Enhancing Productivity: Artificial Intelligence's Effect on productivity of Nepalese large Scale Organizations

Abstract

The primary issue of the study is to explore the effect of AI integration, user interface , user experience and quality on the productivity of the employees working in large scale organizations in Nepal. The aim of this investigation was to assess the impact of artificial intelligence (AI) on employee productivity in Nepalese organizations. The study assesses AI's effect on productivity, that may address the lack of empirical evidence in Nepal. The information was gathered using five-pointLikert scale questionnaires administeredonline. The sample size for the study was 85. The data was analyzed using SPSS software. To explore the direct effect, indirect effect, and total effect of moderating variables, a process tool in SPSS developed by Andrew F. Hayes was used. The findings revealed that quality and AI integration had positive and significant effect on productivity whereas AI user experience and user interface had insignificant effect on employee productivity. The positive correlation between AI integration and productivity signifies the need for organizations to embrace seamless AI adoption. By integrating AI effectively into their workflows, they can streamline processes, harness data-driven insights, and ultimately enhance productivity.

***Keywords*:**AI, AI content Quality, AI integration, AI interface, AI user experience, Productivity

Introduction

A class of information and communication technologies (ICTs) known as Artificial Intelligence(AI) mimics the intelligence of people with the primary objective of increasing job opportunities, increasing productivity, and fostering growth in the economy (Arakpogun et al., 2021). Recent developments in generative AI could have wide-ranging effects on the labor and production markets. In comparison to most earlier examples of automation technologies, novel machine learning platforms such as ChatGPT or DALL-E, that may be instructed to produce fresh textual or the apparent results of enormous information sets, are fundamentally different. The majority of "routine" tasks affected by previous waves of automation were explicit sequences of processes that were simple to codify and program through a computer (Autor and Dorn, 2013; Autor, 2015). Applications of artificial intelligence (AI) have the potential to increase productivity among people. AI models have shown human-level performance in a range of areas, including picture recognition and natural language interpretation (Zhang et al., 2022).

AI- based assistants that are integrated into the workplace can give employees access to a setting that makes it easier for them to complete tasks through conversation-triggered search, data directions, scheduled work and digitalization of routine duties. These could improve people's productivity by rendering labor resources– such as people, files and information conveniently accessible, easily found, and acceptable (Balakrishnan and Dwivedi,2021). The technical capacities of artificial intelligence (AI) have dramatically increased recently. For example, in February 2016, Google's DeepMind used artificial intelligence to defeat Lee Se-dol2, a Korean go expert, and in January 2017, Deepstack used AI to defeat humans in the difficult poker game Texas Hold 'Em. The Electronic Frontier Foundation (EFF) has been tracking the quick advancement of artificial intelligence in the fields like speech recognition, language translation, photographic recognition, and others. These advancements have sparked excitement about the potential of artificial intelligence to spur economic expansion as well as worries about the future of people working in a world where machine learning algorithms can perform many of the jobs that a human would typically perform (Frey and Osborne 2013, Furman 2016a).

The job market and industry may be significantly impacted by AI's possible efficient effects, which could include changes to employment, skill requirements, and organizational structure (Raj and Seamans, 2018, Agrawal et al., 2019). A few age-old concerns are raised once again in fresh contexts by the development of potent generative AI technology. By definition, automation technologies take the place of humans in doing particular jobs. However, more generally, they may either entirely replace people in some occupations or operate in conjunction with human workers already in place to boost prolificacy (Acemoglu and Restrepo, 2020; Boustan et al., 2022; Kanazawa et al., 2022).
Despite the increment in the use of AI by the organization there is still confusion as to whether the increase of AI enhances productivity or not. Especially in the context of Nepal there are very few verifications to assist the claim that the ply of AI enhances the productivity of the employees as there is no sufficient literature. Conducting this research is essential to identify the existing gap regarding the investigation into how AI affects workers productivity in Nepal. The study's main goal is to examine the effects of artificial intelligence (AI) on employee productivity within organizations in Nepal, a context where there is a notable scarcity of empirical evidence. To achieve this, we have outlined a comprehensive set of research objectives. First, we aim to assess the current level of AI implementation across large scale industries in Nepal. The study also seeks to evaluate the degree of AI integration. In addition to evaluating the technological aspect of AI adoption, we assessed the user experience and satisfaction levels of employees interacting with AI tools in their daily work. Furthermore,the purpose of the study is to find out how workers view AI's effect on overall productivity.

