Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 3

ISSN: 1540-3270

Examining Behavioural Intention of Future Managers to Use Big Data Analytics in Management Accounting

Vitin Kumar[1], Prof. (Dr.) Vinod Kumar Singh[2], Preeti Sonker[3]

[1]Research Scholar, Faculty of Management Studies, Gurukula Kangri (Deemed to be University), Haridwar, Uttarakhand, India

[2]Professor, Faculty of Management Studies, Gurukula Kangri (Deemed to be University), Haridwar, Uttarakhand, India drvksingh@gkv.ac.in

[3]Assistant Professor, School of Business Studies, Jigyasa University, Dehradun, Uttarakhand, India

Corresponding Author:

Vitin Kumar

Abstract

The explosion of corporate data has transformed how modern organizations approach strategic decision-making. This paper empirically examines the relevant factors influencing the behavioural intention of future managers to use big data analytics in management accounting. Adopting a quantitative approach, primary data from 167 final year MBA students was collected. The research utilizes the UTUAT framework alongside PLS-SEM and R programming. The findings present a robust model demonstrating significant explanatory power regarding both positive and negative factors that directly influence behavioural intention. Effort expectancy, facilitating conditions, and broader social influence were successfully identified as significant driving factors. Interestingly, performance expectancy and user resistance were conclusively determined to be statistically insignificant positive and negative factors in this study. The practical implications provide actionable inputs for industry leaders, practitioners, academic and professional institutions to evolve appropriate strategies for leveraging BDA in management accounting.

Keywords: Big Data Analytics, Management Accounting, Behavioural Intention, Structural Equation Modelling, Decision Science, Future Managers.

Introduction

Technological innovations in computers and informatics have altered the nature and dynamics of management accounting activities. The advent of IOT, cross-integration of business-related data from various entities, coupled with social feeds and live streaming, leads to the emergence of heterogeneous data reservoirs. By virtue of volume, velocity, and variety, the current form of datasets is different from traditional datasets, and legacy systems have become inappropriate for handling, processing, and extracting requisite decision-oriented information from these data sources. Collectively, data with three basic attributes, namely volume, velocity, and veracity, are referred to as 'big data'. Big data has emerged as one of the most valuable assets in the business world. As per the Mint report (A leading Indian business daily), the spending of Indian enterprises on big data has reached the USD 2 billion mark in 2021 and is likely to grow with a five-year CAGR of 14.6 percent over the forecasted period, 2020-25. Data is the new oil or gold and a valuable strategic business resource. It is valuable, but one cannot really use it directly, as about 80% of the data of any business enterprise is either semi-structured or unstructured. It requires proper refining and to be broken down by loading into an appropriate database management system for extracting the values from it in the form of hidden patterns and actionable insights to address the business-related problems (Alharthi et al., 2017). The advent of cloud computing and advanced big data analytics tools such as APACHE Hadoop, Cassandra, Qubole, Xplenty, Spark, MongoDB, Data Pine, Rapid Miner, etc., makes it possible to handle big data and draw inferences, actionable insights, and unsurfaced hidden patterns on a near-real-time basis. Big data analytics (BDA) transforms the raw data into descriptive, diagnostic, predictive, and prescriptive analytics. BDA empowers data-driven decision makers to have a deeper understanding of supply and demand patterns and their underlying drivers to make informed decisions (Irfan & Wang, 2019). Analytics will play a vital role in the future of finance, so finance managers, management accountants and other finance professionals will be benefited.

The modern management accounting domain encompasses a comprehensive strategic orientation that focuses on the identification, measurement, and management of the entire operational dynamics for enhancing stakeholders' value. Being a data-driven domain, it has to gain much from big data analytics technology. It could enable the management accountants to move beyond their legacy framework to data-oriented decisions. The new heterogeneous data sources provide opportunities and challenges, particularly professional working in data rich domain like management accountants (Tiron-Tudor & Deliu, 2021). Analytics will define the difference between the losers and winners going forward.

Several descriptive and experimental studies have pointed out that despite promising technological leverage, the management accountants have not leveraged big data analytical opportunities. Spraakman et al., (2021) findings include expanding the role of management accountants due to BDA capabilities in decision making, management accountants have not reaped the full benefits from data analytic opportunities and activities confined to descriptive level analysis only. Much use of internal data analysis is prevalent in the practices, rather than applying complex analysis such as simulation and complex modelling with integration of operational and external data simultaneously. Reasons include inappropriate technical training, technical complexities associated with technology, expected effort required, performance level, organizational culture, regulatory regime, concerns with potential job losses, accidental exposure of data, reluctance to accept challenges, and behavioural intention to use BDA (Grosu et al., 2023).

Theoretically, the Resource-Based View suggests that data-driven capabilities like BDA are valuable organizational resources to achieve sustained competitive edge (Barney, 1991). Previous studies examined BDA acceptance and its use in real-world situations with different perspectives. For example, (Tambuskar et al., 2024) investigated BDA in Indian sustainable supply chain management, (Sharma et al., 2023) assessed the factors affecting BDA and its impact on the performance of the Indian tourism and hospitality sector, and (Lutfi et al., 2022) conducted a case study on Jordanian SMEs to examine factors related to BDA adoption. (Dubey et al., 2017) examined the role of big data analytics with reference to sustainable consumption, (Vysotskaya & Prokofieva, 2025) identified strategies for incorporating data analytics technologies in teaching management accounting. (Saud et al., 2025) investigated key determinants responsible for auditors' intentions to adopt BDA technology in public sector audit practices. These works significantly improved the literature and gauged the BDA adoption and implementation in real-world situations (Andrew McAfee; Erik Brynjolfsson, 2012). Despite all these facts and growing knowledge, some important research gaps remain unaddressed.

