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The Impact of Artificial Intelligence on Employment in Financial Sector of United Arab Emirates

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Abstract
With the global advancement of AI, its influence on employment has grown more apparent in nearly all sectors, including the financial sector worldwide. The financial sector in the UAE has experienced substantial changes in job duties and labor requirements, which align with global patterns. This study explores the role of Artificial Intelligence (AI) on employment in financial sector of United Arab Emirates (UAE). The study employed regression analysis to examine AI and employment together with technical variables like Automation, Robotics, and Drones. This study employed a meticulous selection technique to choose 319 experts working in the banking, insurance, and financial sectors from the main emirates of the UAE. Automation, artificial intelligence, and robotics all have negative beta values, implying they could reduce employment, but only AI is statistically relevant. A significance level below 0.05 and a beta value of 0.074 support AI's negative impact on employment. Due to its positive beta value and statistical insignificance, drones' impact on employment is refuted by the study. Originality consists in the combination of a targeted research question, personalized technique, and contextual relevance, which advances technology and employment dynamics in the UAE's financial sector.

Keywords
artificial intelligence, automation, robotics, drones, employment

INTRODUCTION

Artificial Intelligence (AI) has become an essential element of our daily existence, significantly impacting a variety of sectors, including finance. In response to the COVID-19 pandemic, the rapid integration of robotic solutions by companies to address enduring human challenges is well-documented, as Marrone et al. (2022) have noted. For example, Nayak et al. (2023) noticed that robots were employed to perform tasks such as monitoring body temperatures and disinfecting airport floors. In the financial sector, the closure of contact centres has resulted from the displacement of customer support workers by AI-powered chatbots. This development underscores the increasing concern that AI may eventually replace human positions (Raza et al., 2024).

The portrayal of AI in mainstream science fiction films has heightened concerns that AI could replace human employment, particularly as its versatility increases (Kärtner, 2023). In fact, these concerns are not unjustified, as AI's ability to automate and optimise processes has resulted in substantial changes in employment patterns. AI has an impact on managing operations boosting organizations' return on investment, and helping with productivity, quality, and customer satisfaction. It also plays a role in company resource planning to make decisions, develop products, and manage human resources (Wang et al. 2019).

Though, AI's profound influence has given rise to substantial challenges. Parker et al. (2022) point out ethical problems in the workplace such as more monitoring, privacy breaches, and job discrimination. Moreover, the substitution of human labour by AI has laid to the displacement of employment, particularly in roles that require repetitive tasks (Raffik et al., 2023). Companies are comprehending that AI adoption is becoming cost-efficient, leading to job losses, even highly skilled and well-paid employees are at risk of losing their jobs as artificial intelligence systems advance (Agerfalk, 2020; Sima et al., 2020). As per the McKinsey Global Institute prediction, around 70% of businesses will embrace at least one AI technology. However less than half of large corporations are expected to fully utilize all the AI

tools currently available. This highlights the rapid and widespread adoption of AI across various industries (McKinsey Global Institute, 2020).

As AI adoption increases, the UAE's financial sector is particularly susceptible to substantial modifications. The demand for reskilling is on the rise as new job roles are created in response to AI's capabilities (Wilson & Syed, 2021; Kitsios & Kamariotou, 2021). Additionally, the capacity of AI to process and analyse immense quantities of data has the potential to increase productivity throughout the industry, though at the expense of job displacement (Chen et al., 2021; Lazaroiu et al., 2022). For instance, the implementation of AI in customer service has optimised operations by automating frequently asked questions, thereby reducing the necessity for human intervention in these interactions.

Transactional technologies streamline and transparently connect buyers and sellers of products and services. Organizations and workers employ corporate software, factory robots, personal computers, and smartphones as complementary tools. As the Internet and mobile networks become more pervasive, matching tools connect workers with jobs or tasks at different geographic levels. These services connect car drivers with clients Uber and free unused rooms in houses Airbnb in cities. They develop "gigs," where people perform non-tradable jobs like picking up groceries or delivering items for a set amount of time. National and global matching services let companies and workers find each other for employment (e.g., Monster.com or SoukTel Jobmatch) or assignments.