Literature Review

The rise of AI-driven systems within business organizations has indeed transformed workforce demography, the kind and significance of work, the dynamics between employers and employees, people’s interaction with technology customer interactions, as well as the competitive edge in a dynamic market setting(Connelly et al.,2021; Wilson et al., 2017).

The literary works available has stated and detailed numerous advantages associated with the adoption of AI which involves raising corporate productivity optimizing business process and assets (Faulds & Raju, 2021), business model transition(Duan, Edwards, & Dwivedi, 2019), use predictive intelligence to make decisions (Paschen, Wilson, & Ferreira, 2020), lowering labor costs while improving customer service, work happiness, and employee experience(Bughin et al., 2018).After accounting for other patenting activities, it was found that applications for AI patents had an additional favorable impact on small and medium-sized businesses and the service sector. It indicated that the capacity to swiftly adjust and implement AI-based apps in the production process played a significant role in the observed impact of AI thus far (Damioli et al., 2021).

Digital Productivity Assistants (DPAs) were sophisticated solutions that used individualized work-based data to promote productivity and work-life balance. The study’s objective was to better understand the result of DPAs in increasing individual productivity and work-life balance. It investigated and observed 28 workers who faced high job pressures, demonstrating the potential benefits of collaborating with AI. The study also looked at perceived hurdles including precision, openness, feedback, and adaptability, as well as the discrepancy between DPAs and workers' work practices (Cranefield, 2023).

Gao & Feng (2023) analyzed how artificial intelligence has affected corporate productivity using small scale manufacturing information. According to the study, every 1% rise in AI penetration resulted in a 14.2% rise in total factor productivity. The beneficial impact was produced through the effects of technology, skill-biased improvement, and value-added improvement.

By reducing costs and changing innovation tools, AI can increase business innovation efficiency. An analysis of text mining data and panel data from 3185 listed businesses revealed that the use of AI considerably increases the efficiency of innovation. But there is a moderating effect of increased external market rivalry and flattening internal organizational structure (Li et al., 2023).

Fügener (2021) examined human-AI collaboration in classification tasks. Result shows that combined human-AI performance exceeds AI's individual performance, however only when humans are assigned work by the AI, not the other way around. Surprisingly, the AI's delegation improves even with low-performing individuals, while humans struggle to delegate effectively. This is not due to algorithm aversion but a lack of meta knowledge, hindering humans' ability to assess their own capabilities. These findings have implications for work, collaborative environments, and digital-age education.

AI tools' impact on software development productivity, focusing on GitHub Co-pilot. Through a controlled experiment, the research assesses Co-pilot's effect on programming tasks, revealing a significant and practical boost. The group using Co-pilot completed tasks 55.8% faster than the control group. AI assistance can enhance code quality by suggesting improvements or diminish it if programmers become less attentive. Considering code quality's broader implications, including performance and security, AI's real-world impact can vary (Peng, 2023).

The study revealed that many firms have not experienced the benefits they had anticipated, despite the excitement and assurances expressed above regarding the applications, benefits, and effects of AI in HRM. Intentions to deploy AI decreased from 20% in 2019 to 4% in 2020, as only seven out of ten AI initiatives generated meaningful economic value, according to a Boston consulting group and MIT analysis (Fountaine et al.,2019; The Economist, 2020; Deloitte, 2017).

Malik et al. (2021) explored the influence of adoption of AI on employee experiences and technostress, concentrating on 32 workers from nine industries. The findings revealed negative consequences such as information security, data privacy, digital changes, job danger, and insecurity. Work flexibility, autonomy, creativity, invention, and job performance enhancement were all positive effects. Work overload, employment insecurity, and complexity were all factors that contributed to technostress.