The majority of empirical studies on BDA adoption and its use concentrate on the organizational level, targeting working employees or IT professionals. Very limited evidence available in the literature which focuses on future business managers, particularly master's level business administration students, who are expected to work in these organizations tomorrow and have to play a very crucial role in the strategic decision process through technological innovations. While user acceptance of technology was examined by previous researchers utilizing theoretical models such as the Technology Acceptance Model (TAM) (Davis, 1989), these were largely confined to organizational-level environments. The perception and understanding of management students to adopt and use big data technologies in educational settings were largely overlooked. Besides this, most of the work has been conducted in developed countries. Relatively few studies are available on BDA adoption, focusing on emerging economies such as India, owing to IT infrastructural constraints, technical competency, and cost barriers (Wamba et al., 2017). Further, the outcome of research conducted in developed economies cannot be plainly applied in the context of developing countries. This demands context-specific research. Although behavioral intention was considered as a strong predictor in technology actual uses (Davis, 1989), very little work is available in the literature with reference to individuals who are likely to enter managerial roles in the near future. A theoretical gap further exists in educational learning and practical capabilities, and a need is felt to empirically examine whether MBA students acquired the necessary technical skills and practical exposure to deal with big data analytics applications in real-world situations. Current academic curricula and industry requirements may have some misalignment due to the ever-faster pace of technological advancement and industry requirements. Therefore, this study comprehensively explores the above-stated gap contributing to the body of knowledge and practices.

Literature Review

Big data and big data analytics

There is no universal definition of 'big data' in terms of description or threshold. Researchers and practitioners differently interpreted it; all approaches converged to voluminous and heterogeneous characteristics of data, and traditional information systems cannot handle and process the request. Big data possesses all the properties of data itself, extended with semi-structured and unstructured formats. 'Big data' differs from traditional transactional data in three basic attributes, namely volume, velocity, and variety (3Vs) (Hamdam et al., 2022). Over the period, a few more attributes were added, such as veracity, value, viscosity, variability, validity, and visualization for defining the term better. Big data reservoirs, even though superior and information-rich, have no meaning unless proper analysis tooling is in place. BDA refers to extracting values from data reservoirs, finding specific patterns, and supporting the decisions (Razaghi & Shokouhyar, 2021, Murad et al., 2022). BDA is an umbrella term covering appropriate tooling and methods for handling and processing big data and providing actionable insights. BDA enables organizations and institutions to extract meaningful information, actionable insights, and inferences from heterogeneous data reservoirs. Use of BDA offers improved operational dynamics, superior competitive positioning, and is regarded as one of the most implemented modern technologies in the business world (Akter et al., 2016; Lutfi et al., 2023). With a BDA-enabled environment, decision makers can peep into supply and demand patterns and add value to the economic chain through informed decisions (Irfan & Wang, 2019). BDA accumulates and evaluates financial and non-financial data on a real or nearly real-time basis, and business managers can intervene concurrently in the decision environment (Munir et al., 2023).

Big data analytics and management accounting: The Institute of management accountants conducted two survey-based studies to identify the ways of using data analytics in management accounting practices. The findings revealed that more than half of the surveyed population believed that the finance and accounting processes have changed or are going to change dramatically with technological advancements, such as big data analytics. About 2/3 of respondents agreed that using analytics would result in a competitive edge, but about half of the surveyed population was struggling with its actual use in real projects. From a management accounting perspective, BDA provides deeper data-driven insights for improved decision making, helps in better budgeting and accurate sales forecasts, identifies inefficiencies and redundant tasks for implementing prudent cost controls, detects fraud, mitigates financial risk, and supports strategic planning for different time horizons. Performance measurement is one of the core activities of the management accounting domain. Management accountants are always concerned about operational performance, resource utilization, cost of quality, and customer-centric values. Big data analytical capabilities offer promising insights within the data available through exquisite visualization. Management accountants, with the aid of powerful analytical tools, can find and plug wasteful resources, rationalize the cost of quality, and render value-based customer-centric solutions. Another dimension of big data analytics capability is in supply chain management, where management accounting practices such as just-in-time, Kaizen costing, and lean manufacturing are going to gain much (Lutfi et al., 2023). Big data contains a substantial amount of non-financial data originating from internal and external sources. With the aid of analytical capabilities, management accountants are in a position to formulate robust strategies not only with financial numbers, but also in front of corporate accountability, governance, and risk management. The role of management accountants has changed from strategic advisor to strategic partner in business processes due to the shifting of financial-data-driven strategic formulation to decision-driven strategic formulation (Varma, 2018, Ramachandran, 2019; Varma et al., 2021). Alrashidi (2022) found a positive relationship between the use of big data analytics and audit attributes, namely audit planning, evaluation of control systems, performing the preliminary analytical review procedures, initial levels of materiality, audit risk, and accepting the audit task. These findings are equally important for management audit also.

BDA use in management accounting

Despite strong advocacy of BDA benefits to the companies in the decision-making process, its adoption and use in real projects carry several hindrances. It includes a range of actors such as infrastructure readiness, compatibility with existing IT resources, complexity, organizational culture, lack of appropriate skillset, fear of technology, and job losses (Yaqoob et al., 2016; Gong & Janssen, 2021). Schmidt et al. (2020) based on a survey study on 192 working accountants, concluded that switching benefits and perceived value act as a single factor to mitigate resistance, while switching costs directly increase the user resistance. Further, researchers found that some accounting professionals were resisting adopting new analytics technology. User resistance is a crucial factor for BDA adoption, and managerial support is critical to mitigate user resistance (Maroufkhani et al., 2023, Moraes et al., 2022). Varma et al., (2021) pointed out that there is a growing academic interest in the 'big data and accounting theme'; however, 'BDA and management accountancy' was largely overlooked in the literature.

Unified theory of acceptance and use of technology (UTAUT) in BDA adoption

UTAUT is a comprehensive technology acceptance framework, ideal for behavioural studies, as it integrates the previous eight research models. UTAUT accommodates the fundamental features of the technology acceptance model (TAM), theory of reasoned action (TRA), motivation model (MM), theory of planned behaviour (TPB), TAM-TPB hybrid model, PC utilization model, innovation diffusion theory, and social cognitive theory. UTAUT measures 'intention to use' a behavioural dimension with reference to direct determinant constructs, namely performance expectation, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003)

Hypothesis development

Performance expectancy (PE) is an individual's belief. It can be expressed as the degree to which a person believes that by using a system or technology, one can improve job performance, productivity, or effectiveness. Venkatesh et al. (2003) considered PE as one of the critical factors for examining the intention of users to use future technologies. Literature suggests a positive relationship between PE and technology acceptance (Oliveira et al., 2014; Yang et al., 2017; Moraes et al., 2022). Findings of earlier knowledge bodies show that performance expectancy is a key factor for examining technology acceptance due to higher performance expectancy with the use of the technology (Saleh et al., 2023). Thus, we propose our first hypothesis as:

H1: Intention to use big data analytics is positively influenced by performance expectancy.

