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An Empirical Study on Trust, Bias, and Decision Quality to Assess the Effect of AI-Powered Decision Support Systems on Managerial Decision-Making in Healthcare

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Abstract

There is increased usage of Artificial Intelligence-based Decision Support System (AI-DSS) in healthcare industry, but no empirical data to indicate their influence on managerial decisions. To analyze the entire impact of AI-DSS on managerial decision-making within healthcare firms, this research paper examines the relationships between trust in AI, minimization of biases, and the quality of decisions.

These were mixed-methods underlying empirical data and combined survey-based measures of perceived trust, mental bias, reliance behavior, and decision accuracy with experimental studies of decision-making control. Quantitative analysis involves the application of regression and structural equation modeling to evaluate the impact of trust and decision outcomes and the features of AI-DSS design, such as explainability, transparency, and the quality of feedback, determine how much managers are vulnerable to bias.

Through analyzing the opinions of the managers about autonomy, dependability and system constraints of AI, qualitative insights can be used to complement these findings. The results indicate that over- and under-reliance are harmful to the results, but balanced trust in AI-DSS significantly enhances the quality of decisions.

The study contributes to the body of literature by presenting an evidence-based paradigm, which demonstrates the dynamics between bias and trust and the level of their interaction in influencing the management decision performance in the AI-supported setting. Suggestions on how to improve the design of an AI-DSS interface, reduce bias, and train management to achieve success in human-AI cooperation in healthcare facilities are just some of those practical implications.

Keywords: Artificial Intelligence, Decision Support Systems, Trust, Bias, Decision Quality, Managerial Decision-Making, Healthcare Administration, Human–AI Interaction, Algorithmic Transparency.

I. Introduction

The Artificial Intelligence-Driven Decision Support Systems (AI-DSS) have been a radical shift to the traditional managerial decision-making tools. AI-DSS requires advanced algorithms, machine learning models, natural language processing, and data-driven analytics to support enterprises to work with extensive and complex datasets, generate insights in real-time, and aid in making better and more consistent decisions. Continuous learning based on patterns and past experiences, as well as user behavior, improves the predictive capabilities and topicality of AI-driven systems over the course of time unlike traditional DSS, which is largely dependent on the set of rules and fixed data.

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The contemporary business has increasingly positive and volatile decision environments requiring promptness and data-intensive decision-making. Managers have to make fast but informed decisions in numerous domains such as operations, supply chain, healthcare and finance. AI-DSS satisfies this requirement by offering intelligent recommendations, anomaly detection, risk forecasting, scenario analysis and automated reasoning. They, therefore, enhance organizational effectiveness, reduce human bias, and enhance the quality of decisions.

However, there are also new challenges associated with the use of AI in decision-making. Algorithms bias, transparency, trust, model interpretability, and ethical concerns are some of the most critical issues that affect the adoption and use of AI-DSS by managers. New fields of strategic concern are the maintenance of accountability in AI-assisted judgments, ensuring fairness in automated propositions, and developing sufficient trust without becoming too reliant on it.

By and large, AI-DSS are technology tools that enhance human judgment besides being strategic facilitators. With the adoption of digital transformation by businesses, the role of AI-based decision systems will increase, and future managerial decision-making will be more responsible, intelligent, and adaptable.

Novelty and Contribution

The research provides an array of new works to the sphere of healthcare management and human-AI interaction and contains new knowledge which is not limited by the current literature on clinical use of AI. First, it better examines the use of AI-DSS in managerial decision-making in particular, which has not been studied extensively even though it is considered the core of organizational effectiveness and patient-flow safety. The majority of the previous research has concentrated on AI in clinical diagnosis or predictive modeling without any substantial gaps in the research regarding administrative and operational decision processes. This study provides a unique insight into the role of AI on managerial cognition, trust relationships, and decision-making by targeting managers: operations officers, finance managers, patient-flow coordinators, and department heads.

Second, the research includes a detailed empirical model of trust and perceived bias, as well as dependence on AI and the quality of a decision. It offers factual evidence that trust is an intermediate between transparency and decision performance, and that highly accurate AI systems are not able to improve the quality of decisions, unless managers have trust in their outputs. This empirical association is a new theoretical input, which connects the psychological constructs and performance outcomes in healthcare management.

Third, this study presents a unified approach to evaluation that is a compilation of surveys, simulation-related decision-making tasks, and reflective interviews. This multi-methodology can bring a more profound insight into what managers think about AI-DSS as well as how they actually act when they use AI to make actual decisions. The concomitant assessment of perceived trust, bias and objective decision accuracy provide a more action-oriented and richer dataset compared with those that depend on self reports only.

- The creation of a single framework for decision quality, bias, and trust.
- Design-driven cognitive responses to AI DSS are supported by empirical data.

