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Research Article

Digital Transformation in Financial Management Through Artificial Intelligence and Intelligent Automation

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Abstract

Background: Artificial intelligence and intelligent automation are changing the way financial management is done through better analysis, efficiency, prediction, decision making, and response. Yet, there is a lack of empirical literature that brings all these together in a framework for financial transformation. **Methods:** The purposes of this study, a quantitative cross-sectional research method based on an online survey conducted among 175 finance and accounting professionals, as well as experts in business and technology, in the United States was used. The six dimensions considered in this study were AI Capability, Intelligent Automation, Predictive Analytics Capability, Digital Process Integration, Financial Decision Intelligence, and Financial Management Performance. **Results:** The respondents have indicated moderate levels for the study variables, which were 3.91, 3.89, and 3.88 for the variables Digital Process Integration, Financial Management Performance, and Predictive Analytics Capability respectively. Autonomous Financial Reporting showed highest level of usage at 58.3%, followed by Predictive Financial Analytics with 57.1% and Real-Time Financial Intelligence with 55.4%. Financial Decision Intelligence was found to be highly correlated with Financial Management Performance at 0.809, whereas Intelligent Automation and Predictive Analytics Capability showed a correlation of 0.781 and 0.769 respectively with Financial Decision Intelligence. **Conclusion:** The findings show that AI capability, intelligent automation, predictive analytics, and digital process integration are interrelated with financial decision intelligence and performance.

Keywords

Artificial Intelligence, Intelligent Automation, Financial Management, Predictive Analytics, Digital Transformation

1. Introduction

AI technologies have turned out to be a strong force that contributes to digital transformation in modern financial management. AI affects how organizations analyze data, assess risks, predict financial situation, and make decisions. Transition from conventional manual-based financial system into smart, automated, and data-oriented environment is getting more and more rapid[1]. AI technologies can analyze complex datasets related to finances, find patterns, produce predictions, spot deviations, and help with decision-making in real time. Intelligent automation combines such analytical skills with financial processes, eliminating redundant tasks and increasing consistency of operations[2]. Thus, transformation of financial management powered by AI becomes a strategic move, not just digital transformation. However, such a transformation requires proper integration of technological skills with financial processes and decision-making[3].

The increasing complexity of financial environments has

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increased the need for intelligent financial technologies. Uncertainty in the markets, higher volume of transactions, regulatory compliance, cyber security risks, and the demand for timely financial information may pose constraints on the performance of conventional processes that depend highly on historical data and manual operations(Mhlanga, 2020; Pramanik et al., 2019). Forecasting using AI, predictive analytics, automation of reporting, intelligent risk detection, and financial monitoring in real time have chances to address these constraints by providing tools for proactive and informed financial management(Kitsios &Kamariotou, 2021). However, the mere adoption of technology does not ensure better results. It is necessary to build capabilities that will allow leveraging AI technologies to achieve financial benefit. AI Capability is the basis for intelligent analytics, and Intelligent Automation improves the efficiency of processes[5]. Predictive Analytics Capability builds forward-looking financial intelligence, while Digital Process Integration connects financial processes[6]. All these capabilities together may lead to improvement of Financial Decision Intelligence, which contributes to Financial Management Performance through efficiency, accuracy, agility, and better decision-making[7]. Although the adoption of technology is increasing, empirical research integrating all these components into one financial management system is rare(Cantú-Ortiz et al., 2020).

Digital Transformation of Financial Management Using Artificial Intelligence and Intelligent Automation. This study proposes an analytical framework consisting of six key dimensions: Artificial Intelligence (AI) Capability, Intelligent Automation, Predictive Analytics Capability, Digital Process Integration, Financial Decision Intelligence, and Financial Management Performance[8]. Descriptive statistics are employed to analyze the distributional properties of the study variables, whereas percentage analysis is applied to uncover technology adoption and financial transformation patterns. Moreover, Pearson correlation analysis is performed to test the strength of the relationship between the six dimensions. Through integration of technology with decision intelligence and financial performance, this study offers an analytical insight into intelligent financial transformation. The results are anticipated to contribute to research on artificial intelligence in finance.