An innovation, even though superior, may not be accepted or used if it involves a higher level of effort. Easy-to-use technologies / tools are more likely to be accepted and used by users. Required efforts and complexity involved with a technology are collectively referred to as 'effort expectancy'. It refers to the extent to which BDA technology is easy for business managers in management accountancy tasks. Literature outlines a positive association between effort expectancy and acceptance and use of technology (Venkatesh et al., 2003). Thus, the following hypothesis is proposed:

H2. Intention to use big data analytics is positively influenced by effort expectancy.

Venkatesh et al., (2003) incorporated Facilitating Conditions (FC) in the original UTAUT model. It is collectively referred to as a set of organizational technical infrastructure and environmental settings to support individuals and provide the necessary conditions to use a new innovation. These conditions extend the enabling environment, remove barriers, and significantly influence users' intention. The next hypothesis is:

H3. Intention to use big data analytics is positively influenced by facilitating conditions.

Social influence (SI) profoundly affects human behaviour, particularly in the technology adoption phenomenon (Graf-Vlachy et al., 2018). It affects an individual's attitude, belief, and behaviour through the virtual intervention of various social factors. SI creates a basic foundation of social interactions through which people think and act, even though without having subject-specific expertise. People create a perception and give importance to the individual if she / he is using a specific advanced technology. Here, an individual's outlook is viewed as a technology user (Venkatesh et al., 2003; Venkatesh et al., 2012). In the context of modern management accounting work practices, future managers are influenced by peers' other social groups. Their intention to use BDA is affected by SI. Therefore, the following hypothesis is proposed:

H4. Intention to use big data analytics is positively associated with social influence.

Resistance to using a newer technology is a natural phenomenon. User resistance is a natural reaction, and people withstand an effect and try to prevent it by counteraction or argument (Villarejo-Ramos et al., 2021; Schmidt et al.2020; Moraes et al., 2022). The managers' negative reactions before implementing and using such technologies could have an adverse impact on project success. Therefore. Appropriate moderation strategies must be placed to avoid project failure. In this background, the next hypothesis is proposed as:

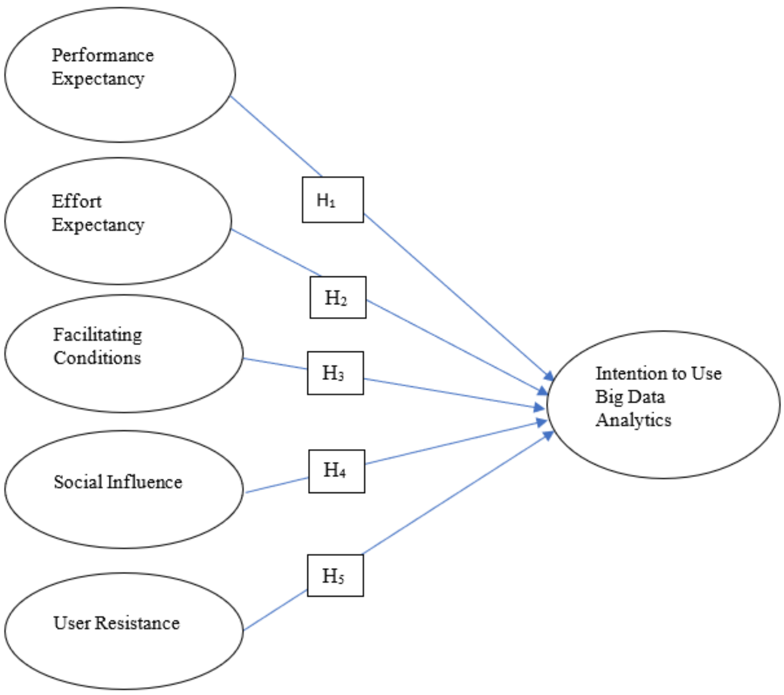
H5. Intention to use big data analytics is adversely influenced by user resistance.

The hypotheses H1 to H5 converged towards the dependent factor 'intention to use' (IU). A strong connection between IU and technology acceptance and actual use of BDA was established by researchers in different contexts and geographical settings (Fishbein, n.d., Venkatesh et al., 2003, Venkatesh et al., 2012)

Conceptual framework

Based on the literature review and consultation with academicians and professionals engaged in management accounting work, a UTAUT-based conceptual model is presented in Figure 1. The model comprises five independent constructs, namely performance expectancy, effort expectancy, facilitating conditions, social influence, and user resistance, which directly influence intention to use big data analytics by future business managers in the management domain. Hypothesized relations are summarized and presented in Table 1.

Figure 1. Conceptual framework



Source: Authors' creation

Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 3

ISSN: 1540-3270

Methodology

This section outlines the methodological description adopted for hypothesis testing.

Measurement

Referring to the factors previously used in research work related to accounting / management accounting and technological adoption, the questionnaire items were adopted with appropriate calibration to suit the context of the study. The draft questionnaire was presented to 10 MBA final year students, three university-level business studies academicians, and two professional management accountants for face validation and suggestions. After incorporating suggestions from stakeholders, the questionnaire was finalized on a five-point Likert scale. Reference sources for items have been summarized in Table 1.

Table 1. Items reference sources

Latent Constructs	Short name	Short description	References
Performance expectancy	PE	Individual's expectations of enhanced job performance, productivity or effectiveness with use of a specific technology or systems.	(Villarejo-Ramos, A. F., & Cabrera-Sánchez, J. P. (2019; Schmidt et al. ,2022; Moraes et al., 2022)
Effort Expectancy	EE	Efforts required to adopt and use of a particular system.	(Villarejo-Ramos, A. F., & Cabrera-Sánchez, J. P. (2019; Schmidt et al. ,2022; Moraes et al., 2022)
Facilitating conditions	FC	Infrastructural or institutional support available to users to adopt and use a new innovation.	(Villarejo-Ramos, A. F., & Cabrera-Sánchez, J. P. (2019; Schmidt et al. ,2022; Moraes et al., 2022)
Social Influence	SI	Influence experienced by individual from peers and other social elements with respect to use of technology.	(Villarejo-Ramos, A. F., & Cabrera-Sánchez, J. P. (2019; Schmidt et al. ,2022; Moraes et al., 2022)
User Resistance	UR	Resisting an effect and trying to evade or prevent that effect by counter-action or argument.	(Villarejo-Ramos, A. F., & Cabrera-Sánchez, J. P. (2019; Schmidt et al. ,2022; Moraes et al., 2022)
Intention to Use	IU	Reflection of user's desire to use future technology.	(Venkatesh et al., 2012; Varma, 2018; Rahman et al., 2021)

