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Predicting the impact of blockchain technology implementation in SMEs

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Abstract

In the last few years, blockchain technology, or BCT, has gained much traction. Small and medium-sized businesses (SMEs) struggle more than their larger counterparts when it comes to technological adaptation because they lack the technology infrastructure required to implement blockchain technologies. The major contribution of this paper is to predict the impact of blockchain technology implementation on the performance of SMEs. A multiple-output regression model is utilized in this research to predict the impact of BCT on SMEs' performance. The cost of implementing and maintaining blockchain technology, IT project management, compatibility, benefit over other available technological options, and trialability are the independent variables that were considered in the analysis. Software revision, sophistication level, innovation complexity, and observability are the dependent variables. Researchers and industry professionals can use the study to comprehend how implementing blockchain technology affects SMEs.

Keywords: Blockchain Technology, SMEs, multiple output regression

1. Introduction

Small and medium-sized businesses are thought to form the foundation of the Indian economy. The world is witnessing a huge digital revolution as we enter Industry 4.0 and the age of digital transformation. As a result, organizations need to evolve their technological infrastructure to survive in the industry (Salim et al., 2022). The various technologies that can bring technological innovation to SMEs include AI, machine learning, blockchain technology, and IoT. Although SMEs are not organizationally ready to adapt to all these modern technologies, adopting this technology will enhance their productivity, performance, and security. This research work focuses on the impact of BCT on SME performance.

Blockchain is defined as "a distributed database, which is shared among and agreed upon as a peer-to-peer network. It consists of a linked sequence of blocks (a storage unit of the transaction), holding timestamped transactions that are secured by public-key cryptography (i.e., "hash") and verified by the network community. Once an element is appended to the Blockchain, it cannot be altered, turning a Blockchain into an immutable record of past activity" (Seebacher & Schuritz, 2017).

Previous research works in this area analyze the impact of BCT on risk management, considering the advantages of BCT, including transparency, security, and traceability (Chowdhury et al., 2022). However, identifying the impact of a technology is also very important to decide whether or not the organization has to go ahead with the new technology. This research work tries to identify the impact of BCT on SME performance. This paper works around the assumption that the implementation of BCT technology improves SME performance. This can be proved by predicting the efficiency of the SME after BCT implementation. The first step in this case is to identify a model that gives an accurate prediction of SME's performance before and after BCT implementation, which can help the users to make a decision based on the results. Hence, the two research objectives of the study are formulated as below

R1: Identifying the best model to predict SME performance after implementation of BCT technology.

R2: Predicting the impact of BCT technology on SME performance.

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While finding solutions to these two research objectives, this paper makes a major contribution to both technologists and SME leaders. None of the existing research works predicts the impact of multiple input variables on multiple output variables. However, current research work aids the researchers in utilizing a multi-output regression model when there are multiple input and multiple output variables. Another contribution of this research work is for SME leaders. SME leaders are clueless about the benefits of implementing BCT in their company. Through a simulation study, this research work elucidates that SME improves efficiency in various factors through BCT implementation. This identification will help the SME leaders to make a decision on whether or not to go ahead with the implementation of BCT.

The remainder of the document is structured as follows: Section 2 details the background of the study. Section 3 includes the methodology used for the analysis as well as the results obtained from the analysis. Section 4 presents limitations of the study and Section 5 concludes the main findings obtained from this study.

2. Background

Even though blockchain technology (BCT) offers numerous benefits, like anonymity, immutability, transparency, and quick transactions (Abubakar & Alyou, 2021), it's critical to comprehend how the adoption of BCT will affect different businesses. A number of frameworks, including the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework, were used to examine the effects of BCT adoption in SMEs (Kamble et al., 2022). The biggest driving variables for blockchain adoption are partner preparedness, perceived usefulness, perceived ease of use, and competitive pressure, which are important variables that must be considered. It is very important to analyze the individual’s intent to adopt the blockchain rather than an organizational perspective (Kamble et al., 2022). Challenges of BCT adoption in the supply chain have been examined by Queiroz and Wamba (2019). The impact of Blockchain Technology (BCT) on variables such as supply chain stakeholders' trust, social influence, performance expectancy, effort expectancy, and facilitating conditions was examined. They employed partial least squares structural equation modeling (PLS-SEM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to detect the impact of BCT. This study shows that adoption behavior varies in different countries Queiroz and Wamba (2019).

