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Leveraging Data Analytics for Better Patient Care and Operational Effectiveness in Indian Hospitals

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Abstract

India's healthcare sector is poised for a growth trajectory, and it is expected to reach approximately $193 billion in 2032, with a CAGR of about 8%, fuelled by a growing population and government schemes like Ayushman Bharat; however, the industry demands immediate attention owing to an enormous and heterogeneous population. This study aims to explore how healthcare professionals, administrators, and IT specialists perceive the consequences of data analytics for decision-making, patient care, and hospital operations by examining trust/charitable, private, and government hospitals through a survey-based approach. Using a sample of 380 respondents and a well-developed questionnaire, the research employs the Technology Acceptance Model (TAM) to evaluate the working competence of hospitals through patient care activities. Statistical techniques including correlation, regression, and Analysis of variance (ANOVA) and Structural Equation Modeling (SEM) using AMOS and the statistical package SPSS were used to find the association among the constructed variables. The results show that all the hypotheses were validated and that adoption is significantly influenced by perceived usefulness ($\beta = 0.067$, $p < 0.001$) and usability/ease of use ($\beta = 0.398$, $p < 0.001$). Furthermore, strong paths between Perceived Ease of Use (PEOU) and Usefulness ($\beta = 0.402$, $p < 0.001$), and Behavioural Intention (BI) and Actual System Use (ASU) ($\beta = 0.416$, $p < 0.001$) are also confirmed by the analysis. The empirical analysis further shows that the biggest obstacles are data integration (74%), training of employees (54%), and data privacy issues (44%). The research concludes that data analytics is an important tool for hospitals to improve their operational performance, but insists on the need for technological investment and strategic planning to overcome barriers to implementing and promoting long-term efficiency in Indian hospitals.

Keywords: Hospital Management, Technology Acceptance Model (TAM), Patient Outcomes, Operational Efficiency, Data Analytics, and Predictive Analytics.

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Introduction

Owing to the rise in awareness among people in the healthcare sector, data analytics is gaining more importance and is often regarded as a strategic tool. In a populous country such as India, the healthcare industry has huge potential where data analytics is a competitive weapon and a strategic tool (Alsabawy et al., 2016). Trends in patient data, hospital operations, and financial measures are useful in providing efficient service. Despite the brighter prospects, the challenge is that of the adoption and implementation of data analytics in most hospitals. Indian hospitals need a solid IT infrastructure, specific training, and a high investment in the implementation of these tools (Pal et al., 2021). To solve these problems, researchers invented a new model: the Technology Acceptance Model (TAM), which is a model that focuses on the relationship between users and the adoption of new systems (Davis, 1989). This study makes several important contributions by presenting empirical evidence on the impact of analytics across trust-managed hospitals, private and government hospitals, in applying the TAM framework to assess working competence in a high-density population, and in identifying specific strategic barriers, such as data integration and privacy, that prevent efficiency of operations. By fixing these discrepancies, this research offers a road map for the healthcare sector to overcome the hurdles of implementation and modernize the care of patients. This paper is structured as follows: Section 1 is an introduction to the present study and gives an overview of the background, including the significance of data analytics in the Indian healthcare sector. Section 2 provides a review of relevant literature related to benefits and barriers of analytics in healthcare, and identifies the research gap that exists in the area, focusing on the lack of empirical research relating to technology acceptance factors to hospital operational performance. It also includes the theoretical model and hypotheses on the basis of the Technology Acceptance Model (TAM). Section 3 discusses the research methodology used, which includes the quantitative approach, a sample size of 380 participants, and SEM to analyze the relationships between key variables. Section 4 addresses the analysis and discussion of the results, including some of the most important aspects of the statistical analysis relate to hospital administrators and authorities. Finally, Section 5 summarizes the study and offers practical suggestions for priority areas for improving operational efficiency and patient care, as well as recommendations for future research.

The Indian health care industry is poised for strong growth, with an 8% annual rate (Lakshmanan & Dass, 2026; Kumar & Duggirala, 2021). Despite the optimistic scenario, the adoption of data analytics in healthcare is expected to be a challenging factor. Significant research gaps remain in the Indian healthcare sector regarding its implementation. Few studies have addressed these issues, but implementing data analytics appears to be the most challenging factor. Hence, the study was conducted to examine and analyse these aspects using the Technology Acceptance Model. This study investigates the challenges hospitals face in using data analytics and examines the factors that hinder the adoption of the TAM framework. The objectives of the study are to study awareness of data analytics tools in Indian hospitals for measuring patient care quality and healthcare outcomes, to examine the implementation of data analytics within Indian hospitals, utilizing the TAM, and to assess the effects on patient outcomes and operational efficiency. It focuses on how data analytics tools are used to improve patient outcomes and make hospital operations more efficient.