2. Materials and Methods

2.1 *Research Design and Study Context*

In this study, a quantitative cross-sectional approach was used in order to analyze digital transformation in financial management through artificial intelligence and intelligent automation. Research was carried out in the US and the population included individuals with experience in the areas of finance, accounting, business, technology, data analytics, and digital financial operations. The theoretical framework involved six contemporary dimensions: AI Capability, Intelligent Automation, Predictive Analytics Capability, Digital Process Integration, Financial Decision Intelligence, and Financial Management Performance[9]. The research considered the role of innovative technologies in transforming traditional financial practices via intelligent predictions, automation, integration of digital platforms, and data-based decisions. The study design facilitated the process of measuring perceptions and experiences of respondents with regard to technology-based financial transformation[10].

2.2 Online Survey and Sampling

The primary data were obtained via a survey carried out using an online format, where the participants were the professionals working in finance, accounting, business, technology, and data management from across the United States. Purposive sampling was used to obtain the target participants having experience of working in the domains of financial management and digital technologies. In total, the online survey tool provided 175 responses, which were selected for further analysis. Participants in the survey responded voluntarily and were aware of the academic nature of the research before taking the survey. The use of the online format facilitated the quick participation of professionals from different organizational and technological settings. The survey collected perceptions regarding AI adoption, intelligent automation, predictive analytics, digital integration, financial decision-making, and financial performance. The standardized set of questions was provided to all participants in the survey.

2.3 Measurement Framework

The measurement model was built on six basic constructs reflecting the technological and managerial aspects of the AI-based financial transformation. AI Capability reflected the capability of an organization to use artificial intelligence in its financial analysis, forecasting and decision-making processes[11]. Intelligent Automation referred to the automation of financial operations, reporting and workflows. Predictive Analytics Capability was related to the usage of analytics for forecasting and future-oriented financial intelligence[12]. Digital Process Integration referred to connectivity of financial systems, processes and workflows. Financial Decision Intelligence was related to the quality and timeliness of financial decisions made by using technologies[13]. Financial Management Performance reflected the financial efficiency and effectiveness due to improvements in financial management. Several survey items were used for the assessment of each construct. All significant items were based on a five-point Likert Scale from 1=Strongly Disagree to 5=Strongly Agree[14].

2.4 Data Analysis

The data was analyzed using a quantitative method that aimed at demonstrating conclusively the extent of transformation by means of AI. The first step involved calculating the descriptive statistics to capture the distribution as well as the core features of all the six study variables[15]. The mean, variance, skewness and kurtosis was evaluated in order to ascertain the patterns in the responses and their distribution. After that, percentage analysis was done to ascertain variations in the degree of adoption of AI technology, intelligent automation, predictive finance and digital transformation practices[16], [17]. In the final step, Pearson correlation was done to determine the strength and direction of the association between AI Capability, Intelligent Automation, Predictive Analytics Capability, Digital Process Integration, Financial Decision Intelligence, and Financial Management Performance[18].

3. Results

3.1 Demographic Profile of Respondents

The demographic profile of the 175 participants together with the main features of the sample population as **Table 1.**The respondentsof58.9% were men, whereas females were 41.1%. The largest age category was comprised of 31-40 year-olds, who were 35.4% of the total number, whereas the second largest age group were the 41-50 year-olds who made up 25.7% of the total number, as well as 18-30 year-olds making 24.6%. Educationally, the highest level was attained by 52.0% of the respondents, who had master's degrees, while 25.7% were PhDs and professionals and 22.3% had their bachelor's degrees. As for the professional experience, the largest category consisted of 5-10 years of experience, which comprised 32.6%, as well as 11-20 years of experience 30.3%. Finally, in terms of occupation, the largest category was finance and accounting professionals, made 34.9% of the total respondents, as well as managers/senior managers 25.7%, as well as executives 24.0%.

