AN EXTENSIVE ANALYSIS OF THE HURDLES IN EMBRACING AI AMONG PEOPLE WITH SPECIAL NEEDS USING AHP

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ABSTRACT

This study aims to uncover the challenges to the mainstream adoption of AI (artificial intelligence) among people with special needs in India. AI has been widely used in real-time healthcare, education, and transportation situations; however, there is a digital divide in the ability to reap the benefits of AI applications for those with special needs due to various socioeconomic factors. The proposed work also intends to examine and undertake in-depth research using the Analytic Hierarchy Process (AHP) to discover, analyze, and offer an accessible overview of the issues surrounding the numerous socioeconomic and technical factors involved with the use of AI. This research will contribute significantly to addressing the ongoing challenges of the special need's population in their use of AI in various real-time applications by addressing technical infrastructure limitations, cultural differences, and other economic concerns. It will also help to bridge the gap between AI and the special needs population by addressing these limitations. By giving attention to this unexplored field, this piece of research will provide a better foundation for how to take preventive measures and overcome the digital gap of AI among special needs from several perspectives.

Keywords: special needs; Artificial Intelligence (AI); Analytic Hierarchy Process (AHP)

1. Introduction

The adoption of AI in several sectors of life dramatically improves the quality of life of people with special needs. However, there are many socioeconomic and other technological obstacles to the use of AI among persons with physical disabilities. This study examines the barriers to AI adoption among people with physical disabilities in depth. To explore the core reason for this digital gap, we evaluated current research on AI adoption problems for the special needs population. Michele et

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al. 2022 discovered that inequalities in education, jobs, and money provide a socioeconomic barrier to the application of AI for those with visual impairments. This digital divide affected students' access to digital resources for academic advancement (Lussier-Desrochers et al., 2017). It is important to consider individuals with disabilities when developing AI decision-making real-time applications (Trewin et al., 2019). The education challenges that deprive students of access to online learning environments and collaboration technologies create a digital divide. There is no doubt that access to assistive technologies creates self-sufficiency, but the limitation of access due to the digital divide results in perceived unfairness and lack of control. There are different strategies to reduce the digital divide for individuals with physical limitations including investment in accessible devices, assistive technologies, and adaptive software (World Bank, 2019). However, according to a UNESCO report (2019), collaboration between governments, educational institutions, technology companies, and disability organizations for developing sophisticated technologies for special needs is not easy. Burgstahler et al. (2015) focused on providing a more accessible learning environment so that the user can be digitally literate and ensure inclusive digital content. A variety of decision-making methods and tools are available to support decision-making. This article aims to assess the application of a well-known and widely used decision-making methodology, the Analytic Hierarchy Process (AHP), to identify the barriers that special needs individuals face when attempting to embrace AI.

The AHP is a mathematical approach that can be used to determine the constraints that hinder AI adoption by the special needs population. This technique helps stakeholders understand the correlation between different variables and propose different challenges and solutions to overcome the challenges. This research paper addresses two research questions as follows:

- What are the barriers to mainstream acceptance of AI among people with special needs?
- How can we use AHP to thoroughly grasp such important issues?

2. Related works

In recent years, AI has been increasingly deployed in real-time environments. The extent to which AI has been used to meet the demands of people with special needs, however, is still an intriguing subject. To fill this gap, we conducted a review of the literature, with Nickerson et al. (2013) providing insight into specific initiatives to develop technology-enhanced teaching tools. Their research focused on helping the most marginalized elements of society, which includes those who are economically poor, members of racial and language minorities, and those who have learning and/or physical impairments. Appropriate access to technology-based services for these underprivileged groups of people is the primary goal. For underprivileged students, merely cutting costs and expanding physical access to computers will not reduce the digital divide. Instead, inequality issues should be addressed by developing tools that enable physically disabled students to overcome disadvantages and realize their full educational potential. Additionally, Nickerson et al. (2013) outlined several approaches to developing computer-based assistive technology for individuals with physical disabilities. These approaches include conducting research that considers the needs of various student populations, training teachers to integrate technology into the classroom, organizing a teacher workshop that includes a broad representation of

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the student body, developing software that caters to various learning styles, and making computers easily accessible for little or no cost. Only 2.8% of people with disabilities can enter higher education, according to Engelbrecht et al. (2014) who studied the accessibility of higher education for students with physical impairments. A thorough mixed-method approach was used in their research, which included focus groups, interviews, and questionnaires. The results highlighted important accessibility challenges, including those related to physical accessibility, service information, attitude, and educational support, as well as other pertinent constraints like the psychological, social, and academic issues that these students faced in higher educational institutions. As a result, the research recommended that standards be created to assist colleges in addressing these intricate problems and improving opportunities for students with disabilities. People with disabilities endure marginalization from society, limited employment possibilities, and difficulty accessing vital services in many developing Asian and Pacific nations (WHO, 2011). Worldwide, there are over a billion individuals with disabilities who frequently lack access to assistive technology, healthcare, and education (Laabidi et al., 2013). According to WHO forecasts, assistive gadgets might help over one billion people (UNESCO, 2013). Microsoft's 2017 annual report emphasized how technology affects every part of life and stressed the need for reliable technology that benefits everyone. Microsoft has empowered individuals with impairments, such as children with dyslexia, by utilizing technology, including artificial intelligence and machine learning (Microsoft, 2017). Recent advancements in AI show promise for enhancing special needs education and assistance (Drigas & Ioannidou, 2012). According to Grewal (2014), AI is a system for gathering, analyzing, and sharing knowledge and information through information agents which can be software or robots. Morrison et al. (2017) underlined that AI developers should keep the technological demands of individuals with special needs in mind while developing AI applications. It is common knowledge that the benefits of AI in education are significant for non-disabled people, but AI also has the potential to support special needs individuals in academic advancement if taken in the right direction (Drigas et al., 2012). The collaboration of AI development with special education for the development of AI-based robots will help people with disabilities according to Laabidi et al. (2013). According to Garg Sharma et al. (2020), voice technologies such as Siri and Alexa might give extra support in learning to children with physical disabilities. They also highlighted the need for teachers to be more open to special needs students and their comfort during teaching sessions to help them be open and share their thoughts and ideas.