Literature Review

Recent studies have discussed the value of data analytics in hospitals and shown it to be involved in enhancing clinical and other operational decision-making. Predictive analytics models are becoming common to predict patient admissions, facilitate patient diagnosis, and guide managerial decisions (Djaya, 2025). However, data security and privacy issues continue to be a major stumbling block for hospitals in the adoption of analytics-driven systems (Raghupathi & Raghupathi, 2014). Several studies bring out the role of data analytics in improving operational efficiency. (Khalifa et al. 2017) reported that patient waiting times and staff allocation were improved by the use of an analytics-based decision support. Similarly, (Ezeh et al. 2019) analysed the operations of hospitals and demonstrated that analytics supports better management of resources and services. More recent evidence indicates that patient flow management and bed utilization forecasting based on analytics provides a substantial reduction in operating costs and enhances hospital performance (Miezah et al., 2020; Bancsik et al., 2020; Djaya, 2025). The majority of researchers are focusing on the usefulness of data analytics in healthcare organizations; however, there are still several intricacies in the implementation. Recent reviews highlight that in spite of proven benefits, hospitals experience challenges in integration into the system, organizational readiness, and resistance to change, which limit large-scale adoption (Holden & Karsh, 2010; Rahimi et al., 2018; Holden & Karsh, 2010; Rahimi et al., 2018). Thus, although analytics technologies are becoming more widely available, effective use of them requires acceptance by healthcare professionals (Karimov & Sattorova, 2024; Djaya, 2025). The existing literature shows that although data analytics has the potential to transform hospital efficiency, resource management, and clinical decision-making, this can occur only when successfully implemented, which is often hampered by problems of system integration,

organizational resistance, and data security (Rahimi et al., 2018). A critical inference can be made from these findings, namely that the technical availability of analytics tools does not guarantee operational success. Instead, the "human element"-in this case, acceptance and readiness of the healthcare professionals- serves as the main intermediary between getting the technology and actual improvements in performance. The literature review has shown that data analytics is positively affecting the efficiency of hospitals, cost reduction, resource management, and patient satisfaction. However, successful implementation is not just dependent on technology itself but also on acceptance and readiness by healthcare professionals as well as in organizational readiness. Despite extensive research on analytics outcomes, few empirical studies have examined how technology acceptance factors relate to operational performance in hospitals. Therefore, the present study is needed to examine the adoption of data analytics in hospitals using the Technology Acceptance Model (TAM), thereby justifying the role of user acceptance in achieving effective implementation and improved hospital performance.

Table 1: Measurement of Study Constructs and Related References

Constructs of the study	Variable/Factors	Scale	References
Perceived Usefulness (PU)	To what extent do you agree that data analytics tools have improved the overall efficiency of hospital operations? Data analytics tools help in making better clinical decisions. Using data analytics tools has enhanced the quality of patient outcomes in the hospital. The adoption of data analytics reduces the time required to complete hospital processes.	Five-point Likert Scale	(Marangunić & Granić, 2015) (Alsabawy et al., 2016)
Perceived Ease of Use (PEOU)	The data analytics tools used in your hospital are easy to operate. Learning to use data analytics tools is straightforward for staff members. Data analytics tools integrate seamlessly with existing hospital systems. Troubleshooting or resolving issues with data analytics tools is simple.	Five-point Likert Scale	(Davis, 1989) (Nguyen et al., 2020)
Attitude toward use (ATU)	I enjoy using data analytics tools in my work environment. The utilization of data analytics tools within the hospital enhances my job satisfaction. I believe implementing data analytics tools is beneficial for hospitals. I would recommend the use of data analytics tools to enhance hospital operations.	Five-point Likert Scale	(Davis, 1989) (Luo et al., 2017)
Behavioural plan to use	I am willing to carry on using data analytics tools in the hospital. I would recommend using data analytics tools to colleagues in the healthcare industry. I plan to use data analytics tools for future hospital projects and decision-making. I find it essential to rely on data analytics tools to improve hospital efficiency and outcomes.	Five-point Likert Scale	(Davis, 1989) (Djaya, 2025)
Actual system use (ASU)	How satisfied are you with the frequency of using data analytics tools in hospital operations? How satisfied are you with the ease of integrating data analytics tools into your daily workflows? How satisfied are you with the accuracy and reliability of data analytics tools for your tasks? How satisfied are you with the outcomes or results achieved using data analytics tools?	Five-point Likert Scale	(Ansong-Gyimah, 2020) (Khan et al., 2023)

Research Methodology

This research adopts both quantitative and qualitative approaches to examine patient outcomes and operational efficiency in the Indian hospital context. The study is based on the Technology Acceptance Model (TAM), which explains user adoption of technology in terms of key constructs such as PU and PEOU. These constructs have an impact on ATU, which, in turn, affects BI and ASU.

The structural relationships among these constructs are expressed through the following equations. As shown in equation (1), ATU is determined by PU and PEOU.

$$ATU = \beta_1 PU + \beta_2 PEOU + \varepsilon \quad (1)$$

Further, equation (2) indicates that BI to use the system is influenced by the user's ATU.

$$BI = \beta_3 ATU + \varepsilon \quad (2)$$

Finally, equation (3) illustrates that ASU is determined by BI.

$$ASU = \beta_4 BI + \varepsilon \quad (3)$$

Where:

- β_1, β_2, β_3, and β_4 represent the structural coefficients estimated using regression or SEM.
- ε denotes the error term, representing unexplained variance in the model.

