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Transforming Financial Services: Ethical Pathways of Workforce Automation towards Achieving SDG 9

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Abstract

Automation, and more specifically artificial intelligence revolution in financial services has delivered unprecedented efficiency gains and cost reductions. However, it simultaneously threatens workforce stability, exacerbates job displacement risks, and raises urgent ethical dilemmas about the human cost of technological progress. This transformation in organizational work environment has some risks associated with the flexibility of the workforce and the ethical consideration on how to deal with the transitions in force. Despite rapid adoption, critical gaps persist in ethical frameworks to ensure transparency, accountability, and equitable workforce transitions in automated financial ecosystems. This research explores the effects of automation initiatives in the HR and financial departments on cost outcomes, productivity, ROI, and successful skilled employee retention; the mediating role of employee adaptability in positive automation integration; and the moderating impact of training and reskilling initiatives in managing the negative effects of automation. In the current study, quantitative research methodology was conducted, and data was collected through structured questionnaires from the financial institutions of Delhi NCR region and Structural Equation Modeling (SEM) was used for analyzing the data. The purpose of this study is to examine the applicability of adopting automation strategies in the realization of the Sustainable Development Goals (SDG 9) that focuses on industrial innovation, sustainable infrastructure, and industrialization, but at the same time taking into account the ethical issues and sustainability of the workforce.

Keywords: Artificial Intelligence, Employee Adaptability, Ethical Considerations, Financial Operations, Financial Services, Sustainable Development Goal 9 (SDG 9).

Introduction

There have been great changes in automation and artificial intelligence across the globe and especially within the financial services industries. Computation is no longer limited to simple functional procedures, but involves the advanced processes starting with predictive models, risk assessment, and immediate decision-making processes (1). These technological advancements have Carl co benefits such as cost reduction, operational improvement and productivity improvement. But they also have several important issues about workforce disruptions, skills, and ethics that need to be discussed in more detail (2). In the Indian financial service industry, automation has been the key driving force in modernizing conventional processes (3). Sources from the Reserve Bank of India show more organisations have adopted AI tools to automate compliance activities, improve audit efficacy, and meet customer needs (4). Likewise, NASSCOM Insights (5) note that Indian financial organizations are using automation to minimize mistakes, enhance choices, and contain expenses. Nevertheless, several research voids regarding automation remain: its effects on the ability, engagement, and performance of the workforce as pertains to flexibility and turnover in India and other developing nations. Various benchmarking papers and studies from across the world have identified that the effects of automation are closely linked to labor markets in complex ways. For example, according to the World Economic Forum, 2023 robotization study, it is predicted that 58% of repetitive positions internationally may become automated in a decade, which would create important issues linked to capabilities erosion and training needed. A recent report by McKinsey Global Institute,2023 note that active management

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of employees and choosing to deploy AI requires embracing new organisation workforce policies that focus on refining and revitalising employee skill sets as well as developing strong and specific training initiatives (3). These challenges are equally massive with the added layers of socio-economic and regulatory environment prevalent in India and further because human capital is most strategic in the Indian financial sector. The late adoption of the use of automation also brings up some ethical issues with the solution's execution. Brynjolfsson and McAfee also point at problem like algorithmic unfairness, data privacy and by which AI may lead to negative outcomes if the problems are not solved (2). Furthermore, implementing automation vision in line with the Sustainable Development Goal 9 (SDG 9) for innovation and sustainable industrialization has been a challenge in recent years demanding a balance to create fairness for the workforce and equal opportunities for them (6, 7).

Although a lot of work has been done analyzing automation's effects on some degree of operational efficiencies, to this date few studies give credit to the potential effects in relation to productivity, job satisfaction and return on investments on workforce in the financial services industry. This study examines the dual impact of workforce automation in financial services, addressing two critical dimensions. First, it investigates how investments in automation influence employee productivity and retention rates, with a specific focus on the mediating role of employee adaptability. Secondly the study examines organizational automation outcomes through cost efficiencies and ROI assessment while examining how employee training and reskilling programs affects these results.