Our study is an attempt to determine the different factors that have an impact on the adoption of AI by the special needs population such as socioeconomic barriers, technological limitations, and other behavioral barriers that prevent them from using AI. From the literature review, we found that the AHP, a mathematical model developed by Saaty (1977, 1980) stands out as an efficient tool for decision-making in healthcare management and other areas. It has also been used in health economics research for efficient decision-making by Dolan et al. (1989). One of the AHP's initial and continuing areas of application has been health care and medical decision-making (Liberatore, 2008). Alrawad et al. (2023) applied the AHP to identify financial and cash flow risks associated with SMEs, as well as to assess how managers perceived these risks. The fundamental goal of going through the existing research works on AHP is to understand the genuine consequences of AHP in decision-making. Xu et al. (2023) analyzed the impact of the COVID-19 pandemic on education, stating that online learning helps students learn more successfully. Big

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data technology transformed traditional teaching methods, yet the fast switch to online education presented challenges. To address this issue, four instructional styles were assessed using the Fuzzy Analytical Hierarchy Process (Fuzzy AHP) method against seven criteria. This technique is both efficient and successful in decision-making, simplifying the decision-making process.

Merhi et al. (2023) analyzed and examined the essential enablers that influence the adoption and deployment of AI in production systems. They identified twelve enablers, developed a conceptual model, and organized them using the Technology, Organization, and Environment (TOE) framework. The findings indicated that technology is more important than organization or environment, and project management was the most significant of the twelve enablers. The study offered insights for practitioners and researchers, allowing them to focus on the most important enablers for increasing the success rate of AI adoption. Mohammed et al. (2021) developed an innovative model for teaching science in Iraqi schools and also looked at how teaching in a flipped classroom affects student achievement, motivation, and innovative thinking using the Multi-Criteria Decision Making (MCDM) methodology of the AHP. The AHP technique in this study consisted of several components, including defining assessment criteria and weights, as well as comparing flipped classroom methods to standard cognitive learning procedures. Saaty et al. (2006) aided decision-makers when confronted with circumstances having many criteria or attributes. The procedure assesses and prioritizes a group of options based on predetermined criteria or their relative relevance. Pairwise comparisons between choice alternatives result in a hierarchical structure that may be employed for complicated decision-making situations (Saaty, 1991). The AHP approach was used in a variety of applications such as the creation of clinical recommendations (Cook et al., 1990; Dolan et al., 1993) and the advancement of biomedical advances and technologies (Cheever et al., 2009). Their studies also aimed to investigate the present situation of the AHP's technique due to its growing implementation. The technique provides the foundation for determining which tool is appropriate in each decision-making scenario and for accurately representing the opinions of all participants. Danner et al. (2011) examined the area of AHP application. They identified several application areas of AHP (e.g., shared decision-making, clinical recommendations, and healthcare management). A complicated choice issue can be paired down into several hierarchical levels using the AHP (Saaty, 1987). The six stages that Dolan et al. (2013) recommended for the application of an AHP problem are as follows. Firstly, specify the criteria, options, and decision goal. Secondly, rate the criteria in pairwise comparisons, then determine the (sub-)criteria's relative priority weight followed by the global priority weights of the criteria and the priorities of the alternatives. Finally, conduct sensitivity testing to check for discrepancies.

The objectives of the study are as follows:

- The study aims to identify and analyze the various barriers that people with physical impairments encounter when trying to use artificial intelligence (AI) technology, including technological, cultural, and economic constraints.

- Using the AHP, the study seeks to prioritize and quantify the significance of these constraints to provide a structured understanding of their impact on accessibility to AI technology.

Table 1
Relevant literature review summary

References	Focus of Study/Key Points
Nickerson et al. (2013)	This article studies inclusive educational technology with a focus on equity for physically disabled students, implementing targeted strategies for computer-based products to address the student's unique needs.
Engelbrecht et al. (2014)	This article examines accessibility challenges in higher education for physically disabled students using a mixed-method approach involving surveys, focus groups, and interviews.
Drigas et al. (2012) Microsoft (2017)	Both research works are about utilizing technology, AI, and machine learning to empower individuals with disabilities, highlighting the growing attention to AI's potential for supporting the development of students with special needs.
Garg & Sharma (2020)	This article explores AI tools' impact on students with special needs, emphasizing inclusive teaching for equitable education while assisting teachers.
Saaty (1977, 1980)	These articles detail the performance of the use of the mathematical model, the Analytic Hierarchy Process (AHP) developed by Saaty in the late 1970s in decision-making for the marketing sector.
Dolan et al. (1989)	This article was the first to apply the AHP to health economics research; since then, it has gradually been accepted in the field of multi-criteria decision-making in healthcare.
Liberatore (2008)	This article focuses on health care and medical decision-making which have been early and ongoing application areas for the AHP.
Danner et al. (2011)	This article studied the use of AHP as a concept and determined the number of criteria and options, individual or group decisions, participants, rating system, and numerous application areas.
Dolan et al. (1993) Cheever et al. (2009)	These articles applied the AHP method in different contexts, for example, the development of clinical guidelines or biomedical innovations and technology development.

