



MACHINE LEARNING IN FINANCIAL FORECASTING: OPPORTUNITIES AND CHALLENGES

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Abstract

AIM In contrast to conventional approaches, this study examines how AI-driven recruitment platforms affect organizational hiring expenses. The study uses a mixed-methods approach, integrating qualitative information from semi-structured interviews with quantitative data from surveys of recruiting managers and HR experts. In addition to examining the perceived advantages and difficulties of both recruitment strategies, this data is examined to evaluate cost parameters including time-to-hire, cost-per-hire, and administrative overhead. **MATERIALS AND METHODS:** To acquire thorough data on recruitment expenses and perceptions, the study combines surveys, interviews, and secondary data analysis. While qualitative data is analyzed using thematic analysis to find important themes and patterns in perceptions and experiences, quantitative data analysis compares cost metrics between AI-driven and conventional approaches using t-tests and ANOVA. **CONCLUSION** According to the study's findings, implementing AI-driven hiring practices would not always result in significant cost savings, and more investigation is required to completely comprehend how AI affects hiring results outside of financial concerns. In order to validate and build upon these findings, future research with bigger and more diverse samples may be necessary. The study's shortcomings, such as its dependence on self-reported data and the possibility of sample size constraints, are noted.

Key Words : AI , Machine learning (ML) , Cost , Recruitment/Hiring , Age , Data , Financial Traditional , Significant , Analysis

Introduction

In financial forecasting, machine learning (ML) is the process of analyzing past data and predicting future financial patterns, such as stock prices, market activity, or economic indicators. (Baumohl 2005) the paper showed about the secrets of economic indicators in using



statistical models and algorithms. More accurate forecasts than using conventional forecasting techniques are made possible by machine learning (ML),[\(Burkov 2019\)](#) the paper showed about a hundred pages of machine learning study. which uses techniques like regression, classification, and clustering to identify patterns in large datasets. The use of machine learning in fields like fraud detection, risk management, and investing strategies has grown significantly as financial markets become more intricate and data- driven.[\(Redman 2008\)](#) the paper show that the profit from your most important business assets.

Machine learning (ML) is the process of evaluating historical data and applying statistical models and algorithms to estimate future financial patterns,[\(Baumohl 2005\)](#) the paper shows that such as stock prices, market activity, or economic indicators. Machine learning (ML), which uses methods like regression, classification, and clustering to find patterns in massive datasets,[\(Unwin et al. 2007\)](#) the paper shows graphics of large datasets visualizing a million. enables more accurate projections than traditional forecasting techniques. As financial markets become more complex and data-driven, machine learning has becoming Machine increasingly used in domains such as risk management, investing techniques, and fraud detection. Machine learning has a wide range of revolutionary applications in financial forecasting.

Important fields include credit scoring, where machine learning increases the precision of determining a person's creditworthiness,[\(Vardi 2022\)](#) the paper shows the creditworthiness and responsible credit . Algorithmic trading, where ML models execute trades quickly based on data-driven predictions. ML is also frequently utilized in risk assessment in portfolio management, fraud detection, and transaction monitoring for irregularities. Another crucial application is sentiment analysis,[\(Tiwari et al. 2025; Chart-Pascual et al. 2025\)](#) understanding social media discourse on antidepressant. In which machine learning algorithms analyze financial news, reports, and social media to estimate market sentiment and forecast price changes. Throughout the financial sector, these applications improve decision- making,[\(Redman 2008\)](#) the paper profiting from your most important business assets. Lower expenses, and increase operational efficiency.

Materials And Methods

Locate the materials and methods for this subject in this manner. Using a mixed-methods approach, this comparative analysis will look at how AI-driven recruiting systems compare to traditional approaches in terms of their effects on organizational recruitment expenses. Quantitative data will be gathered through surveys administered to HR professionals and hiring managers at businesses that utilize both traditional and AI-driven recruitment methods. These



surveys will collect information on key cost factors, including time-to-hire, cost-per-hire, administrative overhead, and candidate sourcing expenses. To support this primary data, secondary data will be collected from publicly available sources, such as industry reports, case studies, and scholarly publications. This integrated quantitative data collection will provide a thorough view of the cost-related components of both hiring techniques.

To provide more in-depth understanding and context, qualitative data will be gathered through semi-structured interviews with the same recruiting managers and HR specialists who were surveyed for quantitative data. These interviews will look at their experiences with AI-driven and traditional recruitment methods, with a focus on perceived benefits and challenges, impacts on the effectiveness and efficiency of the hiring process, perceived cost savings (or lack thereof), and factors influencing the decision to use AI-driven systems. The interview transcripts will be subjected to thematic analysis in order to find recurrent themes and patterns pertaining to these subjects, offering a more nuanced comprehension of the actual workings of each hiring strategy.

