Integration of Artificial Intelligence Technology in Management Accounting Information System: An Empirical Study

Emon Kalyan Chowdhury

Abstract At present, most of the business organizations take their management decisions using traditional approach. In the traditional approach, the freedom to be flexible is limited due to numerous assumptions. This paper aims to establish an artificial neural network-based model to predict management information and verify the accuracy of the model using some real data. The proposed model covers five dimensions, namely, accounting analysis management system, accounting decision support system, performance management information system, risk management information system, and environmental management information system. It is observed that the proposed model can predict the management accounting information by 98.83%, which is extremely good and meets the accounting information requirement.

Keywords Artificial intelligence · Machine learning · Management accounting · Information system · Neural network

1 Introduction

Management accounting provides information to managers who make important decisions in an organization (Garrison et al., 2003). The size and complexity of data is increasing day by day as a result managers are in serious trouble in processing large amount of data (Munim et al., 2020). The success of a decision depends on the quality of the information. Therefore, an efficient management accounting information system where data are processed through artificial intelligence technology plays a vital role in improving the operating efficiency of an organization (Zhang, 2021).

Management enterprises are substantially dependent on advanced information technology to make rational and effective decisions. Among management information systems, the management accounting information system is the most important

E. K. Chowdhury (✉)
CIU Business School, Chittagong Independent University, Chattogram, Bangladesh

M. Z. Abedin, P. Hajek (eds.), *Novel Financial Applications of Machine Learning and Deep Learning*, International Series in Operations Research & Management Science 336, https://doi.org/10.1007/978-3-031-18552-6_3

segment (Hutahayan, 2020). The significance of management accounting information system lies in the economic progress, expansion, scale of economies, acquisition, and continuous improvement of strengths through scientific management decisions (Cai et al., 2019).

Practically, the use of management accounting information system is confined to the cost management, preparation of different budgets, and performance management. Smooth functioning of enterprise management is highly dependent on the comprehensive and stable construction of management accounting information systems integrated with other management information systems (Goetz et al., 2015).

The remaining part continues as follows. Section 2 reviews previous studies. Section 3 analyzes different models based on artificial intelligence technology. Section 4 experiments the success rates of prediction capacity of model using authentic management information data, and Sect. 5 concludes the paper.

2 Literature Review

Management control systems ensure optimal use of limited resources to achieve the organization's goal. In addition to financial data, an efficient management control system also uses psychological and control variables (Nguyen et al., 2017). The data from multiple sources are collected and fed into the management information system so as to generate various sub-objectives from a single organizational objective. It helps to compare the actual performance with the projected plans from diverse perspectives (Al-Ali et al., 2017). To sustain itself in a competitive and technology-based environment, an organization must strengthen its managerial and supervisory functions by introducing a management control system (Chi et al., 2019; Xin et al., 2018). Out of the different wings of the management information system, the development of the management accounting information system is crucial, as it directly contributes to the organization's financial solvency, internal control system, customer retention, and overall sustainability (Chowdhury, 2019; Ward et al., 2016). Recently, the use of an e-commerce-based accounting information system has increased tremendously among the enterprises to enjoy competitive advantages (Shajalal et al., 2021; Hidayat et al., 2020). Management accounting plays an important role in fulfilling the economic needs of an organization's operation and management with the help of responsibility center. The responsibility center ensures optimum uses of internal accounting control systems and further assists in organizing and delivering other functional internal management systems (Ghasemi et al., 2019). Amershi et al. (2014) observed a significantly positive impact of management accounting on innovation management. Management accounting systems simplify the cost calculation of single and batch products (Rodriguez-Galiano et al., 2015). Cooper et al. (2017) noticed the increasing popularity of using balanced scorecards in organizations to measure the performance of different indicators.

The traditional management accounting system mostly depends on the assumptions rather than versatility of data, which imperatively directs to take fixed decisions. This study finds a gap to explore the possibility of taking dynamic decisions by using alternative models where artificial intelligence technology is used in line with machine learning and data mining algorithms.

3 Artificial Neural Network (ANN)

The design of ANN is inspired by the structure of biological neurons such as the human brain. In a human brain, neurons create a network through interconnections. A neuron is known as a cell and executes a single task by responding to an input signal. In an ANN, the nodes are connected to each other and establish a network among themselves. The nodes are designed using artificial intelligence to handle massive amount of data using multiple equations simultaneously. In this network, the equations are established through sequential computations following a trial-and-error approach (Abedin et al., 2021; Chakraborty et al., 2018). The basic structure of ANN is expressed in Fig. 1.