Consequently, along with technological development, one considers the situation where:

- Implement programs to support employees affected by changes due to AI integration in financial sectors of UAE.
- Measure the extent to which AI technologies are currently being adopted in the financial industry of UAE. This includes evaluating the implementation of AI in various financial processes and services.
- Investigate the changes in the composition of the financial sector workforce in UAE. Assess any shifts in job roles, skill requirements, and employment patterns.

Determine the occupations that are most susceptible to automation and the extent to which this influences the overall employment situation.

By assessing the impact of AI on employment patterns, talent demands, and work roles, as well as the implementation of AI technologies and the subsequent job displacement. The research endeavours to clarify the manner in which AI is altering the workforce in the financial sector of the UAE by assessing these dimensions.

The paper is structured as follows: The context for the research is established in the Introduction section, along with study's objectives and significance. The following section is a comprehensive Literature Review that consolidates and critically analyses the extant research on the subject. The Methodology section offers a comprehensive account of the research design and the procedures implemented for data collection and analysis. As a result, we have the Findings and Results section that showcases and analyzes the findings of the research. Finally, the Conclusion section offers a brief overview of key findings and suggests avenues for future research.

LITERATURE REVIEW

Contemporary financial theories are rich in the literature of job polarization, which is being utilized to explore the effects of AI adoption on employment dynamics. This study aims at illuminating the impact of AI on the financial sector. This approach uncovers the pathway of the trends and gives a qualitative prediction of the AI advancement on employment (Frank et al., 2019). These factors, keeping in mind, can help clear the way we're getting new experience about how AI is shifting job roles and workforce dynamics in the financial sector.

Effect of Automation on Employment

There has been a long-standing debate regarding the impact of automation on employment, based on the "Labour Lump Fallacy," which suggests that there is a predefined quantity of work (Wolla, S.A., 2020). This hypothesis states that as automation and AI grows into the field of finance, many jobs will be lost simply because the machines will be doing the work once done by humans. (Estlund, 2021). Numerous scholars have investigated this relationship. Schumpeter introduced the concept of "creative destruction," arguing that automation has the potential to generate new opportunities through innovation, despite the fact that it may eliminate existing employment (Chamberlin, 2006). On the other hand, keynes expressed apprehension regarding "technological unemployment," that is, that the development of technology could outstrip the creation of new jobs, leaving a net deficit in employment (Chrástecký, 2016). Brynjolfsson and McAfee in "Race Against the Machine" emphasized that AI is surpassing human labour, particularly in routine financial duties, which could result in substantial job displacement (Hrdy, 2019). The "overeducated American" concept of Freeman and Medoff suggested that automation could lead to overqualified workers for occupations, causing unemployment or underemployment (Camarota, 1997). Lindsey and Teles highlight how regulatory and policy capture might slow economic growth and exacerbate automation and technological transition (Qureshi, 2022). Frey and Osborne studied work automation susceptibility and proposed routine-biased technological change, arguing that routine tasks are easier to automate, changing the job market (Bezuidenhout, 2017). Porter argues that automation may increase productivity, but its benefits should be dispersed more equally to address social and economic issues (Evans et al., 2020). Zuboff's surveillance capitalism hypothesis holds that automation, especially in the digital domain, displaces workers and captures and sells personal data (Dufva, 2022). Automation may reduce manual work, human error, and operational inefficiencies. Financial organizations can save money and boost efficiency by automating data entry, reconciliation, and transaction processing (Ng et al., 2021). Automating financial risk management and compliance is essential. Automated systems can

track transactions, detect irregularities, and assure regulatory compliance. Financial institutions can reduce risks, avoid regulatory penalties, and maintain strong controls (Al-Shabandar, 2019).

