Original Article
ISSN (Online): 2582-7472

ShodhKosh: Journal of Visual and Performing Arts
June 2024 5(6), 3079–3089

ADOPTING AI-DRIVEN DATA CULTURE IN ORGANIZATION: CHALLENGES AND OPPORTUNITIES FROM EMPLOYEES' PERSPECTIVES

Mr. Harshal Patil [1], Dr. Abhay Kulkarni [2]

[1] Research Scholar, ATSS IICMR Institute Nigdi, Pune
[2] Research Guide and Director, ATSS IICMR Institute Nigdi Pune

Corresponding Author
Mr. Harshal Patil, hpaiml77@gmail.com

DOI
10.29121/shodhkosh.v5.i6.2024.3591

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

Data functions as an organization's growth engine fuel. In the age of digitalization, it is among the most precious resources. Organizations now use data-driven decision-making processes instead of product-centered ones. This is due to the fact that it projects more accurate, impartial, and objective predictions. IT companies have faced challenges over the years relating to big data, including security, accessibility, reuse, automation, and decision-making. So, a lot of businesses have concentrated on implementing AI-driven data culture. The purpose of this paper is to investigate the possibilities for establishing an AI-driven data culture in Pune's IT/ITES companies. Additionally, it attempts to pinpoint the opportunities and difficulties associated with implementing an AI-driven data culture from the viewpoint of the workforce. Regression analysis was used to examine data from a survey of 200 participants from various organizational levels. The results show a substantial gender gap in perception, emphasizing the necessity for gender-specific adoption tactics for AI-driven data culture. Lack of advanced internal expertise, recurrent data use, inadequate infrastructure, restricted or nonexistent finance, and inadequate data management (quality, sources, validity, accessibility, approvals, execution, alignment with organisation goals, etc.) are a few of the main obstacles. Opportunities include standardization, automation, quality report generating, integration, and simplification. From the standpoint of process improvement, performance improvement, compliance, audits, trend analysis, and competitive analysis, the current study is noteworthy. It may result in long-term sustainable growth and the best possible use of available resources.

Keywords: Artificial Intelligence, Data Culture, Organizational Growth, Challenges and Opportunities from Employees' Perspectives

1. INTRODUCTION

Technology has revolutionized almost all walks of life. It has influenced the economies, governments, societies, communities, organizations to the great extent. The high-end technology works like invisible hand transforming the users and enabling them to simplify, automate, integrate, collaborate and innovate at multiple levels. The artificial intelligence has gained the momentum. Applications of artificial intelligence (AI) are becoming increasingly commonplace as innovation advances. Research on the application of artificial intelligence (AI) in business environments has focused on the potential uses of AI while taking into account workers' aspirations to use simulated intelligence tools and their level of big data analytical competency (BDAC) (Anton, et al., 2023). Artificial intelligence, also known as "man-made intelligence," refers to a variety of linked techniques that have been developed in the domains of measuring, software engineering, and mental brain research (Kar & Kushwaha, 2023). The complementary ideas of the green economy and digitization will help to advance a controllable course of events. One example of a computerised invention that can gather, evaluate, and analyse data while also communicating the findings to a wider range of applications is artificial intelligence.

The industrial revolution 5.0 revolution is driven by the various tools in the forms of artificial intelligence (Ledro et al., 2023). It possesses the capacity to analyse vast amounts of data, locate pertinent information, and utilise the data to enhance operations, provide useful insights, and generate new financial and commercial values (Strann, 2022). A company's display can benefit from using computer-based intelligence applications by reducing operating costs and increasing the value of its brand (Chowdhury et al., 2023). It is imperative that staff members use computer-based intelligence apps since their actions might affect the organization's ability to compete. The usage of AI applications in the office has the potential to transform business practices and open up new opportunities for the company to create value. Employees that are driven to learn can become knowledgeable about the industry and are usually highly flexible since they have to adjust to a lot of changes in the job. By making changes to internal processes and enhancing the expertise of willing staff members, the organisation might improve the effectiveness of its products (Jöhnk et al., 2021).