Source: Authors' compilation

Sample size determination

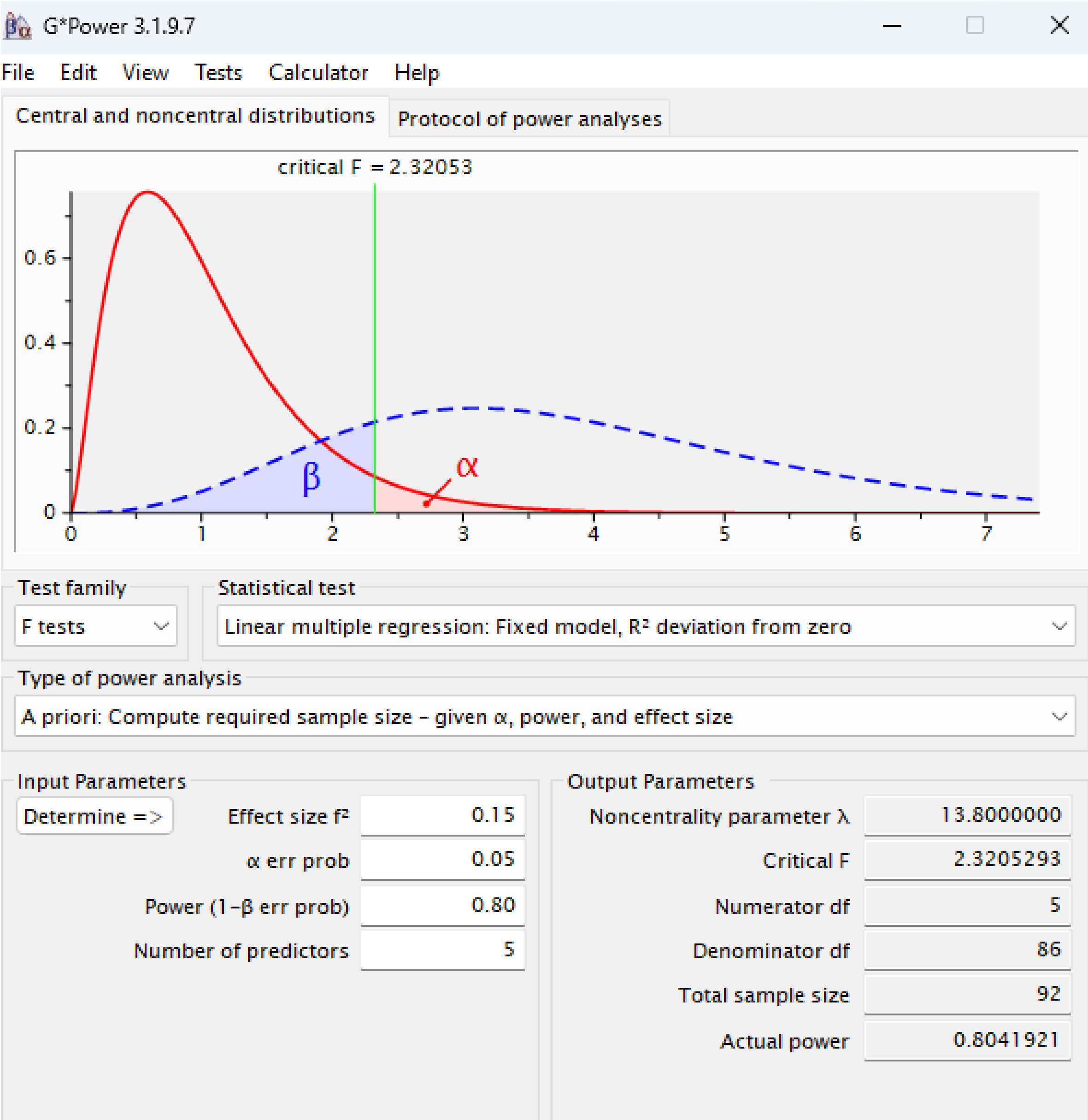
G*Power software was used to calculate the sample size. An 'a priori power analysis' was applied using the F-test family. With five independent predictors, a medium effect size ($f^2 = 0.15$), a significance level of 0.05, and a statistical power of 0.80. With these settings, the required total sample size was 92. However, for maintaining robustness and reliability of results and instrument characteristics (Likert-scale data) and PLS-SEM analysis, 167 responses were collected for testing the hypotheses.

Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 3

ISSN: 1540-3270

Figure 2 (Sample size determination with G*Power)



Source: (Output from G*Power software)

Data collection

This study targets students pursuing the final year of the Master of Business Administration at university-level institution. The population in this study is homogeneous with sufficient academic background. A Google form was posted through email, mobile WhatsApp, and social networks to collect the responses from potential respondents. Finally, a sample of 167 was collected.

Data analysis technique

Partial Least Squares- Structural Equation Model (PLS-SEM) was employed using R programming. A few reasons were identified for this. PLS-SEM is a multivariate statistical technique, appropriate for predicting behavioural intention. It stresses maximizing explained variance rather than testing well-defined theories. PLS-SEM is reasonably robust to non -normal data, which is very common in Likert-scale measures and can be a perfect choice for moderate sample size (Hair et al., 2021). SEMinR package developed by (Ray et al., 2021) was used to test the structural relationship.

Data Analysis and Findings

Bias test

The data was gathered via a self-administered online single-respondent survey, there could be a possibility of common method bias. To rule out this, a single-factor Harman test was performed, so that bias does not distort the findings. Podsakoff et al. (2003) suggested that data is free from bias if the explained variance by the first latent component accounts for less than 50%. The first factor accounted for 34% of the total variance, which is well below the recommended threshold of 50%. Thus, the results of Harman's test confirm that common method bias is not a concern for this study.

Assessment of the outer (measurement) model

The measurement model was tested for construct reliability and validity before testing the final hypothesis. A range of measurements was made to ensure constructs are valid and reliable. Factor loading of each item measures the extent of correlation between observed variables and their latent construct. A value of >= 0.7 indicates good loading of the indicator on the respective constructs. Table -2 shows that all the items are in the range of 0.7 to 0.9, which indicates that the items are effectively measuring the intended latent construct.