Effect of Artificial Intelligence on Employment

Like AI, mathematical decision theory focuses on uncertain decision-making. Despite a relationship, especially in search algorithm research, both domains have offered contrasting paradigms. This set of publications shows how decision theory can solve AI challenges. Mathematical decision theory evaluates decisions using a numerical utility function. Utility functions like the evaluation function used to calculate chessboard positions in programs are widespread (Feldman & Sproull, 1977). The hypothesis states that AI replaces employment at the task level, starting with "lower" (more manageable for AI) intelligence. After augmenting specific service job duties, AI can replace all human labor. The progression of AI task replacement from lower to higher intelligences predicts shifts in service employees' intelligence priorities. As AI performs more analytical jobs, service workers tend to value "softer" intuitive and sympathetic talents over analytical skills. AI may eventually perform perceptive and compassionate activities, enabling creative human-machine service integration but potentially threatening human jobs (Huang & Rust, 2018). AI, which mimics human intelligence, is widely used in the service sector, and drives innovation. AI-powered residential, hospital, hotel, and restaurant robots have automated many daily tasks. Virtual bots make customer assistance self-service, big data AI apps replace portfolio managers, and social robots like Pepper replace greeters. These advances have led some to call this the fourth industrial revolution, as technology blurs the lines between the physical, digital, and biological worlds. AI is a critical source of innovation, but it also threatens human service jobs, like how industrial jobs were displaced to the service industries (Holthöwer & Van, 2021).

Effect of Robotics on Employment

Control theory is used to build algorithms and systems that control robot movement and activities, making it relevant to employment. Control theory applied to robotics affects many businesses and financial sectors (de Wit et al., 2012). Welding, assembling, and material handling are common robot jobs. Development of algorithms for precise and economical robotic arm and end-effector control requires control theory (Xiang et al., 2023). Robots work with humans. Control theory allows safe and adaptable human-robot interactions in shared workspaces (Hameed et al., 2023). Control theory in robotics affects employment directly and indirectly. While robotic systems may automate some operations, they create new jobs in design, programming, maintenance, and monitoring (Hofmann et al., 2020).

Effect of Drones on Employment

Drones, are used in several industries, including finance. Financial organizations invest heavily in buildings and infrastructure. These assets may be monitored regularly by drones for maintenance, security, and other issues that may influence their value. Banks and investing organizations can use drones for security. They can send real-time video to police to report suspicious activity or security breaches. Sensor-equipped drones can collect weather and air quality data for financial modeling and risk management (Xiang et al., 2023). Financial estimates and decisions can benefit from this data. Financial institutions may invest in energy infrastructure or agricultural initiatives in remote places. Remote asset monitoring and inspection by drones reduces costs and improves efficiency. Aerial surveys and mapping with drones can inform real estate investment decisions. This includes evaluating a site's development potential and tracking construction. Financial organizations with several branches can use drones for building inspections and facility management (Dufva, 2022). They can examine structural integrity, recommend repairs, and improve facility management. The literature may examine how drones can improve financial institution security. Monitoring branches, data centers, and other vital infrastructure could detect and respond to security threats. Researchers may examine how drone-collected environmental data affects financial modeling, risk assessment, and decision-making. Sensor kinds and drone data reliability may be discussed (Qureshi, 2022). Drones may affect financial institution operational efficiency in studies. This could include cost-benefit analysis, case studies, and successful drone installations. Amidst the global landscape, the impact of the employment crisis due to artificial intelligence is hastening transformative changes that will reshape not only the methods of work but also our perceptions of work presented in (Fig. 1).
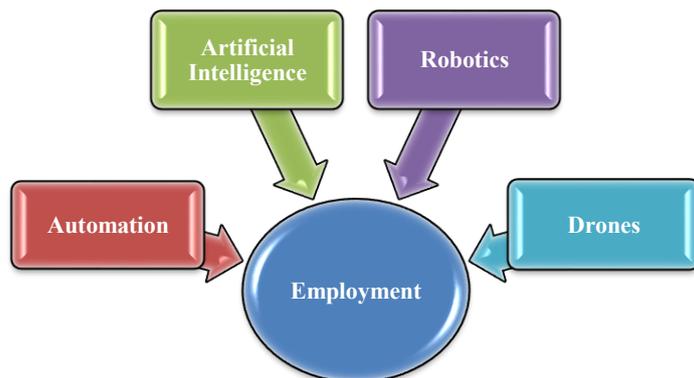

Fig. 1 Research Framework (*Source*: Author)

This study proposed following hypotheses.