The study delivers empirical findings about financial services workforce automation which demonstrates both improved technological advantages and human capability tests. While traditional sampling methods which are commonly employed in empirical studies, often fail to capture workforce dynamics in rapidly automating environments. Our approach implements targeted surveys and strategic sampling of Delhi NCR financial institutions by using data-driven sampling to overcome the sampling method limitations in rapidly automating environments (8). The systematic evaluation of automation effects enables us to connect operational improvements to sustainable workforce practices. Financial institutions now have practical guidelines for deploying automation systems ethically combined with approaches to limit workforce changes and fulfill the SDG 9 mission. Evidence-based frameworks from these research guide policymakers to find appropriate balance between technological implementations and human labor preservation through their mission of inclusive digital finance growth.

In this research, automation and the related adaptability of the workforce, as well as the relationship with organizational performance, is discussed, and following empirical results, there is an identification of major practical implications that may serve as guidelines in formulating optimal employee retention and productivity improvement strategies given an automated context. However, the study reveals the importance of validating automation with the ethical standards and SDG 9 in a bid to achieve positive growth in the delivery of financial services. The research design of this study is articulated in the following manner; Section 2 provides the literature review section as vital tools for this study are outlined, as well as the theoretical frameworks. The research methodology with regard to data analysis methods is outlined in section 3. The outcomes are highlighted in Section 4 and the discussion of their impact follows in Section 5. Last of all, Section 6 presents some concrete suggestions and directions for further research. This structural approach ensures our contemporary findings are conceptualized within the broader historical evolution of technology in financial services.

Automation of workforce in the financial services is still an active area of development, but it involves artificial intelligence, machine learning, and robotic process automation. Theory in the Information Technology (IT) arena has been established by theories like "Technology Acceptance Model" (TAM) and "Diffusion of Innovation" (DOI). Thus, the automation of HR functions and the financial processes in this research refers to not only technology advancements but also organizational change of capital management. As earlier research shows that these technologies hold promise to drive down operating costs while raising productivity, that will in turn, help to incorporate the automobile into strategic business plans (9, 10).

In fact, automation is not only a technical phenomenon it has close relation to human flexibility. Employee adaptability to AI/automation is thus a key moderating variable that lies between automation initiatives and preferred organisational performance. Referring to theories of change management at the organizational level, it is possible to state the necessity of such an adaptability to avoid adverse consequences of automation for people's jobs, but rather create a positive effect on those jobs. The research also analyses human capital theory claiming that human capital is an employee's skills or abilities that require regular updates through training or retraining processes. This research adds to the existing body of literature by empirically testing these relationships in the financial services sector, particularly within the scope of SDG 9, which emphasizes the role of innovation in the driving industry and infrastructure improvements.