Table 2. Factor loading

Item	Construct	Loading
PE1	PE	0.719
PE2	PE	0.759
PE3	PE	0.822
PE4	PE	0.822
PE5	PE	0.724
PE6	PE	0.772
EE1	EE	0.722
EE2	EE	0.779
EE3	EE	0.755
EE4	EE	0.777
EE5	EE	0.763
EE6	EE	0.737

FC1	FC	0.694
FC2	FC	0.739
FC3	FC	0.762
FC4	FC	0.801
FC5	FC	0.770
SI1	SI	0.753
SI2	SI	0.820
SI3	SI	0.814
SI4	SI	0.697
UR1	UR	0.899
UR2	UR	0.846
UR3	UR	0.916
UR4	UR	0.713
IU1	IU	0.766
IU2	IU	0.817
IU3	IU	0.764
IU4	IU	0.829
IU5	IU	0.665
IU6	IU	0.712

Source (R output, Authors' compilation)

Internal consistency or homogeneity was assessed by widely reported measures, namely Cronbach's Alpha Cα, Composite Reliability (ρa and ρc). Values of these measures ≥ 0.70 indicate good internal consistency. Validity is measured in two steps: convergent validity and discriminant validity. Convergent validity means how closely several items measure the same concept. A general rule of thumb, the Average Variance Extracted AVE ≥ 0.50 indicates the convergence of all items towards its construct (Fornell & Larcker, 1981). In Table 3, the value of Cronbach's Alpha, rhoa, rhoc, and AVE are summarized.

Table 3. Construct reliability and validity

Construct	Cα	rhoa	rhoc	AVE
PE	0.863	0.863	0.898	0.594
EE	0.850	0.853	0.889	0.571
FC	0.814	0.838	0.868	0.569
SI	0.774	0.787	0.855	0.597
UR	0.894	0.847	0.910	0.718
IU	0.853	0.860	0.891	0.579

Source (R output, Authors' compilation)

Next to this, discriminant validity was examined through the widely accepted Fornell–Lacker criterion (FL) and Heterotrait–Monotrait ratio (HTMT). Discriminant validity measures how well constructs are differentiated from each other. A distinct construct must measure a different concept (Hair, 2019) Mathematically, FL is the square root of the AVE of each construct. To be distinct from others, its AVE value should be greater than the other correlated latent constructs (Fornell & Larcker, 1981). By referring to Table 4, it can be concluded that the FL criteria are satisfied.

Table 4. Discriminant validity; Fornell–Lacker criterion

Construct	PE	EE	FC	SI	UR	IU
PE	0.771	-	-	-	-	-
EE	0.636	0.756	-	-	-	-
FC	0.335	0.603	0.754	-	-	-
SI	0.673	0.615	0.555	0.773	-	-
UR	-0.179	-0.004	0.198	-0.013	0.847	-
IU	0.622	0.684	0.537	0.676	-0.065	0.761

Source (R output, Authors' compilation)

Henseler et al. (2015), through simulation, found that FL is sensitive to indicators' loading and HTMT is a better measure for achieving higher specificity and sensitivity levels than the FL criteria. Discriminant validity was also confirmed through the HTMT ratio. For conceptually different constructs, the value of HTMT should be less than

0.85 (Hair et al., 2021). HTMT results are presented in Table 5 which indicates that discriminant validity is established.

Table 5. Discriminant validity; HTMT Ratio

	PE	EE	FC	SI	UR	IU
PE	-	-	-	-	-	-
EE	0.730	-	-	-	-	-
FC	0.359	0.715	-	-	-	-
SI	0.812	0.751	0.663	-	-	-
UR	0.186	0.087	0.316	0.102	-	-
IU	0.713	0.796	0.616	0.823	0.110	-

Source (R output, Authors' compilation)

Assessment of the inner (structural) model

After confirming the reliability and validity of constructs, the structural model was evaluated. According to (Kutner, 2005), the assessment of multicollinearity is necessary to ensure regression estimates are not destroyed by intercorrelations among the predictors. Initially, the variance inflation factor (VIF) was checked for a more stringent threshold, VIF < 3. VIF is reported in Table 6. All VIF values are less than 3; therefore, the model is free from collinearity problems (Kutner, 2005; Hair et al., 2021).

Table 6. Multicollinearity; variance inflation factors VIF

IU	PE	EE	FC	SI	UR
	2.378	2.378	1.928	2.382	1.121

Source (R output, Authors' compilation)

The causal relationship of the constructs was examined using the bootstrapping technique (nboot = 5000). Path significance assessment is based on the bootstrapping standard errors and t-values of path coefficients. A path coefficient is significant at the 5% level if the value 'zero' does not fall in 2.5% and 97.5% confidence interval, and the bootstrapped T-statistic estimates (T Stat.) > 1.96. Bootstrapped Structural Paths are presented in Table 8; accordingly, H2, H3, and H4 are confirmed, and H1 and H5 are not supported. The independent variables considered in the model explain 59.5% ($R^2 = 0.595$) of the variance in the dependent variable (IU). This indicates a moderate to strong fit. Adjusted $R^2 = 0.583$ explains 58.3% of the variance. A closeness in R^2 and adjusted R^2 values suggests that the predictors in the model are meaningful and the model is not unnecessarily inflated. Path summary is presented in Table 7, and the graphical SEM model with relevant values is presented in Figure 3.

Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 3

ISSN: 1540-3270

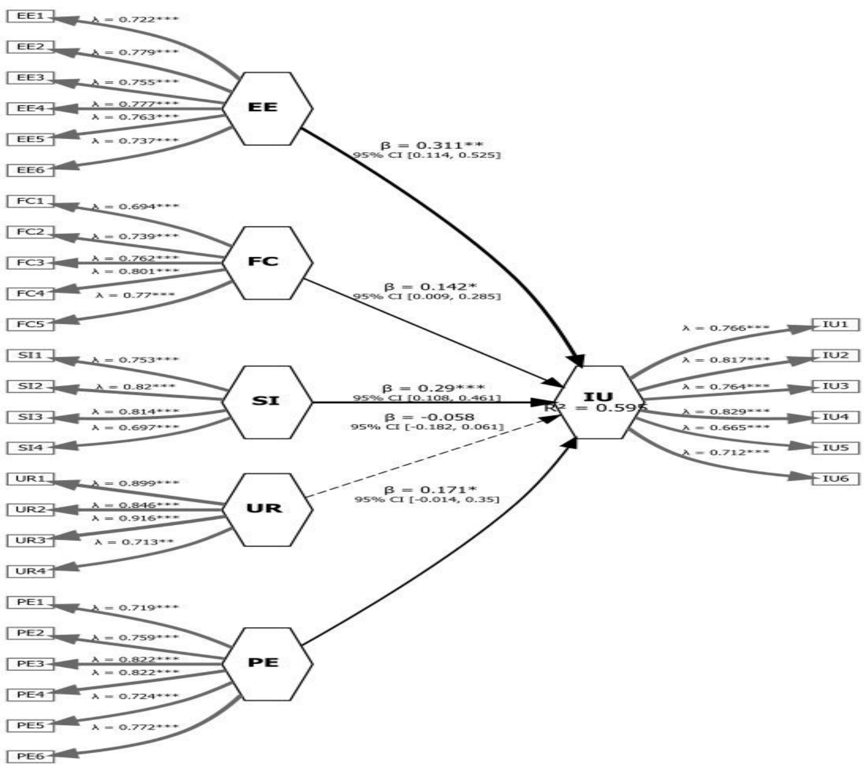
Table 7. Bootstrapped Structural Paths

Predictor	Path Coefficient (→ IU)	Bootstrap Mean	Bootstrap SD	T Stat	2.5% CI	97.5% CI	Bootstrap P Val	Significance
R²	0.595	-	-	-	-	-	-	-
Adj R²	0.583	-	-	-	-	-	-	-
PE	0.171	0.168	0.092	1.852	-0.014	0.350	0.070	Not Significant
EE	0.311	0.316	0.105	2.962	0.114	0.525	0.001	**Significant**
FC	0.142	0.146	0.071	1.993	0.009	0.285	0.036	**Significant**
SI	0.290	0.288	0.090	3.220	0.108	0.461	0.002	**Significant**
UR	-0.058	-0.064	0.063	-0.927	-0.182	0.061	0.300	Not Significant

Source (R output, Authors' compilation)

Summary: Overall model fit: $R^2 = 0.595$, Adj $R^2 = 0.583$ → the model explains ~59% of IU variance; Significant predictors of IU: EE, FC, SI; Non-significant predictors: PE, UR

Figure 3. Path diagram



Source: (Graphics from R)

Discussion

This work presented a research model with five possible predictors to gauge the 'intention to use BDA' by future business managers. The Overall fit: $R^2 = 0.595$ indicates that the model possesses a high explanatory power for the dependent variable 'intention to use BDA'. The research enriched a limited block of knowledge on management accounting and use of BDA. It gives crucial information on behavioural aspect of future managers to firms and industries for necessary organisational policy and environmental interventions. The inputs are equally important for academic and professional institutions imparting education in business administration and management accounting domain. The first hypothesis H1, (PE to IU) was rejected. This is contrary to many prior works (Ayaz & Yanartaş, 2020; Schmidt et al., 2020); Moraes et al., 2022; Saud et al., 2025), but consistent with some 'accounting and use of technologies' related studies, especially among inexperienced users like students (Alquhaif & Al-Mamary, 2025). The findings suggest that performance expectancy is context-specific. This may be due to the fact that future managers are born in the technology era, and already perceive BDA as an inherently useful technology in the management accountancy work. Effort expectancy (EE) was found to be the most statistically significant independent predictor, influencing behavioural intention to use BDA among future managers. A simple and user-friendly system is likely to be embraced more easily. Finding support is one of the main constituents of UTAUT, which stresses that effort expectancy is a key factor of behavioural intention (Venkatesh et al., 2003; Chen & Hwang, 2019; Moraes et al., 2022). In the context of future business managers who are acquiring digitally integrated business education, 'ease of use' is a critical aspect for shaping their willingness to adopt BDA technology. Social influence (SI) was found to be the second dominant predictor impacting intention to use BDA positively. This shows the importance of the opinions of other people on an individual's choice. Finding in consonance with previous works (Kim & Kankanhalli, 2009; Moraes et al., 2022), but departed from the findings of (Saud et al., 2025). This may be due to context-specific environmental settings. In this particular study, it is voluntary for future managers to think about the use of BDA in management accounting prospectively. Social influence is positively and significantly influencing the intention to use BDA. Contrary to established use of technology-related research works, 'user resistance' was not a significant negative predictor. This is an interesting and complete departure in the accounting and technology use context (Schmidt et al., 2020). The future business managers see technology as an important enabler for performing their job efficiently and effectively.

Conclusion and Implications

With ever-growing digital drives across the companies, the BDA capabilities generate enormous opportunities to improve the flow of business information, resulting in a swift decision-making process, competitive edge, and leadership position for BDA adaptors (Seddon et al., 2017). Undoubtedly, BDA is beneficial to businesses / firms of all sizes, but adopting and implementing it involves a range of technological and human-related barriers (Schmidt et al., 2020). Literature suggests that many BDA projects failed or were not implemented effectively, and BDA was not paid equally to all (Spraakman et al., 2021). Among the technical barriers and obstacles in BDA implementation, human factors were integrated in this work, and the behavioural intention of the future human pool was communicated to business managers in advance. Contrary to many previous research findings, performance expectancy and intention to use were found to be statistically insignificant positive and negative predictors. We argue that these factors are context-specific, and this departure can be attributed to the age factor and the technical exposure of young students. The outcome of this work can be used as inputs for industry managers, practitioners, academics, and professional institutions to work in their respective areas for leveraging BDA innovation in the data-rich accounting domain. We suggest that an early address of critical factors and a focused organization's vision on the use of BDA is necessary. The academic institutions need to adjust curricula with more focused practical modules aligned with industry requirements.

Theoretical Implications

Theoretically, this work added to the limited work on management accounting and BDA-related literature (Varma et al., 2021). Although previous works were addressed with the intention to use BDA in different contexts, such as SMEs, manufacturing, supply-chain, hotels, healthcare, auditing, education, etc., researchers have not considered an exclusive study that focuses on the intention to use future business managers who intend to work in a data-rich management accountancy domain in fast-developing economies like India. The robust theoretical UTAUT-based model reveals that predictors PE and UR are not statistically significant in this context. Therefore, while examining the dependency of predictors on the dependent construct, its contextual ingredients are important.