H_1: Automation has negatively significant effect on employment in financial sectors of UAE.

H_2: AI has negatively significant effect on employment in financial sectors of UAE.

H_3: Robotics has negatively significant effect on employment in financial sectors of UAE.

H_4: Drones have negatively significant effect on employment in financial sectors of UAE.

METHODOLOGY

The study utilized a mono-method approach to measure variables using statistical instruments, primarily gathering data from the financial sectors of the UAE. The primary evaluation instrument was a questionnaire that was distributed through online Google Forms. The survey was designed to reach professionals in financial institutions, insurance, and banking industry in prevalent emirates such as Abu Dhabi, Sharjah, and Dubai. The survey was active for 50 days, from July 1, 2024, to August 19, 2024, and was distributed through social networks, particularly within professional groups and communities attracting a sample size of 319 respondents.

The sampling strategy of the study was designed to guarantee that the sample was representative of the broader population, thereby enabling the generalisation of the results. In order to contextualize the responses, demographic data, including age, gender, education, income, and profession, was collected. The study concentrated on one dependent variable, employment, and four independent variables; AI, robotics, automation, and drones. In order to assess the impact of these technologies on jobs in the UAE's banking industry, 21 items of Likert scale questionnaires were employed, including those from Smith (2023) for AI and for drones, Doe (2022) for robotics, and Gundumalla (2021) for automation. The 35 items were used to measure the variables in the study, 14 of which were from Smith Johnson (2020) and used to measure the dependent variable.

ANALYSIS OF THE RESULTS

Understanding respondent profiles is necessary to analyze major survey findings. A demographic profile of respondents is offered. Since the survey was anonymous and relied on professional competence, respondents were graded using their experience to identify and obtain quality results from conventional questions. Gender, age, employment status, type, and level are included in the demographic study. Table 1 presents the demographic analysis of the study we had a total of 319 participants. Out of these, 27 were female, making up 8% of the group, while 292 were male, constituting 92%. This means that most of our participants were male. We had 182 individuals between the ages of 20 and 35, 80 participants aged 36 to 45, 53 individuals aged 45 to 55, and 4 participants aged 56 and above. This breakdown gives us insights into the age distribution of our sample. It's worth noting that most participants fall within the 20-35 age range. Understanding these age groups helps us consider how age may influence our study results, and it provides a snapshot of the diversity in our participant demographics. We had 76 individuals with a diploma, and there are 186 individuals holding a bachelor's degree, and 57 individuals possessing a master's degree. This breakdown reflects the educational diversity within our sample. Most participants hold a bachelor's degree, followed by those with a diploma and a smaller group with a master's degree. Understanding the distribution of educational qualifications is essential as it helps us consider the potential impact of participants' academic backgrounds on our study findings.

We had 59 professional employees, 130 vocational employees, and 130 students. This breakdown provides insight into the occupational diversity within our sample. Most participants are vocational employees, followed by professionals, and an equally substantial number of students. Recognizing these different employment statuses is crucial as it helps us understand the varied perspectives and experiences that our participants bring to the study. We found that 142 participants fell within the income range of Rs. 35,000-50,000, constituting 44% of the total. Additionally, 31 individuals had incomes between Rs. 51,000-100,000, making up 10% of the sample. For the income range of Rs. 110,000-150,000, there were 146 participants, accounting for 6%.

Automation, robotics, drones, artificial intelligence, and employment are all shown to be correlated in Table 2's Spearman's rho study. Automation and Robotics have the strongest association ($\rho = 0.697$), suggesting a strong positive relationship. Just like Robotics and Automation, Drones are strongly related to both fields, indicating that they frequently evolve at the same time ($\rho = 0.740$, $\rho = 0.657$). Among the three technologies, AI demonstrates moderate relationships, the strongest of which is with drones ($\rho = 0.679$). The Employment variable shows the poorest connections compared to all technology factors, with the strongest link being with AI ($\rho = 0.521$), however it is still positively correlated with all other variables. This indicates that although technical progress does influence employment, it is less significant than the interrelationships among the technologies themselves. The results show that technical progress in the modern era has a complicated and subtle effect on employment, but that these effects are interrelated.