Dey et al., (2023) revealed that in order for organizations to reap the benefits of AI adoption, they had to look beyond technical resources and focus on developing non- technical ones, such as leadership, team coordination, organizational culture and innovation mindset, governance strategy, and AI employee integration.

The moderating effect of technological leadership was deemed insignificant. This discovery opens up an essential pathway for further research and exploration of future directions in this area.The findings further supported the idea that information exchange and mental health and wellness played a crucial role in the connection between AI and employee productivity (Shaikh et al., 2023).

Theoretical review

Technology acceptance model:

The Technology Acceptance Model (Davis, 1989), or TAM, posits that perceived usefulness and perceived ease of use are the two elements that influence whether potential users will adopt a computer system. This model's primary characteristic is its focus on the opinions of possible users.In other words, even if a technological product's developer thinks it's helpful and easy to use, potential users won't embrace it until they also think of it that way. Mathieson (1991) found that TAM predicted intention to make good use of information systems, although it is simpler to use, it only provides extremely broad information on the user's opinion about a system. Various studies (Kuo, Rolden Bau & Lowinger, 2015; Rana & Dwivedi, 2015 ; Bouten, 2008) adopted the Technology Acceptance Model for their analysis. They found the similar concepts as Davis stated.

Resource based view theory:

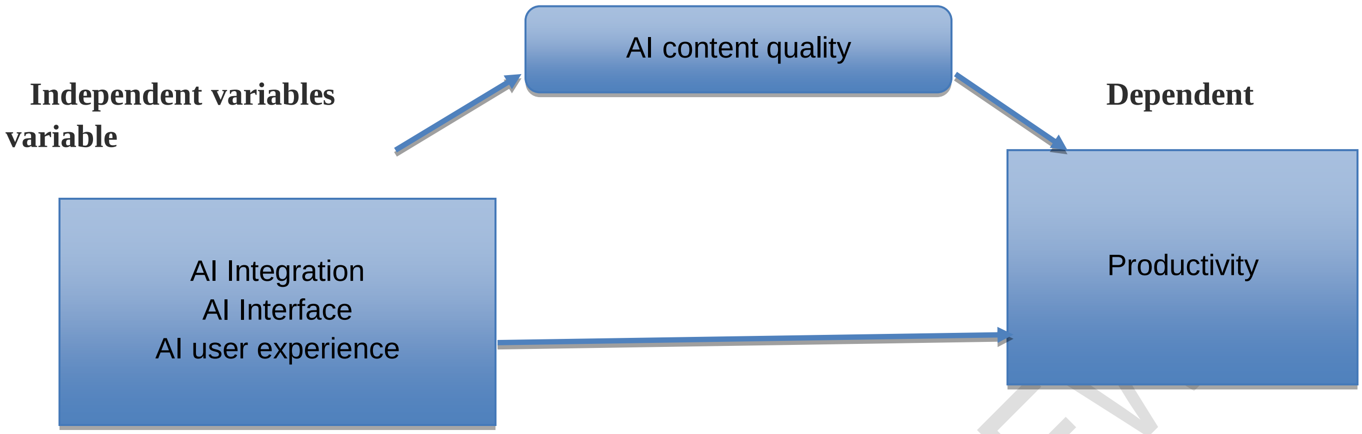
The resource- based view provides a conceptual framework to measure the strategic fit of resources. Worth, uniqueness, insufficient replication, and inadequate interchangeability are the four traits of resources that can contribute to a company's competitive edge. These characteristics are the foundation of the resource-based theory, which holds that a firm's ability to obtain a competitive edge depends on its resources and capabilities. The resource-based perspective aims to explain why businesses expand and change. In the RBV Model, the focus is on the firm and the development of appropriate resources (Barney, 1991).The contribution of the RBV is the idea that firms should focus attention on developing internal assets and processes (Grant, 1991). Accordingly, firms should foster processes that are inimitable and leverage core resources. For firms dependent upon information, processes that assimilate and use information in a superior manner have the potential for creating a sustainable competitive advantage (Kearns & Lederer, 2003).

