are criteria and at the lowest level are alternatives (Saaty, 2008).

Step 2: Formation of Pairwise Comparison Matrices and Superiority: At this stage, the criteria are compared by forming the A matrix as in Equation 1. The purpose is to determine the importance levels of the criteria and sub-criteria among themselves after the criteria and sub-criteria have been determined. The relative importance of each criterion in Equation 1 with respect to its contribution to the purpose is determined by pairwise comparison, according to the experts' judgments. In this step, the importance scale developed by Saaty and given in Table 1 should be used for pairwise comparisons. The size of the matrix is $\boldsymbol{nxn}$ (Saaty, 1990).

$$\begin{bmatrix} 1 & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ {}^{1}/_{x_{1n}} & \cdots & 1 \end{bmatrix} \tag{1}$$

Step 3: Eigenvector (Relative Significance Vector): The next step after creating the pairwise comparison matrices is to calculate the eigenvector that indicates the importance of each element in the corresponding matrix relative to the other elements, as in Equation 2. The size of the matrix is $\boldsymbol{nx1}$. To determine the percentage importance distributions of the criteria, the column vectors $\boldsymbol{w} = [\boldsymbol{w\_i}]\boldsymbol{nx1}$ must be calculated. The column vector $\boldsymbol{w}$ is the arithmetic mean of the row elements of the matrix formed by the $\boldsymbol{bij}$ values given in Equation 3 (Saaty, 1990).

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (2)$$

$$w_{ij} = \frac{\sum_{j=1}^{n} b_{ij}}{n} \quad (3)$$

$$i = 1,2,3, \dots, n \; ve \; j = 1,2,3, \dots, n$$

Step 4: Consistency of Eigenvector: The consistency ratio ($\boldsymbol{CR}$) is calculated for each pairwise comparison matrix and the upper bound for this ratio must be 0,10 (Xu, 2000). The $\boldsymbol{CR}$ above 0,10 indicates inconsistency in the decision maker's pairwise comparisons. In this case, it is necessary to improve the pairwise comparisons or make a group decision by obtaining the opinions of more decision makers (Baby, 2013). To calculate the value $\boldsymbol{CR}$, the largest eigenvector ($\boldsymbol{\lambda_{max}}$) of the $\boldsymbol{A}$ matrix must first be calculated as in Equation 5.

$$D = \left[a_{ij}\right]_{nxn} x \left[w_i\right]_{nx1} = \left[d_i\right]_{nx1} \quad (4)$$

$$\lambda_{max} = \frac{\sum_{i=1}^{n} \frac{d_i}{w_i}}{n} \quad (5)$$

$$i = 1,2,3, \dots, n \; ve \; j = 1,2,3, \dots, n$$

Another value needed to calculate the consistency ratio is the randomness index ($\boldsymbol{RI}$). The data with $\boldsymbol{RI}$ values, which consist of constant numbers and are determined as a function of $\boldsymbol{n}$ value, are given in Table 2 (Lin et al., 2008). Accordingly, the calculation of $\boldsymbol{CR}$ value is given in Equation 6 (Saaty, 1990).

Table 2. Randomness Index (Lin et al., 2008)

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0	0,58	0,9	1,12	1,24	1,32	1,41	1,45	1,49

$$CR = \frac{\lambda - n}{(n-1) \; x \; RI} \quad (6)$$

Step 5: Overall Conclusion: The calculations from the previous four steps are repeated for the entire hierarchical structure. In this step, the $\boldsymbol{mx1}$ large superiority column vectors created by each of the n criteria in the hierarchical structure are merged into the $\boldsymbol{mxn}$ size $\boldsymbol{DW}$ decision matrix. The result vector $\boldsymbol{R}$ is obtained by multiplying the $\boldsymbol{DW}$ matrix by the vector $\boldsymbol{W}$ as in Equation 8 (Saaty, 1990).

$$DW = \left[w_{iJ}\right]_{mxn} \quad (7)$$

$$R = DW \; x \; W \quad (8)$$

$$i = 1,2,3, \dots, n \; ve \; j = 1,2,3, \dots, n$$

Data Analysis

This study uses The Analytic Hierarchy Process (AHP) method, the most commonly used MCDM method. The reason for choosing AHP is that it provided successful results despite the small number of expert opinions. Moreover, AHP is the most commonly used method when it comes to weighting decision criteria. Moreover, AHP is a relatively simple method to understand and implement. The method allows decision makers to arrive at a solution through simple comparisons.