***Table 1**. Demographic Characteristics of Respondents*

Variable	**Category**	**Frequency (n)**	**Percentage (%)**
Gender	Male	103	58.9
	Female	72	41.1
Age	18–30 years	43	24.6
	31–40 years	62	35.4
	41–50 years	45	25.7
	Above 50 years	25	14.3
Education	Bachelor's degree	39	22.3
	Master's degree	91	52.0
	Doctoral or Professional	45	25.7
Work Experience	Less than 5 years	35	20.0
	5–10 years	57	32.6
	11–20 years	53	30.3
	More than 20 years	30	17.1
Job Position	Finance and Accounting Professional	61	34.9
	Manager or Senior Manager	45	25.7
	Executive or Officer	42	24.0
	IT, Data and AI Professional	27	15.4

3.2 Descriptive Statistics of Study Variables

A generally high degree of perceived digital and AI-financial capability was observed among the respondents as presented in **Table 2.** Digital Process Integration had the highest mean score of 3.91, followed by Financial Management Performance of 3.89 and Predictive Analytics Capability of 3.88. The variable that had the comparatively low mean was Intelligent Automation with a mean score of 3.76; however, it still exceeded the halfway point of the measurement scale. The values of variance were between 0.423 and 0.548, which means moderate spread of responses regarding the constructs. The variables showed negative skewness, which indicated an aggregation of the responses to the high end of the scale. However, the skewness values were moderately distributed between 0.35 and 0.58. The kurtosis values were nearly equal to zero and varied from −0.24 to 0.14.

Table 2. *Descriptive Statistics of Study Variables*

Variable	Mean	Variance	Skewness	Kurtosis
AI Capability	3.82	0.504	−0.42	−0.18
Intelligent Automation	3.76	0.548	−0.35	−0.24
Predictive Analytics Capability	3.88	0.462	−0.51	0.08
Digital Process Integration	3.91	0.423	−0.58	0.14
Financial Decision Intelligence	3.86	0.449	−0.47	−0.06
Financial Management Performance	3.89	0.449	−0.55	0.11

3.3 AI-Driven Financial Transformation Practices

As shown in **Figure 1**, the distribution of the AI-based financial transformation practices is presented in terms of low, moderate, and high adoption levels. The data suggests a general tendency towards adopting advanced AI-based financial practices. Autonomous Financial Reporting showed the largest share of high-level adoption (58.3%), followed by Predictive Financial Analytics (57.1%) and Real-Time Financial Intelligence (55.4%). The practice of Intelligent Financial Decision-Making also demonstrated relatively large high-level adoption rate (54.9%), which reflects the growing application of intelligent technologies in making financial decisions. AI-Driven Risk Prediction constituted 50.9% of high-level adoption, whereas AI-Powered Financial Forecasting was equal to 50.3%. The category of moderate adoption was significant for all practices within the range of 29.7%-34.3%, implying the continuous transition to advanced adoption levels.

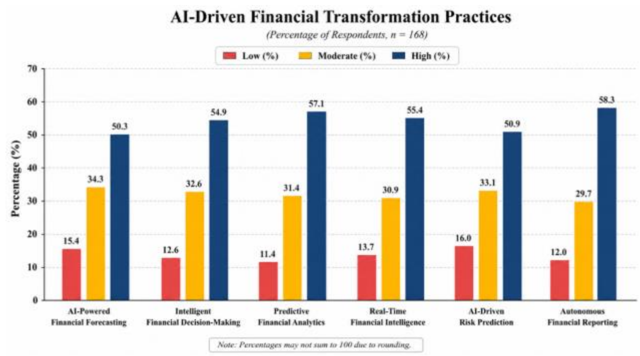
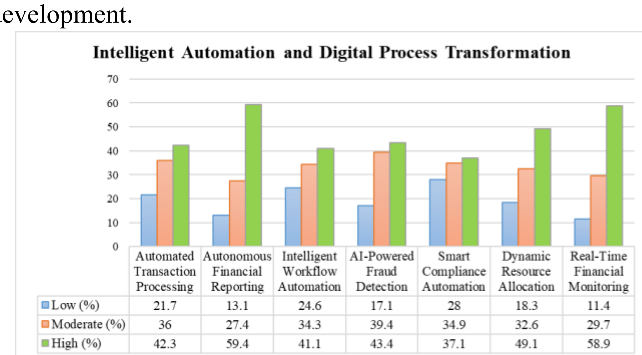