The structured research instrument uses both quantitative and qualitative question formats. It starts with demographic questions in order to identify the respondent's role, experience, and type of hospital. The core sections mainly make use of multiple-choice questions related to operational benefits and implementation challenges. For the assessment of subjective perceptions of impact and effectiveness, the questionnaire makes use of Likert scales from "Very Effective" to "Very Ineffective" or "Significantly Improved" to "Significantly Worsened". A separate section focusing on TAM employs a standardized 5-point Likert scale (Strongly Disagree to Strongly Agree), which measures perceived usefulness, ease of use, attitude, BI, and ASU. The fig. 1 model suggests that the healthcare professional's attitude and intention to use the analytics systems are affected by PU and PEOU. Recent studies confirm that TAM is of relevance in healthcare settings, especially regarding the role TAM plays in understanding the acceptance of data analytics and decision support systems by clinicians (Holden & Karsh, 2010). By focusing on usability issues and perceived value, hospitals can improve the integration of technology and increase operational efficiency (Balogun et al., 2024; Balogun et al., 2024).

TAM is focused on explaining the concept of technological adoption. The fig. 1 model suggests that healthcare professionals' attitudes and desires towards using analytics systems are affected by PU and PEOU. Recent studies confirm that TAM is still relevant in healthcare settings, especially for understanding the acceptance of data analytics and decision-support systems by healthcare clinicians. By focusing on usability issues and perceived value, hospitals can improve integration of technology and improve operational efficiency.

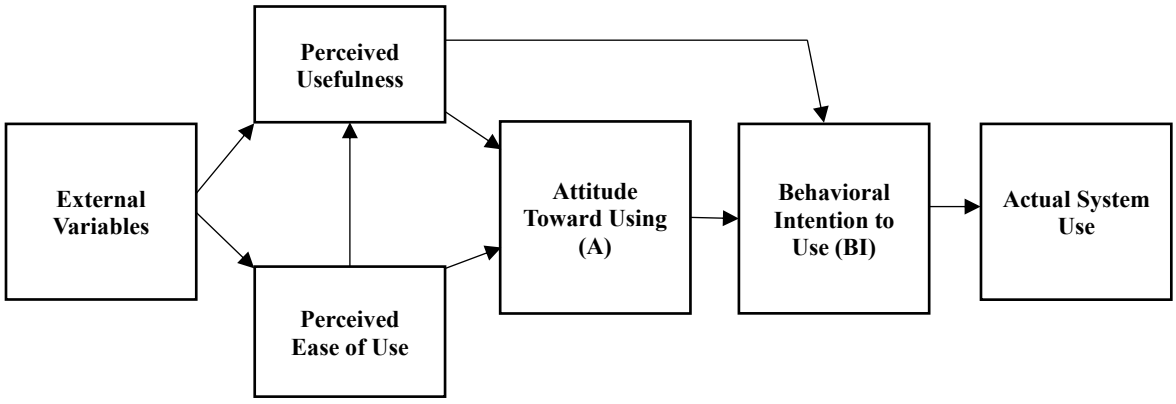


Fig. 1: Technology Acceptance Model (TAM)

This study proposes the Hypothesis for the TAM used in this research based on table 1: PEOU refers to the extent to which an individual believes that the adoption of Information and Communications Technology (ICT) is effortless and that their performance has been improved through the utilization of this learning method.

Hypothesis-1(H1): The PEOU of the data analytical tools has an optimistic effect on the performance of hospitals.

PU pertains to a person's conviction that utilizing a tool can improve their efficiency (Marangunić & Granić, 2015).

Hypothesis-2(H2): The noticeable effectiveness of data analytics tools significantly improves the performance of the selected hospitals.

Attitude pertains to how users behave and their willingness to interact with data analytics technologies in hospitals.

Hypothesis 3 (H3): Employees' intention to employ technology will be positively impacted by their attitude toward data analytics.

Perceived Usefulness: Hospital employees have a more positive attitude regarding adopting data analytics technologies since think it enhances their job performance. Technology adoption is strongly predicted by usefulness (Alsabawy et al., 2016).

Hypothesis (H4): Perceived utility has a positive impact on attitudes toward the use of data analytics.

Even if technology is well-received, actual adoption depends on the user's intention to integrate it into daily operations. Strong intention often leads to consistent system usage (Nguyen et al., 2020).

Hypothesis (H5): BI to Use Positively Influences ASU

Finally, the survey includes open-ended questions to provide qualitative suggestions for improvement and future perspectives on data analytics adoption. A Likert scale was used for the estimation of the constructs. The research was carried out on a total of 380 respondents in the Indian states, through a well-structured questionnaire, which was distributed to the hospital administrators, such as physicians, nurses, healthcare administrators, and data analysts. The primary data was collected over a period of six months using stratified random sampling technique as the Indian hospital sector is highly heterogeneous including trust, private and government institutions with extreme levels of resources. By separating healthcare professionals, administrators, and IT specialists into different strata, this technique guarantees that each stratum is proportionately represented in the sample of 380 respondents. This approach minimizes sampling bias and considers differing perceptions of the PEOU and ASU in various management structures The collected data were analysed using IBM SPSS, and AMOS application software for the quantitative techniques and thematic analyses for gathering accurate results for a better understanding of how data analytics can be leveraged in healthcare. The statistical techniques were applied to check the consistency, reliability (Skewness and kurtosis test) and normalcy (Cronbach Test) of the collected data.