In this study, the opinions of 5 experts were obtained to prioritize the challenges in AI applications in healthcare. The experts were asked to make their pairwise comparisons on a scale of 1-9. The study identifies 12 challenges through literature review . The 12 challenges are analyzed under 3 main headings according to literatüre review (Sunarti et al., 2021; Vellido, 2019; Lee and Yoon, 2021; Briganti, Le, 2020; Verghese et al., 2018). The hierarchical structure created for the research problem can be seen in Figure 2.

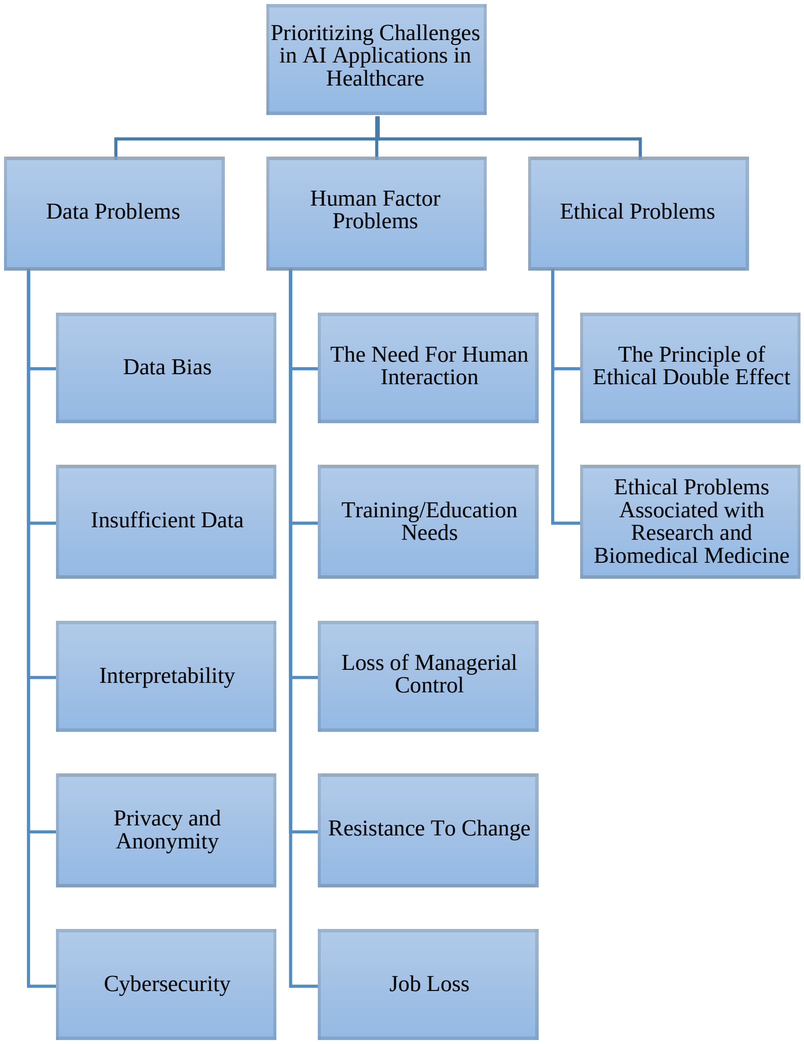

Figure 2. The Hierarchical Structure of The Research Problem

The review of the literature shows that the number of experts consulted depends on the nature of the topic studied and the number of experts that can be reached. The literature includes both studies in which the opinion of a single expert is obtained and studies in which the opinion of three or more experts is obtained , e.g. (Al-Harbi, 2001), (Shapira and Goldenberg, 2005),. In the study, AHP, one of the MCDM, was chosen as the method and 12 challenges were prioritized by obtaining the opinions of 5 experts, 3 of whom are medical doctors and 2 are academicians working in the field of AI. After the hierarchical structure of the decision problem is created, the second step of the AHP method is to create decision matrices. Table 3, Table 4, Table 5, and Table 6 summarize the pairwise comparisons made by the experts whose opinions were obtained, according to the scale in Table 1.

