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Article

Data Analytics Capability for Improving Financial Decision-Making and Organizational Performance

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Abstract: The fast integration of digital technology has transformed the financial management process and made the capacity to use analytics more important in decision making and organizational performance. Nevertheless, the joint impact of analytics capability, data quality, technology integration, financial decision making, and risk management is still under researched. A quantitative cross-sectional research design with a USA-based online survey of 155 respondents having financial, analytical, technological, and managerial background knowledge was conducted. The data were gathered through a structured survey instrument with five-point Likert scale variables of Data Analytics Capability, Data Quality and Accessibility, Analytical Technology Adoption, Quality of Financial Decision Making, Financial Risk Management Capability, and Organizational Performance. The Financial Decision-Making Quality variable had the highest mean score of 4.21, followed by Data Analytics Capability with a mean score of 4.18 and Organizational Performance with a mean score of 4.16. The Data Analytics Capability variable had strong positive correlations with the Financial Decision-Making Quality variable at r = .746 and with the Organizational Performance variable at r = .693. The Financial Decision-Making Quality variable had the highest value of beta (β) coefficient of .241 followed by the Data Analytics Capability variable with a beta (β) coefficient of .214 and Financial Risk Management Capability with a beta (β) coefficient of .203. The model explained 70.6% of the variance in Organizational Performance. Data analytics capability is an important organizational resource that enhances financial decision-making and organizational performance.

Keywords: Data Analytics Capability, Financial Decision-Making, Organizational Performance, Predictive Analytics, Financial Risk Management

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1. Introduction

The fast-growing use of digital technologies in the process of organizations' functioning has changed the basis of modern financial management. Analytics has increasingly become viewed as not only the technology but also an organizational tool helping companies turn financial and other operations information into useful managerial insights [1]. The growing presence of digital data, cloud-based architectures, artificial intelligence, predictive analytics, and automated business intelligence has significantly expanded the ability of the company to track its financial state, to forecast possible risks and to allocate resources more efficiently [2]. Hence, the efficiency of analytics development and use by the company has become crucial for making financial decisions [3]. Nevertheless, the problem is in the necessity of turning data into the valuable information. Data quality and availability are crucial for successful analytics because poor or incomplete data may cause incorrect results and poor financial decisions [4]. On the other hand, the use of analytics technology has an impact on the effectiveness of information conversion to intelligence by organizations [5]. Such technologies as real-time analytics, predictive modeling, automated reporting, and business intelligence systems can be used to overcome lags in the provision of information and make an organization more responsive to changes [6]. Such features are especially important in complex financial environment where decision-makers need to constantly consider different factors like changes in the market, uncertain operations, availability of resources and possible financial risks [7].

The connection between the capabilities for analytics and the performance of an organization can also work through the quality of financial decision-making and financial risk management capability [8]. The decisions in financial sphere become increasingly complicated in terms of the necessity to integrate different sources of information, scenario analysis and predictions [9]. With the help of analytics, it is possible to improve forecasts, discover some patterns which can stay unnoticed using traditional approaches and provide better financial management of the resources. In turn, risk management based on data can improve the capacity of the organization to discover, analyze, monitor and mitigate financial risks [10]. While much academic and business interest exists regarding digital transformation, there is still an empirical gap that needs addressing. Previous literature has tended to investigate one aspect such as the adoption of analytics, data quality, decision-making, or organizational performance independently [11]. Little consideration has been given to the investigation of these aspects concurrently in an integrated finance management model. More specifically, empirical insights have not been provided regarding whether there are unique effects of each component including data analytics capability, data quality and availability, technology adoption, decision-making quality, and risk management capabilities towards organizational performance [12]. This is crucial as technological investments do not guarantee organizational performance; instead, the performance might be based on the interaction between all of the above [13].

In view of the above context, the current research study attempts to propose and empirically test an integrative model between six constructs: Data Analytics Capability, Data Quality and Accessibility, Adoption of Analytical Technologies, Financial Decision-Making Quality, Financial Risk Management Capability, and Organizational Performance. This study employs an online survey involving 155 respondents from the USA and employs descriptive statistics, Pearson correlation, and multiple linear regression techniques to assess the relationship between these constructs. The current study makes a contribution to the existing literature in the way that it looks at the issue of data analytics from the point of view of finance management. It tests empirically if there is any performance impact associated with data analytics capability development.