Table 1 Demographic Analysis

		Frequency	Percentages
Gender	Male	292	92%
	Female	27	8%
Age	20-35	182	
	36-45	80	
	45-55	53	
	55+	4	

Qualification	Diploma	76	
	Bachelors	186	
	Masters	57	
Employment Status	Professionals	59	
	Vocational	130	
	Students	130	
Income Level	35000-50000	142	
	50000-100000	31	
	100000+	146	

Source: Author's output from SPSS software

Table 2 Spearman's rho Analysis

Spearman's rho	Automation	Robotics	Drones	A_I	Employment
Automation	1.00				
Robotics	0.697	1.00			
Drones	0.657	0.740	1.00		
AI	0.601	0.607	0.679	1.00	
Employment	0.395	0.458	0.505	0.521	1.00

Source: Author's output from SPSS software

The reliability statistics for our automation items, as measured by Cronbach's Alpha, is 0.796. This indicates a high level of internal consistency among the items related to automation in our study. Cronbach's Alpha values above 0.7 are generally considered acceptable, suggesting that the automation items reliably measure the same underlying construct. The reliability of these items enhances the assurance in the consistency and validity of our items, which further supports the reliability of our analysis of automatization in the context of our study. The reliability statistics for our robotics items, as measured by Cronbach's Alpha, is 0.813. That shows a great deal of internal consistency among the items related to robotics items in the study. Cronbach's Alpha values above 0.7 are generally considered acceptable, suggesting that the robotics items reliably measure the same underlying construct. The reliability of these items enhances the confidence in the consistency and dependability of our measurements, reinforcing the validity of our assessment of robotics in the context of our study. The reliability statistics for our drone-related items, as measured by Cronbach's Alpha, is 0.835. This indicates a high level of internal consistency among the items related to drones in our study. Cronbach's Alpha values above 0.7 are generally considered acceptable, suggesting that the drone items reliably measure the same underlying construct. The reliability of these items enhances the confidence in the consistency and dependability of our measurements, reinforcing the validity of our assessment of drones in the context of our study. The reliability statistics for our artificial intelligence (AI) items, as measured by Cronbach's Alpha, is 0.816. This indicates a high level of internal consistency among the items related to AI in our study. Cronbach's Alpha values above 0.7 are generally considered acceptable, suggesting that the AI items reliably measure the same underlying construct. The reliability of these items enhances the confidence in the consistency and dependability of our measurements, reinforcing the validity of our assessment of artificial intelligence in the context of our study. The reliability statistics for our artificial intelligence (AI) items, as measured by Cronbach's Alpha, is 0.882. This signifies an exceptionally high level of internal consistency among the items related to AI in our study. Cronbach's Alpha values above 0.7 are generally considered acceptable, and in our case, the 0.882 value suggests a robust and reliable relationship among the AI items. This high level of reliability enhances our confidence in the consistency and dependability of our measurements, reinforcing the validity of our assessment of artificial intelligence in our study found in Table 3.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for our dataset is 0.922 presented in Table 4. The KMO statistic assesses the degree to which our data is suitable for factor analysis. A KMO value close to 1 indicates high sampling adequacy, suggesting that our dataset is well-suited for extracting meaningful factors. In our case, the KMO of 0.922 strongly suggests that the variables in our dataset have substantial common variance and are suitable for further exploration through factor analysis.