Practical Implications

Practically, the outcome of this work can be utilized by academic and professional institutions, industries, and regulators. Advance intimation on behavioural aspects of prospective business managers enables corporate leaders to evolve appropriate policies, training plans, and strategies for current and upcoming BDA projects. The tangible BDA's technical capabilities and intangible organizational human dimension need to be looked at in an integrated manner for successful project implementation. The results clearly show which factors facilitate and impede use of BDA. Thus, corporates can appropriately moderate these factors in decisions related to technology adoption. The academic and professional institution imparting such education may consider incorporating appropriate academic content, practical modules, and mini-projects in the curriculum. Under the new education policy, different relevant courses / modules of NPTEL, SVAYAM, or like bodies can be mapped in business studies with appropriate academic credit points. Facilitating conditions such as modern IT Infrastructure, inter-institutional resource pooling, and a sense of academic competition are likely to improve the competencies and adaptability toward BDA adoption.

Limitation

Despite several important contributions on the theoretical and practical front, this study has a few limitations. Generalizations of outcome from this work need further reinforcement from like-nature studies. The respondents are young people pursuing a business administration / management accountancy course, who may have high-end use of technology. A sample of older people could have different results. A moderate sample size, limited geographical range, and cross-sectional questionnaire-based survey may lead to some weakness in the causal relationship established by the study. Future work can be carried out by adopting a longitudinal research approach for more precise and reliable results. A qualitative inquiry is suggested for further peeping in the topic.

Conflicts of interest

All authors declare that they have no conflicts of interest.

References

[1] Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

[2] Alharthi, A., Krotov, V., & Bowman, M. (2017). Addressing barriers to big data. *Business Horizons*, 60(3), 285–292. https://doi.org/10.1016/j.bushor.2017.01.002

[3] Alquhaif, A. S., & Al-Mamary, Y. H. (2025). Examining factors influencing the adoption of accounting information systems: An analysis of behavioral intentions and usage behavior. *Human Systems Management*, 44(3), 460–476. https://doi.org/10.1177/01672533241297453

[4] Alrashidi, M.; A. A.; Z. O. (2022). The impact of big data analytics on audit procedures: evidence from the Middle East. The Journal of Asian Finance, Economics and Business, 9(2), 93–102.

[5] Andrew McAfee; Erik Brynjolfsson. (2012). Big data: The management revolution. H*arvard Business Review*, 90(10), 60–68.

[6] Ayaz, A., & Yanartaş, M. (2020). An analysis on the unified theory of acceptance and use of technology theory (UTAUT): Acceptance of electronic document management system (EDMS). *Computers in Human Behavior Reports*, 2, 100032. https://doi.org/10.1016/j.chbr.2020.100032

[7] CABRERA-SÁNCHEZ, J.-P., & VILLAREJO-RAMOS, Á. F. (2019). Factors affecting the adoption of big data analytics in companies. *Revista de Administração de Empresas*, *59*(6), 415–429. https://doi.org/10.1590/s0034-759020190607

[8] Chen, P.-Y., & Hwang, G.-J. (2019). An empirical examination of the effect of self-regulation and the unified theory of acceptance and use of technology (UTAUT) factors on the online learning behavioural intention of college students. *Asia Pacific Journal of Education*, 39(1), 79–95. https://doi.org/10.1080/02188791.2019.1575184

[9] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. https://doi.org/10.2307/249008

[10] Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Hazen, B., Giannakis, M., & Roubaud, D. (2017). Examining the effect of external pressures and organizational culture on shaping performance measurement systems (PMS) for sustainability benchmarking: Some empirical findings. *International Journal of Production Economics*, 193, 63–76. https://doi.org/10.1016/j.ijpe.2017.06.029

[11] Fishbein, M., & A. I. (n.d.). Belief, attitude, intention, and behaviour: An introduction to theory and research. *Addison-Wesley*.

[12] Fornell, C., & Larcker, D. F. (1981). evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

[13] Gong, Y., & Janssen, M. (2021). Roles and capabilities of enterprise architecture in big data analytics technology adoption and implementation. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(1), 37–51. https://doi.org/10.4067/S0718-18762021000100104

[14] Graf-Vlachy, L., Buhtz, K., & König, A. (2018). Social influence in technology adoption: taking stock and moving forward. *Management Review Quarterly*, 68(1), 37–76. https://doi.org/10.1007/s11301-017-0133-3

[15] Grosu, V., Cosmulese, C. G., Socoliuc, M., Ciubotariu, M.-S., & Mihaila, S. (2023). Testing accountants' perceptions of the digitization of the profession and profiling the future professional. *Technological Forecasting and Social Change*, 193, 122630. https://doi.org/10.1016/j.techfore.2023.122630

[16] Hair, J. F.; B. W. C.; B. B. J. ; A. R. E. (2019). Multivariate data analysis (Vol. 8). Cengage.

[17] Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial least squares structural equation modelling (PLS-SEM) Using R. *Springer International Publishing*. https://doi.org/10.1007/978-3-030-80519-7

[18] Hamdam, A., Jusoh, R., Yahya, Y., Abdul Jalil, A., & Zainal Abidin, N. H. (2022). Auditor judgment and decision-making in big data environment: a proposed research framework. *Accounting Research Journal*, 35(1), 55–70. https://doi.org/10.1108/ARJ-04-2020-0078

[19] Harman, H. H. (n.d.). Modern factor analysis (2nd ed.). *University of Chicago Press*.

[20] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

[21] Irfan, M., & Wang, M. (2019). Data-driven capabilities, supply chain integration and competitive performance. *British Food Journal*, 121(11), 2708–2729. https://doi.org/10.1108/BFJ-02-2019-0131

[22] Kim, H.-W., & Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: a status quo bias perspective1. *MIS Quarterly*, 33(3), 567–582. https://doi.org/10.2307/20650309

[23] Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). Applied linear statistical models (5th ed.)