Input neurons $X_1, X_2, \ldots, X_n$ indicate various inputs to the network, synapse weights $W_1, W_2, \ldots, W_n$ signify the weights of connections. The weights are very important in ANN as these represent the strength of each node. The weights that govern the effect of neurons are measured in the numerical parameters, which determines the output by converting the input.

The hidden layer performs the processing task. It applies two operational functions, the summation function and the transfer or activation function. The summation function multiplies each input (X_i) with the corresponding weight (W_i) and all products ($W_i \times X_i$) result in the summation function $\xi = \sum W_i \times X_i + B$, where B represents the bias value. It controls the output of the neuron in line with the weighted sum of inputs.

The activation function transforms the input signal from the summation function into to output of a node for an ANN model. Each ANN is made up of three components. First, the node character determines inputs and outputs through signal processing. Second, the network topology determines how the nodes are connected

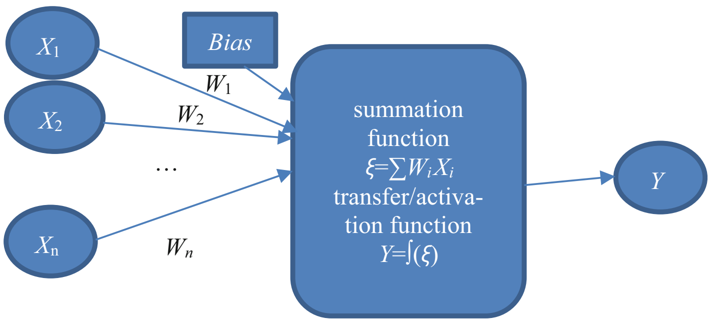

Fig. 1 Model of an artificial neuron

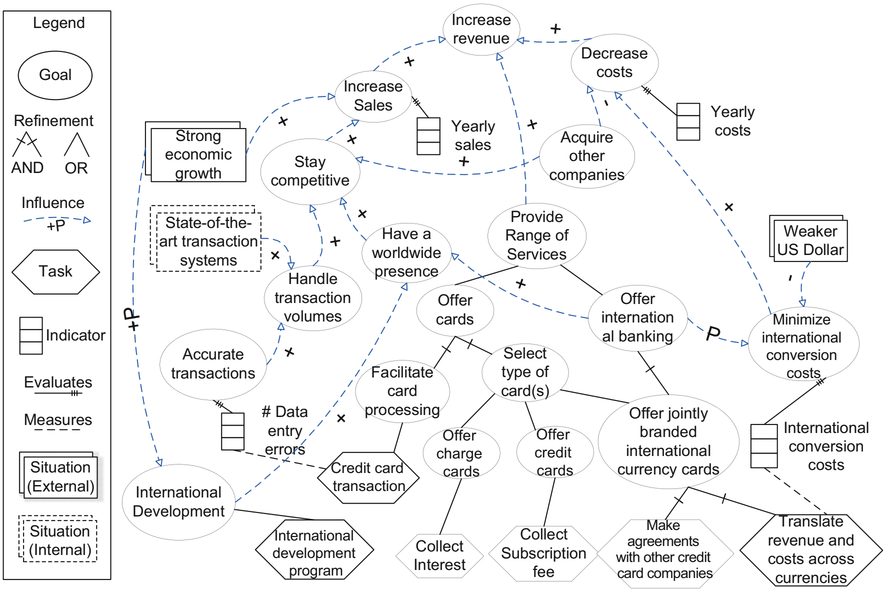

Fig. 2 Business intelligence model for a credit card company. Source: Horkoff et al. (2012)

and organized. Third, the learning rules create and adjust weights. A few widely used ANN-based models have been discussed below.

Business Intelligence (BI) Model

BI helps an organization excel at operational activities in such a way that helps tap the opportunities in the market while overcoming potential threats. It has the capacity to generate effective information to take strategic decisions by processing massive volume of data. BI establishes a network between an organization and the external environment with the support of different reasoning techniques that controls influences, situations, and the indicators (Fig. 2). The reasoning tools for this model are "what if" a bottom-up approach and "is it possible?" a top-down approach (Horkoff et al., 2012).