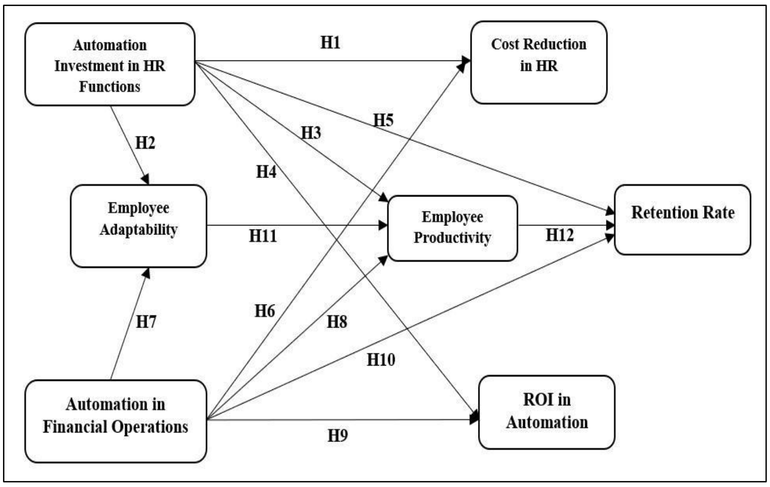

Figure 1: Conceptual Model

The conceptual model in Figure 1 elucidates a multifaceted, interdependent framework wherein strategic investments in HR and financial automation synergistically catalyze employee adaptability and productivity—mediating the optimization of cost efficiencies, maximizing return on automation investments, and culminating in the augmentation of organizational retention rates through a cascade of interconnected hypothesized causal pathways. Table 1 lists all variables in the study along with the citations associated with them. After employing relevant research tools, the relationship between these variables will be constructed, allowing the conclusion regarding research questions to be made.

Table 1: Citations of Model Variables

S.No.	Name of Model Variables	Citation of Model Variable
1	Automation Investment in HR Function	(11)
2	Employee Adaptability	(12)
3	Automation in Financial Services	(5)
4	Employee Productivity	(3)
5	Cost Reduction in HR	(2)
6	ROI in Automation	(10)
7	Retention Rate	(12)

Methodology

Research Design

This study utilizes a multi-variable model to investigate the effects of workforce automation in financial services, with a focus on ethical implications and contributions to SDG 9. Data was gathered from a range of professionals, including HR Directors, Financial Managers, and Operations Managers from financial institutions in Delhi NCR region. These organizations span various sectors within financial services. The study employs a cross-sectional design, with data collected during June, 2024 to Sep, 2024, combining both survey responses and secondary data analysis. To investigate how the relationship between automation investments and organisational outcomes is mediated by employee adaptability to AI and automation, this research applies the Baron and Kenny approach and Structural Equation Modeling (SEM). By examining the mediating role of employee adaptability, the study seeks to understand how automation impacts cost reduction, productivity, ROI, and employee retention. The research follows a descriptive design to provide insights into these critical variables.

Measurement Scales

To gather primary data from the target respondents, a structured, closed-ended questionnaire was developed, utilizing a Likert scale to measure responses. The questionnaire was structured as: Section I collected demographic details, while Section II focused on the key variables related to workforce automation, such as automation investments, employee adaptability, productivity, and reskilling programs. All scales used were standardized and ensured relevance to the unique context of the financial sector and addressed the ethical considerations and contributions to SDG 9. To get consistent and measurable responses across all variables, Likert scale was used.

Sampling and Data Collection

This research used data-driven adaptive sampling due to limitations of traditional sampling methods to capture workforce changes. This study employed data-driven adaptive sampling of Delhi NCR financial institutions which supported the current design which maintained both research precision and realistic data collection methods (8). The research targeted 374 professionals in institutions of different functions and sizes with diverse automation status and received 326 usable responses that maintained 313 through data cleaning beyond sample threshold requirements of SEM. This final sample size was above the minimum G power recommended for this research and this showed that the chosen sample size was adequate for the intents and purposes of this study.

Data Analysis

Data collected for this study were non-parametric since they did not have a normal distribution. However, where normality is not present, PLS-SEM is regarded as the appropriate analysis technique as has been noted by Henseler (13). Due to the collection of formative indicators and the overall complexity of the developed research conceptual model, the process of structural equation modeling analysis was conducted using SmartPLS software (14). Moreover, employing the purposive sampling approach also meant that the construct validity and reliability of this tool could be tested to offer a rich evaluation of the relationships within the given model to support the hypotheses testing in this study.

Demographics of Respondents

The Table 2 presents the demographic profile of the respondents (N=237). A significant majority, 84.35%, were male, while 15.65% were female. In terms of age, the largest group was between 35-45 years (38.66%), followed by those aged 25-35 years (32.91%). Regarding annual income, nearly half of the respondents (49.84%) earned between 6-12 lacs, with 24.28% earning less than 6 lacs, and 25.88% earning above 12 lacs. This distribution reflects a diverse and financially stable sample displayed in Table 1.