Evaluating the theories' predictions was difficult due to the need to identify and measure relevant resources. However, this frequently indicated to be difficult because the essential assets in question were commonly associated with concepts like organizational learning and were typically not directly observable. Determining and understanding causal links in large organizations was challenging as well. It was extremely challenging to separate the operational effects of individual resources due to the sheer complexity of large organizations (Lockett et. al, 2009).

Research gap

Despite the global surge in AI adoption within organizations, a conspicuous research gap exists concerning the specific implications and outcomes of AI implementation on worker productivity in the Nepalese context. While studies from more technologically advanced regions have investigated this phenomenon, the quantity of empirical research directly addresses the dynamics, challenges, and outcomes of AI utilization within Nepalese workplaces. To close this information gap, this study will conduct a detailed examination of the AI-employee productivity nexus in Nepal and provide evidence-based insights to inform both academic discourse and practical decision-making within Nepalese organizations.

Figure 1. Conceptual Framework



Methodology

Positivist philosophy of research was applied in undertaking the research. As the research applied quantitative approach and empirical method so the analysis was based on mathematical models which draws single reality.The study followed causal comparative research design so as to draw the impact of independent variables on dependent variables under study. The population of the study are the employees of large companies operating in Nepal. Very few large companies are operating in Nepal. Thus, the sample size is only 85 employees. It is considered sufficient because Malik (2021) conducted research in the similar issue taking 32 sample size.The study was conducted on large-sized organizations. Sample was chosen purposively as every employeecannot respond properly in issues under study.Data were collected using five-point Likert scale questionnaire.Questionnaire was divided into two parts; one was to collect the demographic information of respondents and another part was to collect the data regarding the variables. The Second part of the questionnaire contained Likert scale questions where we used a 5-point Likert scale that ranges from 1 - strongly agree and 5 strongly disagree. We used Correlation analysis to assess the association between dependent and independent variables.We also looked at the direct, indirect, and total effect of moderating variable using bootstrap resampling method.

Analysis and Results

Relationship between

The study and discovery of relationships between variables is accomplished through correlation analysis. To evaluate the strength or degree of the association between the research variables, a correlation matrix was created. Using SPSS, we determined the correlation between our independent and dependent variables at the significance level of 0.01. The table below displays the correlation between the independent and dependent variables.

Table 1. Relationship between AI and Productivity

Correlations

		Integration	Uinterf	Uexp	productivity
Integration	Pearson Correlation	1			
	Sig. (2-tailed)				
Uinterf	Pearson Correlation	.656**	1		
	Sig. (2-tailed)	.000			
Uexp	Pearson Correlation	.486**	.467**	1	
	Sig. (2-tailed)	.000	.000		
productivity	Pearson Correlation	.820**	.609**	.376**	1
	Sig. (2-tailed)	.000	.000	.000	

**. Correlation is significant at the 0.01 level (2-tailed).

AI domains under study i.e. AI integration, AI interface and user experience have positive and significant relationship with productivity ($r = 0.820$, $p < 0.01$, $r = 0.609$, $p < 0.01$, $r = 0.376$, $p < 0.01$ respectively). It shows that the intervention in the AI domains lead to positively leverage the productivity of the organizations operating within capital city of Nepal i.e., Kathmandu.

Analysis of moderating variables

To explore the direct effect, indirect effect and total effect of moderating variables process tool in SPSS developed by Andrew F. Hayes was used. This tool conducts Bootstrapping where Bootstrap resampling can provide valid and robust estimates of the parameters and confidence intervals.