2. Materials and Method

2.1 Research Design and Study Context

The study in question used a quantitative cross-sectional research design to empirically investigate the connection between data analytics capabilities and organizational performance with regard to financial management. The survey was carried out among individuals working within the United States using an online survey technique. The conceptual model included six interrelated constructs such as Data Analytics Capability, Data Quality and Accessibility, Adoption of Analytical Technologies, Quality of Financial Decision-Making, Financial Risk Management Capability, and Organizational Performance [14]. The conceptual model was designed to find out whether companies that have higher capabilities for analysis and adoption of technology can use financial information more effectively, make quality decisions, manage risks more efficiently, and thus perform better organizationally [15]. The cross-sectional design was chosen since the goal of the study was to investigate the perception of the participants at a certain moment in time.

2.2 Population, Sampling, and Data Collection

The study population comprised of professionals in the United States who had experience in the following areas: financial management, accounting, business analytics, risk management, corporate management, information systems, and organizational decision making. Primary data was collected via a structured online survey using a purposive sampling technique that ensured that all respondents had professional knowledge in any of the selected fields. A total of 180 questionnaires were sent out via e-mail, and 155 valid and completed questionnaires were collected for use in the analysis, representing an 86.1% response rate. Respondents were qualified if they had exposure to any of the decision-making areas of finance, analysis, technology, or organizations. The survey asked demographic questions on gender, age, education, and professional experience. All the received questionnaires were screened for completeness and validity before being included in the analysis.

2.3 Measurement Instrument and Study Variables

The data were collected through the administration of a structured questionnaire that was designed to capture the demographic characteristics of the respondents, and multiple measurement items reflecting the constructs being studied. The substantive constructs were measured through a five-point Likert scale ranging from 1=strongly disagree to 5=strongly agree. Data Analytics Capability was used to measure the organizational capability for collecting, processing, analyzing and interpreting data for management and financial decision-making purposes [16]. Data Quality and Accessibility was used to measure the accuracy, completeness, consistency, timeliness and accessibility of organizational data [17]. Analytical Technology Adoption was used to measure the level of adoption of real-time analytics, predictive analytics, automated business intelligence and integrated analytical technologies by the organizations. Financial Decision-Making Quality was used to measure the accuracy, timeliness, consistency and evidence-based nature of financial decision-making [18]. Financial Risk Management Capability was used to measure the capability of organizations to identify, assess, monitor and mitigate financial risks. Organizational Performance was used to measure perceived increases in decision efficiency, forecasting accuracy, resource allocation and financial risk management capability [19].

2.4 Statistical Analysis

The statistical analysis was done using a systematic four-step process. Descriptive statistics were used as the first step to describe the demographic profile of the respondents and the distribution of the study constructs [20]. Categorical variables were described by frequency counts and percentage distribution, while descriptive statistics such as mean, standard deviation, variance, and coefficient of variation were calculated for the key study constructs [21]. Second, the Pearson correlation analysis was carried out to determine the direction and strength of the linear relationships between the six study constructs. Multiple linear regression analysis was used in the third step to determine the independent effects of the six constructs on organizational performance [22]. Standardized regression coefficients, standard errors, t-values, p-values, R2, Adjusted R2, and overall F-statistic were generated through the analysis. Variance analysis was not part of the last analysis technique used. Internal consistency and multi-collinearity were checked before carrying out regression analysis [23].

3. Results

3.1 Demographic Characteristics of Respondents

A demographic profile of the 155 professionals participating in the online survey conducted in the USA is presented in Table 1. In the demographic terms, the sample was predominantly composed of male respondents, which accounted for 60.6%. The largest age group was represented by the respondents between the ages of 35-44 years old accounting for 37.4%, which points to significant involvement of established and working professionals. In terms of educational qualification, the level was relatively high since 50.3% of the sample held a Master's degree, which points to high academic qualification of the sample. Professional experience was also relatively high with 32.9% of the sample having 11-20 years of experience and 30.3% of the sample with 5-10 years of experience. Therefore, one can say that the demographic profile reveals high academic and professional qualifications of the sample, which allows making a good evaluation of data analytics and financial management.