Table 3 Factor Loading and Reliability Analysis

Items	Factors Loading	Name of Items	Cronbach's Alpha
I see automation as a threat to employment.	0.615		
I believe automation increase the rate of employment.	0.633		
I believe automation results in losing jobs among accounting/banking sectors.	0.642	Automation	0.796
I believe and accept automation improves the overall business thus employability.	0.621		
I lack in certain skills which are required for real time employment.	0.761		
Robot will lead to widespread job loss in various industries.	0.775		
The integration of robots in the workplace will enhance overall productivity.	0.717		
The use of robots in low-skilled jobs will negatively impact employment for less-educated workers.	0.739	Robotics	.813
I am concerned that robots will replace human workers in my industry.	0.646		

Government should implement policies to regulate the deployment of robots in the workplace.	0.807		
Drones will lead to a significant decrease in job opportunities in the delivery and logistics industry.	0.885		
Drones have the potential to create new job opportunities in industries such as drone manufacturing and maintenance.	0.850		
The integration of drones will positively impact job efficiency and crop yields.	0.667	Drones	.835
Government should establish clear regulation to govern the use of drones in various industries.	0.628		
I am concerned that drones will replace human workers in my industry.	0.641		
The increasing use of AI in various industries is likely to lead to widespread job displacement.	0.601		
AI technologies can improve efficiency and productivity in the workplace.	0.676		
The integration of Ai will create new and diverse job opportunities.	0.797		
Implementation of AI in the workplace requires careful regulation to protect employment.	0.768	AI	.816
Concerns about job loss due to AI have influenced you're your career decisions.	0.710		
Government should invest in education and training programs to prepare the workplace for AI-related changes.	0.889		
My job provides me with a sense of purpose and meaning.	0.886		
I feel valued and appreciated in my current position.	0.509		
The workload in my job is reasonable and manageable.	0.507		
I have opportunities for professional growth and development.	0.708		
I am satisfied with the level of communication within the organization.	0.964		
The work environment is conducive to productivity and well-being.	0.803		
I receive constructive feedback on my performance.	0.729		
I have a good work-life balance.	0.756	Employment	.882
I feel a sense of camaraderie and teamwork in my workplace.	0.759		
The organization supports a healthy work culture.	0.771		
I am satisfied with the opportunities for advancement in my career.	0.705		
I have the necessary resources to perform my job effectively.	0.861		
The compensation and benefit package is fair and competitive.	0.835		
Overall, I am satisfied with my current employment.	0.705		

Source: Author's output from SPSS software

Table 4 KMO Analysis

Kaiser-Meyer-Olin Measure of Sampling Adequacy.	.922
Bartlett's Test of Sphericity Approx. Chi-Square	5678.105
Df	595
Sig.	.000

Source: Author's output from SPSS software

Table 5 presents the regression effects on AI on employment in financial markets in UAE. R-squared signifies the proportion of the variance in the dependent variable elucidated by the independent variables within your model. Here, it stands at 0.729, indicating that around 72.9% of the variability in the dependent variable is accounted for by your regression model. Adjusted R-squared modifies the R-squared value to account for the number of predictors in your model, which proves valuable when comparing models with varying predictor counts. The adjusted R-squared here is roughly 0.725. The beta value of automation is 0.164 means that if 1% increase in automation than the employment will decreased by 16%. Since the significance value is below than 0.05, hence H_1 has accepted. The beta value of AI is 0.074 means that if 1% increase in AI than the employment will decreased by 7%. Since the significance value is below than 0.05, hence H_2 has accepted. The beta value of Robotics is 0.090 means that if 1% increase in robotics than the employment will decreased by 9%. Since the significance value is below than 0.05, hence H_3 has accepted. The beta value of drones is 0.262, coefficient is positive and significance value is above than 0.05, hence H_4 has rejected.

Table 5 Regression analysis

	Unstandardized Coefficients	Std. Error	t-statistics	P-Values
Automation	-.164	.056	-2.913	.004
Artificial Intelligence	-.074	.059	-1.244	.004
Robotics	-.090	.051	-.173	.003
Drones	.262	.055	4.740	.861
Constant	1.787	.147	12.160	.000
R-Square	0.729	Adjusted R^2	0.725	