1.1. ELEMENTS AND NEEDS FOR THE APPLICATION OF AI

In digital transformation contexts, artificial intelligence (AI) is typically applied to critical components, whereas machine learning (ML) techniques are used for task-based applications. Taherizadeh & Beaudry (2023) state that advanced analytics, IoT operations, internal processes, and the company's customer offers are among the initiatives that are usually covered. The deployment and acceptable use of AI has changed over the past few years due to its opaque nature, making it more difficult to regulate. Therefore, identifying the prerequisites and traits for successful AI projects is essential before starting an organisational AI project. This will enhance the action-oriented consequences for the deployment of AI. The artificial intelligence can transform the firms at three stages: Processes, People and Technology (PPT). It enables the firms to grow in terms of sustainable development.

1.1.1. PEOPLE

People are the most dynamic assets for any organization. They play the different roles at different levels. It is challenging to recognise what is appropriate and compatible in real life. Disagreements or misalignments can give rise to sources of conflict and technical issues for projects. In contrast to earlier software solutions, the discovery, management, and model customization may call for new abilities and viewpoints. The strategic importance of launching AI projects is impacted by top-level management support. The successful application of AI requires the cooperation of top management, since organizations can only fully commit to AI if management sends out a signal to integrate AI into the entire business plan. This is because AI needs to be a part of the fundamental organizational procedures (Aldoseri et al., 2024). However, the implementation can be difficult if management-level decision-makers neglect to take into consideration a disparity in the appreciation of AI. While bottom-up initiatives can falter due to a lack of initiative, top-down implementation could fail in the face of skeptical lower management.

1.1.2. PROCESS

Establishing the requisite connections between an organization's digital operations and business model enhances the organization's capacity to apply AI solutions. This is because adjustments made to AI systems have an impact on organizational procedures as well. For example, the implementation of AI involves digital procedures since data collecting is one of the critical competencies that require a lot of data. If not, there would be a detrimental effect on the process output from insufficient data. Furthermore, it is imperative for organizations to develop sustainable data architectures that may either complement or completely replace their current processes. Lack of desire to integrate AI technologies into the organization's core operations may stem from a poor grasp of how to extract value from digital processes.

According to Allioui & Mourdi (2023), client AI-trust is the understanding and acceptance of customers towards the use of AI solutions. The degree of technical maturity of the organisation, as well as the external market and the organization's positioning in it, are common sources of technological uncertainty. The desire of both internal and external customers to implement the AI solution is influenced by the transparency of AI. Given the complexity of artificial intelligence (AI), the "black box" problem—a lack of transparency—may make it difficult for both internal and external customers to recognise the benefits of AI, particularly for non-experts. Users who don't know enough about AI may have irrational expectations of it or may not even trust the system.

1.1.3. TECHNOLOGY

The implementation of AI necessitates significant financial outlays in order to customise resources and capabilities to the particular data and surroundings within the company. This is because artificial intelligence (AI) is a time- and money-consuming process that necessitates developing and enhancing technical expertise and overcoming technological uncertainties within the company (Zabala, 2023). Furthermore, having the right digital strategies in place is necessary when switching from analogue to digital data collection procedures. Because software is so adaptable, businesses that want to create value and capture activities need to be prepared to adjust to shifts in demand and be able to extend their capabilities accordingly. Therefore, financial constraints that ultimately prevent the project from progressing into further stages may prevent organizations from continuing forward with AI projects.

1.2. RESEARCH OBJECTIVES

The below objectives are framed for the present study:

1) To examine the present status of AI-based data culture in IT firms in Pune
2) To evaluate the degree of artificial intelligence (AI) use in decision-making processes
3) To identify the major challenges while adopting AI-based data culture
4) To analyze the perceptions of IT employees towards the AI-adopted data culture in IT firms

1.3. HYPOTHESIS OF THE STUDY

H01: Employees in IT/ITES companies in Pune don't have different perspectives about the adoption of AI-driven data cultures depending on their gender.