Descriptive statistical measures such as the mean, variance, and percentage analysis were used to analyze the data collected through the structured questionnaires. Additional statistical methods, such as Levene's test, determination of outliers, and AMOS path construction analysis, were employed. The regression analysis was used to quantify the relationships between PEOU and perceived usefulness. The regression model is expressed in Equation (4), where PU is predicted by PEOU.

$$PU = \beta_0 + \beta_1 \times PEOU + \epsilon \quad (4)$$

Where:

$\beta_0$is the intercept,

$\beta_1$is the coefficient estimating the effect of $PEOU$ on PU,

$\epsilon$is the error term.

To validate the test TAM and determine the correlations between the variables created for the study, regression analysis and SEM are frequently employed. The general structural equation model can be expressed as shown in Equation (5):

$$Y = \alpha + \lambda X + \epsilon \quad (5)$$

Where:

Y is the dependent variable (e.g., BI or Actual Usage),

$\alpha$is the intercept,

$\lambda$is the path coefficient from X(independent variable, such as PU or $PEOU$),

$\epsilon$is the error term.

Furthermore, skewness and kurtosis tests are used to assess the distribution of the data. A skewness value between -1 and 1 and kurtosis between -3 and 3 typically indicates normality. Levene's test is used to assess the equality of variances across groups. The null hypothesis assumes equal variances.

Analysis and Discussion

Descriptive Analysis

Table 2: Profile of Healthcare Professionals and Hospital Attributes

Personal factors	No of responses	%
Role of the Respondent		
Doctor	80	21
Experienced Nurse	61	16
Healthcare Administrator	84	22
Data Analyst	103	27
Other roles	53	14
Years of Experience		
Less than years	65	17
Between three and five years	91	24
Between six and nine years	118	31
Greater than years	106	28
Hospital's size and type		
Small (Hospitals with up to 50 beds with basic facilities)	239	63
Medium (Hospitals with 51 to 300 beds with multi-specialty services)	110	29
Large (Hospitals with more than 300 beds with advanced healthcare services)	30	8
Type of Hospital		
Government Hospitals	15	4
Private Hospitals	327	86
Trust/Charitable Hospitals	30	8
Employee-Specific Hospitals	8	2
Hospital's Average Number of Patients per Day		
Less than 100 patients	91	24
101–300 patients	167	44
301–500 patients	76	20
More than 501 patients	46	12
Utilisation of Data Analytics in Hospital Operations		
Daily	68	18
Weekly	91	24
Monthly	106	28
Rarelyo	61	16
Never	53	14

Table 2 reveals the demographic and operational profile of the healthcare professionals and reveals insightful trends in the data analytics adaptation. The 27 % of the respondents are Data analysts/Business Analysts and 22 % are Healthcare Administrators, showing that the insights were mostly picked from individuals who are intimately involved with the operational and analytical side of decision making of the Hospitals. Most of the healthcare professionals are experienced in the healthcare industry, with 59% of them having over six years' experience in the healthcare industry. A high percentage of responses (63%) was from small hospitals with basic facilities, and the healthcare landscape is dominated by private hospitals (86%), with a negligible representation of government and trust-based facilities. In terms of patients, almost half of the hospitals (44%) serve 101-300 patients per day, which is mid-level operation loads. As regards the usage of data analytics, even though 28% of hospitals use analytics on a monthly basis and 24% on a weekly basis, only 18% use it on a daily basis.

Fig. 2 highlights key trends in data analytics tool adoption in Indian Hospitals. It shows that Inventory Management, Financial Analysis and Descriptive Analysis are the most commonly used, which indicates that there is a big focus on

efficient resource management, optimising revenue and tracking basic operational metrics. These basic analyses are critical for day-to-day operations in a hospital. On the lower end, there are Operational Analysis, Comparative Analysis, and Diagnostic Analysis, which are less frequently used and which may reveal areas where hospitals can do more in terms of internal process evaluation and benchmarking. Advanced analytics such as Population Health Analysis, Prescriptive Analysis and custom analytics are the least utilised and this could be due to a limitation in infrastructure, awareness or skilled personnel. The Pareto curve is cumulative: the minimum number of types of analysis are responsible for the greatest use: about 80% of the benefits come from the top 4-5 categories only. This is a reflection of the current state of healthcare analytics in India with a dominance of basic analytics and more complex applications in the early stages of adoption.