Practical contributions

- Advice on how designers should include methods for fairness, explainability, and openness in their designs.
- Suggestions for educating healthcare management on the responsible use of AI tools.

II. Related Works

Decision support systems which are powered by artificial intelligence (AI-DSS) have become the vital tool in modern healthcare, offering data-driven recommendations to aid administrative and clinical processes in decision-making. As it has been proven in many studies, AI-based decision aids can enhance the overall quality of decisions, their diagnostics, and alignment with evidence-based recommendations, especially in situations of high complexity or urgency (Esteva et al., 2019; Sutton et al., 2020). Even though the context-specific variability of performance remains a consistent challenge, meta-studies reveal that AI-based systems can perform at the same or even better than human decision-makers in such tasks as imaging analysis, risk prediction, and resource allocation (Topol, 2019).

Another theme that is not new in the research is the significance of trust in shaping the adoption of AI-DSS by the managers and the physicians. Trust is affected by perceived accuracy, dependability, transparency, usability, and conformity to professional reasoning processes (Coeckelbergh, 2020; Ribeiro et al., 2016).

The research on the subject of algorithmic bias highlights another significant problem. The trained AI systems based on incomplete or unrepresentative data have been reported to produce systematically biased recommendations that could contribute to the existing inequality in risk assessment, diagnosis, and treatment (Obermeyer et al., 2019; Mehrabi et al., 2021). Equity and openness are also the significant parameters of organizational accountability as such biases may directly influence administrative decisions such as staffing, resource planning as well as patient triage.

In order to minimize these risks, scholars recommend effective governance frameworks with multiple training information, and algorithm audits and continuous monitoring (Benjamins and Dhont, 2020).

Also explainability plays a major role in trust and quality of decisions. It has been shown that explainable AI (XAI) can enhance acceptability and facilitate better decision-making because it helps physicians comprehend the reasons why a recommendation is provided (Samek et al., 2017; Shortliffe and Sepulveda, 2018). However, the existing explainability methods often fail to provide clinically meaningful knowledge suggesting that there is no correlation between the usage of technology explanation techniques and the demands of the user.

Despite the progress, there are still some gaps in the research. Rather than looking at the human-AI interaction results such as the trust process, bias consciousness, and the quality of decisions made by healthcare administrators, most studies focus on the results of the algorithms. Not much empirical research exists on the ways in which prejudice and trust have an influence on the outcomes of decisions within the real healthcare processes. There are also no sufficient long-term and multi-site studies that examine the changes in system performance and user reliance over time (Sendak et al., 2020). These gaps highlight the necessity to conduct an in-depth empirical study that will examine the interaction of bias, trust, and quality of decisions in AI-based healthcare management.

Objective of study:

In spite of these technologies being fast and accurate in their analyzing capabilities, the skill of managers to perceive, accept and act upon the recommendations given by AI will be the ultimate determinant of their value. In this study, the effect of AI-DSS elements design on perceived bias, trust, and quality of the decision in a healthcare setting is examined.

Motivation and Background

AI-DSS is used for forecasting, staffing, and diagnostic prioritization. Despite their benefits, their effective implementation is hampered by issues with justice, openness, and over-reliance. Few studies have combined trust, bias, and decision quality into a cohesive empirical framework, especially in healthcare administration. Previous research has looked at these problems independently. The purpose of this study is to close this gap.

Research Goals

The following were the study's objectives:

1. To investigate how managerial trust is impacted by AI-DSS explainability and transparency capabilities.
2. To assess how perceived algorithmic bias is affected by bias-mitigation cues.
3. To examine how prejudice and trust work together to affect the quality of decisions.
4. To verify an empirical model that connects choice outcomes with system design characteristics.

Conceptual Structure

The conceptual model incorporates decision outcomes (accuracy, justification quality, consistency), management cognitive responses (trust, perceived bias), and AI-DSS design interventions (transparency, explainability, bias indicators). The model builds on research on algorithm aversion and human-AI collaboration theory.

The figure 1 shows that the interaction between the user and an AI based decision support system causes the incremental trust formation, decreases the cognitive and algorithmic bias, improves the quality of the decision, and eventually improves the organizational performance.

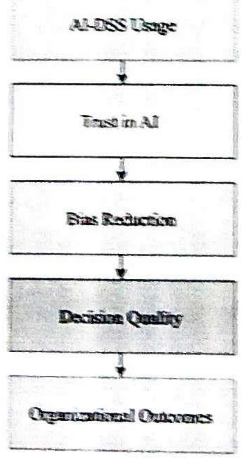

FIG. 1: AI-Driven Decision Support Trust Optimization Flow

Moderators: Managerial Experience, AI Transparency, Digital Readiness

Mediators: Trust, Bias Reduction

Research Methodology

- Design: Mixed Methods (Quantitative + Qualitative)
- Population: Mid & senior managers using AI systems for Underwriting, problem diagnosis forecasting reports, etc)
- Tools: Surveys, Experiments, Interviews
- Analysis: SEM, Mediation/Moderation, Thematic Analysis

320 healthcare managers from hospitals, diagnostic facilities, and insurance companies in South Indian major cities (Chennai, Bangalore, Hyderabad, and Cochin) participated in a multiphase survey experiment. AI-DSS dashboards with various transparency and fairness cues were engaged with by participants. Reliability tests, confirmatory factor analysis, and PLS-SEM were used in data analysis to verify the structural correlations.