Table 1. Demographic Characteristics of Respondents

Characteristic	Category	n	%
Gender	Male	94	60.6
	Female	61	39.4
Age	25–34 years	32	20.6
	35–44 years	58	37.4
	45–54 years	41	26.5
	≥55 years	24	15.5
Education	Bachelor's degree	35	22.6
	Master's degree	78	50.3
	Doctoral degree	29	18.7
	Professional qualification	13	8.4
Experience	<5 years	28	18.1
	5–10 years	47	30.3
	11–20 years	51	32.9
	>20 years	29	18.7

3.2 Descriptive Statistics of Study Constructs

Descriptive characteristics of the six study constructs as provides in Table 2. From the results, the constructs have fairly high averages across the board, averaging between 4.05 to 4.21. Financial Decision Making Quality was the highest construct with an average of 4.21, followed by Data Analytics Capability with an average of 4.18 and Organizational Performance with an average of 4.16, indicating very high perceptions of data analytics capability and financial decision quality. The lowest average in terms of all the constructs is for Data Quality and Accessibility, which is at 4.05, albeit still fairly high. Relative variation was moderate across all the constructs, with standard deviation values ranging between 0.58 to 0.66. Financial Decision Making Quality had the lowest relative variation, indicated by the lowest coefficient of variation of 13.78%. On the other hand, Data Quality and Accessibility has the highest relative variation at a coefficient of variation of 16.30%.

Table 2. Descriptive Statistics of Study Constructs

Construct	Mean	SD	Variance	CV (%)
Data Analytics Capability	4.18	0.61	0.372	14.59
Data Quality & Accessibility	4.05	0.66	0.436	16.30
Analytical Technology Adoption	4.12	0.64	0.410	15.53
Financial Decision-Making Quality	4.21	0.58	0.336	13.78
Financial Risk Management Capability	4.09	0.63	0.397	15.40
Organizational Performance	4.16	0.62	0.384	14.90

SD = standard deviation; CV = coefficient of variation.

3.3 Data Analytics Capability and Financial Management Effectiveness

There is the perceived effectiveness of six analytical dimensions as depicted in Figure 1. Real-Time Analytics ranked the highest with highly effective perception rate of 53.7%, while Automated Business Intelligence rated 46.1%. Financial Risk Analytics and Financial Data Integration scored highly effective rates of 40.5% and 38.5%, respectively. Data Quality and Accessibility received the rate of 33.6% under highly effective and 22.6% need improvement. Predictive Analytics received the least highly effective score of 28.5% and the highest need for improvement of 27.4%. Satisfactory score varied from 34.5% for Real-Time Analytics to 44.1% for Predictive Analytics, indicating significant variations in the perceptions regarding the effectiveness of the analytical dimensions. The higher performance of real-time analytics points to higher actual use of analytical information compared to other categories, while the low effectiveness of predictive analytics implies higher room for improvement. Financial risk analytics had a moderate level of effectiveness with 35.4% satisfactory perception rate.