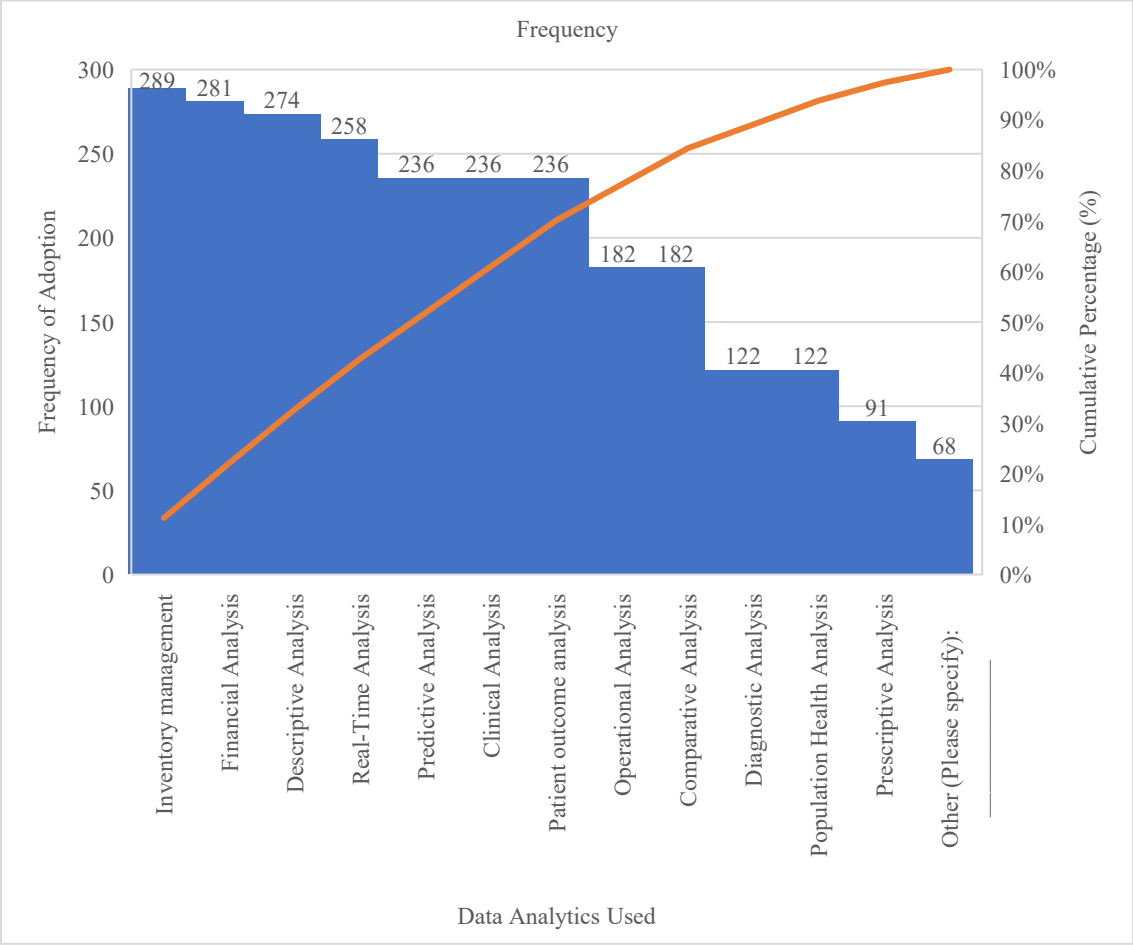


Fig. 2: Frequency Distribution of Data Analytics Applications in Hospital Operations

Reliability and Normality Statistics

Table 3: Assessment of Normality and Internal Consistency of Study Variables

Variables	No. of Items	Result of Skewness		Result of Kurtosis		Cronbach Alpha	Mean	Variance
		Statistic	Std. Error	Statistic	Std. Error			
Perceived Usefulness	4	-1.171	.125	.508	.250	0.902	3.624	0.014
Perceived Ease if Use	4	-.348	.125	-.658	.250	0.823	3.280	0.012
Attitude	4	-.760	.125	-.329	.250	0.894	3.445	0.003
BI to use	4	-1.019	.125	.085	.250	0.894	3.551	0.003
ASU	4	-1.410	.125	1.707	.250	0.853	3.713	0.043

The TAM constructs in this study have a good internal uniformity among all of the variables based on the reliability and distribution analysis (Table 3).

Reliability was assessed using Cronbach's Alpha, calculated as:

$$\alpha = \frac{N}{N-1}\left(1-\frac{\sum\sigma^2_{\text{items}}}{\sigma^2_{\text{total}}}\right) \quad (6)$$

where:

$N$is the number of items in the scale,

$\sigma^2_{\text{items}}$is the variance of individual items,

$\sigma^2_{\text{total}}$is the variance of the total scale.