Note: Dependent Variable: Employment

DISCUSSION

We examined in this paper the widespread adoption of AI in the financial sector may lead to job displacement, particularly for roles that involve routine, rule-based tasks. Workers in affected roles may need to acquire new skills to remain relevant in the evolving job market. AI can assist in regulatory compliance by automating processes related to risk management and ensuring adherence to financial regulations. This can contribute to a more robust and compliant financial system. The impact of AI on employment may vary across different job levels. While some entry-level and routine jobs may be at risk, but the high-skilled jobs requiring creativity, critical thinking, and complex problem-solving will still be high in demand. However, the effect of AI on jobs in UAE's financial sector will be determined by the adoptability of its labor force, the approaches taken by financial organizations and the regulatory structures that will oversee the ethical deployment of AI. Robotics and AI have potential to affect any sector, and one of them is the financial sector, in the UAE. Robotics could take care of all the mundane repetitive stuff in the financial sector such as data entry, transaction processing, customer service inquires. With automation comes efficiency, fewer mistakes, quick processing, which in turn means financial institutions are capable of handling with larger volumes of work. With robotics and AI, banks would be able to cut down on the operational costs of using manual labor. This cost reduction will likely lead to higher profitability and maybe even lower prices for consumers as financial services become more efficient. While the integration of robotics and AI in the financial sector of UAE can bring about increased efficiency and innovation, it is essential for policymakers, businesses, and educational institutions to work collaboratively to address potential challenges, including job displacement, and ensure that the benefits of technology are distributed equitably across society. Upskilling the workforce and implementing thoughtful regulations are crucial elements in navigating the impact of AI on employment in the financial sector. Categorized by product, the Malaysia Robotics Market is divided into Industrial Robots and Service Robots. Industrial robots refer to a robot system programmed to execute repetitive tasks with consistent precision and accuracy. Service Robots, on the other hand, aid human beings and are described as robots that perform useful tasks for humans. (Azman & Ahmad, 2023). The imperative to implement fresh cost efficiencies, enhance digitization, and expedite transactions has compelled banks to swiftly delve into the incorporation of robotics in their processes. Robotic Process Automation (RPA), as articulated by the Institute of Robotics Process Automation (IRPA), enables company employees to set up computer software or a 'robot' to comprehend and interpret existing applications for transaction processing, data manipulation, response triggering, and communication with other digital systems. (Smeets et al., 2019). This necessitates a system capable of handling large volumes of information, employing algorithms to identify patterns, and facilitating decision-making based rules. (Liu et al., 2021). Automation Algorithmic trading, also known as algo trading, involves the use of algorithms to execute trades in financial markets. These algorithms analyze market data and execute trades at high speeds, leveraging automation to respond to market conditions in real-time (Lenczewski, 2019). Automation is crucial for handling large volumes of financial data. Automated tools can analyze data, generate reports, and provide insights for decision-making. This is particularly important in areas such as financial forecasting and budgeting. Automated tools are employed to monitor and respond to cybersecurity threats in the financial sector. This includes the use of AI-driven systems to detect and mitigate potential security breaches (Sarker, 2021).

AI Historically, financial processes, including tasks such as data entry, data collection, data verification, consolidation, and reporting, have relied extensively on manual labor. All of these manual activities tend to make the finance function costly, time-consuming, and slow to adapt. At the same time, many financial processes are consistent and well defined, making them ideal targets for automation with AI. The advent of ERP systems allowed companies to centralize and standardize their financial functions (Romao et al., 2019). Early automation was rule-based, meaning as a transaction occurred or input was entered, it could be subject to a series of rules for handling. While these systems automate financial processes, they require significant manual maintenance, are slow to update, and lack the agility of today's AI-based automation. Unlike rule-based automation, AI can handle more complex scenarios, including the complete automation of mundane, manual processes. Increased automation also means improved accuracy across your financial processes (Anbukkarasi & Varadhaganapathy, 2022). High volume, mundane processes, such as invoice entry, can lead to fatigue, burnout, and error in humans. Computers, however, don't have these same limitations. They can also process drastically higher volumes of transactions in each period (Met, et al., 2020). The result is better data to work with and more time for the finance team to focus on putting that data to use. Drones can be used to inspect physical assets such as properties and infrastructure owned by financial institutions. This includes aerial assessments of real estate properties, insurance claims inspections, and monitoring of construction projects. Aerial imagery captured by drones can provide valuable data for risk assessment and underwriting processes. Insurers can use high-resolution images to assess the condition of properties, assess risks, and determine appropriate insurance coverage. Drones equipped with cameras and sensors can be used for security and surveillance purposes. Financial institutions may deploy drones to monitor large areas, especially in locations where traditional security measures may be challenging. Drones can be used to monitor the security of Automated Teller Machines (ATMs) and their surroundings (Lykou, et al., 2020). This can aid in detecting and preventing criminal activities such as skimming devices or unauthorized access. Some financial institutions have explored the use of drones for document or small package delivery between branches. This can enhance efficiency and reduce the time and cost associated with transporting sensitive documents (Sułkowski, et al., 2022).