Table 2: Respondents' Demographic Profile

	Characteristics	**(N=237)**	**Percentage**
Gender	Male	264	84.35
	Female	49	15.65
Age	25-35 years	103	32.91
	35-45 years	121	38.66
	Above 45 years	89	28.43
Annual Income (Rs.)	Less than 6 lacs	76	24.28
	6-12 lacs	156	49.84
	Above 12 lacs	81	25.88

Results

Measurement Model Assessment

In assessing the measurement model for first and second order, this study relied on past studies (15-17). First, the construct validity was evaluated based on the indicator loadings where any item should have an indicator loading of more than 0.708 in order to be retained in the model (18). Table 3 reported all indicator loadings were above this threshold, confirming their appropriateness for the model. Cronbach's alpha and Composite Reliability (CR) were calculated for each construct was applied to evaluate internal consistency, with all values surpassing the 0.70 threshold, indicating high reliability (18, 19).

Table 3: Measurement Model Assessment Results

Construct	Coding	"Indicator Loading"	"Cronbach's Alpha"	"Composite Reliability(rho_a)"	"AVE"
Automation of Financial operations	AFO1	0.909	0.92	0.922	0.807
	AFO2	0.887			
	AFO3	0.906			
	AFO4	0.89			
Automation Investment in HR functions	AIHR1	0.886	0.938	0.953	0.842
	AIHR2	0.912			
	AIHR3	0.945			
	AIHR4	0.927			
Cost reduction in HR	CR1	0.9	0.915	0.925	0.855
	CR2	0.938			
	CR3	0.934			
Employee Adaptability	EA1	0.95	0.953	0.96	0.914
	EA2	0.962			
	EA3	0.956			
Employee Productivity	EP1	0.912	0.933	0.954	0.881
	EP2	0.951			
	EP3	0.952			
ROI in Automation	ROI1	0.918	0.915	0.926	0.854
	ROI2	0.929			
	ROI3	0.925			
Retention Rate	RR1	0.944	0.923	0.924	0.867
	RR2	0.942			
	RR3	0.907			

In addition, the convergent validity of the measures was tested, and the Average Variance Extracted (AVE) from each construct was calculated. All the AVE values were greater than the acceptable value of 0.50, which again indicated that each construct accounts for at least 50 per cent of the variance in the indicators (15, 18). The same results for factor loading can be interpreted through Figure 2, which contains the results of the application of the PLS algorithm on the conceptual model.

Table 4: Discriminant Validity – Fornell-Larcker Criterion

	Automation Investment in HR functions	Automation of Financial operations	Cost reduction in HR	Employee Adaptability	Employee Productivity	ROI in Automation	Retention Rate
Automation Investment in HR functions	0.918						
Automation of Financial operations	0.344	0.898					
Cost reduction in HR	0.436	0.481	0.924				
Employee Adaptability	0.313	0.355	0.325	0.956			
Employee Productivity	0.233	0.415	0.148	0.219	0.939		
ROI in Automation	0.204	0.346	0.293	0.474	0.032	0.924	
Retention Rate	0.514	0.425	0.363	0.244	0.381	0.148	0.931

Therefore, for checking quality criteria of the study the study has used “Fornell Larcker Criterion” (20) and Heterotrait-Monotrait ratios to determine discriminant validity (21). As highlighted in Table 4 and Table 5, all the constructs satisfy the two criteria for the reflective and formative measures. Discriminant validity is supported by using the Fornell-Larcker criterion as the AVE for each construct is higher than the cross loadings. As shown the square root of the AVE for "Employee Adaptability" (0.956) is higher than its correlations with other constructs such as "Cost reduction in HR" (0.325) and "Employee Productivity" (0.219).