Table 3. Pairwise Comparison of Criteria

	Data Problems						*Human Factor Problems*						*Ethical Problems*					
Expert No:	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**
Data Problems	1	1	1	1	1	1	3	3	5	3	5	3,7	0,2	0,2	0,2	0,3	0,1	0,2
Human Factor Problems	0,3	0,3	0,2	0,3	0,2	0,3	1	1	1	1	1	1	0,2	0,2	0,2	0,3	0,3	0,2
Ethical Problems	5	5	5	3	7	4,8	5	6	5	3	3	4,2	1	1	1	1	1	1
					Sum	6,1					Sum	8,9					Sum	1,4

Table 4. Pairwise Comparison of Data Problem's Sub-criteria

Data Problems																														
	Data Bias						*Insufficient Data*						*Interpretability*						*Privacy and Anonymity*						*Cybersecurity*					
Expert No:	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**
Data Bias	1	1	1	1	1	1	2	0,5	1	1	1	1	0,3	0,3	0,5	0,3	0,3	0,3	0,3	0,3	0,5	0,3	0,3	0,3	0,2	0,2	0,3	0,2	0,2	0,2
Insufficient Data	0,5	2	1	1	1	1	1	1	1	1	1	1	0,5	0,3	0,5	0,3	0,3	0,3	0,5	0,2	0,5	0,3	0,3	0,3	0,3	0,1	0,3	0,2	0,2	0,2
Interpretability	3	3	2	4	3	2,9	2	4	2	4	3	2,9	1	1	1	1	1	1	0,3	0,3	0,3	0,3	0,3	0,3	0,2	0,2	0,2	0,2	0,2	0,2
Privacy and Anonymity	3	4	2	3	3	2,9	2	6	2	3	3	2,9	3	4	4	3	4	3,6	1	1	1	1	1	1	0,5	0,3	0,3	0,5	0,5	0,4
Cybersecurity	5	6	4	5	5	5	4	7	4	5	5	4,9	6	6	5	5	5	5,4	2	3	3	2	2	2,4	1	1	1	1	1	1
					Sum	13					Sum	13					Sum	11					Sum	4,3					Sum	2

Table 5. Pairwise Comparison of Human Factor Problem's Sub-criteria

Human Factor Problems																														
	The Need For Human Interaction						*Training/Education Needs*						*Loss of Managerial Control*						*Resistance To Change*						*Job Loss*					
Expert No:	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**
Human Interaction	1	1	1	1	1	1	1	0,5	0,3	0,3	0,5	0,5	3	2	3	3	3	2,8	2	2	3	3	3	2,6	0,3	0,3	0,2	0,2	0,3	0,2
Training/Education Needs	1	2	3	3	2	2	1	1	1	1	1	1	3	4	3	3	3	3,2	2	2	2	3	3	2,4	0,3	0,2	0,2	0,2	0,3	0,2
Loss of Managerial Control	0,3	0,5	0,3	0,3	0,3	0,4	0,3	0,3	0,3	0,3	0,3	0,3	1	1	1	1	1	1	1	0,5	0,5	0,5	0,5	0,6	0,2	0,2	0,2	0,2	0,2	0,2
Resistance To Change	0,5	0,5	0,3	0,3	0,3	0,4	0,5	0,5	0,5	0,3	0,3	0,4	1	2	2	2	2	1,7	1	1	1	1	1	1	0,3	0,3	0,3	0,3	0,3	0,3
Job Loss	4	4	5	5	4	4,4	4	5	5	5	4	4,6	5	6	5	6	6	5,6	3	4	4	4	4	3,8	1	1	1	1	1	1
					Sum	8,2					Sum	6,8					Sum	14					Sum	10					Sum	1,9