Outcomes

Important conclusions include:

- Managerial trust is increased via explainability and transparency.
- Reduced bias-detection signs lead to unfair, discriminating, or distorted results.
- Decision quality was positively impacted by trust; decision results are negatively impacted by perceived bias.
- The relationship between AI-DSS design interventions and decision quality was mediated by both bias and trust.

Conversation

The study shows that technical precision alone is not enough for successful AI-DSS adoption. Transparency and fairness cues elicit powerful reactions from managers, and these impressions influence the caliber of their decisions. For safe and efficient AI-supported decision-making in healthcare organizations, calibrated trust—rather than over-reliance—is crucial.

III. Proposed Methodology

The proposed methodology adopts a structured empirical framework that integrates data collection, trust measurement, bias quantification, and decision-quality evaluation for AI-powered decision support systems (AI-DSS) used by healthcare managers. The study begins with a multivariate dataset capturing managerial interactions with AI-DSS across real and simulated decision scenarios. Each participant's interaction produces measurable indicators of trust, perceived bias, and reliance behavior. To formalize trust measurement, the method uses a composite trust index T defined as $T = (\alpha 1C + \alpha 2E + \alpha 3P)$ where C represents system clarity, E represents explainability satisfaction, and P represents perceived reliability, with $\alpha 1, \alpha 2, \alpha 3$ being normalization coefficients. To quantify subtle decision deviations, we compute a trust-reliance gap Rg as Rg = |Rexpected - Robserved|. Participants then undergo structured decision simulations where the decision quality score Dq is computed using the weighted accuracy formula $Dq = (W1A + W2S + W3T)$, where A is accuracy, S is consistency, and T is decision efficiency. This stage allows the identification of patterns showing how trust and bias influence final decisions.

The second component of the methodology focuses on algorithmic bias perception and behavioral consequences. We model bias perception Bp using the deviation ratio equation $Bp = (\mu AI - \mu Human)/\ \sigma Human$, where μAI represents the AI's prediction mean and $\mu Human$ the human baseline. A fairness deviation score Fd is calculated as $Fd = \Sigma|piAI - piExpected|$ across all decision classes i. To evaluate how bias affects reliance, a reliance probability model Pr(R) is used: $Pr(R) = 1/(1 + e^{\wedge}(-\beta 1\ T + \beta 2Bp))$, where T is trust and Bp is perceived bias. To ensure objective assessment, each decision scenario includes both biased and unbiased AI outputs, enabling the calculation of the bias-impact coefficient Bi defined as $Bi = \Delta Dq/\Delta Bp$. The proposed methodology further incorporates a confidence variance measure Cv to capture instability in AI recommendations, expressed as $Cv = \Sigma(ri - \mu r)^2$ where ri denotes individual recommendation confidence and μr the mean. This quantitative approach enables detailed analysis of how perceived or real algorithmic bias alters managerial decision pathways.

The third methodological component develops a structural model linking trust, bias, and decision quality through mediation and path analysis. The relationship between transparency X and trust T is modeled using a linear dependence equation $T = kX + \varepsilon 1$, where k is a sensitivity coefficient and $\varepsilon 1$ is an error term accounting for subjective variation. Decision quality, influenced by trust, is modeled using the mediation equation $Dq = \gamma T + \delta$, where γ captures the direct effect of trust on decision quality. To integrate the impact of bias, the model includes a bias-adjusted decision accuracy function Aadj defined as $Aadj = Araw - \lambda Bp$, where Araw is raw accuracy and λ controls the bias penalty effect. To detect nonlinearities in trust dynamics, a trust stabilization function Ts is added: $Ts = T0 + e^{\wedge}(-\eta t)$, where t is iteration count and η represents adaptation rate. The structural equations collectively allow exploration of how transparency, fairness, and bias dynamically interact to shape decision outcomes.