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This study's results are concerning because they demonstrate that AI is having a major effect on the labor market and is displacing individuals from their jobs. Artificial intelligence (AI) is expected to change or eliminate jobs in nearly every industry. This includes the financial sector, where AI is going to automate tasks, change the way financial instruments are delivered, impact life insurance policies, and accounting and finance. The present employees, who require preparation for what the future holds, will feel the effects first and foremost. However, the likelihood of this unemployment differs across nations since technological adaptation rates vary widely. Yet, AI isn't perfect; sometimes, you just need human hands to get the job done. Better employment opportunities may arise in the future because of the AI revolution, but in order to keep up with the technology, you must be flexible and ready to face new challenges. This is intended to serve as the paper's further expansion. This study has several limitations, one of which being the small sample size. The primary limitations of this research investigation were the available time and the available cash. More particular information can be derived from future studies by include larger samples from other demographic and geographical groups. This work has focused on the negative effects of AI, however in future research, the flip side of this issue can be examined. The breadth that AI has developed, and the effects of that scope can be studied by researchers. Researchers might also investigate the elements that influence businesses' decisions to adopt AI in their banking and finance departments.

Practical Implications

Several real-world consequences, affecting different parts of operations, services, and employment, result from the incorporation of artificial intelligence, robotics, automation, and drones into the UAE financial sector. The following is an examination of these real-world consequences. AI and Automation: Data entry, processing transactions, and basic customer support are just a few examples of the mundane jobs that automation technology may expedite. By making these processes easier and faster, operational efficiency is improved.

Artificial intelligence: State-of-the-art AI systems can sift through mountains of financial data and deliver reliable insights for decision-making. Investment plans, risk management, and the detection of fraud can all benefit from this. Financial transactions and reporting can benefit from automation since it helps to decrease human error in routine chores. Chatbots and virtual assistants: These AI-driven tools may respond to consumer questions, help, and tailor their offerings to everyone. By delivering prompt and effective responses, this enhances the overall customer experience. Financial organizations can save money and make better use of their resources by automating routine operations. Because of this, we can save money, which we can then put into new products and better services. There are a lot of different ways in which artificial intelligence, robots, automation, and drones could affect the UAE banking industry. While these technologies do increase efficiency, decision-making, and consumer experiences, they also pose risks to jobs, data security, and regulatory compliance, so lawmakers and financial institutions need to plan.

Theoretical Implications

This study significantly contributes to the existing body of knowledge on the relationship of AI and employment, particularly within the context of the financial sector in the United Arab Emirates (UAE). The study's statistically significant regression analysis shows that AI negatively impacts employment, supporting the rising debate on new technologies' ability to destroy labour. This research helps us understand how AI, automation, and robotics affect labour markets, potentially affecting job availability and skill demand.

This research centers on the UAE and shows how global advancements in technological patterns can affect a region with distinct economic and cultural qualities. This implies that the results suggest that government, corporate leaders, and educators in the UAE and other similar economies must take preemptive action to counteract the negative impacts that AI and related technologies will have on jobs. Reskilling, upskilling, AI literacy, and technology enabled job creation policies are all possible.

Additionally, the study takes a novel view of the financial sector employment dynamics by incorporating AI, automation, robotics, and drones which may stimulate further research in other sectors or other regions.

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