HA1: Employees in IT/ITES companies in Pune have different perspectives about the adoption of AI-driven data cultures depending on their gender.

H02: Employee satisfaction is not greatly impacted by the perceived opportunities and problems faced by IT/ITES companies in Pune while implementing an AI-driven data culture.

HA2: Employee satisfaction is greatly impacted by the opportunities and problems IT/ITES companies in Pune see while implementing an AI-driven data culture.

2. LITERATURE REVIEW

Weber et al. (2023) studied organisations should build specialised capabilities for implementing AI in order to handle these problems. As of right now, the study doesn't fully grasp how specific skills make AI implementation easier. It's yet unclear how they assist organisations in adjusting to the peculiarities of AI. The study utilizes a subjective examination strategy and do 25 exploratory meetings with experts on the use of computer based intelligence to close this examination hole. Four organizational capacities with respect to carrying out man-made intelligence are determined by us: Co-improvement and simulated intelligence project arranging help with tending to the ambiguity of man-made intelligence, which makes partner correspondence and undertaking arranging more troublesome. Data reliance in computer based intelligence presents issues for associations, including giving the right data establishment and persistently changing computer based intelligence frameworks as the data advances. Data the board and man-made intelligence Model Lifecycle. The executives help to adapt to this data reliance. The study advances the possibility of organizational capacities as a vital achievement component for man-made intelligence execution and extends our understanding of the sociotechnical results of computer based intelligence's highlights.

Yilmaz, (2024) drawed attention to AI's dynamic qualities and stresses the countless potential it offers in the modern digital era. The field of "AI-driven data analytics" has emerged as a quickly developing field as a result of the integration of numerous technologies. This makes it possible for data mining, natural language processing, and machine learning algorithms to efficiently extract useful insights from complex datasets for information scientists and organisational managers alike. This includes a discussion of machine learning techniques and how they may be used to identify relationships and patterns in data as well as the use of natural language processing in obtaining knowledge from unstructured textual material. Predictive analytics is made easier by AI-powered data analysis and visualisation, which also improves the conveyance of complex data through interactive visual representations.

Fredriksen & Skjærvik, (2021) examined how 1) organisational culture affects AI capabilities in order to quantify this and 2) how competitive, market, and social performance is affected by AI capabilities. The study four hypotheses are supported by our analysis. First, artificial intelligence capabilities are positively impacted by organisational culture. Second, social performance benefits from artificial intelligence skills. Third, the performance of the market is positively impacted by artificial intelligence capabilities. Fourth, competitive performance benefits from artificial intelligence skills. The study draw the following conclusions: AI capabilities improve an organization's performance, and organisational culture plays a significant role in their development. organizations can enhance their AI capabilities by examining their organisational culture in order to better leverage AI technologies. Keywords: Competitive performance, market performance, social performance, organisational culture, and artificial intelligence capabilities.

Agrawal (2023) focused on the difficulties in standardizing these kinds of optimisation intelligence systems. To enable a theoretical investigation of this standardisation process, it makes use of the Normalization Process Theory (NPT). It explains how NPT might be utilized to give a coordinated structure for appreciating and guessing the methodology engaged with coordinating and keeping up with GenAI-OI frameworks, which are critical in deciding where organizational nimbleness will take from here on out. This is valid from both an examination and down to earth standpoint. The objective of this examination is to give helpful data to associations that need to execute and keep up with this innovation effectively. Devices for generative artificial intelligence (computer based intelligence), like ChatGPT, have a ton of commitment for the business area and for organizational initiative. To expand its benefits, organizations are forcefully consolidating Generative man-made intelligence (GenAI) into their activities. The components supporting the continuation of GenAI-controlled Streamlining Intelligence (GenAI-OI) processes in organizational settings, in any case, have not yet been entirely researched.