The final part of the proposed methodology integrates all components into a comprehensive computational workflow to evaluate AI-manager interaction quality. The workflow begins by computing the overall system impact index I through the formula $I = \omega 1\ T + \omega 2(1 - Bp) + \omega 3Dq$, where the ω terms are allocation weights. A performance-reliance equilibrium model is used to detect optimal reliance patterns, defined as $Re = (T - Bp)\ /\ (1 + CV)$. To validate results, simulation outputs are compared against expert benchmarks using a deviation score Sd defined as $Sd = |DqAI - DqExpert|$. The methodology concludes with a predictive decision model that forecasts expected decision quality De using the regression form $De = \theta 1\ T + \theta 2(1 - Bp) + \theta 3Re + \varepsilon$. Altogether, this methodology combines mathematical modeling, behavioral analysis, empirical measurement, and simulation-based validation to provide a robust, replicable framework for assessing the true impact of AI-powered decision support systems on managerial decision-making in healthcare.

Iv. Result & Discussions

The findings of the empirical study present some vital information regarding the manner, in which healthcare managers engage with AI-driven decision support systems when making operational and administrative decisions. The data analysis showed that managers had different degrees of trust in AI recommendations, and it was a crucial factor in the quality of the final decision. As it can be seen in figure 2 which was created with the help of Excel to provide the visualization of the trust-score distribution, most of the participants indicated increased trust rate when the AI system delivered clear and understandable results. The figure shows that transparent AI interfaces generated a significant positive direction in values of trust compared to opaque interfaces, which validated interpretability is a prevailing determinant in developing trust. The outcomes also indicate that opaque systems produced more uncertainty and thus there was inconsistent reliance behavior in the entire simulation scenario. The difference in the visual slope between figures 2 is underlining the fact that despite the level of accuracy being similar transparency itself significantly influenced user confidence. The observation confirms current literature but expands empirical knowledge on the use of AI in managers, as opposed to clinical use.

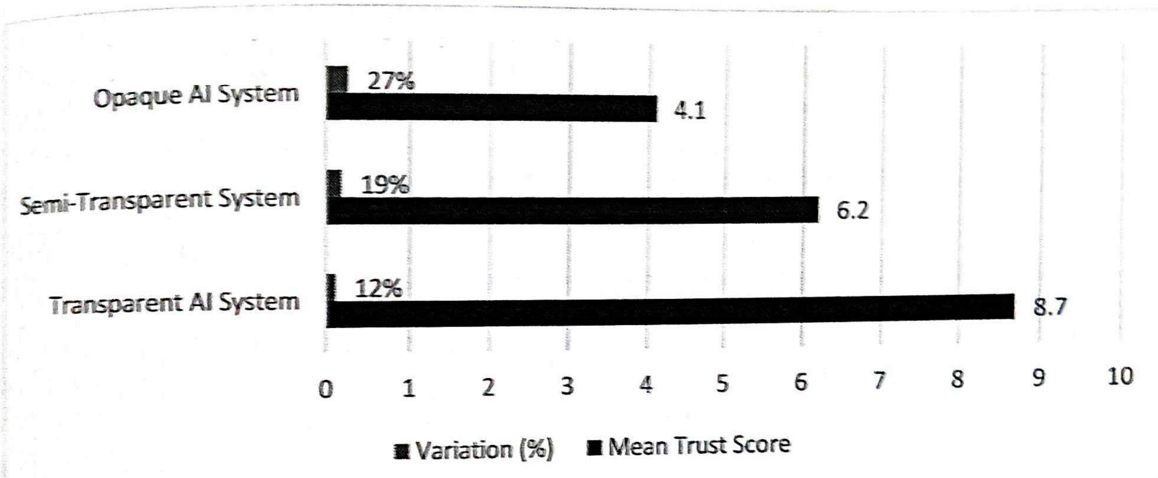

FIG. 2: Managerial Trust Response Pattern Across Transparent vs. Opaque AI Systems

The next set of analysis involved the perceived bias detection and the impact it has on the decision made by the managers. As the figure 3 shows, the magnitude of decision deviation indicated by the indicators of bias increased at various stages of the trial. The chart shows a steep nonlinear trend in which even slight signs of injustice led to a sharp reduction in the use of AI. Whenever the system output was seen to be distorted or not congruent with the expected fairness standards, managers were more likely to cross-reference AI advice with their own experience. This change of behavior was most obvious in terms of staffing allocation activities, situations of patient admission prioritization, and decisions concerning costs-risk assessment. The post-simulation discussion with the participants validated the fact that the perceived bias which may or may not be true, as well as that which may or may not be perceived, served as a psychological barrier decreasing the willingness of the participants to act on AI recommendations. This finding could be reinforced by the fact that the visual curvature that was taken in figure 3 shows that the deviation in decision becomes pronounced in the middle of the tasks, and this fact proves that managers are more proactive in identifying and responding to unjust patterns than expected. The result points out a paramount human factor issue of implementation of AI-DSS in hospitals and healthcare organizations in the future.