Table 2:

AI integration

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OUTCOME VARIABLE:

productivity

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7538	.5682	.3630	53.9606	2.0000	82.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.8018	.1566	5.1202	.0000	.4903	1.1133
Integra	.4686	.0722	6.4857	.0000	.3248	.6123
quality	.2529	.0846	2.9905	.0037	.0847	.4212

************************** TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:

Productivity

Model Summary

R	R-sq	MSE	F	df1	df2	p
.8197	.6720	.2725	170.0222	1.0000	83.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.0700	.1344	7.9637	.0000	.8028	1.3372
Integrat	.6340	.0486	13.0393	.0000	.5373	.7307

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
.6340	.0486	13.0393	.0000	.5373	.7307

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.4686	.0722	6.4857	.0000	.3248	.6123

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
quality	.1655	.0694	.0358	.3069

In table 2, AI integration alone explains 67.20% variance in dependent variables. AI integration and quality together account for 70.42% variance in productivity and the p value is less than 0.05 so the relationship is significant.One unit change in AI integration will have 0.4686 unit change in productivity and one unit change in quality will have 0.2529 unit change in productivity.In direct effect, one unit change in AI integration will have 0.634 unit change in productivity and the p value is less than 0.05. So, the relationship is significant.In indirect effect , the impact of AI integration on productivity through AI content quality is 0.1655 units and the relationship is significant as both the lower limit confidence interval and upper limit confidence interval are positive.As both the direct and indirect effects have significant impact on productivity, there exists partial mediation.

Table 3:

user interface

Y : productivity

X : User interface

M :AI content quality

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OUTCOME VARIABLE:

productivity

Model Summary

R	R-sq	MSE	F	df1	df2	p

.7538	.5682	.3630	53.9606	2.0000	82.0000	.0000

Model

coeff	se	t	p	LLCI	ULCI	
constant	.7515	.1961	3.8317	.0002	.3613	1.1416
Uinterf	.1526	.0882	1.7293	.0875	-.0229	.3281
quality	.5621	.0918	6.1238	.0000	.3795	.7448

************************** TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:

Productivity

Model Summary

R	R-sq	MSE	F	df1	df2	p
.6089	.3708	.5227	48.9107	1.0000	83.0000	.0000

Model

coeff	se	t	p	LLCI	ULCI	
constant	1.3058	.2088	6.2552	.0000	.8906	1.7210
Uinterf	.5300	.0758	6.9936	.0000	.3793	.6807

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
.5300	.0758	6.9936	.0000	.3793	.6807

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI

.1526	.0882	1.7293	.0875	-.0229	.3281

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
quality	.3774	.0714	.2479	.5210

In table 3, AI user interface alone explains 37.08% variance in productivity. AI user interface and AI content quality together account for 56.82% variance in productivity and the p value is less than 0.05 so the relationship is significant.In direct effect, one unit change in AI user interface will have 0.1526 unit change in productivity and the p value is greater than 0.05. So, the relationship is not significant.In indirect effect , the impact of AI user interface on productivity through quality is 0.3774 units and the relationship is significant as both the lower limit confidence interval and upper limit confidence interval are positive.As the direct impact is insignificant and indirect effects have significant impact on productivity, therefore,there exists full mediation.

Table 4

user experience

Y : productivity

X : user experience

M : AI content quality

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OUTCOME VARIABLE:

productivity

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7466	.5574	.3721	51.6333	2.0000	82.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.9322	.2137	4.3628	.0000	.5071	1.3572
Uexp	-.0768	.0806	-.9527	.3435	-.2372	.0836

quality	.7185	.0819	8.7753	.0000	.5556	.8814

************************** TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:

productivity

Model Summary

R	R-sq	MSE	F	df1	df2	p
.3765	.1417	.7129	13.7083	1.0000	83.0000	.0004

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.7269	.2678	6.4477	.0000	1.1942	2.2597
Uexp	.3356	.0907	3.7025	.0004	.1553	.5159

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
.3356	.0907	3.7025	.0004	.1553	.5159

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
-.0768	.0806	-.9527	.3435	-.2372	.0836

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
quality	.4124	.0813	.2612	.5852

In table 4, AI user experience alone explains 14.17% variance in productivity. AI user interface and AI content quality together account for 55.74% variance in productivity and the p value is less than 0.05. So, the relationship is significant.In direct effect, one unit change in AI user experience will have -0.0786 unit change in productivity and the p value is greater than 0.05 so the relationship is not significant.In indirect effect , the impact of AI user experience on productivity through quality is 0.4124 units and the relationship is significant as both the lower limit confidence interval and upper limit confidence interval are positive.As the direct effect is insignificant and indirect effects have a significant impact on productivity, therefore, there exists full mediation.