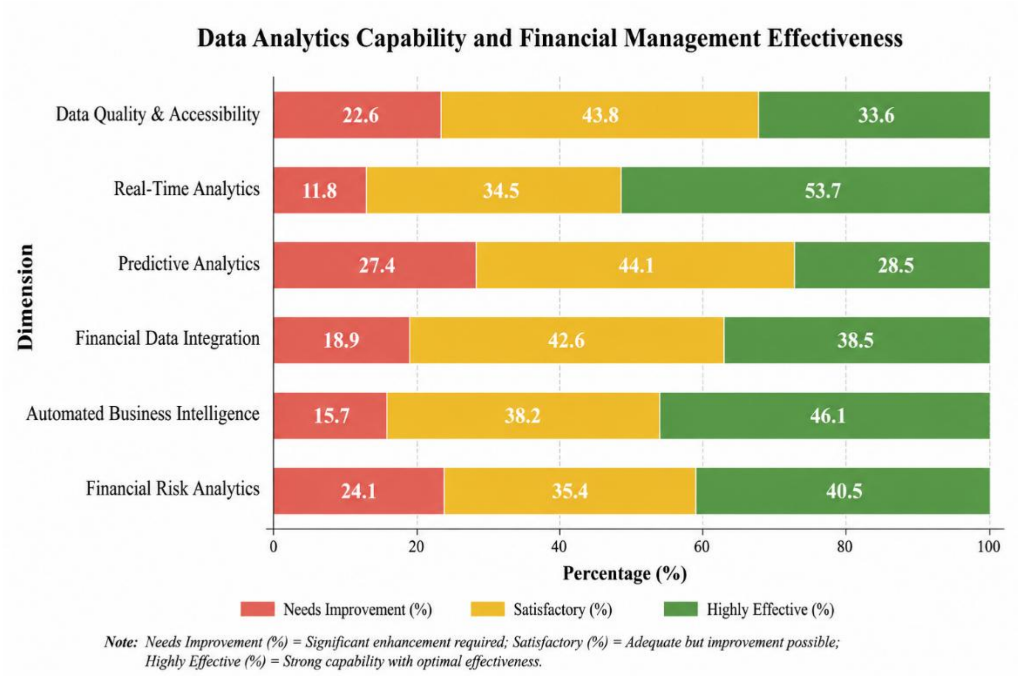

Figure 1. Data Analytics Capability and Financial Management Effectiveness

3.4 Perceived Organizational Outcomes of Data Analytics

The high-level and low-level organizational outcomes related to analytics based on the six performance dimensions illustrates in Figure 2. Faster Financial Decisions is ranked first in terms of high-level outcomes with 62.7%, implying a high level of contribution made by analytics in decision making. The next in line is Organizational Performance with 54.7%, whereas Financial Risk Management and Forecasting Accuracy have 51.7% and 51.3%, respectively. High-level outcome for Risk Identification is relatively lower at 45.2%, while 18.6% of participants reported low-level outcome for Risk Identification. Low-level outcome for Resource Allocation is the highest among all others with 21.4% while high-level outcome for Resource Allocation is 42.9%. This implies a relatively higher variation in contributions to resource-related decisions made by analytics. In addition, moderate outcomes vary between 28.6% and 36.2%, with Risk Identification being the highest among the six performance dimensions.