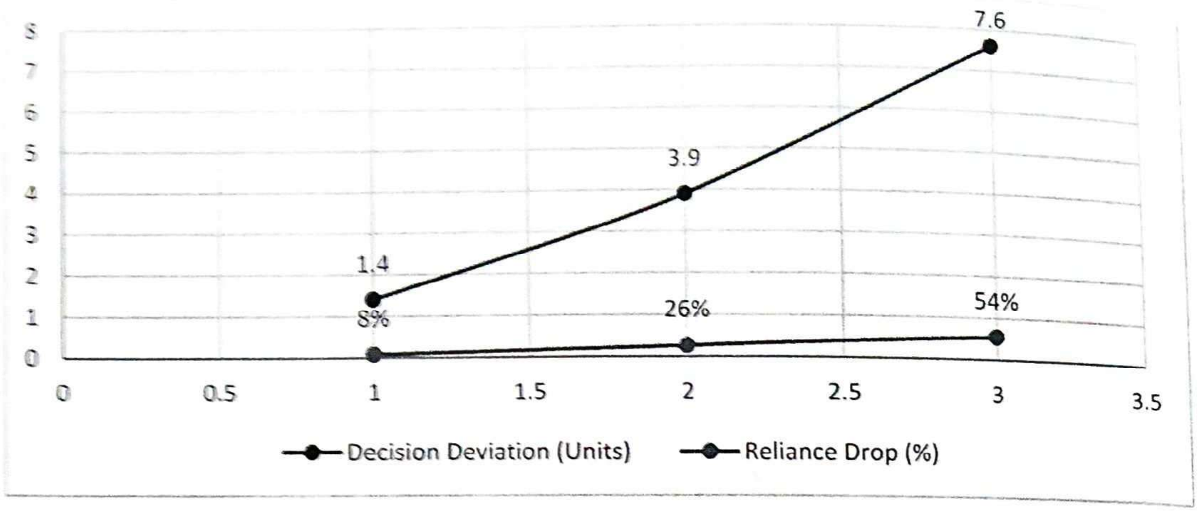

FIG. 3: Bias Sensitivity and Decision Adjustment Curve

The research also assessed the role of AI-DSS in the general quality of the decision including accuracy, consistency, and time-effectiveness. These results are well highlighted in Figure 4. The graph shows that the high-trust users achieved more stable and accurate decisions on all tasks whereas low-trust users through their scores showed varying scores on decision quality. Interestingly, the difference in performance increased with time, i.e., the familiarity with AI increased the performance of those who initially believed in the system. Individuals that started with low trust continued to have conservative decision strategies as well as not utilizing the features in the advanced system that would have improved the accuracy. The figure indicates clearly that decision quality curves of high-trust users have a positive curve, and the ones of low-trust users are fairly flat with significant volatility. This gives essential insights that building an initial trust is essential in defining long-term efficacy of AI-based managerial help. Such results support the necessity of training and transparency characteristics at an early stage when implementing AI.