[24] Lutfi, A., Alrawad, M., Alsyouf, A., Almaiah, M. A., Al-Khasawneh, A., Al-Khasawneh, A. L., Alshira'h, A. F., Alshirah, M. H., Saad, M., & Ibrahim, N. (2023). Drivers and impact of big data analytic adoption in the retail industry: A quantitative investigation applying structural equation modelling. *Journal of Retailing and Consumer Services*, 70, 103129. https://doi.org/10.1016/j.jretconser.2022.103129

[25] Lutfi, A., Alsyouf, A., Almaiah, M. A., Alrawad, M., Abdo, A. A. K., Al-Khasawneh, A. L., Ibrahim, N., & Saad, M. (2022). Factors influencing the adoption of big data analytics in the digital transformation era: case study of Jordanian SMEs. *Sustainability*, 14(3), 1802. https://doi.org/10.3390/su14031802

[26] Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2023). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems*, 123(1), 278–301. https://doi.org/10.1108/IMDS-11-2021-0695

[27] Moraes, G. H. S. M. de, Pelegrini, G. C., de Marchi, L. P., Pinheiro, G. T., & Cappellozza, A. (2022). Antecedents of big data analytics adoption: an analysis with future managers in a developing country. *The Bottom Line*, 35(2/3), 73–89. https://doi.org/10.1108/BL-06-2021-0068

[28] Munir, S., Abdul Rasid, S. Z., Aamir, M., Jamil, F., & Ahmed, I. (2023). Big data analytics capabilities and innovation effect of dynamic capabilities, organizational culture and role of management accountants. *Foresight*, 25(1), 41–66. https://doi.org/10.1108/FS-08-2021-0161

[29] Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management*, 51(5), 497–510. https://doi.org/10.1016/j.im.2014.03.006

[30] Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

[31] Rahman, N., Daim, T., & Basoglu, N. (2023). Exploring the Factors Influencing Big Data Technology Acceptance. *IEEE Transactions on Engineering Management*, 70(5), 1738–1753. https://doi.org/10.1109/TEM.2021.3066153

[32] Ramachandran, R. (2019). Big data analytics and the management accountant. *The Management Accountant*, 54(5), 40–43.

[33] Ray, S., Danks, N., & Calero Valdez, A. (2021). SEMinR: domain-specific language for building, estimating, and visualizing structural equation models in R. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3900621

[34] Razaghi, S., & Shokouhyar, S. (2021). Impacts of big data analytics management capabilities and supply chain integration on global sourcing: a survey on firm performance. *The Bottom Line*, 34(2), 198–223. https://doi.org/10.1108/BL-11-2020-0071

[35] Saleh, I., Marei, Y., Ayoush, M., & Abu Afifa, M. M. (2023). Big Data analytics and financial reporting quality: qualitative evidence from Canada. *Journal of Financial Reporting and Accounting*, 21(1), 83–104. https://doi.org/10.1108/JFRA-12-2021-0489

[36] Saud, I. M., Sofyani, H., Utami, T. P., Haq, M. M., & Fathmaningrum, E. S. (2025). Big data analytics-based auditing adoption in public sector: Indonesian evidence. *Cogent Business & Management*, 12(1). https://doi.org/10.1080/23311975.2025.2454320

[37] Schmidt, P. J., Riley, J., & Swanson Church, K. (2020). Investigating Accountants' Resistance to Move beyond excel and adopt new data analytics technology. *Accounting Horizons*, 34(4), 165–180. https://doi.org/10.2308/HORIZONS-19-154

[38] Seddon, P. B., Constantinidis, D., Tamm, T., & Dod, H. (2017). How does business analytics contribute to business value?. *Information Systems Journal*, 27(3), 237–269. https://doi.org/10.1111/isj.12101

[39] Sharma, M., Gupta, R., Sehrawat, R., Jain, K., & Dhir, A. (2023). The assessment of factors influencing Big data adoption and firm performance: Evidences from emerging economy. *Enterprise Information Systems*, 17(12). https://doi.org/10.1080/17517575.2023.2218160

[40] Spraakman, G., Sanchez-Rodriguez, C., & Tuck-Riggs, C. A. (2021). Data analytics by management accountants. *Qualitative Research in Accounting & Management*, 18(1), 127–147. https://doi.org/10.1108/QRAM-11-2019-0122

[41] Tambuskar, D. P., Jain, P., & Narwane, V. S. (2024). An exploration into the factors influencing the implementation of big data analytics in sustainable supply chain management. *Kybernetes*, 53(5), 1710–1739. https://doi.org/10.1108/K-07-2022-1057

[42] Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing and controlling for common method variance: a review of available methods. *Journal of Management Sciences*, 4(2), 142–168. https://doi.org/10.20547/jms.2014.1704202

[43] Tiron-Tudor, A., & Deliu, D. (2021). Big data's disruptive effect on job profiles: management accountants' case study. *Journal of Risk and Financial Management*, 14(8), 376. https://doi.org/10.3390/jrfm14080376

[44] Uddin Murad, M. A., Cetindamar, D., & Chakraborty, S. (2022). Identifying the key big data analytics capabilities in Bangladesh's healthcare sector. *Sustainability*, 14(12), 7077. https://doi.org/10.3390/su14127077

[45] Varma, A. (2018). Big data usage intention of management accountants: blending the utility theory with the theory of planned behavior in an emerging market context. *Theoretical Economics Letters*, 08(13), 2803–2817. https://doi.org/10.4236/tel.2018.813176

[46] Varma, A., Piedepalumbo, P., & Mancini, D. (2021). Big data and accounting: a bibliometric study. *The International Journal of Digital Accounting Research*, 203–238. https://doi.org/10.4192/1577-8517-v21_8

[47] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: toward a unified view1. *MIS Quarterly*, 27(3), 425–478. https://doi.org/10.2307/30036540

[48] Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. https://doi.org/10.2307/41410412

[49] Villarejo-Ramos, Á. F., Cabrera-Sánchez, J.-P., Lara-Rubio, J., & Liébana-Cabanillas, F. (2021). Predicting big data adoption in companies with an explanatory and predictive model. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.651398

[50] Vysotskaya, A., & Prokofieva, M. (2025). Management accounting and data analytics: technology acceptance from the educational perspective. *Accounting Education*, 34(3), 410–433. https://doi.org/10.1080/09639284.2024.2338140

[51] Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: effects of dynamic capabilities. *Journal of Business Research*, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

[52] Yang, H., Lee, H., & Zo, H. (2017). User acceptance of smart home services: an extension of the theory of planned behavior. *Industrial Management & Data Systems*, 117(1), 68–89. https://doi.org/10.1108/IMDS-01-2016-0017

[53] Yaqoob, I., Hashem, I. A. T., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N. B., & Vasilakos, A. V. (2016). Big data: from beginning to future. *International Journal of Information Management*, 36(6), 1231–1247. https://doi.org/10.1016/j.ijinfomgt.2016.07.009