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Hummel et al. (2011)	This study aims to assess the diverse applications of the AHP in healthcare decision-making, revealing its suitability for complex decision problems, information sharing, and situations requiring improved decision outcomes.
Saaty et al. (2006) Saaty (1991)	These studies explore decision-making in complex situations using a hierarchical structure, focusing on assessing and prioritizing options based on predetermined criteria or relevance.
Mohammed et al. (2021)	This study developed a flipped classroom model for science teaching in Iraqi schools, examining its impact on student achievement, motivation, and innovative thinking using the Multi-Criteria Decision Making (MCDM) methodology and AHP technique.
Xu et al. (2023)	This research study examined the effects of COVID-19 on education, highlighting the advantages and challenges of transitioning to online learning. It used the Fuzzy Analytical Hierarchy Process to assess instructional styles and simplify decision-making processes.
WHO (2011)	This report discusses how people with disabilities face marginalization from society, restricted economic opportunities, and difficulties obtaining crucial services in many emerging Asian and Pacific nations.
Laabidi et al. (2013)	This study covers the concepts of basic electronic accessibility, universal design, and assistive technologies with an emphasis on accessible e-learning systems.

3. AHP's mathematical foundation

To fully understand the AHP, it is necessary to understand the fundamental mathematical concepts and terminology involved. These concepts are described below.

3.1 Positive Reciprocal Matrix

A square matrix of order n, A=[aij], satisfies the following requirements and has only positive entries. A positive reciprocal matrix is represented by $aij=1aji \ \forall \ i, j=1$with i=j.

Let P be a n-dimensional matrix with a single member for each dimension. Nontrivial positive reciprocal matrices of the same order as the matrix can be created. In this instance, a nontrivial reciprocal matrix is a positive reciprocal matrix whose components are not always 1. Given a diagonal matrix of rank n with positive diagonal elements, let D=diag (d1, d2…dn) =1, 2... be neither an identity nor a null matrix in the nontrivial case. Hence, $A=DPD-1$ is a positive reciprocal matrix. Another way to create a reciprocal matrix A=[aij] of order n is to take $aij=wi/wj$, where wi, wj are the elements of a finite set W $\{w1, w2\ldots wn$: $wi\in$R, $i=1,2\ldots n\}$. The structure of an order of n pair comparison matrix is as follows:

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$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \qquad (1)$$

where j, i, and aij>0 and aji=1/aij.

If w = {w1, w2, wn: wi∈R, i=1, 2…} is the weight vector (priority vector), then the components of the previously given matrix can be approximated as aij≈wi/wj, (Saaty, 1987). As a result, the weight ratios A= [wi/wj] may be used to describe the matrix A=[aij] as follows:

$$A = \begin{bmatrix} 1 & \frac{w_1}{w_2} \dots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & 1 \dots & \frac{w_2}{w_n} \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & 1 \end{bmatrix} \qquad (2)$$

The square of the eigenvalues gathered in a matrix's spectrum (A), where the eigenvalues are repeated according to their algebraic multiplicity, is known as the matrix's spectrum and spectrum radius. The multiplicity of an eigenvalue in the spectrum equals the generalized eigenspace dimension. The largest value of the modulus of A's eigenvalues is its spectral radius (A),

$$(A)=max\ \{|\lambda|: \lambda\in (A)\} \qquad (3)$$

3.2 Simple Matrix

If all of the elements in a square matrix A, or aij, are nonnegative, that is, aij≥0≥0, then matrix A is said to be non-negative. A primitive matrix is a subtype of a nonnegative matrix. The matrix A is considered primal if there is a natural integer k such that aij k >0, ∀ (i, j)>0, ∀, and $aijk$ is the element of 'Ak' in the i^{th} row and j^{th} column. Any positive reciprocal matrix is therefore a primitive matrix. One well-known theory for determining the fundamental matrix is the Perron-Frobeniuos theorem. This theorem states that, given A as a primitive matrix of spectral radius (A), (A)=|λmax|, i.e.,

• λmax algebraic multiplicity must be one, and consequently, the geometric multiplicity is one. This theorem holds for a single maximum eigenvalue λmax. The eigenvectors corresponding to λmax are strictly positive.

Let A be a positive reciprocal matrix of order n. If max is an eigenvalue of A such that (A)=|max|, then the major eigenvalue, or Perron value, of A, is λmax, i.e., $\lambda max \geq n$ cannot be smaller than 'n'. If and only if λmax equals n, then the matrix A fulfills the consistency property, also referred to as the transitive relation $aijajk$=aik.

Since A is a consistent reciprocal matrix, it will have the following properties:

- If and only if a positive reciprocal matrix A of order n is consistent, then $\lambda\, m\, a\, x = n$.

- If, and only if, the characteristic polynomial of a positive reciprocal matrix of order n is of the form $(\lambda)= \lambda\lambda^{n} - n\lambda^{n-1}$, then the matrix A is consistent.

- A consistent positive reciprocal matrix always has a rank of one since the column vectors of A are proportionate.