Three-Tier Data Model

The three-tier data model is widely used in the data warehouse management of an organization. It provides subject-wise analytical environment in the global context (Abedin et al., 2020; Lau et al., 2018). The three tiers have been outlined below:

(a) Conceptual model: This is the top level of the model which is expressed by topics. Topics are derived from the dimensions and measures. Dimension refers to a perspective through which people observe the world, and measurement is related to data information of the dimension. For example, sales volume.
(b) Logical model: Logical model may be classified into two models such as the star model and the snowflake model. The star model includes the fact table and dimension model, while at the same time, they are connected to each other. The

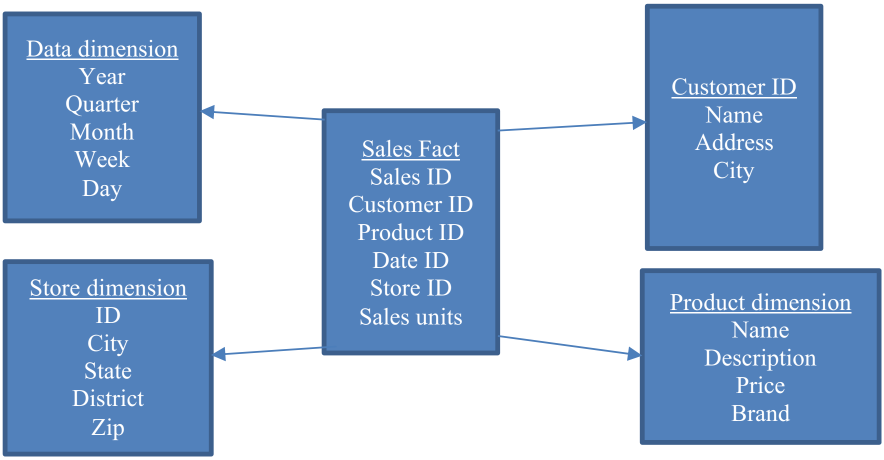

Fig. 3 Star model

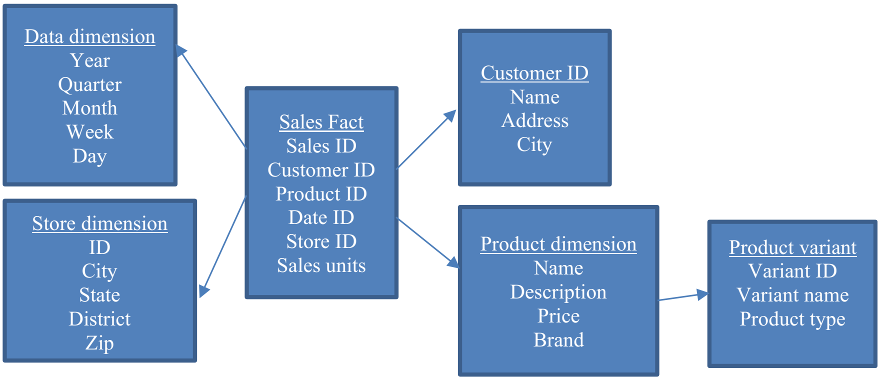

Fig. 4 Snowflake model

star model is shown in Fig. 3. The sales data are generated in different time dimension including customer details, store details, and product details.

A snowflake model is an extension of the star model. It includes additional information about a particular dimension (Fig. 4). It uses similar disk space, is easy to install, and reduces query performance for multiple tables.

Extract, Transform, Load (ETL) Model
In this model, data are extracted from multiple source systems and then converted to final data after necessary calculations. The converted data are loaded into the data warehouse system for managerial decision. Source points include relevant stakeholders such as analysts, developers, testers, and top brass executives. Since ETL activities occur regularly, the data warehouse required to be updated, agile, and properly documented. ETL helps to make critical business decisions, and compare