Table 6. Pairwise Comparison of Ethical Problem's Sub-criteria

Ethical Problems												
	The Principle Of Ethical Double Effect						*Ethical Problems Associated with Research and Biomedical Medicine*					
Expert No:	**1**	**2**	**3**	**4**	**5**	**G.M.**	**1**	**2**	**3**	**4**	**5**	**G.M.**
Ethical Double Effect	1	1	1	1	1	1	2	1	1	1	2	1,3
Res. and Biomedical Medicine	0,5	1	1	1	0,5	0,8	1	1	1	1	1	1
					Sum	1,8					Sum	2,3

It may be necessary to benefit from the experience, knowledge and judgments of group members when making a group decision consisting of experts in evaluating alternatives and criteria. In this case, group members may reach a consensus on the issue or methods such as combining different judgments with the geometric mean may be used. The most commonly used method in the literature is reaching consensus through the geometric mean. There are basically two approaches to group decision making. In the first method, opinions are combined and a single decision is made. In the second method, the geometric mean is used. In this study, the opinions of 5 experts whose opinions were obtained were reconciled using the geometric mean (Liberatore and Nydick, 1997; Saaty and Shang, 2007). These results are shown in Tables 3-4-5 and 6 by the G.M. column.

Table 7. The Weights of The Criteria

	Data Problems	*Human Factor Problems*	*Ethical Problems*	*Criteria Weight*
Data Problems	0,164	0,413	0,150	0,242
Human Factor Problems	0,045	0,112	0,171	0,109
Ethical Problems	0,792	0,474	0,725	0,664
			Sum	1

Table 8. The Weights of The Data Problem's Sub-criteria

	Data Bias	*Insufficient Data*	*Interpretability*	*Privacy and Anonymity*	*Cybersecurity*	*Criteria Weight*
Data Bias	0,078	0,079	0,032	0,079	0,100	0,074
Insufficient Data	0,078	0,079	0,033	0,079	0,101	0,074
Interpretability	0,229	0,226	0,094	0,065	0,092	0,141
Privacy and Anonymity	0,229	0,231	0,335	0,232	0,211	0,247
Cybersecurity	0,387	0,386	0,506	0,545	0,496	0,464
					Sum	1

Table 9. The Weights of The Human Factor Problem's Sub-criteria

	The Need For Human Interaction	*Training/Education Needs*	*Loss of Managerial Control*	*Resistance To Change*	*Job Loss*	*Criteria Weight*
Human Interaction	0,078	0,039	0,260	0,591	0,113	0,216
Training/Education Needs	0,160	0,079	0,299	0,545	0,108	0,238
Loss of Managerial Control	0,028	0,025	0,094	0,133	0,089	0,074
Resistance To Change	0,031	0,034	0,164	0,232	0,131	0,118
Job Loss	0,341	0,361	0,525	0,875	0,496	0,519
					Sum	1

Table 10. The Weights of The Ethical Problem's Sub-criteria

	The Principle Of Ethical Double Effect	Ethical Problems Associated with Research and Biomedical Medicine	Criteria Weight
Ethical Double Effect	0,569	0,569	0,569
Res. and Biomedical Medicine	0,431	0,431	0,431
		Sum	1

In order to compare the expert opinions of the decision makers, the relative comparisons in the decision matrices should take a value between 0 and 1. For this purpose, the decision matrices were normalized using Equations 2 and 3. As a result of these calculations, the weights of the criteria in Table 7 and the local weights of the sub-criteria in Table 8, 9, 10 were calculated.

Table 11. Calculation of CR

	Consistency	Number of Comparision	3
Data Problems	3,228308964	Average Consistency	3,111627116
Human Factor Problems	2,6460913	CI	0,055813558
Ethical Problems	3,460481084	RI	0,58
Sum	9,334881348	CR	0,096230272
Data Bias	5,078345675	Number of Comparision	5
Insufficient Data	5,081851398	Average Consistency	5,265925313
Interpretability	5,133489303	CI	0,066481328
Privacy and Anonymity	5,57733888	RI	1,12
Cybersecurity	5,458601309	CR	0,059358329
Sum	26,32962656		
Human Interaction	4,425488671	Number of Comparision	5
Training/Education Needs	5,487511963	Average Consistency	5,312760422
Loss of Managerial Control	5,255947706	CI	0,078190106
Resistance To Change	4,825653542	RI	1,12
Job Loss	6,569200229	CR	0,069812594
Sum	26,56380211		
Ethical Double Effect	2	Number of Comparision	2
Res. and Biomedical Medicine	2	Average Consistency	2
Sum	4	CI	0
		RI	0
		CR	0