Identifying the significance of every component is the primary goal of any multi-criteria decision-making process. As the name implies, the AHP decision-making method starts by decomposing the multi-criteria decision-making problem into a hierarchical model. Then, the weights are calculated mathematically, mostly with the use of linear algebra. By comparing two options pairwise using the specified criterion, their weights may be determined. The decision-maker assigns a preference rating of strong, extremely strong, weak, or very strong based on the specific criterion.

A total of n(n-1)/2 pairwise comparisons results in the order n pairwise comparison matrix A=[aij] (PCM). The PCM diagonal entries are all equal to one, while the remaining components consist of the reciprocal n $(n-1)/2$ comparisons. When i, j=1, 2..., n, and aij indicate a preference for the i^{th} preference over the j^{th} choice, then

$$i = \begin{cases} 1 \\ a_{ij} \end{cases} \quad i = j \;\&i < j \Big\} \qquad (4)$$

This matrix A may or may not be consistent, but it is always positive. Using this pairwise comparison approach, Saaty (1987) established the AHP as a tool for multi-criteria decision-making. He demonstrated a pairwise comparison between two criteria using a number scale ranging from 1 to 9. Between the set of possibilities and the discrete set {9,8,7,6,5,4,3,2,1,1/2,1/3,1/4,1/5,1/6,1/7,1/8,1/9}, this scale establishes a one-to-one equation $a_{ij}a_{jk} = a_{ik}$, as previously described in the mathematical process of the AHP, then matrix A is consistent. The characteristic polynomial of A is of the form $\lambda_n - n\lambda_{n-1} = 0$ if it is consistent. The significance of the criteria in the AHP is evaluated using the priority weights derived from a pairwise comparison matrix (PCM).

4. Materials and methods

4.1 Constraints

The constraints that are revealed by a comprehensive analysis of the literature are depicted in Figure 1. These constraints were considered as they were found to be the most common hurdles to the adoption of AI among the special needs population in the literature.

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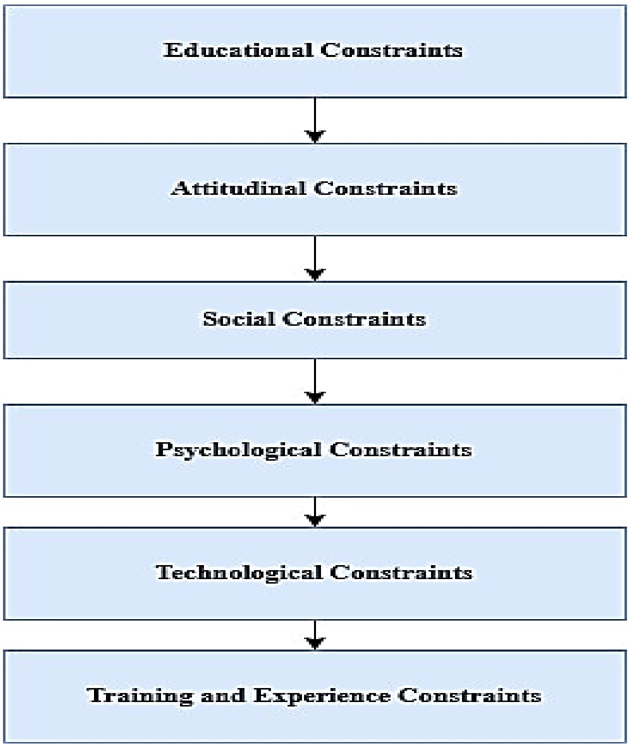

Figure 1 Selected constraints

4.2 AHP methodology

A survey questionnaire developed based on earlier AHP investigations and found in the existing literature was used to collect the data in our study. Primary data were gathered from 280 respondents, including educators and government organizations functioning in various Indian states, specifically the northeastern states. The study population chosen for our research was students who are physically challenged and have faced various constraints during their education. The questionnaire was given to five different education and healthcare specialists and was divided into two parts. The first part focused on socio-demographic information, and the second part aimed to capture the perceptions of different special needs individuals regarding the adoption of AI applications and the difficulties in using them. The responses were ranked (1 to 10 ranking). The respondents were invited to take part in the study and asked to fill out the online survey using Google Forms within four weeks. To enhance the response rate, a reminder email was sent on August 27, 2023. The survey was sent to 400 people, and 280 responded. Some of the participants were hesitant to respond due to various restrictions such as a lack of communication (sign language), a lack of understanding about the usage of AI, and other cultural restraints. The hesitation to interact with the online survey was probably caused by a lack of understanding of the survey instructions as a result of communication barriers, a lack of experience with AI and worries about cultural appropriateness. The final number of respondents was 280 people, and since the AHP does not rely on statistical analyses to generalize research findings, this low response rate did not affect the validity of the study's findings. It is better to analyze genuine responses in the research rather than include induced responses. The low number of responses might be a limitation of this study; however, future studies can address this limitation to ensure a nuanced interpretation. The AHP is an essential tool in today's intricate decision-making environment and is a widely used decision-making statistical tool (Saaty, 1980). It is a mathematical model that is based on the following three fundamental criteria: hierarchy, criteria comparison, and decision synthesis for representing human cognitive processes.