Dwivedi et al. (2021) features the various opportunities, practical evaluation of effect, challenges, and potential examination plan presented by the quick development of computer based intelligence inside various areas: science and innovation, business and the board, government, and the public area. While recognizing the impact of society and industry on the rate and heading of artificial intelligence advancement, this examination gives significant and current experiences into simulated intelligence innovation and its suggestions for the eventual fate of industry and society at large. Critical headways in mechanical advancement have had the option to change over numerous manual positions and cycles that had been set up for quite a long time, when people had arrived at the constraints of their actual capacities, tracing all the way back to the modern transformation. Inside a wide scope of monetary, scholarly, and social applications, artificial intelligence (simulated intelligence) offers this equivalent groundbreaking potential for the expansion and possible substitution of human capabilities and exercises. With late advances in algorithmic AI and independent navigation, the speed of improvement in this new time of artificial intelligence innovation is surprising and presents new roads for progressing development. The development of computer based intelligence innovation can possibly fundamentally upset a large number of enterprises, including finance, medical care, fabricating, retail, production network, strategies, and utilities.

3. RESEARCH METHODOLOGY

3.1. RESEARCH DESIGN

The study used a quantitative research design to evaluate the state of data culture and AI adoption in Pune's IT/ITES companies and to pinpoint the difficulties in establishing a data culture driven by AI. Data from employees in these firms was gathered using a cross-sectional survey approach.

3.2. SAMPLE POPULATION

The intended audience was Pune-based employees of IT/ITES companies. To choose the participants, a stratified random selection procedure was employed. With a 5% margin of error and a 95% confidence level, the sample size was calculated. Based on earlier research, a sample size of at least 200 individuals was advised.

3.3. SAMPLE SIZE

The study included 200 participants, all of whom were employed by IT/ITES companies in Pune. To guarantee representation from various organisational levels and departments, stratified random sampling was employed.

3.4. SAMPLING TECHNIQUE

Participants in the study were chosen using a stratified random selection procedure.

3.5. DATA COLLECTION

3.5.1. PRIMARY DATA COLLECTION:

A broader sample of employees received standardised questionnaires for the quantitative component. Both closed-ended and Likert-scale items were included in the questionnaires, which were created with the research aims in mind. The purpose of the questionnaire was to collect quantitative data on employees' opinions of the adoption of an AI-driven data culture, in addition to their job-related and demographic data. Participants received the surveys either in person or electronically, and they had enough time to do them. To find trends and patterns in the employee responses, statistical methods were used to analyse the data gathered from the questionnaires.

3.5.2. SECONDARY DATA COLLECTION:

Secondary data sources were used in addition to original data collecting. An extensive analysis of previous research, papers, and studies on the adoption of AI-driven data cultures in IT/ITES companies was carried out. Through this literature evaluation, the researchers were able to identify gaps in the present state of the field's research and provide context and background information for their study. The results and analysis of the study were supported by data from related sources and earlier research, which offered more insights into the opportunities and difficulties of adopting an AI-driven data culture in Pune's IT/ITES companies.

3.6. VARIABLES OF THE STUDY

3.6.1. INDEPENDENT VARIABLES:

- AI-driven data culture acceptance: The degree of AI-driven data culture adoption in Pune's IT/ITES companies, as determined by the opinions and experiences of the staff.

3.6.2. DEPENDENT VARIABLES:

- Difficulties faced: According to staff members, the biggest difficulties IT/ITES companies in Pune have had establishing an AI-driven data culture.
- Perceived opportunities: The advantages that employees of Pune-based IT/ITES companies see in implementing an AI-driven data culture.

3.7. TOOLS USED FOR DATA ANALYSIS

Statistical analysis was done for the quantitative data from the structured questionnaires. Descriptive statistics were utilised to provide an overview of the data, while inferential statistics like regression were applied to evaluate the research hypotheses. For this investigation, statistical programmes like Excel or SPSS may have been utilised.