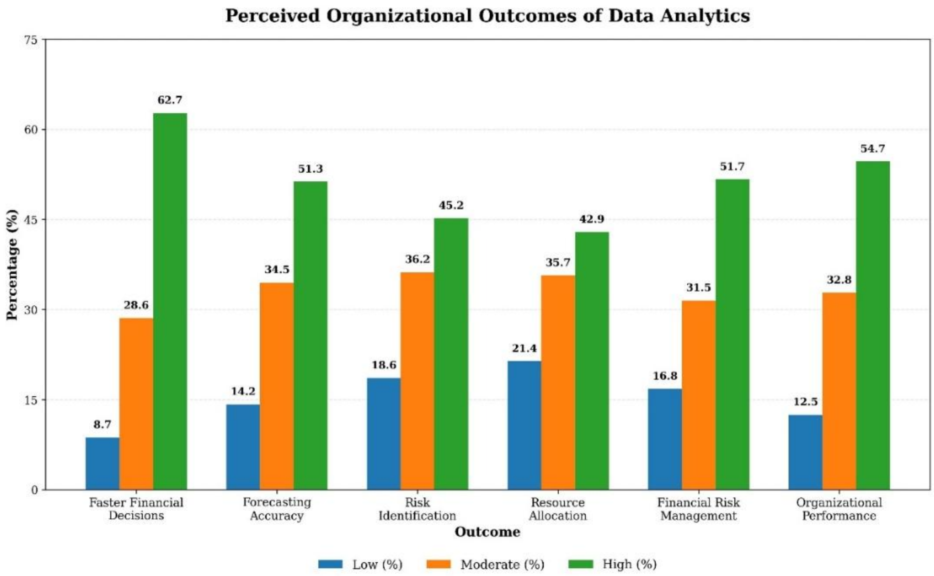

Figure 2. Perceived Organizational Outcomes of Data Analytics

3.5 Pearson Correlation Matrix of Study Constructs

The correlation coefficients between the six constructs under study are presented in Figure 3 below. It can be noticed that all the correlations found were positive and statistically significant, which indicates high relationships among analytics capabilities, financial management practices, and organizational performance. The highest relationship is that between Data Analytics Capability and Financial Decision-Making Quality, r = .746, and the second one is that between Financial Decision-Making Quality and Financial Risk Management Capability, r = .734. There is a very high relationship between Financial Decision-Making Quality and Organizational Performance, r = .731, as well as Financial Risk Management Capability and Organizational Performance, r = .716. Data Analytics Capability is highly related to Analytical Technology Adoption, r = .721, and Organizational Performance, r = .693. The lowest relationship is observed between Data Quality and Accessibility and Organizational Performance, r = .617.

Pearson Correlation Matrix of Study Constructs

Variables	DAC	DQA	ATA	FDQ	FRMC	OP
DAC	1.000					
DQA	.684	1.000				
ATA	.721	.638	1.000			
FDQ	.746	.652	.709	1.000		
FRMC	.712	.625	.681	.734	1.000	
OP	.693	.617	.674	.731	.716	1.000

Note: DAC = Data Analytics Capability; DQA = Data Quality & Accessibility; ATA = Analytical Technology Adoption; FDQ = Financial Decision-Making Quality; FRMC = Financial Risk Management Capability; OP = Organizational Performance.

Figure 3. Pearson Correlation Matrix of Study Constructs

Note: DAC = Data Analytics Capability; DQA = Data Quality & Accessibility; ATA = Analytical Technology Adoption; FDQ = Financial Decision-Making Quality; FRMC = Financial Risk Management Capability; OP = Organizational Performance.

3.6 Multiple Linear Regression Predicting Organizational Performance

The multiple linear regression findings for Organizational Performance are displayed in Table 3. The regression results revealed that the model has high explanatory power, where $R^2 = 0.706$ and adjusted $R^2 = 0.696$, showing that the predictor variables accounted for a significant portion of the variance in organizational performance. The overall model had high statistical significance, where $F = 71.62$. Financial Decision-Making Quality turned out to be the best predictor, where $\beta = 0.241$, signifying the importance of sound financial decision-making in organizations. Data Analytics Capability was another significant predictor, where $\beta = 0.214$, showing its considerable influence on performance. Another important dimension was Financial Risk Management Capability, where $\beta = 0.203$, while the contribution of Analytical Technology Adoption was $\beta = 0.187$. On the other hand, the contribution of Data Quality and Accessibility was relatively lower, where $\beta = 0.126$. Thus, it is clear that financial decision quality, analytics capability, and risk management capability are some of the most significant dimensions in relation to organizational performance, and there are other factors too.

Table 3. Multiple Linear Regression Predicting Organizational Performance

Predictor	β	SE	t	p-value
Data Analytics Capability	0.214	0.067	3.19	0.002
Data Quality & Accessibility	0.126	0.059	2.14	0.034
Analytical Technology Adoption	0.187	0.064	2.92	0.004
Financial Decision-Making Quality	0.241	0.065	3.71	<0.001
Financial Risk Management Capability	0.203	0.061	3.33	0.001
R^2		0.706		
Adjusted R^2		0.696		
F-statistic		71.62		

Dependent variable = Organizational Performance; n = 155. β = standardized regression coefficient; SE = standard error.