To test acceptance in terms of behavioral intention to use, two forms of information processing competency (private and public blockchain-based cooperation) are used (Giri & Manohar, 2021). Barriers to adopting blockchain technology in SMEs have been analyzed by Kaur et al. (2022). This study emphasizes the role of Government officials to concentrate on building infrastructure throughout the nation's various regions to support hosting blockchain systems. Such a homegrown blockchain platform can speed up and lower the cost of blockchain adoption for SMEs (Kaur et al., 2022). Another important factor that has to be considered for BCT adoption by SMEs is building the confidence of SMEs and making them aware of the positive impacts of BCT technology in their organization (Kaur et al., 2022).

Studies on the impact of BCT to improve the quality of accounting information, to help investors better understand the company was conducted by researchers such as Wu and Jin (2022). Several studies on the impact of BCT technology on various sectors, such as the maritime supply chain (Nasih et al., 2019), business models (Morkunas et al., 2019), and business interactions (de Oliveira et al., 2021).

Various methodologies such as additive symbiotic networks by Ferreira et al. (2023) are used to understand the impact of BCT technology. Content analysis was used by de Oliveira et al. (2021) and case study analysis was utilized by Stranieri et al. (2021). None of the methodologies in the literature make use of machine learning methods to identify the impact of BCT on various industries.

All these existing works in the literature do not utilize machine learning approaches to predict the impact of BCT in SMEs. This research utilizes a machine learning-based approach to identify the impact of BCT implementation on SMEs. The next section identifies the important variables to determine the impact of BCT implementation on SMEs and applies a machine learning model to predict the impact of BCT on SMEs’ performance.

3. Methodology

In order to understand the impact of BCT on SME performance various factors that affect SME performance have to be analyzed first. These variables are identified by using various grounded theories such as the sense-making theory (Savolainen, 1993),

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Organizational information processing theory, and Resource Based View (RBV) (Savolainen, 1993). Organizational information processing theory (Koh, 2016) believes that "the greater the uncertainty of the task, the greater the amount of information that must be processed between decision makers during the execution of the task to get a given level of performance". Diffusion of Innovation (Yu et al., 2021) helps to pinpoint the aspects of innovation that affect acceptance.

Based on the above-mentioned theories, this research identified the important variables for this study, which are listed in Table 1.

Table 1. Variables influence the BCT adoption in SMEs

Sl. No.	Variables	Notation
1	Cost of BCT implementation	V1
	Software Revision of BCT	V2
	Maintenance cost of BCT	V3
2	Level of sophistication of IT usage	V4
	IT Project Management	V5
3	Innovation Complexity	V6
	Organization Compatibility	V7
	Benefits among other technologies	V8
	Observability	V9
	Trialability	V10

Using these variables, a machine learning model has been developed in this research work to forecast the impact of BCT on SME's performance.

3.1 Multi-output regression model

Prediction of two or more numerical variables is the goal of multi-output regression. This model was developed to address the gap where the multivariate regression approach is preferred over separate univariate predictions (Rogers, 2010; Schmid, et al., 2023). The method used in this research includes a simulation study with different weights for the blockchain technology variables.

The model used for this model is given in **Figure 1.**

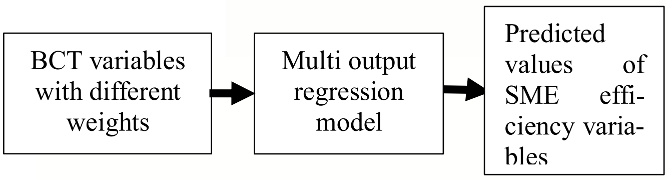

Fig 1. Structure of multi-output regression model

Three different types of algorithms are used to develop a multi-output regression model.