Figure 1. *AI-Driven Financial Transformation Practices*

3.4 Intelligent Automation and Digital Process Transformation

The adoption of intelligent automation and digital process transformation practices among respondents is illustrated in **Figure 2**. Autonomous Financial Reporting was found to have the largest share of high-level adoption, making 59.4%, with Real-Time Financial Monitoring close behind at 58.9%. Dynamic Resource Allocation had a relatively high rate of high-level adoption of 49.1%. AI-Powered Fraud Detection and Automated Transaction Processing constituted 43.4% and 42.3%, respectively. Intelligent Workflow Automation had a high-level adoption of 41.1%, whereas Smart Compliance Automation had the lowest high-level adoption rate of 37.1%. However, the rate of moderate adoption also remained high for all types of practices, especially for AI-Powered Fraud Detection at 39.4% and Automated Transaction Processing at 36.0%. Therefore, it can be concluded that automated reporting and real-time monitoring are the most advanced areas of intelligent financial transformation, while compliance automation and workflow automation still have some room for development.



	Automated Transaction Processing	Autonomous Financial Reporting	Intelligent Workflow Automation	AI-Powered Fraud Detection	Smart Compliance Automation	Dynamic Resource Allocation	Real-Time Financial Monitoring
Low (%)	21.7	13.1	24.6	17.1	28	18.3	11.4
Moderate (%)	36	27.4	34.3	39.4	34.9	32.6	29.7
High (%)	42.3	59.4	41.1	43.4	37.1	49.1	58.9

Figure 2. *Intelligent Automation and Digital Process Transformation*

3.5 Financial Transformation Variables and Percentage Distribution

The relative proportion of different financial transformation results as depicts in **Figure 3.** Financial Management Performance was the category with the largest proportion of 21.6%, which signifies its significant place in the entire process of transformation. Financial Decision Intelligence followed with 18.7%, which shows the significant attention to the quality of decisions made through technology in finance. Risk Management Effectiveness was another category with a proportion of 17.4%, which highlights the significance of intelligent technologies in the identification and management of financial risks. Financial Forecasting Accuracy and Cost Optimization followed with proportions of 15.9% and 13.8%, respectively. Financial Agility had the smallest proportion of 12.6%, which is still an important dimension of financial transformation.

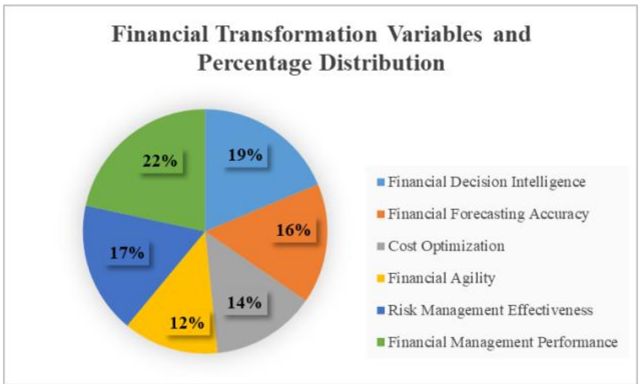


Figure 3. *Financial Transformation Variables and Percentage Distribution*

3.6 Correlation Matrix of Study Variables

Pearson correlation matrix between the six research variables as presented in **Table 3.** As shown from the results, it is evident that all variables have positive correlation implying a very strong interconnectedness of AI-enabled financial transformation. The highest correlation coefficient (0.809) was seen between Financial Decision Intelligence and Financial Management Performance, meaning that financial decision-making supported by technology is directly linked to the financial management performance. Also, there was a high correlation (0.781) between Intelligent Automation and Financial Decision Intelligence while Predictive Analytics Capability was highly correlated (0.769) with Financial Decision Intelligence. There were also strong correlations (0.751 & 0.756) between Digital Process Integration and Financial Management Performance as well as Financial Decision Intelligence. Lastly, there was positive correlation of AI Capability with other constructs especially Financial Decision Intelligence (0.746). From the results, it can be seen that AI capabilities, automation, predictive analytics and digital processes are very strongly interconnected with intelligent financial decision-making and financial management performance.