The AHP is an effective method for prioritizing decisions to solve real-time complex problems (Costa et al., 2016). It offers the best solutions by accounting for a range of quantitative and qualitative assessment factors. The main advantage of the AHP is its potential for elemental analysis and prioritization by building hierarchies and conducting pairwise comparisons. The main goal of the AHP is to select a set of workable alternatives to be compared to the specified criteria, and the criteria and sub-criteria that are assessed through pairwise comparisons make up the hierarchy of the AHP decision problem. The problem is structured using a hierarchy which is checked by the experts. Then, all the elements within the various hierarchy levels are compared to make a decision. A similar process is also completed for sub-criteria. The three-step process of the AHP's prioritization approach includes collecting opinions from experts, normalizing them to establish priorities, and computing global weights by factoring in item weights. According to Garuti and Sandoval (2006), expert knowledge needs to be combined and checked in the survey report on which AHP will be evaluated to obtain reliable outcomes.

The literature review showed that the AHP technique has been used extensively by researchers to rank or prioritize factors in a variety of real-time scenarios, including organizational readiness (Reza Sadeghi et al., 2013), employee adoption of e-government (Gupta et al., 2017), and factors influencing adoption of Massive Open Online Courses (Mahajan et al., 2019). Figure 2 shows the steps that are part of the AHP method (Saaty, 1980; Millet and Saaty, 2000).

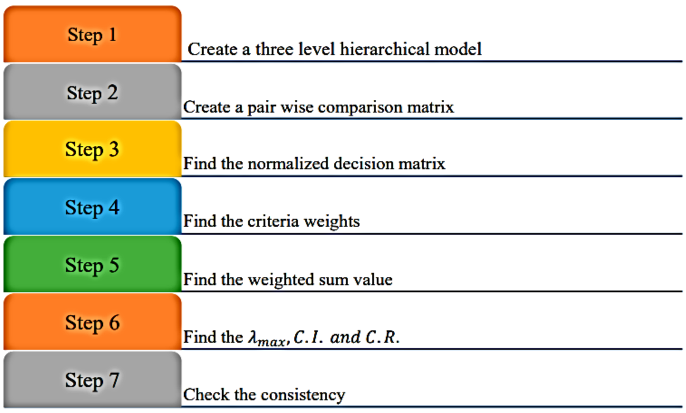

Figure 2 AHP steps

4.2.1 Hierarchy model

The four-level hierarchy design utilized in this study is shown in Figure 3 below. The upper level (Level 1) of the hierarchy illustrates the major goal of the research which was to identify the factors that inhibit the adoption of artificial intelligence among people with special needs. The second level (Level 2) of the structure shows the criteria/attributes which include the two categories of adoption readiness and technical feasibility. Level 3 shows the sub-criteria which include educational, attitudinal, social, psychological, training, and experience constraints within adoption readiness, and technological constraints within technical feasibility. The Level 2 constraints have a significant impact on the sub-criteria, or decision possibilities which comprise a list of characteristics that influence AI adoption. Level 4 shows the

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alternatives which include AI adoption and no AI adoption. This study aimed to explore the criteria that have a genuine influence on AI adoption, how they are connected, and how they affect the whole cognitive process. For this, we used the AHP to determine which criteria (limitations) are most important for the adoption of AI among special needs individuals.

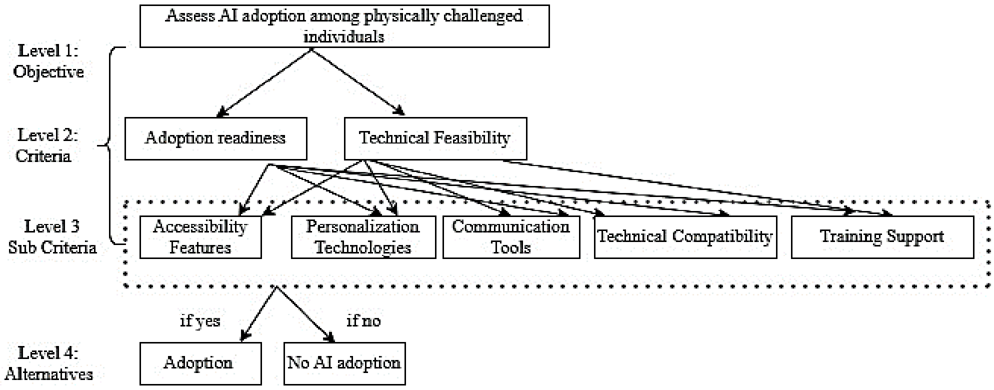

Figure 3 Hierarchy model for AI adoption decision

4.2.2 Pairwise Comparison Matrix

In this step, the data acquired from the respondents from the pair-wise comparisons of the variables was translated into reciprocating comparison matrices. The pair-wise comparisons were produced using Saaty's nine-point scale of relative significance, as shown in Table 2.

Table 2
Saaty scale for pairwise comparison (Saaty, 1980)

Numerical value	Definition	Explanation
1	Equally important	The attribute in row (i) is of equal importance to the one in column (j).
3	Moderately important	The attribute in row (i) is more moderately important than the one in column (j).
5	Strongly important	The attribute in row (i) is more strongly important than the one in column (j).
7	Demonstrated importance	The attribute in row (i) is more strongly important than the one in column (j).
2,4,6,8	Intermediate values	Used when there is no certainty of one of the odd values.
9	Absolute importance	The attribute in row (i) is more important than the one in column (j).

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A matrix is created by providing each attribute with a precise score on the Saaty scale (Table 2) based on the needs of the expert. Suppose E1, E2, · · ·, En are n alternatives available for decision-making, the pairwise comparison matrix is indicated as

$$\mathbf{m}_{ij} = \begin{cases} 1/\,\mathbf{m}_{ji} & i \neq j \\ 1 & i = j \end{cases} \tag{5}$$

Where mij represents the relative importance of Ei over Ej.