Discussion

The aim of this study was to assess the influence of artificial intelligence (AI) on employee productivity in Nepalese organizations. It assesses AI implementation, integration, user experience, satisfaction, and perception of AI's effect on work output, efficiency, and overall productivity, addressing a lack of empirical evidence in the region.

The results of this investigation offer insightful information about the variables influencing productivity within our regression model. Notably, some predictors demonstrated a statistically significant positive impact, while others exhibited minimal influence or lacked statistical significance. Comparing our results with prior research on related topics reveals both consistencies and disparities, shedding light on the complexity of productivity determinants.

AI integration was found to have positive and significant relationship with productivity which is in line with the results of the research that Balakrishnan and Dwivedi (2021), Dey et al., (2023) had conducted. It shows that proper integration of AI into its operation helps boost the productivity of employees in every context.

In the case of AI user experience there was insignificant relationship with productivity which disagreed with the conclusions of Bughin et al., (2018). The difference could be due to differences in measurement methods and techniques so we would like to suggest that more investigation is required to clear up the discrepancies.

Similarly, AI user interface also showed insignificant relationship with productivity which contradicts with the finding of Damioliet al.,(2021). While disparities in findings may be due to industry-specific variations or unique organizational contexts as the previous study was focused on SMEs in comparison to our study which includes large scale industries.

AI content quality showed a positive and significant relationship with productivity which is consistent with the finding of (Cranefield, 2023; Peng, 2023; A. Hemalatha et al.,2021).The similarity is because of use of AI does not itself produce positive results but only if the AI is generating qualitative and accurate AI content it will help increase employee productivity.

The study findings confirm to the technology acceptance model and resource based view. As the effective implementation of AI requires sufficient resources and infrastructure.

Conclusion

In our research, we delved on the effects of integrating AI into organizational processes on employee productivity. What we discovered is that when companies use AI to streamline their operations, it really does help employees get more work done efficiently. We also found that making things look good and user-friendly, which is often emphasized as user experience and interface design, doesn't directly translate into increased productivity for employees. What truly matters, we found, is the quality of the content or information available to employees. When the content is top-notch, that's when employees experience a real surge in their productivity levels. So, to sum it up, AI is an asset for boosting employee productivity, but the gist lies in having high-quality content and resources rather than just focusing on how things look or feel.

Implications

AI integration and productivity signifies the need for organizations to embrace seamless AI adoption. By integrating AI effectively into their workflows, they can streamline processes, harness data-driven insights, and ultimately enhance productivity. This emphasizes the imperative for organizations to invest in robust AI infrastructure and strategies that facilitate this integration. Furthermore, the study highlights the critical role of user experience and interface design in AI systems. Positive user experiences, driven by intuitive interfaces, can enhance user adoption and engagement with AI tools. Organizations should, therefore, prioritize user-centric designto maximize the usability and effectiveness of AI applications. By doing so, they can capitalize on the full potential of AI to drive productivity.

Additionally, the significance of AI accuracy cannot be overstated. Accurate AI outputs are not only essential for informed decision-making but also for fostering trust in AI systems. To optimize productivity, organizations must ensure that their AI models are continually refined to deliver precise and reliable results. Investing in AI model development, validation, and ongoing improvement processes is crucial in this regard.However, it's crucial to note that while these AI-related factors have shown promise in enhancing productivity, they operate within the broader organizational context. The study underscores the need for a holistic approach, considering factors such as organizational culture, workforce readiness, and the specific industry in which AI is implemented. Each organization must tailor its AI adoption strategy to suit its unique needs and challenges.

The future researchers can include variables such as;prejudice, false information, insensitivity to context, privacy concerns, moral conundrum and security for undertaking further research. Similarly, they can change the area of research so as to generalize the findings in every context.

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