In this research, a multi-output regression model is developed, which takes different BCT variables as input and identifies the impact of those variables on SME's efficiency. The parameters to represent the SME's efficiency are selected as the output variables. Based on the literature we found that the Implementation cost of blockchain technology, the Maintenance cost of blockchain technology, IT Project Management, Compatibility with the organization, Benefit compared to other existing technological choices, and trialability are the input variables for the multi-output regression model. From the literature, we have identified the amount spent on Software Revision of BCT, the Level of sophistication of IT usage by the employees and customers, the Complexity of the innovation, and the Observability that determines the efficiency of SMEs after BCT implementation. Current research work uses a hypothetical situation of a company that implements BCT. In order to represent the hypothetical company, an input dataset is generated using simulation. A thousand samples are generated using simulation, which is utilized for the current analysis. In order to identify the best model that predicts the impact of BCT implementation on SME's efficiency, three different types of machine learning models are utilized. The first model presents a linear regression model with multiple outputs, the second one presents a KNN regressor model, and the last one presents a decision tree model. All these three models predict the impact of SME's efficiency after BCT implementation. A comparative analysis of the three models determines the one that has higher accuracy during prediction.

3.1.1 Simulation

Case A: Multi-output Linear Regression Model

Step 1: Create datasets

Step 2: X, y = make_regression (n_samples=1000, n_features=6, n_informative=5, n_targets=4, random_state=1, noise=0.5)

Step 3: Define model Linear Regression ()

Step 4: Fit the regression model using model.fit(X, y) function

Step 5: Make a prediction when all the selected variable inputs are zero

Step 6: Summarize prediction using regression

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Step 7: Obtain the output for the selected output variables

Step 8: Evaluation of the model using cross-validation

Step 9: Generation of Mean absolute error to get the accuracy of the model

Case B: Multi-output Knn Regression Model

Step 1: Create datasets

Step 2: X, y = make_regression (n_samples=1000, n_features=6, n_informative=5, n_targets=4, random_state=1, noise=0.5)

Step 3: Define model KnnRegression()

Step 4: Fit the regression model using model.fit(X, y) function

Step 5: Make a prediction when all the selected variable inputs are zero

Step 6: Summarize prediction using regression

Step 7: Obtain the output for the selected output variables

Step 8: Evaluation of the model using cross-validation

Step 9: Generation of Mean absolute error to get the accuracy of the model

Case C: Multi-output Decision Tree Regression Model

Step 1: Create datasets

Step 2: X, y = make_regression(n_samples=1000, n_features=6, n_informative=5, n_targets=4, random_state=1, noise=0.5)

Step 3: Define model Decision_TreeRegression ()

Step 4: Fit the regression model using the model.fit(X, y) function

Step 5: Make a prediction when all the selected variable inputs are zero

Step 6: Summarize prediction using regression

Step 7: Obtain the output for the selected output variables

Step 8: Evaluation of the model using cross-validation

Step 9: Generation of Mean absolute error to get the accuracy of the model

After implementing three different types of multi-output regression models, cross-validation has been done to identify the best model for predicting SME performance. SME performance is measured by predicting the values of variables such as Software Revision of blockchain technology which represents how much is assistance obtained from BCT variables for software revision, how much the improvement in the Level of sophistication of IT usage, how better the complexity of the innovation factor improves with implementation of BCT and how much improvement BCT creates in the observability of SME.

3.2 Results and Discussion

Initially, all the input BCT variables are set to zero to understand how much the performance of SMEs without the implementation of BCT is given as Case A: Scenario 1.

Case A: Multi-output linear regression output

Scenario 1: SME performance before implementation of BCT variables:
[0.00679014 0.00967136 -0.00181127 -0.00393957]

Later the same algorithm can be implemented by setting up the weights of BCT variables as one. This represents a scenario in which the BCT algorithm is implemented in the SME, and we can identify the SME output variable performance that can be calculated.