Table 5: Discriminant Validity –Heterotrait Monotrait Ratio (HTMT)”

	Automation Investment in HR functions	Automation of Financial operations	Cost reduction in HR	Employee Adaptability	Employee Productivity	ROI in Automation	Retention Rate
Automation Investment in HR functions							
Automation of Financial operations	0.359						
Cost reduction in HR	0.455	0.521					
Employee Adaptability	0.321	0.375	0.342				
Employee Productivity	0.242	0.439	0.156	0.224			
ROI in Automation	0.212	0.373	0.314	0.506	0.046		
Retention Rate	0.552	0.456	0.398	0.256	0.407	0.16	

Similarly, the HTMT ratios are all below the threshold of 0.85, with the highest ratio being 0.552 between "Automation Investment in HR functions" and "Retention Rate," further validating the distinctiveness of the constructs. Additionally, Full Collinearity VIFs were assessed in the inner model to evaluate common method bias. The analysis showed negligible common method bias, as all VIF values were below the threshold of 3.3, indicating that multicollinearity does not pose a significant issue in the past study (22).

Structural Model Assessment

After evaluating the first order measurement model, it was checked that how well the second-order model worked by looking at the path coefficients from our structural model to see if connections between constructs matched our predictions. Interestingly, in the measurement models of formative assessment, no expectation is made for high intercorrelations among the indicators as these indicators are not substantively interchangeable. All the indicators are useful in defining the construct and high correlation would lead to multicollinearity; this distorts the correct estimation of weights and the statistical significance of the indicators (15). To that end, while conducting this analysis, the VIF of all the constructs was checked to make certain that multicollinearity was not a problem. As stated earlier, all "VIF values" were less than 3.3 indicating that collinearity was not a problem and the estimates of the model are accurate.

The Q^2 values (Stone- Geesser test) of the primary factors have also been calculated and based on such findings, the holistic theoretical and empirical implication of the recommended model was substantiated. The outcomes of the result showed all the Q^2 values more than zero thus showed that the model has some level of predictive accuracy to the mentioned constructs which was suggestive of reasonable fit of the data (19). Further, the results supported by coefficient of determination (R^2) showed the extent to which the endogenous constructs' variance was accounted for by the independent variables showing the in sample predictive capability of the model (15). The essence of R^2 depends on the type of the analysis and even small values can be acceptable in case of Partial Least Squares Structural Equation Modeling (23). To support the proposed hypotheses, bootstrapping with 5,000 subsamples was used and the results are presented in Table 6.

Hypothesis 1 (AIHR → CR) was supported, showing that automation investment in HR functions significantly influences cost reduction in HR (β = 0.306, T = 4.369, $p < 0.01$). This suggests that organizations investing in automation for HR processes can achieve substantial cost reductions, leading to greater efficiency and reduced operational costs. Similarly, Hypothesis 2 (AIHR → Employee Adaptability) was significant (β = 0.216, T = 3.338, $p < 0.01$), indicating that investment in HR automation positively influences employee adaptability. This implies that employees are more likely to adapt to new technologies and workflows when HR processes are automated.

Table 6: Hypothesis Testing and Relationship with Variables

		"β"	"T statistics"	"CI 0.95"	"Significance"	"VIF Inner"	"R^2"	"Q^2"	"f^2"
H1	AIHR -> CR	0.306	4.369**	[0.171-0.447]	Yes	1.134	0.316	0.251	0.147
H2	AIHR -> EA	0.216	3.338**	[0.095-0.344]	Yes	1.134	0.128	0.127	0.487
H3	AIHR -> EP	0.089	1.381	[-0.036-0.217]	No	1.19	-	-	0.196
H4	AIHR->ROI	0.097	1.741	[-0.012-0.208]	No	1.134	-	-	0.225
H5	AIHR -> RR	0.396	6.546**	[0.279-0.517]	Yes	1.147	-	-	0.05
H6	AFO -> CR	0.376	6.225**	[0.253-0.492]	Yes	1.134	0.184	0.173	0.025
H7	AFO -> EA	0.28	4.093**	[0.142-0.412]	Yes	1.134	-	-	0.049
H8	AFO -> EP	0.363	4.723**	[0.217-0.514]	Yes	1.228	0.148	0.093	0.03
H9	AFO -> ROI	0.312	4.831**	[0.186-0.44]	Yes	1.134			