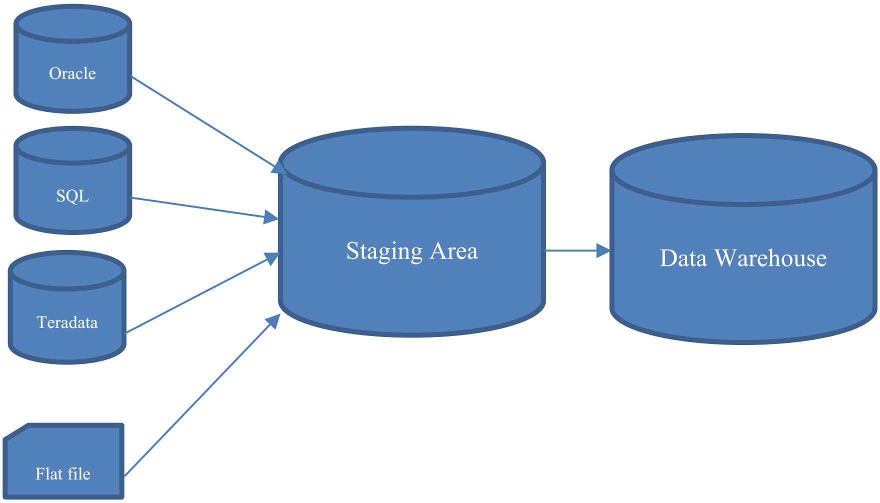

Fig. 5 ETL model

the data of the source and target system through data migration and manipulation. Where the transactional database fails to answer complex business questions, ETL can easily and quickly address them (Hajek & Abedin, 2020; Sabtu et al., 2017). Figure 5 shows the ETL process in three steps.

In the ETL model, data are fed into the staging area by extracting them from the source points after due validations. Data are extracted from the source points in raw format, and at the transformation stage, data are cleaned, mapped, and converted. In this stage, the ETL assigns values and modifies the data so that business intelligence-based reports can be generated. Warehousing data is the last step of the ETL model. Here, a huge volume of data can be loaded in significantly less time. If the loading process fails, the recovery mechanism is activated without failure of any sort of data integrity. The entire ETL process is controlled by the warehouse administrator (Abedin et al., 2018).

Cube Structure

The data cube is a three-dimensional way of presenting data. In this model, the data are judged from various perspectives. When data cannot be presented in traditional column and row format due to more variables and context, data cube can make it so simple by utilizing different angles (Augenstein et al., 2018). Data cubes have the following categories.

(a) Multidimensional data cube: Most of the online analytical processing (OLAP) products are designed using a multidimensional array. These OLAPs perform better than other approaches, as they can be indexed straight to collect subsets of data. The larger the dimension, the sparser the cubes.
(b) Rational OLAP (ROLAP): This model uses a relational database to store and manage warehouse data. ROLAP servers are highly scalable and analyze

massive volumes of data across multiple dimensions. It also stores and analyzes highly volatile and changeable data.

To understand the presentation of the data in cube structure, the following information can be considered (Table 1).

The above information is shown in a three-dimensional cube (Fig. 6).

The essence of the cube structure lies in the capacity to show different data in a single image.

Data Mining (DM) Process

DM is an essential part of the management accounting information system (Kara et al., 2020). It combines database, statistics, machine learning, and other relevant technologies. It generates required information for managers amalgamating different data to enjoy competitive advantages (Abedin et al., 2019). Figure 7 depicts the data mining process.

4 Proposed Model

In light of the above analysis, this study recommends an Intelligent Management Accounting Information System (IMAIS) for the decision-making process where the following aspects are integrated. This model is the extension of Zhang (2021) where the environmental management information system was not included. In this model, the impact of the management decision on the environment has been considered. The integrated systems are as follows:

(a) Accounting analysis management system
(b) Performance management information system
(c) Accounting decision support system
(d) Risk management information system, and
(e) Environmental management information system

This recommended model can provide customized information to take decisions in time and also helps to run its business in a way better ensuring a sound internal control system. Figure 8 shows an IMAIS formation structure.

The recommended IAMAIS model covers reporting systems, risk management, performance management, decision support issues, and environmental issues. Each sub-system works autonomously and combinedly to fulfill segment and enterprise requirements.

Test of Model Efficiency

To verify the degree of accuracy of the proposed model, this study has used real management accounting data. Out of 380 observations, a total of 125 observations have been used classifying into 13 categories to train the model. The predicted results and actual results are shown in Fig. 9.