4. DATA ANALYSIS AND INTREPRETATION

Table 1: Participants' demographic profile in the study

		F	%
Gender	Male	140	70%
	Female	60	30%
Age	18-25	140	20%
	26-30	80	40%
	31-35	60	30%
	36-40	16	8%
	40+	4	2%
Educational Background	Undergraduate,	56	28%
	Graduate,	80	40%
	Postgraduate	40	20%
	Others	24	12%
Job Role	Executive	120	60%
	Manager	60	30%
	Technical Staff	20	10%
Years of Experience	0-5	70	35%
	6-10	80	40%
	11-15	40	20%
	16+	10	5%

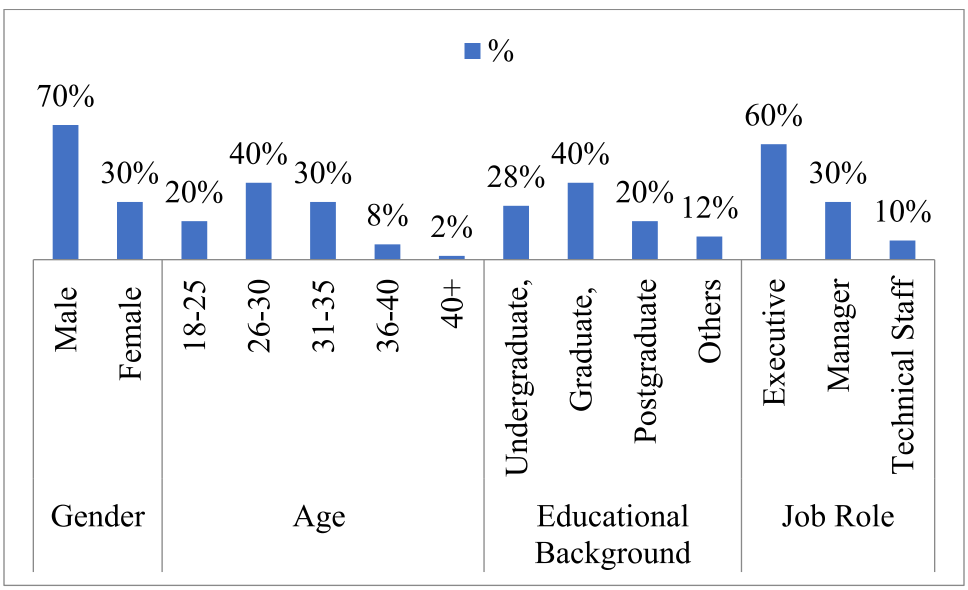

Figure 1: Participants' demographic profile in the study

The demographic profile of the study participants is broken down in detail in the table. It demonstrates that men made up 70% of the sample and participated in the study at a higher rate than women **(30%).** Age distribution showed that the largest group was in the 26–30 age range **(40%)** followed by the 31–35 age group **(30%)** and the 18–25 age group **(20%)**. The educational backgrounds of the participants varied: 40% had a graduate degree, 28% had an undergraduate degree, 20% had a postgraduate degree, and 12% were classified as "Others." As far as occupations go, 60% of participants held executive jobs, 30% held managerial positions, and 10% held technical positions. Years of experience were analysed, and 40% of participants had 6–10 years, 35% had 0–5 years, 20% had 11–15 years, and 5% had 16 or more years.

4.1. RELIABILITY TEST

The findings of the Cronbach's Alpha reliability test for the study variables pertaining to the adoption of an AI-driven data culture are shown in Table 2.