Case A: Multi-output linear regression output

Scenario 2: SME performance after implementation of BCT variables:
[188.8041768 269.25581906 196.06294426 340.31991746]

MAE: 0.395 (0.010)

Similarly, SME's performance is predicted using Multi-output Knn regression in Case B. Scenario 1 presents SME's efficiency before BCT implementation, and scenario 2 presents SME's efficiency after BCT implementation.

Case B: Multi-output Knn regression output

Scenario 1: SME performance before implementation of BCT variables:
[-21.65768054 -14.59638324 -5.78102635 -10.62669042]

Scenario 2: SME performance after implementation of BCT variables:

[167.81018346 199.85623374 136.88660717 262.07654543]

MAE: 28.537 (2.179)

Same scenarios are replicated using Multi-output Decision Tree regression which is given in Case C.

Case C: Multi-output Decision Tree regression output

Scenario 1: SME performance before implementation of BCT variables:
[7.63187532 -4.92012703 -9.25101485 -9.2697882]

Scenario 2: SME performance after implementation of BCT variables:

[75.28231803 128.24568503 107.82181375 206.19706852]

MAE: 53.369 (3.364)

With the aim of selecting the best methodology for prediction, a comparative study of outputs of multi-regression output models has been performed through a simulation study. Results obtained from the study revealed that multi-output linear regression has higher performance compared to the other models. This can be identified by checking the three models' Mean Absolute Error (MAE). From the outputs, it is clear that the multi-output regression model implemented using linear regression has a higher performance compared to Knn regressor or the decision tree model.

In scenario 1, where BCT is not implemented in the SME, output variables, which show the performance of SME, are very low compared to scenario 2, in which the output variables are measured after implementing the BCT. Predicting the output variables helps the SME to understand their performance improvement while implementing BCT. Thus, the hypothesis that implementation of BCT improves the performance of the SME is well established through this simulation study.

Modern technologies like machine learning, AI, IoT, and BCT improve the performance of various industries. Various studies exist about the barriers and enablers of all these technologies. Many researchers use models to understand how BCT affects different industries, including the Technology Acceptance Model (TAM), Technology-Organization-Environment (TOE), and Unified Theory of Acceptance and Use of Technology (UTAUT). However, a forecasting model is very important in predicting the impact of BCT implementation on SMEs. Therefore, studies related to predicting the performance of SMEs after and before BCT technology is very important. This research work tries to predict the impact of BCT in SMEs. Three different models have been utilized to predict SME's efficiency. A detailed explanation regarding the implementation of these three models given in section 3.2 helps future researchers to select the best model to predict the output variables in their study. SME leaders can benefit from this study by identifying the improvement in each output variable after BCT implementation.

4. Limitations of the study

A major limitation of this research work is the fact that this research doesn't collect real-life datasets from an SME. Instead, a simulation study based on the hypothetical situation is implemented in this research paper. Hence, in the future, the same set of variables can be collected from an SME through an empirical study, which brings more clarity to the procedure. Pre and Post analysis (before and after implementation of BCT) can be conducted in a real-life situation.

5. Conclusion

Due to the lack of technological infrastructure, many SMEs struggle to implement BCT technology. Many of the factors, like perceived ease of use and usefulness, came into the picture while analyzing the probability of implementing BCT. The implementation cost of BCT, the maintenance cost of BCT, IT project management, compatibility, the benefit compared among other technologies, and trialability with the organization are considered as the input variables for this study. Their impact on the dependent variables' software revision, level of sophistication, complexity of innovation, and observability are analyzed using a multi-output regression model. Results show that BCT implementation increases the efficiency of SMEs with respect to all these dependent variables. Therefore, implementing BCT in SMEs is recommended for better efficiency.

References

Abubakar, A.M. & Al-zyoud, M.F. (2021). Problematic internet usage and safety behavior: does time autonomy matter, Telematics and Informatics, 56, 1-11.