Cronbach's Alpha test values range from 0.823 to 0.902, which is great reliability. PU and ASU both have shown high mean scores (3.624 and 3.713 respectively), indicating that hospital staffs are aware of the usefulness of data analytics, and actually applying it in practice. The negative skewness across all the factors shows that responses are left-skewed, indicating that most of the participants rated the items positively, skewing towards agreement. In addition, the positive kurtosis in ASU (1.707) indicates that there may be a peaked distribution, indicating a high degree of consensus among respondents. In contrast, the slightly negative kurtosis in other variables shows a more flattened response pattern, indicating some variability in perceptions. The low variance across most constructs further supports the consistency of responses. Overall, these results affirm the robustness of the TAM structure in this situation, with healthcare professionals showing a favourable attitude and BI toward using data analytics tools in India, particularly when it find the system useful and easy to use.

Measurements of the TAM Model

The constructs were created by the modification of scales that were used in earlier investigations and had already been validated (Table 2). AMOS software was utilized in conjunction with SEM (Fig. 3). In recent years, this method has been used extensively (Jirón & Dicovskiy, 2022). Both the model's prediction ability and the observation of the connections between constructs are made easier by this system. A comprehensive analysis of the literature was consulted in order to establish the constructs, this study complete understanding of the scales used as well as the items that were part of each construct.

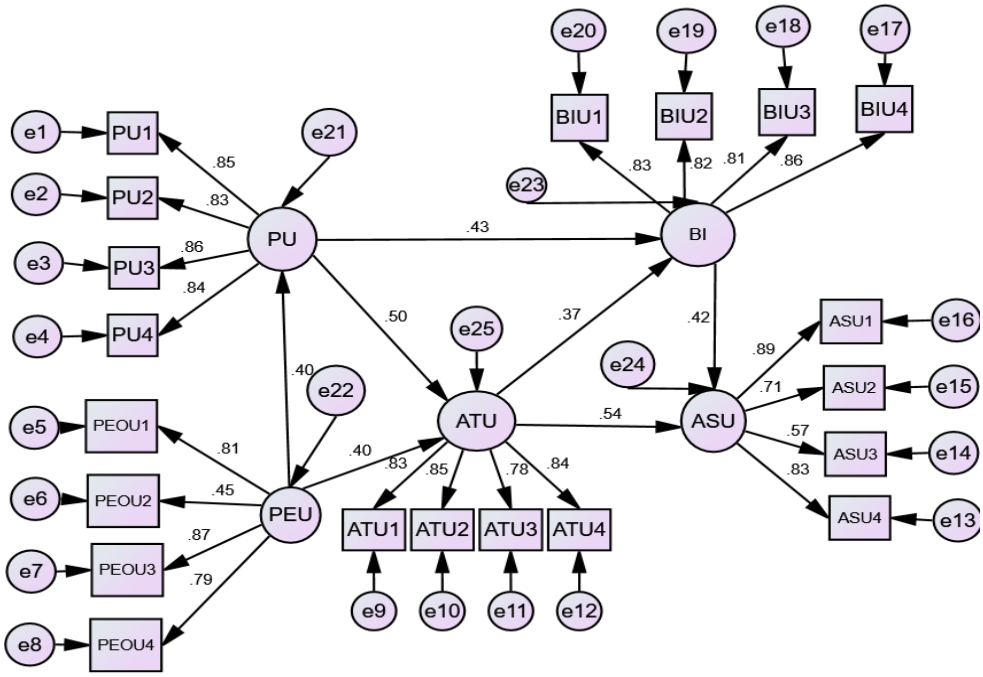


Fig. 3: SEM Path Model Showing Relationships Among TAM Constructs

This study examines the relationships between technological elements and the adoption of data analytics in healthcare operations to validate the TAM in the setting of Indian hospitals. Fig. 3 shows that all TAM dimensions, including perceived usefulness, ease of use, contentment, attitude, and BI, showed positive associations with one another, supporting the hypotheses (H1 to H5).

It is observed that the adoption of data analytics is influenced by the perception of usefulness and ease of use by hospital staff. For example, data analysts and administrators had a stronger relationship with satisfaction compared to positive attitude (H5), indicating their willingness to consider analytics tools to make routine decisions, whereas clinicians/Nurses had a higher level of resistance, probably because of the impacts on workflow or lack of direct perceived benefit. These findings line up with studies that emphasize the importance of seeming helpfulness and ease of use in driving technology adoption across organizational roles. Conversely, while doctors and nurses also rely on hospital technology, may not

In conclusion, the study confirms that the adoption of data analytics in Indian hospitals is significantly impacted by the technology's alleged value and simplicity of use, and that user satisfaction directly influences the intention to use it. Adoption might be further boosted by staff role-based interventions, which would guarantee that clinical and administrative teams understand the importance of data-driven practices in enhancing healthcare delivery.

Model Fit Summary

Table 4: Goodness-of-Fit Statistics for the Structural Equation Model

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	47	443.831	163	.00000	2.723
Saturated model	210	.00000	0		
Independence model	20	4684.444	190	.00000	24.655

Table 4 highlights different parameters (q) being estimated are called CMIN. C. is a "p-value" used to test the hypothesis that the model fits the population exactly. CMIN is the minimum value of the discrepancy. The P value indicates that the value is below 0.05. As a result, the model fits the population exactly. A satisfactory model fit is shown by the CMIN/DF ratio of 2.723, which is substantially within the acceptable range.