Table 2: Cronbach's Alpha

Reliability Statistics		
Research Variables	**Observable Variables**	**Coefficient**
Adoption of AI-driven data culture	4	0.745
Challenges	3	0.748
Opportunities	4	0.851

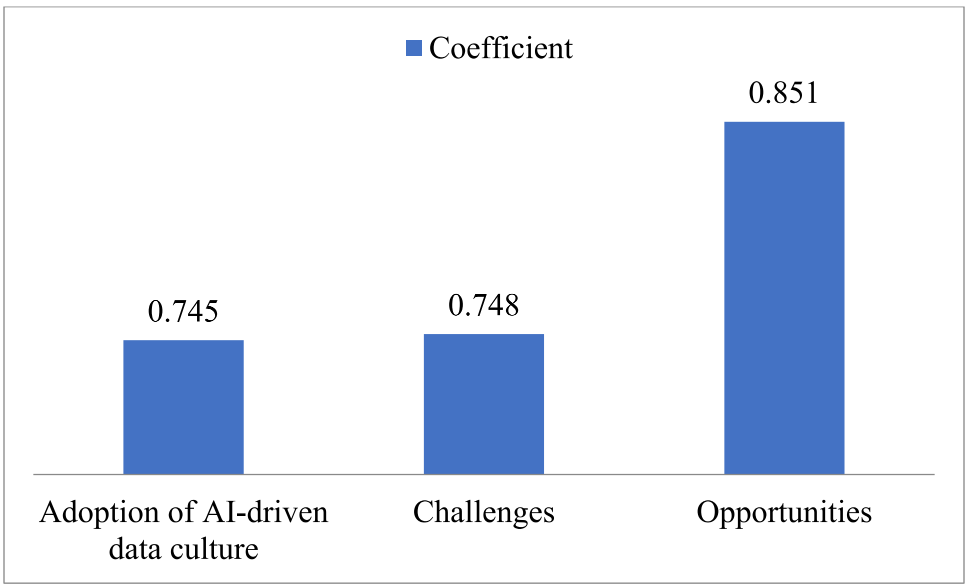

Figure 2: Cronbach's Alpha

Table 2 present the study variable's number of observable variables and matching Cronbach's Alpha coefficient are displayed in the table. A moderate amount of internal consistency among the observable variables within the variable "Adoption of AI-driven data culture," which consists of four observable variables, was indicated by the Cronbach's Alpha coefficient of **0.745.** Similarly, the Cronbach's Alpha coefficient for the variable "Challenges," which consists of three observable variables, was **0.748**, indicating a modest degree of internal consistency among the observable variables that make up this variable. With a Cronbach's Alpha coefficient of **0.851,** the variable "Opportunities," which is made up of 4 observable variables, on the other hand, showed a higher degree of internal consistency. This suggests that the observable variables that make up this variable have a high degree of internal consistency.

The results of the exploratory factor analysis (EFA) used to determine the underlying variables associated with IT/ITES companies' adoption of AI-driven data culture are shown in Table 4. The rotated component matrix, which presents the loadings of every observable variable on the extracted factors upon rotation, is displayed in the table.

Table 3: Results of the exploratory factor analysis (EFA)

	Rotated Component Matrix[a]		
	1	2	3
Leadership Support	.878		
Organizational Culture	.860		
Data Quality and Availability	.795		
Technological Infrastructure	.780		
Employee Skills and Training	.612		
lack of high-end in-house expertise		.796	
repetitive use of data		.711	
lack of infrastructure		.652	
limited/less funding		.602	
lack of data management		.600	
Simplification			.785
Integration			.755
quality report generation			.682
Standardization			.674
Automation			.605

Table 3 presents the three factors were retrieved as a consequence of the EFA and are designated as Factor 1, Factor 2, and Factor 3. The factors "Leadership Support," "Organisational Culture," "Data Quality and Availability," and "Technological Infrastructure" all had high loadings on Factor 1, indicating a strong correlation between them and a potential contributor to organisational readiness for the adoption of AI-driven data cultures.