A comprehensive cost-benefit analysis will be conducted using the collected quantitative and qualitative data. This study will evaluate the costs and benefits of AI-driven hiring systems versus traditional methods, accounting for both the direct financial expenses and the indirect effects on efficiency and efficacy. The study identifies a few potential limitations, including a potentially small sample size that could impair generalizability, a dependence on self-reported data that could introduce bias, and a focus on cost-benefits that could mask other important factors like candidate quality or diversity outcomes. Every aspect of the research will be conducted ethically, ensuring participant anonymity and data confidentiality.

Statistics Analysis

locate the STATISTICS ANALYSIS as follows: SPSS will be utilized for statistical analysis on this subject. Cost metrics (time-to-hire, cost-per-hire, administrative overhead, and sourcing costs) will be compared between businesses that use AI-driven systems and those that employ traditional methods using an Independent Samples t-test. This test will determine whether the differences between the two groups are statistically significant. A Paired Samples t-test will be used to compare cost metrics before and after the adoption of AI for firms that have transitioned from traditional methodologies to AI-driven systems in order to assess the impact of the change within the same firm. If the study includes more than one category of AI implementation, ANOVA will be used to examine cost metrics across different AI adoption levels. If the study includes more than one type of AI implementation (e.g., basic AI screening, advanced AI matching, AI-powered interviewing), ANOVA will be used to examine cost metrics across different AI adoption levels. A significant ANOVA result will be followed by post-hoc testing to

determine which specific AI implementation categories differ significantly from one another. These studies will provide a statistical basis for evaluating the relative cost-effectiveness of AI-driven hiring systems vs traditional methods.

Results

Table: 1 Since the Sig. (2-tailed) values (0.398 and 0.429) are more than 0.05, the Independent Samples Test indicates that there is no statistically significant difference between the groups. AI-driven and conventional recruitment techniques may not have significantly different effects on hiring prejudice and diversity, as seen by the mean difference of -0.204, which indicates a slight influence but is not statistically significant.

Table: 2 With a sample size of 106, the table shows a statistically significant negative correlation (-.194, $p = .047$) between age and the way financial institutions handle regulatory and compliance issues. This suggests that as people age, their perception of the effectiveness or strategy used to address these issues tends to decline.

Table: 3 The mean age of the two groups under comparison does not differ statistically significantly ($F(1, 104) = 3.508$, $p = .064$), according to the ANOVA test. Consequently, it is likely that the observed age disparities between the groups are the result of pure chance.

Fig : 1 There is no discernible trend or significant variation in the mean age among the various levels of agreement with the advantages of machine learning in finance, as seen in the chart. The overlapping ranges shown by the error bars, which represent 95% confidence intervals and ± 2 standard deviations, imply that opinions of the advantages of machine learning are not much correlated with age.

Discussion

Table: 1 Equal variances cannot be assumed since the Sig. value (0.030) under "Equal variances assumed" is less than 0.05. The two groups do not appear to vary statistically, though, as indicated by the t-values (-0.848 and -0.796) and the Sig. (2-tailed) values (0.398 and 0.429), both of which are greater than 0.05. Although it is not significant, the Mean Difference (-0.204) suggests a slight variation in group means. The observed difference may be the result of random chance rather than a significant influence, as further evidenced by the high standard error (0.241 and 0.257).



Table:2 The table shows that age and the perceived efficacy of financial institutions' handling of regulatory and compliance concerns are statistically significantly correlated, albeit weakly (-0.194 , $p < 0.05$). This suggests that older respondents have a tendency to give financial organizations a worse rating for how they handle these issues. Although there is a substantial association, the relatively low coefficient indicates that only a tiny amount of the diversity in opinions of regulatory and compliance measures can be explained by age.

Table: 3 According to the ANOVA, there is a nearly significant age difference between the groups ($F(1, 104) = 3.508$, $p = .064$). A trend rather than a conclusively statistically significant result is indicated by the p-value, which is near but falls short of the significance threshold of 0.05. This implies that although age differences between the groups might exist, the apparent difference might just be the result of chance. A bigger sample size and additional research could help determine whether this trend is consistent.

Limitation Of The Study

This research is subject to several limitations. Reliance on self-reported data from HR professionals and recruiting managers increases the risk of biases because their judgments may not correctly reflect actual process improvements or cost reductions. The sample size may limit the findings' generalizability to different industry contexts or larger demographics, even though it may be enough for some investigations. Other potentially significant factors, like diversity outcomes, candidate quality, and long-term effects on employee retention or performance, are overlooked when the focus is on cost-benefits. Furthermore, findings may become outdated as soon as new tools and applications are created because to the rapid advancement of AI technology. Finally, by underrepresenting the complexity of hiring practices, the study's scope may simplify the relationships between various factors influencing cost and efficiency.