In order for the AHP method to be interpretable, all pairwise comparison matrices created by the decision makers should be consistent. To this end, CR was calculated for each pairwise comparison matrices using Equations 4 and 5 and Table 2. The results are presented in Table 11. Examination of Table 11 shows that the value CR calculated for all pairwise comparison matrices satisfies the CR<0,10 condition. Thus, the results are interpretable.

Table 12. Calculation of The Local Weights of The Criteria

Weights of Criteria		Local Weights of Sub-Criteria		Local Weights of Criteria	Rank
Data Problems	0,242	Data Bias	0,074	0,018	9-10
		Insufficient Data	0,074	0,018	9-10
		Interpretability	0,141	0,034	6
		Privacy and Anonymity	0,247	0,060	4
		Cybersecurity	0,464	0,112	3
Human Factor Problems	0,109	Human Interaction	0,216	0,024	8
		Training/Education Needs	0,238	0,026	7
		Loss of Managerial Control	0,074	0,008	12
		Resistance To Change	0,118	0,013	11
		Job Loss	0,519	0,057	5
Ethical Problems	0,664	Ethical Double Effect	0,569	0,377	1
		Res. and Biomedical Medicine	0,431	0,286	2
			Sum	1	

Figure 3. Pie Chart of Local Weights

Equations 7 and 8 are used in this phase, where the hierarchical structure is integrated and the final results are obtained. In this step, the local weights of the criteria are calculated and the ranks are determined. The results are given in Table 12. The highest local weight of the criteria indicates the most important challenge, while the lowest local weight of the criteria indicates the least important challenge. The distribution of the weights is shown in Figure 3.

Conclusions and Recommendations

AI applications in healthcare are at an early stage, both in terms of adaptation, development and research. There are no quantitive studies in the literature on the challenges that AI applications in healthcare may face. Accordingly, policy makers and practitioners do not have a proper understanding of the challenges that may arise.

Examination of the results of the study shows that the challenge with the highest weight according to the criteria weighting is "Ethical Problems". This challenge is followed by "Data Problems". "Human Factor Problems" are ranked last. The ranking was done according to the local weights of the criteria and can be seen in Table 12 and Figure 3. Accordingly, it can be seen that the challenge to focus on the most is "The Principle of Ethical Double Effect" with a weighting of 0,377. The second challenge is "Ethical Problems Associated with Research and Biomedical Medicine" which is also an ethical problem with a weight of 0,268. Examination of these results shows that studies should be conducted to clarify the uncertainties associated with ethical issues in the application of AI in healthcare. The third most important challenge is "Cybersecurity" with a weighting of 0,112. "Privacy and Anonymity" is the next challenge with a weighting of 0.060. The fact that these two challenges related to data come together in order of importance shows that, data in healthcare is sensitive. Protecting this data is costly, difficult and risky. In this regard, it is necessary to pay attention to the challenges in data area. The fifth challenge is "Job Loss" with 0,057. The fear that AI applications in healthcare will lead to unemployment emerges as a challenge. These challenges are followed by "Interpretability", "Training/Education Needs", "Human Interaction", "Insufficient Data", "Data Bias", "Resistance To Change" and "Loss loss of Managerial Control".

In order to obtain more comprehensive results in future studies, a contribution to the literature can be made by integrating the qualitative and quantitative approaches. Accordingly, it is recommended to use in-depth interviews and nominal group techniques to identify challenges and replicate prioritization with other MCDM methods such as BWM and ANP.