Chowdhury, S., Rodriguez-Espindola, O., Dey, P. & Budhwar, P. (2022). Blockchain technology adoption for managing risks in operations and supply chain management: evidence from the UK. Annals of Operations Research. https://doi.org/10.1007/s10479-021-04487-1

de Oliveira F.C., Zanoni R., Dalla-Rosa R. & Verschoore J.R. (2021). Blockchain technology and relational gains in business interactions: a fuzzy set qualitative comparative analysis of supply chain specialists' perceptions, International Journal of Advanced Operations Management, 13 (4), 372 – 390.

Ferreira, A. I., Palazzo, G. & Carvalho, H. (2023). Implications of the blockchain technology adoption by additive symbiotic networks, Cleaner Logistics and Supply Chain, 6, 100095 https://doi.org/10.1016/j.clscn.2023.100095

Giri, G. & Manohar, H.L. (2021). Factors influencing the acceptance of private and public blockchain-based collaboration among supply chain practitioners: a parallel mediation model, Supply Chain Management: An International Journal. 28 (1), 1-24.

Kamble, S., Gunasekaran, A., Kumar, V., Belhadi, A. & Foropon, C. (2022). A machine learning based approach for predicting blockchain adoption in supply Chain, Technological Forecasting and Social Change, 163. 10.1016/j.techfore.2020.120465.

Kaur, J., Kumar, S., & Narkhede, B.E. (2022). Barriers to blockchain adoption for supply chain finance: the case of Indian SMEs, Electronic Commerce Research. https://doi.org/10.1007/s10660-022-09566-4

Koh, S. C. L., Morris, J., Ebrahimi, S. M., & Obayi, R. (2016). Integrated resource efficiency: Measurement and management, International Journal of Operations & Production Management, 36 (11), 1576–1600.

Morkunas V.J., Paschen J., & Boon E. (2019). How blockchain technologies impact your business model, Business Horizons, 62 (3), 295 – 306. 10.1016/j.bushor.2019.01.009

Nasih S., Arezki S. & Gadi T. (2019). Blockchain technology impact on the maritime supply chain. ACM International Conference Proceeding Series. DOI: 10.1145/3368756.3369104

Queiroz, M. M. & Wamba, S.F. (2019). Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA, International Journal of Information Management, 46, 70-82. https://doi.org/10.1016/j.ijinfomgt.2018.11.021.

Rogers, E.M. (2010). Diffusion of Innovations. Simon and Schuster.

Salim, T. A., Barachi, M. E., Alfatih D. A. Mohamed, Halstead, S. & Babreak, N. (2022). The mediator and moderator roles of perceived cost on the relationship between organizational readiness and the intention to adopt blockchain technology, Technology in Society, 71. https://doi.org/10.1016/j.techsoc.2022.102108

Savolainen, R. (1993). The sense-making theory: Reviewing the interests of a user-centered approach to information seeking and use, Information

Processing & Management, 29 (1), 13-28, https://doi.org/10.1016/0306-4573(93)90020-E

Schmid, L., Gerharz, A., Groll, A. & Pauly, M. (2023). Tree-based ensembles for multi-output regression: Comparing multivariate approaches with separate univariate ones, Computational Statistics & Data Analysis, 179. https://doi.org/10.1016/j.csda.2022.107628

Seebacher, S. & Schuritz, R. (2017). Blockchain technology as an enabler of service systems: a structured literature review. Lecture Notes in Business Information Processing, Springer, Cham, 279.

Stranieri S.,Riccardi F., Meuwissen M.P.M. & Soregaroli C. (2021). Exploring the impact of blockchain on the performance of agri-food supply chains, Food Control, 119. DOI: 10.1016/j.foodcont.2020.107495

Wu C. & Jin S. (2022). Does Blockchain Technology Promote the Quality of Enterprise Accounting Information? Journal of Global Business and Trade, 18 (5). DOI: 10.20294/jgbt.2022.18.5.1

Yu, W., Zhao, G., Liu, Q. & Song, Y. (2021). Role of big data analytics capability in developing integrated hospital supply chains and operational flexibility: An organizational information processing theory perspective, Technological Forecasting and Social Change, 163. https://doi.org/10.1016/j.techfore.2020.120417