Table 5: Comparative Goodness-of-Fit Statistics of the SEM Model

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.905	.890	.938	.927	.938
Saturated model	1.0000		1.0000		1.0000
Independence model	.0000	.0000	.0000	.0000	.0000

From table 5 it is clear that NFI, Models with overall fit indices is 0.905. The is obtained by substituting *Fd* for *F*. close to 1 indicate a very good fit. The typical range lies between zero and one, but it is not limited to that range. The NFI value is 0.905, which indicates that this model is substantially good. RFI the rho1 value is 0.890, and it is inferred that it is a good fit model. IFI the value of delta2 is 0.938, and hence it also reveals that the model is fit. TLI the rho2 value is 0.927 is close to the high range. This infers that very good fit. CFI also closes the value of 1. The model has an excellent fit, as all indices (NFI, RFI, IFI, TLI, CFI) are above 0.9, indicating that the proposed model explains the data well.

Table 6: Parsimony-Adjusted Fit Indices of the Structural Equation Model

Model	PRATIO	PNFI	PCFI
Default model	.858	.777	.804
Saturated model	.0000	.0000	.0000
Independence model	1.0000	.0000	.0000

Table 6 shows that the PRATIO (0.858) indicates a well-balanced model, effectively using degrees of freedom. PNFI (0.777) & PCFI (0.804) are above 0.77, suggesting a parsimonious and well-fitting model. Overall, the model achieves both good fit and efficiency, meaning no unnecessary complexity.

From the table 7 it is clear that the suggested model and the observed data match each other reasonably, as seen by the default model's Root Mean Square Error of Approximation (RMSEA) of 0.072, which is within the acceptable fit range (usually ≤ 0.08). This result is further supported by the 90% RMSEA confidence interval (0.064 to 0.080), which remains inside the acceptable threshold. Strong statistical evidence for the model's good fit is shown by PCLOSE = 1.000.

Table 7: Root Mean Square Error of Approximation (RMSEA) for the Structural Equation Model

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.072	.064	.080	1.0000
Independence model	.0668	.062	.075	1.0000

Table 8: Expected Cross-Validation Index (ECVI) for Model Comparison

Model	ECVI	LO 90	HI 90	MECVI
Default model	1.635	1.456	1.837	1.654
Saturated model	1.277	1.277	1.277	1.364
Independence model	14.360	13.693	15.049	14.368

Table 8 shows that the saturated model fits the data significantly better, the default model's ECVI of 1.635 is greater than the saturated model's ECVI of 1.277. The default model's moderate and adequate predictive capacity is demonstrated by the fact that it performs much better than the independence model (ECVI = 14.360). The default model's stability is further supported by the MECVI value of 1.654. The model's fit and prediction power is well-balanced overall.

Table 9: Absolute Goodness-of-Fit Indices for the Structural Equation Model

Model	RMR	GFI	AGFI	PGFI
Default model	.072	.880	.845	.683
Saturated model	.0000	1.0000		
Independence model	.546	.198	.113	.179

The default model shown in table 9 shows a reasonable fit, with an RMR of 0.072 (acceptable as it's close to 0) and a GFI of 0.880, indicating a good overall fit. The AGFI (0.845) and PGFI (0.683) further support model adequacy.

Hypotheses Testing Results

This study aimed to create connections between PU, PEU, ATU, BI, and ASU in the Indian hospital industry, even though multiple studies have highlighted the multifaceted nature of TAM and the relationships between multiple variables. SEM is used to analyse the model's proposed linkages. Using SPSS AMOS 20, the proposed structural equation modelling was examined. The findings indicate that every hypothesis was validated.

H1: PU and ATU (β = 0.067, p = 0.000)

Hospital employees are more likely to have a positive attitude toward digital tools like data analytics systems or electronic health records when believe that using them improves their work—by enhancing operational outcomes or decision-making. According to (Alsabawy et al., 2016) who highlighted the crucial role that perceived utility plays in health IT adoption within organizational contexts, this is in line with Davis's seminal TAM theory.

H2: PEOU and Attitude Toward Usage ATU (β = 0.398, p = 0.000)

The ease with which hospital employees can learn and operate a health technology system significantly shapes their attitude toward its use. In high pressure clinical settings, intuitive interfaces and low training needs are extremely important. Findings from (Nguyen et al., 2020) support this position, underscoring the fact that user-friendly systems are more easily accepted by members of healthcare staff, especially in resource-constrained hospitals.

H3: PEOU and PU (β = 0.402, p = 0.000)

There is often a very strong correlation between the ease of use of a system and the usefulness of the system. In the context of the hospitals, if a system requires very little efforts for its operation, the professionals tend to perceive it as better in supporting their tasks. This relationship was reflected in the study conducted by researchers who found that ease of use increased perceptions of a system's functional value amongst medical users interacting with digital learning and information platforms (Wu & Chen, 2017).

H4: ATU and BI (β = 0.370 p = 0.000)

A positive attitude to hospital information systems or data analytics tools often equates to a stronger intention to use them in practice. When these systems are seen as valuable by the clinicians and administrators and are in their interest, more likely to incorporate them into their daily work. (Ansong-Gyimah, 2020) has a similar trend in his research where positive perceptions had a significant impact on intent to use.