The components that make up Factor 2 are "lack of high-end in-house expertise," "repetitive use of data," "lack of infrastructure," "limited/less funding," and "lack of data management." These variables may indicate obstacles or difficulties in adopting AI-driven data cultures, pointing out issues that companies must resolve in order to successfully support adoption.

Factor 3 includes characteristics such as "Simplification," "Integration," "quality report generation," "Standardisation," and "Automation" that are related to prospects for adopting AI-driven data culture. These factors demonstrate possible advantages and openings that businesses might take advantage of by implementing an AI-driven data culture.

4.2. REGRESSION MODEL AND HYPOTHESIS TESTING

Table 4: A summary of the variables in the model

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.845[a]	.656	.650	.84526
a. Predictors: (Constant), Leadership Support, Organizational Culture, Data Quality and Availability, Technological Infrastructure, Employee Skills and Training				

According to the table 4, the model's R-squared value is **0.656**, meaning that its independent variables can account for about **65.6%** of the variance in the dependent variable. Given that the model takes into account both the number of predictors and the sample size, the adjusted R-squared value of **0.650** indicates that the model fits the data well. The model's prediction accuracy is gauged by the standard error of the estimate, where a value of **0.84526** denotes a comparatively low degree of error.

Table 5: Results of multiple linear regression analysis

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	356.232	4	62.123	542.36	.000[b]
	Residual	114.233	195	.745		
	Total	470.465	199			
a. Dependent Variable: Opportunities & Challenges						
b. Predictors: (Constant), Leadership Support, Organizational Culture, Data Quality and Availability, Technological Infrastructure, Employee Skills and Training						

The table 5 shows that, with a p-value of less than **0.001** and an F-value of **542.36**, the regression model is statistically significant. This indicates that the perception of opportunities and challenges related to the adoption of AI-driven data culture is significantly influenced by the independent variables included in the model (Leadership Support, Organisational Culture, Data Quality and Availability, Technological Infrastructure, Employee Skills and Training) taken together.

Table 6: Regression model coefficients

Coefficients[a]						
		Unstandardized Coefficients		**Standardized Coefficients**		
Model		**B**	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	.512	.104			.000
	Leadership Support	.202	.024	.312	8.589	.000
	Organizational Culture	.178	.035	.215	4.892	.000
	Data Quality and Availability	.195	.032	.184	5.958	.000
	Technological Infrastructure	.209	.021	.235	10.333	.000
	Employee Skills and Training	-.162	.015	-.178	-8.379	.000
a. Dependent Variable: Opportunities & Challenges						

The table 6 is organised into rows that correspond to distinct independent variables. According to the table, every independent variable has statistically significant coefficients ($p < 0.001$), indicating that each one contributes differently to the prediction of the perception of opportunities and difficulties associated with the adoption of AI-driven data cultures.

The following is the regression equation that uses the coefficients from Table 6:

Perception of Opportunities and Challenges = 0.512 + 0.202 (Cultural Leadership) + 0.178 (Data Availability and Quality) + 0.195 (Perception of Opportunity and Challenges) + 0.209 (Technological Infrastructure) - 0.162 (Worker Competencies and Training).

5. CONCLUSION

The study examined how IT/ITES companies in Pune were embracing AI-driven data cultures, with an emphasis on the perceived benefits and difficulties that came with this change. The investigation produced some important findings; most notably that employees' impressions of the adoption of AI-driven data culture are significantly shaped by their gender. This result defied the original theory and showed that gender differences indeed affect how people view and accept this technological change. Additionally, the study confirmed the notion that perceived difficulties and opportunities have a large impact on employee happiness by highlighting their substantial impact. The study also identified important variables that affect the adoption of AI-driven data culture, such as organisational culture, staff skills and training, technology infrastructure, data availability and quality, and leadership support. These elements became clear as being essential in determining how organisations will adopt an AI-driven data culture. These results led to the formulation of several useful recommendations. These include establishing a culture of innovation and data-driven decision-making within the organisation, providing high-quality and easily available data, investing in staff development, and building strong leadership support. The report offers IT/ITES companies in Pune that want to embrace AI-driven data culture practical insights. Organizations can improve employee satisfaction, enable a more seamless adoption of AI-driven data cultures, and ultimately propel organizational growth and success in the digital age by tackling the study's primary themes and difficulties.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