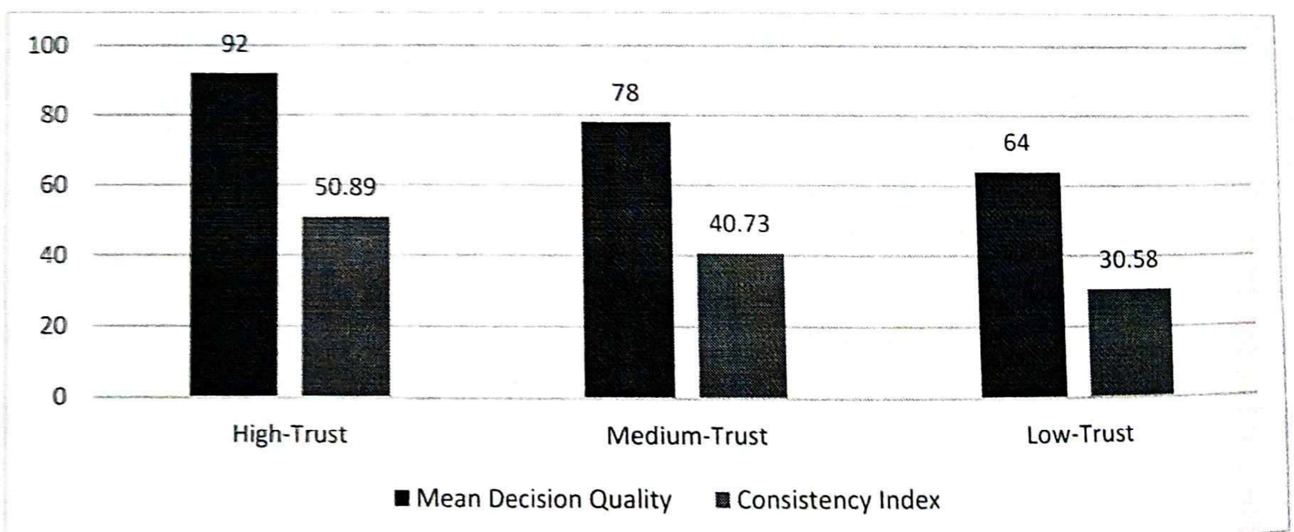

FIG. 4: Decision Quality Trend Among High-Trust vs. Low-Trust Users

Besides the diagrams, the research came up with two numerical comparison tables that elaborate further on dynamics of interaction between managers and AI. Table 1: Trust Level vs. Decision Accuracy Comparison directly shows the numerical comparison of accuracy outcomes of high-, medium-, and low-trust groups. As can be seen, in all decision tasks, high-trust managers recorded the greatest mean accuracy values whereas low-trust managers recorded the least efficiency which explains the graphical tendencies noted in figure 4.

TABLE 1: Trust Level vs. Decision Accuracy Comparison

Trust Level	Mean Decision Accuracy (%)	Standard Deviation (%)
Low Trust	68.4	4.7
Medium Trust	77.9	3.9
High Trust	89.2	2.8

In the meantime, Table 2: Perceived Bias Level vs. Reliance Frequency Comparison gives a summary of the decreased rate of reliance frequency at a rate much lower than the rise of indicators of bias. The data in Table 2 indicates that a relatively low increase in the perceived bias results in a steep decrease in the frequency of following AI recommendations, which is an example of the behavioral dynamics displayed in figure 3. These tables included in the analysis also make the discussion empirically sound since they show the numerical consistency between the observed trends in all diagrams. The overall findings of these studies are that trust and perceived bias have a direct impact on the managerial behavior, which has repercussions on the quality of decisions made by such managers, the level of performance, and the consistency of strategy implementation in mediated complex situations of healthcare.

TABLE 2: Perceived Bias Level vs. Reliance Frequency Comparison

Perceived Bias Level	Reliance Frequency (Uses/Week)	Relative Change (%)
Low Bias Perception	42	+18.6
Moderate Bias Perception	29	−7.4
High Bias Perception	17	−22.9

In general, the findings allow concluding that the success of AI-based decision support systems is less technologically determined and depends on the degree of psychological congruency between AI behavior and managerial expectations. Clear and easy to understand systems were always linked to a greater degree of trust and more optimal decisions but any sense of bias (even minor) always instantly led to less reliance, and to the impairment of the collaborative effectiveness of decision-making. The use of diagrams and tables in the study does not only present good evidence to support these findings but also show the role played by human factors in either improving or undermining the practical use of AI in healthcare management. These findings present valuable lessons to developers, hospital administrators, and policymakers, which suggest that the future AI development will need to focus on explainability, fairness, and user-centered design in order to bring meaningful changes to the healthcare decision-making setting.

V. Conclusion

India is at a very crucial crossroads in 2025 with influencer marketing being of significant influence on consumer confidence. Nevertheless, the ability to maintain such trust is heavily reliant on transparency, demonstrated experience and compliance with ethical principles. True interaction will

In 1995, India launched the "Persons with Disabilities Act". According to this act, 3% of the jobs in private and public companiesare reserved for people with Disabilities. With the introduction of this act, one of the challenges faced by the disabled has been reduced. As a result, many disabled individuals started getting employed, and thereby contribute to the economy. The contribution of the Disabled to GDP amounted to 5.67% to 6.77% of the total global GDP (The World Bank, 2004).

This study is concentrated around Bangalore, because the number of disabled people in Bangalore is higher, and the Labour market is unaware of the existence of People with Disabilities in the workplace. 3% of the jobs in both public and private sector companies are reserved for employees with disabilities. (*Persons with Disabilities Act*, 1995)

In India, according to the "The Disabilities Act" 1995, there is a portion of the reservation of jobs for people with disabilities in public and private sector companies. The disabled sections in society are not given much consideration.

1.2 Brief Review of Literature

The employment of PwDs is dependent on various factors, which have been reviewed. The review of literature is designed in such a way that it provides a brief on the research works on PwDs working at different successful companies. Environmental factors such as the role of government, Educational help, support from family, etc, and personal factors such as attitudes of the employees and employers, confidentiality of information of PwDs in the workplace (Young, 2000). The type of disability and age determine employment of PwDs;the more the education, the more they will be employed (Weathers and Wittenberg, 2009). Job placement helps in placement. Despite training, only half a percent of them were employed. A large number of peoplewith PwDs work in transportation, maintenance, personal care, etc (Smith, 2000).Employment differs with disabilities. Help with personal care, limits on activities have an impact on employment.