Conclusion

Although the graphical data indicates a potential negative link between age and agreement with AI's benefits in recruitment (optimizing job ads), the overlapping confidence intervals raise questions about the statistical significance of these associations. Statistical tests that reveal no appreciable age differences between groups or between individuals before and after AI installation support this. This implies that age is not the main factor influencing perceptions of AI's potential to reduce hiring expenses. This finding is moderated by the study's limitations, which include sample size constraints, potential self-reporting biases, and the exclusion of non-cost-related factors. More research with larger, more diverse sample sizes and objective

performance standards is needed to confirm these findings and provide a more complete picture of AI's true impact on recruiting.

Tables And Figures

Table: 1 This indicates that there is no statistically significant difference between the two groups because the Sig. (2-tailed) values (0.398 and 0.429) are greater than 0.05. The minor mean difference (-0.204) and negative t-values (-0.848 and -0.796) indicate only a slight variance, suggesting that the effects of AI-driven and traditional recruitment methods on hiring bias and diversity are not statistically different.

	Independent Samples Test	
	Equal variances assumed	Equal variances not assumed
Sig.	0.030	
t	-0.848	-0.796
Sig. (2-tailed)	0.398	0.429
Mean Difference	-0.204	-0.204
Std. Error Difference	0.241	0.257

Table: 2 Age and how financial institutions handle regulatory and compliance issues have a statistically significant, weak negative correlation (-.194, $p=.047$), according to the table. This suggests that as people get older, the perceived efficacy of these institutions' strategies somewhat declines, though the correlation is not very strong. A sample size of 106 is used to calculate this connection.

Correlations



		Age	How do financial institutions address regulatory and compliance
Age	Pearson Correlation	1	-.194*
	Sig. (2-tailed)		.047
	N	106	106
How do financial institutions address regulatory and compliance	Pearson Correlation	-.194*	1
	Sig. (2-tailed)	.047	
	N	106	106
*. Correlation is significant at the 0.05 level (2-tailed).			

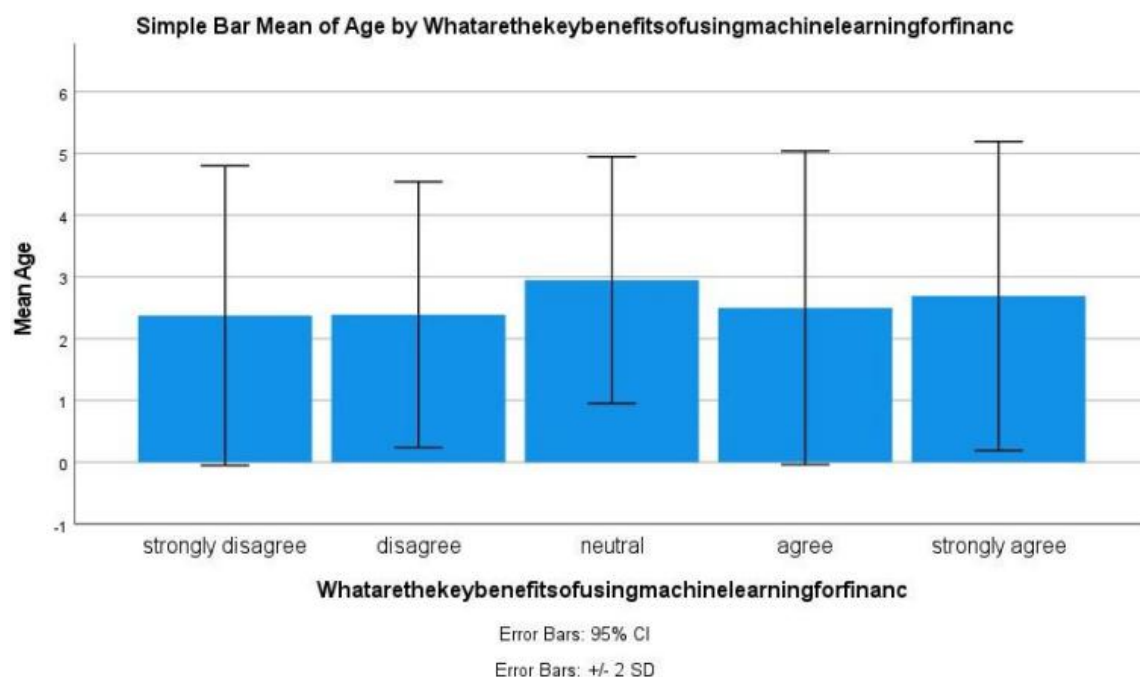
Table :3 There is no statistically significant age difference between the two groups under comparison, according to the ANOVA table ($F(1, 104) = 3.508, p = .064$). Despite indicating a trend, the F-statistic falls short of the traditional significance criterion of 0.05. As a result, the observed variations in the groups' mean ages are most likely the result of chance.

ANOVA					
Age					
	Sum of Squares	df	Mean Square	F	Sig.
Between	4.580	1	4.580	3.508	.064



Groups				
Within Groups	135.769	104	1.305	
Total	140.349	105		

Fig: 1 There is no discernible difference in the mean age between the various agreement levels about the advantages of machine learning in finance.



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