H10	AFO -> RR	0.204	3.299**	[0.084-0.329]	Yes	1.311
H11	EA -> EP	0.062	0.803	[-0.094-0.211]	No	1.2
H12	EP -> RR	0.203	3.225**	[0.076-0.321]	Yes	1.222

Note: ** significant at 1%; * significant at 5%;

As per Table 6, Hypothesis 5 (AIHR → Retention Rate) also supported a significant positive relationship (β = 0.396, T = 6.546, p < 0.01), highlighting that automation investment in HR is crucial for enhancing employee retention as such investments may improve their job satisfaction, work processes, and career growth opportunities. However, Hypothesis 3 (AIHR → Employee Productivity) and Hypothesis 4 (AIHR → ROI) were not supported, as the path coefficients were not statistically significant (p > 0.05) as both having a non-significant path coefficient with confidence intervals.

Hypothesis 6 (AFO → CR) was supported with a significant positive path (β = 0.376, T = 6.225, p < 0.01), confirming that automation in financial operations significantly influences cost reduction. This suggests that automating financial operations can lead to significant savings and more efficient financial management. 8 (AFO → Employee Productivity) was also found to be significant (β = 0.363, T = 4.723, p < 0.01), indicating that automation in financial functions boosts employee productivity.

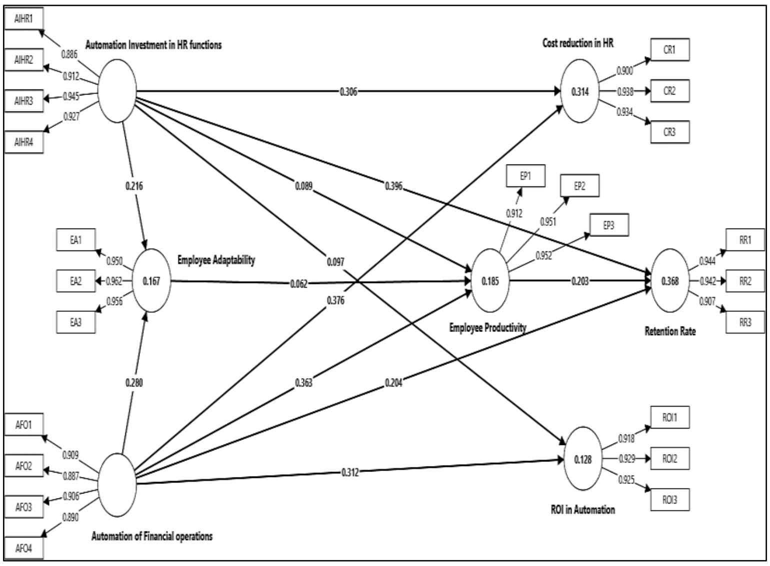

Figure 2: Structural Equation Model

Results states (Figure 2) that employee productivity strongly influences retention rates through its correlation (β=0.203, T=3.225, p<0.01). Higher levels of employee productivity create better job satisfaction which increases their desire to remain part of the organization. Organizations need to combine automated tools and supportive practices to keep workers more engaged and retain them. This model demonstrated an average ability to predict employee retention with R^2 values between 0.128 and 0.316. Based on f^2 analysis AIHR influenced employee retention by f^2=0.05 but staff productivity showed the greatest direct impact from AFO with f^2=0.093. The Q^2 values supported our conclusions about the model's prediction accuracy.

Discussion

The research demonstrates what financial services companies gain and lose when they automate work processes. Automation systems save money and make staff more efficient but create training needs for employees to stay employed. Our findings support earlier findings in past studies which showed that automated financial institutions became more efficient (10, 11). Variation in employee adaptability determines how well automation projects will succeed in different organizations. Organizations without a learning-focused environment will generate employee opposition which negatively impacts performance and results in more workers choosing to leave. One past research supports that successful AI automation depends on how well employees accept and prepare for these changes (23). The research shows automation improves operations yet companies must prepare for worker shifts and develop new skills.