H5: BI and AU (β = 0.416 p = 0.000)

BI is an important predictor of actual usage (and this would be particularly true in the context of hospitals, where workflow adoption relies on consistent usage by users).

4.6 Challenges and Barriers

Table 10 and fig. 4 shows that the analysis of challenges faced by the Indian hospitals in the adoption of data analytics tools, it can be seen that data integration issues (74%) are the most significant challenges facing the use of data analytics tools, which indicates that there are widespread problems in the integration of information from a variety of systems and departments. This is followed by the high cost of analytics tools (68%) and lack of infrastructure (58%), both of which suggest a lack of financial and technological resources, particularly in smaller or resource-constrained hospitals. Insufficient staff training (54%) is also revealed as a major hurdle showing the urgent need for capacity building and skill development in data literacy. Organizational and cultural barriers that prevent smooth implementation are highlighted by these concerns over data privacy and security (44%), resistance from staff (42%), and lack of time/resources (38%). Only a small percentage (7%) reported other issues such as support from leadership and dependency on vendors.

Table 10: Challenges Reported by Hospitals in Implementing Data Analytics

S.No.	Challenge	No. of Responses	% of Hospitals Reporting
1	Data integration issues	281	74%
2	High cost of analytics tools	258	68%
3	Lack of infrastructure (hardware/software)	220	58%
4	Insufficient staff training	205	54%
5	Data privacy and security concerns	167	44%
6	Lack of time/resources for implementation	144	38%
7	Resistance from staff/clinicians	160	42%
8	Other (e.g., leadership support, vendor issues)	27	7%

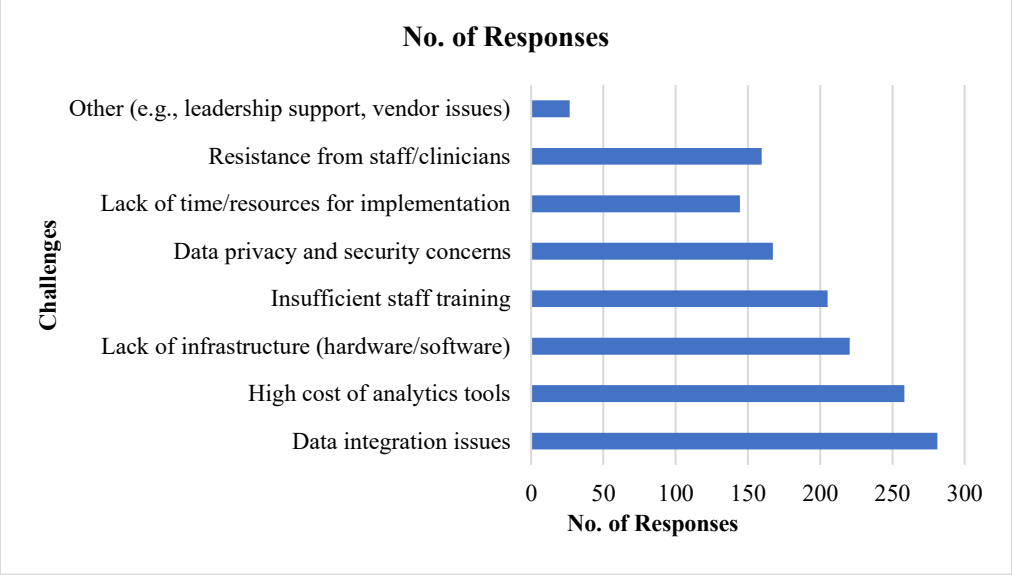


Fig. 4: Major Challenges in Implementing Data Analytics in Hospitals

Conclusion

The research shows the importance of data analytics, which sets a benchmark for hospitals to enhance operational performance in India. The empirical results reveal that those hospitals that implement data analytics in areas of real-time monitoring, predictive analytics, and data-driven decision support systems were successful in identifying high-risk patients, reduce the readmission rates, and minimize inefficiencies in their operations. While the research points out critical areas of resistance such as integration of data, privacy, security, and lack of proper training, the results support the idea that adoption is strongly determined by the ascribed efficacy and usability. It thus seems clear that the

digital transformation of the Indian healthcare is not only dependent on the sophistication of the software but also on establishing a data resilient culture that places patient confidentiality and ethical data governance at the forefront. Consequently, there is an essential need for technological investment and strategic planning in order to promote operational efficiency. Moving forward, future research should spread across healthcare analytics by exploring the integration AI for automated clinical documentation and performing longitudinal studies of the ROI of predictive tools in chronic disease management across a variety of socio-economic demographics. Furthermore, research on technology adoption in hospital settings needs to be expanded to look at "Cultural Resistance" and "Digital Literacy" as moderators in the TAM framework. There is also a critical need to be exploring standardized interoperability protocols and blockchain-based security frameworks to address the identified data integration and privacy issues in this study for compliance with emerging national health data regulations.

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