4. Discussion

The study has revealed that data analytics is becoming an essential part of financial management and performance. The indicator with the highest mean value is Financial Decision-Making Quality, having 4.21, followed by Data Analytics Capability, equaling 4.18, indicating positive opinions regarding the use of analytics for financial activities. Meanwhile, the effectiveness evaluation of Real-Time Analytics was the highest, whereas that of Predictive Analytics had comparatively more room to improve. The distinction might imply that companies are currently receiving more practical use out of the current analytical data than from the predictive capabilities [24]. It is additionally notable that Data Quality and Accessibility had the comparatively lowest mean value of 4.05, indicating the necessity of having good-quality and accessible financial information. Overall, these results indicate that the effectiveness of analytics is dependent not only on analytical capabilities but also on the quality of information available for the financial analysis [25]. The perceived organizational outcomes give additional insights on the practical importance of data analytics. Faster Financial Decisions proved to be the strongest high-level outcome with the share of 62.7% since respondents mostly recognized analytics as an instrument for making faster decisions. Organizational Performance was also positively estimated, while Financial Risk Management and Forecasting Accuracy gave clear high-level outcomes. Thus, it can be said that analytics allows managers to use financial information in a more effective way and adapt to the changes in the organization's environment [26]. The Resource Allocation turned out to have a rather low level of positive response that can indicate different contributions of analytics to various managerial activities. Similar situation is observed for Risk Identification where higher variability can be explained by the complexity of the evaluation of financial risks and further managerial actions [27]. Therefore, analytics proves to be more beneficial for the activities that are connected to the usage of information in decision making than for other tasks.

The correlation results further highlight strong relationships amongst the main constructs used in this study. There were strong correlations between Data Analytics Capability and Financial Decision-Making Quality (r = .746), between Financial Decision-Making Quality and Financial Risk Management Capability (r = .734), and between Financial Decision-Making Quality and Organizational Performance (r = .731). These strong correlations reveal that there is a high level of connection between stronger analytical capabilities and financial decision-making process and organizational performance. There was a strong correlation between Financial Risk Management Capability and Organizational Performance, which highlights the significance of efficient risk management practices in the case of data driven financial management [28]. A strong correlation was also found between Data Analytics Capability and Organizational Performance, revealing the importance of analytical capability in the process of organizational performance. On the other hand, there was weaker correlation between Data Quality and Accessibility and Organizational Performance [29]. It means that the mere availability of information may not have an impact on organizational performance if organizations do not have the required capability to analyze and manage that information [5].

The findings of the regression analysis help in gaining more insights on the contribution of the variables under consideration. The model accounted for 70.6% of variance in Organizational Performance, having an adjusted R^2 of 0.696. Thus, it can be concluded that the regression equation is highly explanatory. Financial Decision-Making Quality has turned out to be the best predictor, having a β value of 0.241. Data Analytics Capability had the second highest β value of 0.214, followed by Financial Risk Management Capability having a β value of 0.203. Analytical Technology Adoption was a good contributor, having a β value of 0.187. Data Quality and Accessibility was not such a great contributor, as it only had a β value of 0.126. The model was statistically significant, having $F = 71.62$. This implies that the contribution of Financial Decision-Making Quality is the greatest; hence, the analytical resources contribute to organizational performance in case they are well incorporated in the financial decision-making process [11]. On the whole, the empirical evidence points to a position where it may be argued that the role of data analytics in supporting the performance of organizations operates via a network of financial and managerial determinants. The empirical support for the theory is found in regard to financial decision making, analytical and risk-management capabilities [30]. The issue of technology adoption also plays a role, yet in conjunction with other factors, it seems to have a greater significance for organizational performance [23]. It follows from the obtained findings that an organization should pay attention not only to obtaining data analytics technology, but also to building up capabilities related to interpretation of financial data and analytics application to decision making. Data quality also plays a role in this case, though a minor one compared with other factors considered.

5. Conclusion

The This study provides an understanding of the contribution of data analytics to the field of finance management and organizational performance. Financial Decision-Making Quality was the variable which emerged as the most dominant variable, followed by Data Analytics Capability and Financial Risk Management Capability. The multiple regression analysis accounted for 70.6% of the total variation in Organizational Performance, showing high explanatory power of the model. The results show that data analytics adds more value if it is done in conjunction with effective financial decision making and risk management.

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