Automation creates distinct outcomes in all organizational functions based on this research study. HR automation has made recruitment and payroll much simpler while financial operations automation has transformed risk management and transaction processing. The McKinsey Global Institute and the Reserve Bank of India report financial service automation has increased rapidly because of regulatory changes and competitive pressures.

The review finds several key problems stand in the way of automation becoming practically effective. The study finds that organizations face significant costs and concerns about safety and privacy while trying to comply with regulations during implementation. The solution requires both technology upgrades and workforce training that go hand in hand with strict regulations to support automation adoption. The study points out that automated systems create ethical challenges when AI decisions have biases, impact jobs through automation, and require clear explanations about automated financial services. Brynjolfsson and McAfee believe companies need to use responsible AI methods to protect stakeholders and solve these problems (2). This research shows that financial service organizations need to find the right balance between technology use and effective human resources management.

Conclusion

Theoretical Implications

Our research adds knowledge about workforce automation to current studies that examine how organizations use automation and manage their employee skills. Research builds on Technology Acceptance Model and Human Capital Theory by demonstrating that technological investments need employee adaptability to create organizational success. The study demonstrates how effective use of automation technologies with human resources creates valuable advantages for financial services companies. The findings match Sustainable Development Goal 9 by demonstrating ways to promote innovative thinking and develop more reliable systems. Through this work we develop a framework to show how organizations can use technology advancements responsibly while supporting their workforce.

Practical Implications

The conclusions from this research lead to straight-forward improvements for both banking institutions and their rule makers. Financial organizations should balance investment in automation technology with programs that develop their workforce abilities. Training employees extensively and encouraging a flexible workplace setup will help automate systems work better. Financial institutions must put money into better cybersecurity protection to handle privacy risks and follow new regulations. By acting now companies strengthen customer confidence and reduce future risks to their legal standing and brand reputation.

The government should establish programs to encourage businesses to upgrade their workforce capabilities because talented employees drive better competition. Working together between public and private sectors to support worker training minces the skills gap created by automation in workplaces. Organizations need to make AI decision-making systems more open and unbiased. Organizations need to follow AI responsible practices and ethical rules to avoid discrimination between staff members and users. Financial institutions can use automation to empower both economic growth and sustainable development by creating better access to financial services and supporting business continuity methods. Automation lets financial institutions provide better customer support with enhanced access and lowers expense costs.

Study Limitations and Future Scope

Along with its contributions, this study also has few limitations despite its contributions. First, the sample is geographically limited to specific regions and sectors within financial services, which may restrict the generalizability of the findings to other industries or regions. Future studies should aim to explore workforce automation across a broader array of industries, including manufacturing, healthcare, and retail, to better understand the sector-specific impacts of automation. Expanding the geographical focus beyond India to global contexts would also enhance the study's external validity, considering how automation adoption varies across different economic and regulatory environments.

Second, it is challenging to pinpoint the exact reasons behind automation's long-term effects on organisational outcomes due to the study's cross-sectional methodology. Future research could adopt longitudinal designs to track changes over time and provide more robust evidence on how automation investments and employee adaptability evolve and interact. Additionally, while this research emphasizes the role of employee adaptability, future studies could delve deeper into the psychological and organizational factors that influence adaptability, such as employee resistance to change, organizational culture, and leadership support during automation transitions.

Another area for future research could explore the ethical implications of automation in greater detail, particularly how organizations can ensure fair distribution of automation's benefits and mitigate the risks of job displacement. Studies could investigate automation's impact on workforce diversity, inclusivity, and the ethical concerns tied to its deployment in decision-making processes. By exploring these issues, future research can help shape the development of frameworks that address both the economic and ethical dimensions of automation, offering more holistic solutions for managing human capital in increasingly automated work environments.

Abbreviations

None.

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Author Contributions

The authors contributed equally to this article's conceptualization phase, methodology adaptation, interpretation, and writing.

Conflict Of Interest

The authors have no conflicts of interest related to the research article, its authorship, or publication.

Ethics Approval

University School of Business, Chandigarh University has granted ethics approval.

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