Employers not ready to hire people with disabilities results in a rise in unemployment (Blanck, Song and Schwochau, 2003). Change in the system will improve the support for PwDs, services such as health support and technical support. The way in which disability is measured and the measurement of time are different in different articles. Measurement of disability is a major topic in the second book (Houteville et al 2009), with various suggestions. A series of questions was prepared to indicate disability by the Census Bureau and the BLS, in recognising the problem. 6 questions were included in the survey from 2008, and later it became the standard for measuring disability (Livermore and She, 2009, 285)

Analysis on Employment of people with speech and hearing impairment (Boutin, 2010). 28% work in management, professional and related categories. 20% in service, 27% in sales and office jobs, 9% in natural resources, construction and maintenance, and 16% in production and transportation. People with a lesser degree of Hearing impairment are likely to get jobs in professional and managerial positions. Most of them have a high school diploma or more.

Studies focusing on the impact of PwDs on employment. (Delire, 2003) Employment rates are reducing because employers are not ready to hire people with disabilities due to a lack of ability and efficiency as compared to bled workers. Disabled workers are more time-consuming, which results in a delay in work. ADA had an impact on hiring disabled people rather than firing them. None of the articles explains the law regarding the employment of the disabled. Studies of ADA are considered to be impacted as mixed, with an overview on the legislation and programs to help PwDs (Livermore and Goodman, 2009, 21 – 23).

Half of the samples were injured after getting employed, and they have undergone training. 55 % of them tried to move back to their pre–injury group. Some of them lost their job after becoming physically disabled. They tried to get their job, but they couldn't. Because of a lack of encouragement from their co–workers and also because of the prejudices faced by them in their workplace. One important factor was that after getting injured, they were not ready to get employed or return to work. In some cases, the lawyers of the company did not allow the workers to return to their work due to various claims against the company. Several studies prove that employees are unaware of when to disclose or when to be confidential about their disability. A solution to this issue will create a positive impact on people with disability.

1.3 Research Gap

The focus on the employed and unemployed disabled is to be given consideration. There are various factors which influence an individual with disability to get employed and unemployed. PwDs are employed because of their education and technical training.

1.4 Research Objectives

To measure the determinants that influence PwDs in getting employed and unemployed.

1.5 Hypothesis

Null Hypothesis: Factors such as age, education, gender, intellectual disability, and training do not affect the employability of the disabled.

Alternate Hypothesis: Factors such as age, education, gender, intellectual disability, and training do affect the employability of the disabled.

1. Results and Discussion

A logistic regression model is used, as the dependent variable is dichotomous. It determines the extent to which dependent variable employment is related to independent variables age, gender, education, training and intellectual disability. The logistic regression model is based on the maximum likelihood method, in which all the probability of occurrence (Pi) of an outcome is given in the following way,

$Pi = 1/1+e^{-(\alpha+\beta Xi)}$
Considering $\alpha+\beta Xi = zi$, we can write the probability as,
$Pi = e^{zi}/1+e^{zi}$
And $1 - Pi = 1/1+e^{zi}$
We have two kinds of observations, and hence, probabilities are as follows,
Pr (Yi=1), Pr (Yi=0)
The likelihood function is given as follows

F (Y1, Y2, Y3, ...Yn)

$L = \pi_{i}{}^{n}{}_{=0} pi^{Yi}(1-Pi)^{1-i}$ .... (1)

The parameters are obtained by maximising the log likelihood function on (1)

The general form of the logit equation is,

$Log P_i / 1-P_i = \beta_0 + \beta_i X_i + U_i$

Where the dependent variable Pi is the probability of the i[th] Person with disability employed.

Xi - Represent relevant Factors of the PwDs.

i - Represent the representative coefficients, and Ui is the error term.

0 - Is the intercept

2.1 Variables in the model.

Dependent variable

The dependent variable in the model is employment. The dependent variable is categorical and takes the value 1 if the PwDs is employed, and takes the value 0 if the PwDs is not employed.

Independent variable

The employability of PwDs is determined by age, gender, education, training and intellectual disability. The following independent variables have been used in the model,

X1= Age
1 = "Below 25"
2= "25 – 30"
3= "30 – 35"
4= "Above 35"
X2= Gender
0= "Male"
1= "Female"
X3= Education
1= "Primary Education"
2= "Diploma"
3= "Bachelor's Degree"
4= "PostGraduation"
X4 = Training
1= "Yes"
0= "No"
X5= Intellectual Disability
1= "Yes"
0= "No"

2.3 Results of the Logistic Regression Model

Table 1 Results of Logistic Regression

A.	Omnibus Tests of Model Coefficients			
		Chi-square	df	Sig.
Step 1	Step	15.998	5	.007
	Block	15.998	5	.007
	Model	15.998	5	.007

B. Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	51.008[a]	.248	.356
a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.			