On examining the matrices below, we note that a pair of elements (i, j) in a level of the hierarchy are compared concerning a parent element in the level immediately above as a common property or criterion used to judge the dominant factor. A typical question used to fill in the matrix of comparisons is "when considering two elements, 'I' on the left side of the matrix and 'j' on the top, which exhibits the property more, or which one satisfies the criterion more?" or "which one is considered more important under that criterion and how much more (using the fundamental scale values from Table 2)?" This provides the aij or aji. The reciprocal value is then automatically taken as input for the transpose. The way the question is asked when making a pairwise comparison can influence the judgments provided and therefore the priorities. It must be made clear from the start what the focus of the hierarchy is and how the elements in the second level either serve to fulfill that focus or what their consequences are for each parent element and its descendants.

Table 3
AHP questionnaire

	Educational constraints	**Attitudinal constraints**	**Social constraints**	**Psychological constraints**	**Technological constraints**	**Training/ experience constraints**
Educational constraints	1					
Attitudinal constraints	x	1				
Social constraints	x	X	1			
Psychological constraints	x	X	x	1		
Technological constraints	x	X	x	x	1	
Training/ experience constraints	x	X	x	x	x	1

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Table 4
Pairwise Comparison Matrix

	Educational constraints	**Attitudinal constraints**	**Social constraints**	**Psychological constraints**	**Technological constraints**	**Training /experience constraints**
Educational constraints	1	1/3	3	5	3	1/2
Attitudinal constraints	3	1	5	5	7	1
Social constraints	1/3	1/5	1	1	2	1
Psychological constraints	1/5	1/5	1	1	1	1/7
Technological constraints	1/3	1/7	1/2	1	1	1/2
Training/ experience constraints	2	1	1	7	2	1
Sum	6.86	2.87	11.5	20	16	4.14

In Table 4, the first nontrivial comparison is educational constraints and attitudinal constraints. The question is "how much more are attitudinal constraints preferred over educational constraints?" Attitudinal constraints are preferred very strongly (3 times) over educational constraints, so the reciprocal value l/3 is entered in the (1,2) position. The value 3 is automatically entered in the transpose position (2,1) for educational constraints and attitudinal constraints. Another example shows that attitudinal constraints are judged to be five times more important than social constraints and therefore the value 5 (5 times) is entered in the (2,3) position with the reciprocal (l/5) automatically entered in the (3,2) position and so on. A matrix is said to be consistent if $a_{ij}a_j$, = a_{ik}, v_{ij}, k.

4.2.3 Normalized Matrix

As shown in Table 5 below, the required normalized matrix can be calculated using Equation 6. The initial score was given to each criterion and alternative, after which the pairwise comparison was carried out. The various infrastructures included infrastructure 1 to infrastructure 6. These show the different situations for which the pairwise comparisons were carried out.

$$\text{Normalized matrix} = \frac{\text{Xij}}{\text{sum of each column}} \qquad (6)$$

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Table 5
Normalization matrix

	Educational constraints	**Attitudinal constraints**	**Social constraints**	**Psychology constraints**	**Technology constraints**	**Training/ experience constraints**
Educational constraints	0.14	0.11	0.260	0.25	0.18	0.12
Attitudinal constraints	0.4	0.34	0.434	0.25	0.43	0.24
Social constraints	0.04	0.069	0.086	0.05	0.12	0.24
Psychological constraints	0.02	0.069	0.086	0.05	0.06	0.034
Technological constraints	0.04	0.049	0.04	0.05	0.06	0.12
Training/ experience constraints	0.29	0.347	0.086	0.35	0.125	0.24
Sum	1	1	1	1	**1**	1

4.2.4 Criteria Weights (CWs)

As shown in Table 6, the average of each row of the normalized pair-wise comparison matrix is used to determine each criterion's weight (Equation 7).

$$\text{Priority vectors (C.W.)} = \frac{\Sigma \text{Xij}}{\text{n}} \tag{7}$$

Table 6
Calculating the priority vectors (CWs)

	Educational constraints	**Attitudinal constraints**	**Social constraints**	**Psychology constraints**	**Technology constraints**	**Training/ experience constraints**	**C.W. (Priority vectors)**
Educational constraints	0.14	0.11	0.260	0.25	0.18	0.12	0.17
Attitudinal constraints	0.4	0.34	0.434	0.25	0.43	0.24	0.349
Social constraints	0.04	0.069	0.086	0.05	0.12	0.24	0.100
Psychological constraints	0.02	0.069	0.086	0.05	0.06	0.034	0.05
Technological constraints	0.04	0.049	0.04	0.05	0.06	0.12	0.059
Training/ experience constraints	0.29	0.347	0.086	0.35	0.125	0.24	0.23

After calculating the priority vector, it is necessary to check whether the answers are consistent or not. Some of the necessary parameters needed to perform the consistency test are given below:

- Consistency Index (CI)
- Random Value Index (RI)
- Compliance Rate/Consistency Ratio (CR)

For calculating the CI, we need the Lambda value which is obtained by calculating the D vector and EI values from the priority vectors.

Calculating the D vector uses Equation 8 which is the matrix multiplication of the pair comparison matrix with the priority vector.