Table 1 Location-wise quarterly data

Location = "Chicago"					Location = "New York"				Location = "Toronto"			
Item					Item				Item			
Home					Home				Home			
Time	Ent.	Comp.	Phone	Sec.	Ent.	Comp.	Phone	Sec.	Ent.	Comp.	Phone	Sec.
Q1	854	882	89	623	1087	968	38	872	818	746	43	591
Q2	943	890	64	698	1130	1024	41	925	894	769	52	682
Q3	1032	924	59	789	1034	1048	45	1002	940	795	58	728
Q4	1129	992	63	870	1142	1091	54	984	978	864	59	784

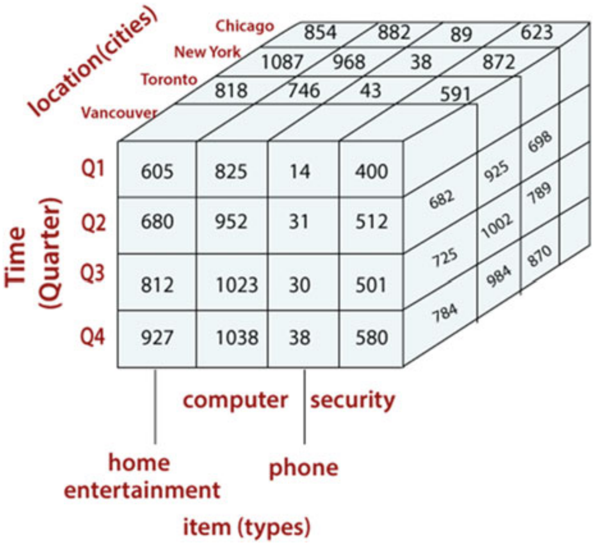

Fig. 6 Cube structure

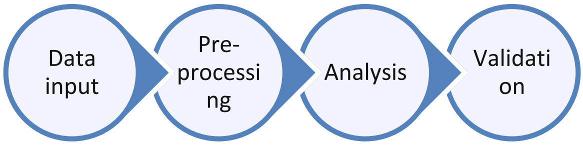

Fig. 7 Data mining process

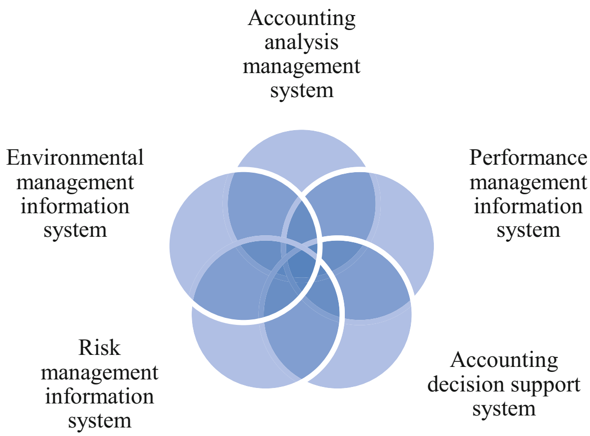

Fig. 8 Intelligent management accounting information system

It is observed that the prediction is very close to the actual results for most of the observations. To get a further clear scenario, the residuals of the actual and predicted data are shown in Fig. 10.

It is also observed that most residuals hover within 0.05 to −0.05 and a very insignificant number of observations are above 0.1 to −0.01. This clearly indicates that the model is capable of predicting management information with an accuracy rate of 98.83%. As the rate is very close to 100%, it may be applied in the real world.