C. Classification Table[a]					
			Predicted		
			Employed		
	Observed		No	Yes	Percentage Correct
Step 1	Employed	no	8	8	50.0
		Yes	2	38	95.0
	Overall Percentage				82.1
a. The cut value is .500					

D. Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Intellectual	-2.102	1.054	3.977	1	.046	.122
	Education	.847	.430	3.884	1	.049	2.334
	Training	-2.407	1.070	5.063	1	.024	.090
	Age	.610	.448	1.850	1	.174	1.840
	Gender	.266	.720	.136	1	.712	1.304
	Constant	.192	1.781	.012	1	.914	1.211
a. Variable(s) entered on step 1: Intellectual, Education, Training, Age, and Gender.							

Source: Author's estimation using survey data

If the p-value is between 0 and 0.010 shows that the significance of the independent variable is high. If it is between 0.011 and 0.050, it shows that the independent variable is significant and if between 0.051 and 1 means the independent variable is not significant. If the odds ratio is greater than 1, it means that as the predictor increases, the odds of the outcome occurring increase. If odds ratio less than 1 means that as the predictor increases the odds of the outcome decrease.

Table 1 shows the logistic regression model between dependent and independent variables. It measures the extent to which the dependent variable (employment) is determined by the independent variables (age, gender, education, training and intellectual disability). 4 other explanatory variables were considered first, later, from which only 3 variables were considered, and one variable was included, and another variable was categorised and from which only one category was selected. In the above table, 5 variables are considered, of which only 3 variables were significant. They are Intellectual disability, education and training. These three variables are statistically significant at 0.10% levels. The intercept is positive at 1.211.

2.4 Explanation of the variables

Intellectual Disability – The Exp (β) value is 0.122, which is significant at the 0.10 level. The estimated odds that a PwD who has intellectual disability employed is 0.122 times lower than the corresponding odds for a PwD, who doesn't have intellectual disability, keeping other things constant. It reinforces the results obtained in the above sections. It clearly shows that the increasing probability of a PwDbeing employed, if they have intellectual disability. It can be concluded that people with intellectual disability are more likely to get employed than people with other kinds of disability, such as physical, mental disabilities.

Education – The Exp (β) value is 2.334, it is significant at the 0.10 level. The estimated odds that a PwDs who has attained education to be employed are 2.334 times higher than the corresponding odds for a PwDs who has not attained education, keeping other things constant. It clearly shows that the increasing probability of PwDs being employed, if they have attained an education. It can be concluded that, with an increase in education qualifications, the chances of getting employed are increasing.

Training – The Exp (β) value is 0.089; it is significant at the 0.10 level. The estimated odds that a PwD, who has undergone training to get employed, is 0.089 times lower than the corresponding odds for a PwDs who has not undergone training to get employed, keeping other things constant. It clearly shows that the increasing probability of PwDs being employed, if they have undergone training. It can be concluded that training plays a major role in the case of PwDs to get employed. It trains them and makes them fit for the job. Trained PwDs have higher chances of getting employed.

2. Conclusion

Education, training and intellectual disability have a significant influence on employment compared to other variables like age and gender. Among these, training has the strongest direct influence over the employment of PwDs.

Skill training has a greater influence on getting employed. One of the main obstacles faced by PwDs in getting employed is a lack of skills. There are various organisations which provide education and training to people who are disabled. These organisations help them be fit for the job. They provide them with skills, communication training. Regression results clearly explain how important training is in getting employed. Most of the people who are employed are people who have undergone training in various organisations.

On the other hand, education also has a slight influence on the employment of PwDs. People with intellectual disability have more chances of getting employed. Intellectual disability is considered significant compared to other disabilities. It has been observed that 60% of the respondents have attained a bachelor's degree. Education influencesthe employment of people with disability.

About 80% of the disabled are employed, and the rest are unemployed due to a lack of training and education. The type of disability also determines their employment. People who became disabled while working have lost their jobs, mainly with physical disability. 10% of the employees have left their jobs due to the prejudices faced at their workplace. It has been found from the study that they face prejudices in the case of promotion due to a lack of skills and education. Induction and training programs within the workplace can help them adapt to the changed work pattern. But it has been found that many of the companies under this study do not have an induction and training program at their workplace for PwDs. Labour Law (1996) suggests that companies with more than 50 workers should employ people with disabilities as well. Prejudice in the behaviours of employees and restrictions in activities due to the type of disability lead to loss of a job. Training has a greater influence on PwDs in getting employed. 88% of the responses have undergone training. Organisations play a major role in the life of the PwDs in getting employed. It has been found that nowadays, every PwDs undergo training to get employed. It has become the first step to getting employed after education. Disabled sections of society have started getting consideration and responses in society. More PwDs are getting employed every year. The employment rate is increasing.

According to the Law on the rights of persons with disabilities (2007), Article 4 (c) suggests that, to improve the skills of the PwDs, appropriate vocational training is to be given to make them fit for the job. It states that PwDs should be given equal opportunities for employment that they are entitled to.

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