REFERENCES

Agrawal, K. (2023). Organizational Sustainability of Generative AI-Driven Optimization Intelligence. Journal of Computer Information Systems, 1-15. https://www.tandfonline.com/doi/abs/10.1080/08874417.2023.2286540

Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2024). Methodological Approach to Assessing the Current State of Organizations for AI-Based Digital Transformation. Applied System Innovation, 7(1), 14. https://www.mdpi.com/2571-5577/7/1/14

Allioui, H., & Mourdi, Y. (2023). Unleashing the potential of AI: Investigating cutting-edge technologies that are transforming businesses. International Journal of Computer Engineering and Data Science (IJCEDS), 3(2), 1-12. https://ijceds.com/ijceds/article/view/59

Anton, E., Oesterreich, T. D., Aptyka, M., & Teuteberg, F. (2023). Beyond digital data and information technology: conceptualizing data-driven culture. Pacific Asia Journal of the Association for Information Systems, 15(3), 1. https://aisel.aisnet.org/pajais/vol15/iss3/1/

Campos Zabala, F. J. (2023). The Barriers for Implementing AI. In Grow Your Business with AI: A First Principles Approach for Scaling Artificial Intelligence in the Enterprise (pp. 85-110). Berkeley, CA: Apress. https://link.springer.com/chapter/10.1007/978-1-4842-9669-1_4

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. Human Resource Management Review, 33(1), 100899. https://www.sciencedirect.com/science/article/pii/S1053482222000079

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://www.sciencedirect.com/science/article/pii/S026840121930917X

Fredriksen, S. F. B., & Skjærvik, M. E. (2021). Understanding the role of organizational culture on Artificial Intelligence capabilities and organizational performance (Master's thesis, University of Agder). https://uia.brage.unit.no/uia-xmlui/handle/11250/2825428

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—an interview study of organizational AI readiness factors. Business & Information Systems Engineering, 63, 5-20. https://link.springer.com/article/10.1007/s12599-020-00676-7

Kar, A. K., & Kushwaha, A. K. (2023). Facilitators and barriers of artificial intelligence adoption in business–insights from opinions using big data analytics. Information Systems Frontiers, 25(4), 1351-1374. https://link.springer.com/article/10.1007/s10796-021-10219-4

Ledro, C., Nosella, A., & Dalla Pozza, I. (2023). Integration of AI in CRM: Challenges and guidelines. Journal of Open Innovation: Technology, Market, and Complexity, 9(4), 100151. https://www.sciencedirect.com/science/article/pii/S2199853123002536

Strann, P. (2022). Adopting artificial intelligence to support knowledge work: drivers of trust according to experts. https://www.tandfonline.com/doi/abs/10.1080/13662716.2023.2242285

Taherizadeh, A., & Beaudry, C. (2023). An emergent grounded theory of AI-driven digital transformation: Canadian SMEs' perspectives. Industry and Innovation, 30(9), 1244-1273. https://www.tandfonline.com/doi/abs/10.1080/13662716.2023.2242285

Weber, M., Engert, M., Schaffer, N., Weking, J., & Krcmar, H. (2023). Organizational capabilities for ai implementation—coping with inscrutability and data dependency in ai. Information systems frontiers, 25(4), 1549-1569. https://link.springer.com/article/10.1007/s10796-022-10297-y

Yilmaz, A. A. (2024). AI-Driven Data Analytics in Information Sciences and Organizational Management. In AI and Data Analytics Applications in Organizational Management (pp. 19-35). IGI Global. https://www.igi-global.com/chapter/ai-driven-data-analytics-in-information-sciences-and-organizational-management/338504