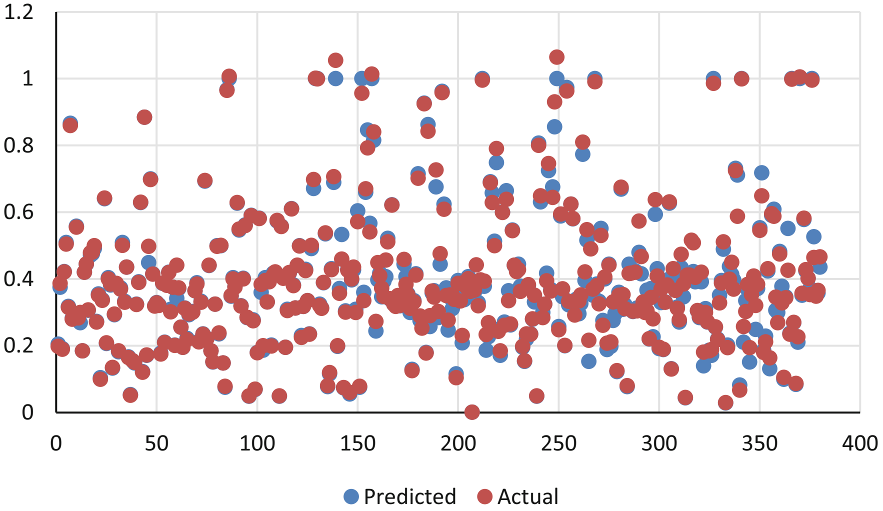

Fig. 9 Actual vs. predicted data

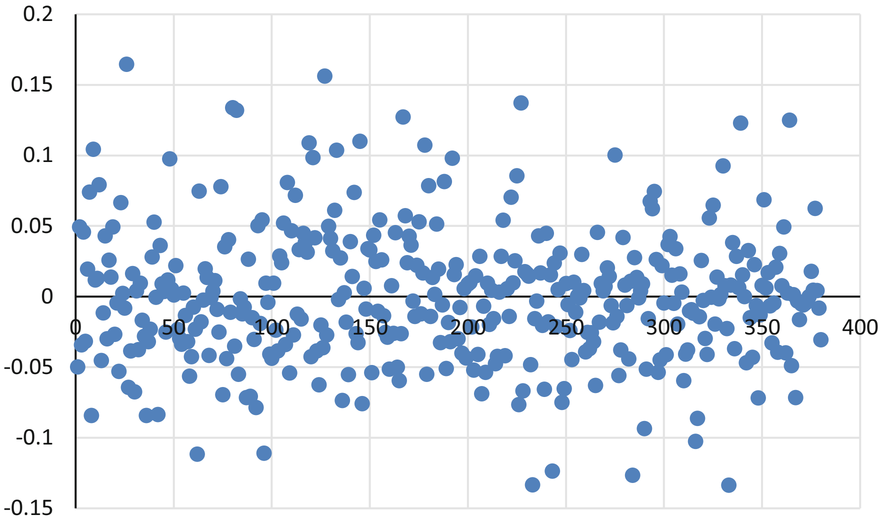

Fig. 10 The residuals of actual vs. predicted results

5 Conclusion

This study aimed to formulate a management accounting information system using machine learning and an artificial neural network model. Being a vital sub-information system of management information system, the management accounting information system plays a very important role in the accounting development, therefore it should incorporate the accounting analysis management system, performance management information system, accounting decision support system, risk management information system, and environmental management information system. The recommended model can predict the accounting data with an accuracy rate of 98.83%. As the business world is complex and affected by many factors, the use of artificial intelligence technology to make management accounting decisions knows no bounds. It is assumed that the synergy of five dimensions helps in taking appropriate business decisions. Future researchers may include legal and ethical issues in the model to make this model more reliable and applicable as these issues vary from country to country.

References

Abedin, M. Z., Chi, G., Colombage, S., & Moula, F. E. (2018). Credit default prediction using a support vector machine and a probabilistic neural network. *Journal of Credit Risk*. Accessed from https://ssrn.com/abstract=3175776

Abedin, M. Z., Guotai, C., Moula, F. E., Azad, A. S., & Khan, M. S. U. (2019). Topological applications of multilayer perceptrons and support vector machines in financial decision support systems. *International Journal of Finance & Economics, 24*(1), 474–507.

Abedin, M. Z., Chi, G., Uddin, M. M., Satu, M. S., Khan, M. I., & Hajek, P. (2020). Tax default prediction using feature transformation-based machine learning. *IEEE Access, 9*, 19864–19881.

Abedin, M. Z., Hassan, M. K., Khan, I., & Julio, I. F. (2021). Feature transformation for corporate tax default prediction: Application of machine learning approaches. *Asia-Pacific Journal of Operational Research, 2140017*.

Al-Ali, A. R., Zualkernan, I. A., Rashid, M., Gupta, R., & AliKarar, M. (2017). A smart home energy management system using IoT and big data analytics approach. *IEEE Transactions on Consumer Electronics, 63*(4), 426–434.

Amershi, S., Cakmak, M., Knox, W. B., & Kulesza, T. (2014). Power to the people: The role of humans in interactive machine learning. *AI Magazine, 35*(4), 105–120.

Augenstein, D., Fleig, C., & Maedche, A. (2018, June). Development of a data-driven business model transformation tool. In *International Conference on Design Science Research in Information Systems and Technology* (pp. 205–217). Springer.

Cai, J., Huang, W., Yang, S., Wang, S., & Luo, J. (2019, August). A selection method for Denoising auto encoder features using cross entropy. In *International Conference on Intelligent Computing* (pp. 479–490). Springer.

Chakraborty, T., Chattopadhyay, S., & Chakraborty, A. K. (2018). A novel hybridization of classification trees and artificial neural networks for selection of students in a business school. *Opsearch, 55*(2), 434–446.