Table 3*. Correlation Matrix of Study Variables*

Variables	AIC	IA	PAC	DPI	FDI	FMP
AIC	1.000					
IA	.684	1.000				
PAC	.721	.657	1.000			
DPI	.612	.638	.704	1.000		
FDI	.746	.781	.769	.756	1.000	
FMP	.681	.724	.716	.751	.809	1.000

AIC = AI Capability; IA = Intelligent Automation; PAC = Predictive Analytics Capability; DPI = Digital Process Integration; FDI = Financial Decision Intelligence; FMP = Financial Management Performance.

4. Discussion

The results confirm that the role of artificial intelligence and intelligent technology is becoming increasingly significant in today's financial management systems. The participant profiles provide an educated and professional sample that serves as a valid sample for assessing financial transformation through technology[19]. The descriptive results show a rather positive attitude towards the capabilities that can be provided by the application of AI. Digital Process Integration showed the highest mean at 3.91, which means that connection between financial systems and flow of information are very important elements of today's financial system. Financial Management Performance had a mean score of 3.89, proving the relationship between digital transformation and financial success. Predictive Analytics Capability had a mean of 3.88 and proves that forward-looking financial intelligence becomes more important. Intelligent Automation received the lowest mean score of 3.76, which means that automation is more difficult to implement. Negative skewness shows an inclination towards more positive attitude to the importance and implementation of the AI financial capabilities(Hrustek, 2020;Cao et al., 2021).

The identified findings on financial transformation practices show a distinct trend towards more advanced and intelligence-focused application areas. Autonomous Financial Reporting reached 58.3% at the high level, indicating that automated reporting is becoming a common element of digital financial transformation. Predictive Financial Analytics amounted to 57.1%, implying a strong interest shown by organizations in applying their data and intelligent algorithms in order to make forecasts and plans. Real-Time Financial Intelligence showed 55.4%, indicating that an organization pays particular attention to the availability of information about its financial status. Thus, AI application is especially pronounced when it allows increasing the accessibility of information, reducing the reporting period and improving analytical opportunities[21]. Meanwhile, some process-related areas show slower development rates, which indicates that the transformation cannot rely only on the availability of technology[22]. It may be influenced by employee readiness, digital infrastructure, process improvement, data quality, management support and organizational capacity to integrate intelligent systems into existing financial processes[23]. Thus, it can be assumed that currently ongoing transformation proceeds not only from automation to a new model featuring predictive intelligence and constant monitoring of financial situations and automatic financial information generation[24].

The correlation results present additional evidence that the technological factors of the financial transformation process are highly related to decision-making quality and performance results. The highest correlation coefficient of 0.809 was found between Financial Decision Intelligence and Financial Management Performance, proving that decision intelligence is one of the key factors in transforming technological capabilities into financial results. The correlation coefficient of 0.781 shows the connection between Intelligent Automation and Financial Decision Intelligence. This means that by applying automated solutions, companies can benefit from improving the quality of information necessary for making the right decision. Predictive Analytics Capability was correlated with Financial Decision Intelligence at 0.769, proving the significance of predictive capabilities in assisting the management in their decisions. It is evident that artificial intelligence cannot be treated as a separate technological tool but as a complex capability consisting of automation, analytics, digital integration, and decision intelligence[25], [26]. By integrating all these capabilities, companies can improve their information processing speed, increase the quality of predictions, understand risks better, and make informed financial decisions.

5. Conclusion

This study shows that artificial intelligence and intelligent automation are transforming the current financial management practice in terms of predictive, integrated, and data-driven capacity. From the study, it is apparent that there are good developments in digital process integration, predictive analysis, and financial management performance. Reporting, forecasting, and real-time intelligence with the use of AI are significant aspects of the current financial transformation. The correlation analysis reveals a strong relationship between financial decision intelligence and financial management performance, stressing the significance of intelligent decision-making.

Author Contributions

M.Y.A. conceptualized and designed the study, developed the methodology, conducted the data collection and analysis, interpreted the results, and drafted the original manuscript. N.U contributed to the study design, data interpretation, critical revision of the manuscript, and overall supervision. Both authors reviewed and approved the final version of the manuscript.

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