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GENİŞLETİLMİŞ ÖZET

Sağlık hizmetlerinde yapay zeka uygulamaları adaptasyon ve ar-ge bakımından henüz erken aşamada yer almaktadır. Bu duruma bağlı olarak da literatürde sağlık hizmetlerinde yapay zeka kavramına ilişkin literatürde nicel uygulama içerek az sayıda çalışma bulunmaktadır. Bu çalışmanın amacı, sağlık hizmetlerinde yapay zeka uygulamaları gerçekleştirilirken uygulayıcıların ya da politika yapıcıların karşılaşmaları olası zorlukların önceliklendirilmesidir. . Bu ampirik çalışmayı yürütmek için analizde karar kriteri olarak yer alan zorluklar zorluklar literatür taraması yoluyla belirlenmiştir. Literatür taramasından sağlık hizmetlerinde yapay zeka uygulamalarında karşılaşılan zorlukların veri sorunları, insan sorunları ve etik sorunlar ana başlıkları altında toplandığı görülmektedir Sunarti vd., 2021; Vellido, 2019; Lee ve Yoon, 2021; Briganti, Le, 2020; Verghese ve diğerleri, 2018).

Çalışmada Analitik Hiyerarşi Süreci (AHP) yöntemi kullanılmaktadır. AHP'nin seçilmesinin nedeni, az sayıda uzman görüşüne rağmen başarılı sonuçlar vermesidir. Ayrıca, AHP önceliklendirme konusunda en sık kullanılan Çok Kriterli Karar Verme (ÇKKV) yöntemidir. AHP, anlaşılması ve uygulanması nispeten basit bir yöntemdir. Yöntem, karar vericilerin basit karşılaştırmalar yoluyla bir çözüme ulaşmasını sağlamaktadır. Bu çalışmada 5 uzmanın görüşü alınmıştır. Uzmanlardan ikili karşılaştırmalarını 1-9 arası bir ölçekte yapmaları istenmiştir.

Araştırma sonuçları incelendiğinde en önemli zorluğun “Etik Sorunlar” olduğu görülmektedir. Bu zorluğu "Veri Sorunları" takip etmektedir. "İnsan Faktörü Sorunları" en son sırada yer almaktadır. AHP sonuçlarına göre en çok üzerinde durulması gereken zorluk 0,377 ağırlıkla “Etik Çift Etki Prensibi” olduğu görülmektedir. İkinci zorluk ise 0,268 ağırlığı ile yine bir etik sorun olan “Araştırma ve Biyomedikal Tıpla İlişkili Etik Sorunlar”dır. Bu sonuçların incelenmesi, sağlık hizmetlerinde yapay zekanın uygulanmasında etik konularla ilişkili belirsizliklerin netleştirilmesine yönelik çalışmaların yapılması gerektiğini göstermektedir. Üçüncü en önemli zorluk ise 0,112 ağırlık ile "Siber Güvenlik" zorluğu olmaktadır. "Gizlilik ve Anonimlik" zorluğu 0.060 ağırlıkla bir sonraki önem sırasında yer almaktadır. Verilerle ilgili bu iki zorluğun önem sırasına ön sıralarda arka arkaya yer almaları, sağlıkta verilerin hassas olduğunu göstermektedir. Sağlık verilerini korumak maliyetli, zor ve risklidir. Bu bağlamda veri alanındaki zorluklara dikkat edilmesi gerekmektedir. Beşinci zorluk ise 0,057 ağırlık ile "İş Kaybı"dır. Sağlık hizmetlerinde yapay zeka uygulamalarının işsizliğe yol açacağı korkusu, sağlıkta yapay zeka uygulamaları açısından bir zorluk meydana getirmektedir. Bu zorlukları “Yorumlanabilirlik”, “Eğitim İhtiyaçları”, “İnsan Etkileşimi”, “Yetersiz Veri”, “Veri Önyargısı”, “Değişime Direnç” ve “Yönetimin Kontrolü Kaybı” zorlukları takip etmektedir.

İleride yapılacak çalışmalarda daha kapsamlı sonuçlar elde edebilmek için nitel ve nicel yaklaşımlar bütünleştirilerek literatüre katkı sağlanabilir. Çalışma BWM ve ANP gibi diğer ÇKKV yöntemleriyle tekrarlanabilir.