Chi, G., Uddin, M. S., Abedin, M. Z., & Yuan, K. (2019). Hybrid model for credit risk prediction: An application of neural network approaches. *International Journal on Artificial Intelligence Tools, 28*(05), 1950017.

Chowdhury, E. K. (2019). Transformation of business model through blockchain technology. *Accounting and Finance, 47*(5), 4–9.

Cooper, D. J., Ezzamel, M., & Qu, S. Q. (2017). Popularizing a management accounting idea: The case of the balanced scorecard. *Contemporary Accounting Research, 34*(2), 991–1025.

Garrison, R. H., Noreen, E. W., Brewer, P. C., & Mardini, R. U. (2003). *Managerial accounting*. McGraw-Hill/Irwin.

Ghasemi, R., Habibi, H. R., Ghasemlo, M., & Karami, M. (2019). The effectiveness of management accounting systems: Evidence from financial organizations in Iran. *Journal of Accounting in Emerging Economies, 9*(2), 182–207.

Goetz, J. N., Brenning, A., Petschko, H., & Leopold, P. (2015). Evaluating machine learning and statistical prediction techniques for landslide susceptibility modeling. *Computers and Geosciences, 81*, 1–11. https://doi.org/10.1016/j.cageo.2015.04.007

Hajek, P., & Abedin, M. Z. (2020). A profit function-maximizing inventory backorder prediction system using big data analytics. *IEEE Access, 8*, 58982–58994.

Hidayat, A. T., Dewantara, A. M. D., & Saifullah, S. (2020). The development of website on management information system for e-commerce and services. *Jurnal Sisfokom (Sistem Informasi dan Komputer), 9*(3), 380–386.

Horkoff, J., Borgida, A., Mylopoulos, J., Barone, D., Jiang, L., Yu, E., & Amyot, D. (2012, September). Making data meaningful: The business intelligence model and its formal semantics in description logics. In *OTM Confederated International Conferences. On the move to meaningful Internet systems* (pp. 700–717). Springer.

Hutahayan, B. (2020). The mediating role of human capital and management accounting information system in the relationship between innovation strategy and internal process performance and the impact on corporate financial performance. *Benchmarking: An International Journal, 27*(4), 1289–1318.

Kara, M. E., Fırat, S. Ü. O., & Ghadge, A. (2020). A data mining-based framework for supply chain risk management. *Computers & Industrial Engineering, 139*, 105570.

Lau, H. C., Ip, A., Lee, C. K. M., & Ho, G. T. (2018). Development of a three-tier assessment model: A case study. *Benchmarking: An International Journal, 25*(7), 2216–2229.

Munim, Z. H., Dushenko, M., Jimenez, V. J., Shakil, M. H., & Imset, M. (2020). Big data and artificial intelligence in the maritime industry: A bibliometric review and future research directions. *Maritime Policy & Management, 47*(5), 577–597.

Nguyen, T. T., Mia, L., Winata, L., & Chong, V. K. (2017). Effect of transformational-leadership style and management control system on managerial performance. *Journal of Business Research, 70*, 202–213.

Rodriguez-Galiano, V., Sanchez-Castillo, M., Chica-Olmo, M., & Chica-Rivas, M. J. O. G. R. (2015). Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. *Ore Geology Reviews, 71*, 804–818.

Sabtu, A., Azmi, N. F. M., Sjarif, N. N. A., Ismail, S. A., Yusop, O. M., Sarkan, H., & Chuprat, S. (2017, July). The challenges of extract, transform and loading (ETL) system implementation for near real-time environment. In *2017 International Conference on Research and Innovation in Information Systems* (ICRIIS) (pp. 1–5). IEEE.

Shajalal, M., Hajek, P., & Abedin, M. Z. (2021). Product backorder prediction using deep neural network on imbalanced data. *International Journal of Production Research, 2021*, 1–18.

Ward, L., Agrawal, A., & Choudhary, A. (2016). A general-purpose machine learning framework for predicting properties of inorganic materials. *NPJ Computational Materials, 2*, 16028. https://doi.org/10.1038/npjcompumats.2016.28

Xin, Y., Kong, L., Liu, Z., Chen, Y., Li, Y., Zhu, H., Gao, M., Hou, H., & Wang, C. (2018). Machine learning and deep learning methods for cybersecurity. *IEEE Access, 6*, 35365–35381.

Zhang, X. (2021). Application of data mining and machine learning in management accounting information system. *Journal of Applied Science and Engineering, 24*(5), 813–820.