D Vector = [Pair comparison Matrix] * [Priority vector] (8)

$$\text{D Vector} = \begin{bmatrix} 1 & 1/3 & 3 & 5 & 3 & 1/2 \\ 3 & 1 & 5 & 5 & 7 & 1 \\ \frac{1}{3} & 1/5 & 1 & 1 & 2 & 1 \\ 1/5 & 1/5 & 1 & 1 & 1 & 7 \\ 1/3 & 1/7 & 1/2 & 1 & 1 & 1/2 \\ 2 & 1 & 1 & 7 & 2 & 1 \end{bmatrix} * \begin{bmatrix} 0.17 \\ 0.349 \\ 0.100 \\ 0.05 \\ 0.059 \\ 0.23 \end{bmatrix}$$

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Calculating the EI values by Equation 9 as shown in Table 7 below:

EI Values = D Vector/Priority vector (9)

Table 7
Calculating EI values

Priority Vector	D vector	EI Values
0.17	1.103	6.488
0.349	2.196	6.292
0.100	0.6079	6.079
0.05	0.337	6.74
0.059	0.370	6.271
0.23	1.471	6.39

Lambda (λ) values are calculated by taking the arithmetic average of the EI values from Table 7 resulting from multiplying the comparison matrices by their weights and dividing the matrices again by their weight values.

$$\lambda max = (6.488+6.292+6.079+6.74+6.271+6.39)/6 = 6.376$$

The lambda (λ) value is subtracted from the number of matrix dimensions and divided by one less than the number of matrix dimensions, and the consistency index (CI) is calculated.

$$\textbf{C.I} = \frac{|\lambda max - n|}{n-1} \quad (10)$$

Where, n = number of matrix dimensions (number of items); Where, ᵞmax = 6.376.

$$\textbf{C.I} = 6.376\text{-}6/5=0.07$$

Compliance Rate/Consistency Ratio (CR): This is the final step to check the consistency. To confirm the dependability of the weights generated, the CR for each comparison matrix is determined. CR is calculated from Equation 11.

$$\textbf{CR} = \frac{C.I}{R.I} \quad (11)$$

Where CI is the consistency index, which is 0.07, while RI is the random consistency index.

Random Index (RI) is the mean value of randomly derived pairwise comparison matrices based on the n number (Subasi, 2011; Paksoy 2017). The random value indices determined according to the number of criteria are shown in Table 8 (Gul et al., 2021).

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Table 8
Random Consistency Index

N	1	2	3	4	5	6	7	8	9	10	11
RCI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

Here, the number of items = 6 , the R.I value for n=6 is 1.24 (see Table 8) and the C.I. value that we have calculated is 0.07.

C.R. = 0.07/1.24 = 0.05 (5%)

The result is within the compliance rate limits, below 10%, so the inconsistency is acceptable. For n=6 pairwise comparisons, the CR is 0.05 which is less than 0.10 and is considered consistent. Therefore, the weights are acceptable. If the CR reaches 0.10, revaluation is recommended (Singh, et al., 2016). According to Vargas (1982), if the estimated C.R. is less than 0.1, the judgment matrix is considered consistent.

5. Results and discussion

Physical impairment affects individuals in the context of society. Physical disability is defined as a condition that impairs an individual’s mobility, capacity, dexterity, or endurance and is a socially constructed issue as well as a physical one. Individuals with disabilities are regarded differently because of societal ideals and the cultural environment. Physical handicaps may have a significant impact on social interactions and mental health. For example, someone who is blind may become very reliant on others for everyday duties, which can lead to difficulties in social relationships and self-identity. People with physical limitations are frequently judged by society, which makes them feel bad about themselves. Some people may even strive to conceal their disability to conform to cultural expectations. Despite these obstacles, some people embrace their physical impairments and seek to live productive lives within their constraints. They may, however, endure criticism and contempt for standing up for their rights. The negative effects of social isolation, economic reliance, and personal needs on handicapped people's mental health as a result of their physical disability can eventually impact their overall quality of life (Sharma, Yadav, & Sharma, 2021). This study investigated two research questions: “What are the constraints that most hinder the adoption of AI among those with special needs?” and “What are the measures that can be taken to prevent such challenges?” We collected data through survey questionaries which were formulated and evaluated by experts from the education and healthcare fields. The data was analyzed using the AHP as shown in Tables 5-8. Table 9 discusses the consistency and reliability of the preference ratings for factors related to special needs students. The Compliance Rate/Consistency Ratio (CR) of 0.05 is acceptable (i.e., below 0.10), indicating consistent ratings. The study identifies key factors influencing AI adoption as attitudinal constraints (35.8%), training and experience constraints (24.0%), educational constraints (18.0%), and social constraints (10.4%) as shown in Table 9 and Figure 4. These findings emphasize the importance of considering these factors when addressing students’ AI utilization needs. Some of the steps that should be implemented to increase the acceptance of AI among physically disabled people include adopting a highly inclusive teaching style and undertaking suitable training and research methodologies. This will undoubtedly help create more equitable education for all special needs students, regardless of socioeconomic status.

Table 9
Relevant factors

AHP	Percentage
Educational constraints	18.0%
Attitudinal constraints	**35.8%**
Social constraints	10.4%
Psychological constraints	5.5%
Technological constraints	6.2%
Training/ experience constraints	**24.0%**

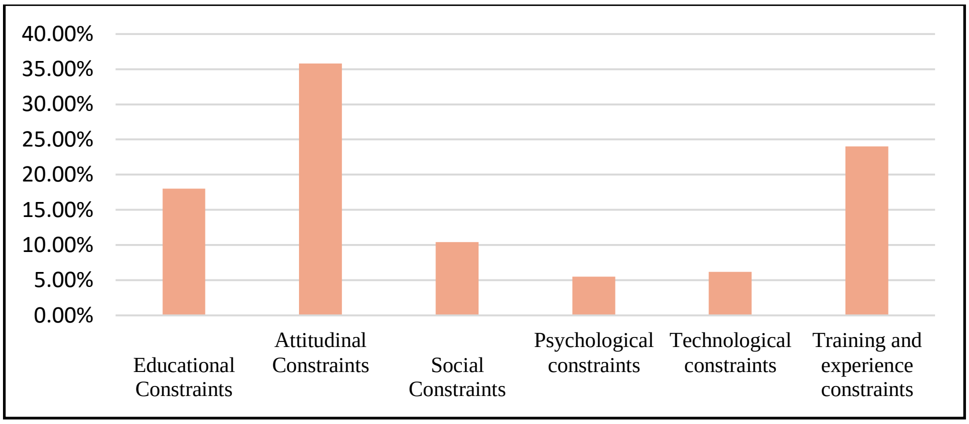

Figure 4 Normalized principal eigenvector

6. Conclusions

After adopting AHP analysis throughout our research work, we found that it is an efficient statistical technique for decision-making in real-time environments. In our research, the AHP assisted in identifying the precise difficulties that physically challenged people experience while using AI in real-time applications. Even though AI has made huge promises to improve accessibility, our research revealed that various hidden constraints such as technological boundaries, cultural attitudes, and economic issues have created barriers to integrating the use of AI with those who have special needs. The current study emphasizes the need and necessity to take proactive actions to address these hurdles and offer equitable access to AI-driven applications by having a comprehensive grasp of the limitations. The most significant obstacles identified by the AHP approach are attitudinal constraints and teaching and training constraints, both of which impede the adoption of AI among people with special needs.

6.1 Practical implications and theoretical contribution

There is a need for collaboration among technical companies and governments to develop, design, and execute solutions that will enable special needs individuals to

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effectively use AI. This research also addresses AI technology's revolutionary credibility in increasing the standard of living for people with special needs and building a continuous process to eliminate the constraints that hinder them from taking advantage of AI in real-time scenarios. By developing a more accessible AI environment, we may be able to envision a future in which AI improves the independence and quality of life for all people, regardless of physical limitations. The measures that can be taken to mitigate the challenges that hinder the adoption of AI among those with special needs include making learning cost-effective for training in educational organizations, implementing highly inclusive pedagogy and teaching in the educational sectors and other training institutes, and providing financial incentives to those who are unable to afford education. This is possible if the thought process for creating and implementing AI is not manipulated by attitudinal and social constraints. In education, real equality is concentrating on each student's needs rather than treating every student uniformly. Special needs students have all the potential to use AI for their self-development and the overall development of society if they are given equal opportunities to explore their intelligence.

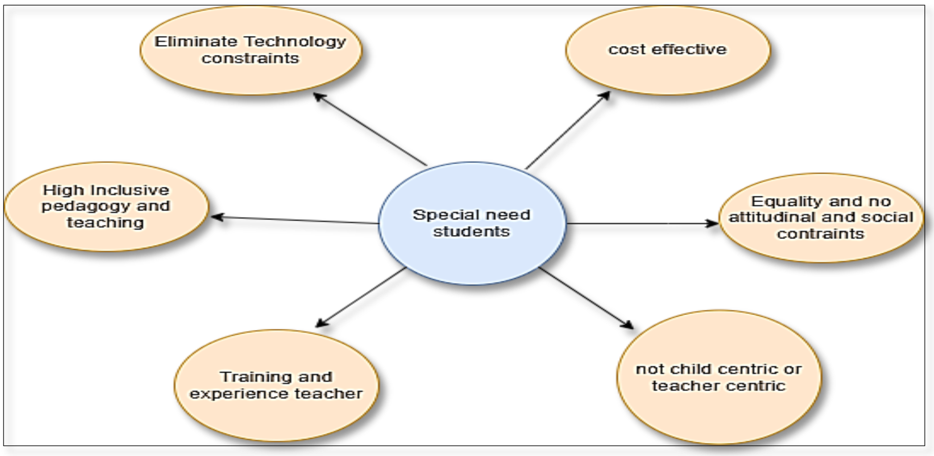

Figure 5 Preventive measures

Moreover, this study provides an understanding of how the AHP can be used as a methodological approach to underline the constraints in AI adoption for individuals with physical limitations and to take appropriate measures to develop real-time applications focusing on the special needs population, thereby removing the digital divide.

6.2 Future scope and limitations

The study envisions a future in which AI significantly improves the independence and quality of life of people with physical disabilities, and calls for ongoing efforts to break down persistent barriers that prevent them from reaping the benefits of transformative AI. The future aim of this research is to build AI technology that is targeted towards special needs students, as well as to identify the most effective measures that governments should take to educate special needs students about AI. There were various limitations in this study. First, using self-report approaches in data collection, such as survey questions can result in low response rates for attitude constraints and social constraints; distracted respondents; and missing data which might jeopardize the validity and reliability of statistical analyses. In contrast to commonly used statistical studies (e.g., regression, correlation, and factor analysis), the AHP methodology employs a dependability technique that is not reliant on

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sample size. Furthermore, the current study was exploratory, to provide some evidence to support AHP usage. Future research can focus on developing AI solutions by integrating with the AHP.

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