The Impact of Artificial Intelligence on Business Performance in Saudi Arabia: The Role of Technological Readiness and Data Quality

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ABSTRACT

This study aims to examine the impacts of Machine Learning (ML) and Artificial Intelligence (AI) capabilities on Business Performance (BP) of technology enterprises in the Kingdom of Saudi Arabia (KSA). Building on established theories such as the Resource-Based View (RBV) and the Technology Organization Environment (TOE) framework, the study proposes that AI and ML capabilities impact business performance. Their effects are anticipated to be mediated by Technological Readiness (TR) and moderated by Data Quality (DQ). A total of 190 executives and IT professionals in KSA participated in this study. Smart PLS 4 was used to analyze the data. The findings showed that AI and ML capabilities positively affected business performance. Technological readiness acted as a mediator in the relationship between AI and ML capabilities, and BP. Data quality significantly increased the impact of AI capabilities on BP. The business performance of enterprises in KSA will increase with the presence of efficient AI and ML capabilities as well as the development of a high level of technological readiness and data quality.

Keywords-artificial intelligence capability; machine learning; technological readiness; data quality; business performance

I. INTRODUCTION

During the last decades, the usage of technology has become a source of competitive advantages. Organizations have increased their investment in technology to achieve better Business Performance (BP) [1]. The development of technology usage went through several stages from the initial usage of internet to e-commerce and social media [2]. AI and ML are examples of the distributive technology that requires high investment in human capital [3]. The need to use these technologies was more urgent during and after the COVID19 period. Human capital that has the required knowledge to use such technology can be a source of competitive advantage to enhance the organizational capabilities and achieve better performance [4]. Against this background, existing studies in the field are mostly related to the usage of AI by large scale companies in developed countries. This is because these organizations are more capable of utilizing this technology, which is associated with high infrastructure readiness [5]. Furthermore, there are some studies that have examined how the usage of AI can result in a better BP [6]. Existing studies are in the initial stage of conducting a review or conceptualizing a framework to understand the linkage between AI and BP [7].

Since the topic is still new, the number of articles that are related to the effect of AI on BP is small but growing. Authors in [8] associated the usage of AI with the organizational readiness and agility during a crisis [8]. This is connected with increasingly viewing AI as an opportunity to achieve new goals (80%) or as a competitive advantage (85%). An important tool in the current business environment is ML, which helps organizations to enhance their business process and re-engineer their operations, which ultimately leads to operational excellence and improved BP [9]. Again, ML is still an emerging technology and there is limited research on how ML can lead to better BP. In [10], both ML and AI were investigated for improving the marketing capabilities of firms in dealing with big data. ML and AI were able to explain high level of variation in the marketing performance of organizations. To effectively utilize ML and AI, an organization should have a decent level of Technological Readiness (TR) in terms of infrastructure, human capital, and financial capability. Therefore, the importance of TR is high in enabling effective usage of AI and ML. In addition, AI and ML depend heavily on the Data Quality (DQ) to produce accurate output. Thus, DQ is essential in the usage of AI and ML [11]. DQ has been acknowledged as an important aspect of good decision-making. However, its application in business is widely ignored [12].

The Kingdom of Saudi Arabia (KSA) is in the process of transforming and diversifying the economy to rely not only on oil production, but also on knowledge and technology-based activities by creating a digital and knowledge-based economy [13]. The 2030 Vision aims to enhance the contribution of all sectors and aims to nationalize the technology in the country [13]. However, it is not known to what degree AI and ML are being used among technological companies. Therefore, this study aims to understand the implementation of AI and ML among these companies and to examine the mediating role of TR and the moderating role of DQ.

A. Theoretical Framework

This study considers AI, ML, TR, and DQ. One of the important theories that can lead to the understanding of the association among the variables is TOE, which was initially coined in [14]. This framework indicates that decision to use an innovation that will impact the performance of adopters is related to the technological aspect as well as the organizational aspect [15]. This study uses AI and ML as technologies and represents the technological part of TOE, while the organizational part is related to the TR of the organization as well as the DQ. Another theory that can explain performance is the Resource-Based View (RBV). Companies when using technology as their resource will be able to achieve a competitive advantage and better organizational performance [16]. Therefore, this study deploys a combination of RBV and TOE. This combination is expected to explain how ML and AI as well as TR and DQ can contribute to BP.

B. Business Performance

BP is one of the most important dependent variables. It refers to the outcome of business in terms of Learning and Growth (LG), Internal Business Processes (IBP), and Financial Performance (FP) [17]. This definition of performance is adopted from the Balanced Scorecard (BSC) which divides BP into financial and non-financial performance. The non-financial performance includes Customer Satisfaction (CS), LG, and IBP. Authors in [18] measured this performance based on the context of their studies. In this study, BP is measured using IBP, LG, and FP. This measurement is in line with BSC and other existing research [19].

C. Machine Learning

ML is the process of making models that can learn (extract knowledge) from previous data and predict future data [20, 21]. ML is the practice of, and the development of, automated systems that can learn and adapt without being explicitly programmed to do so via the use of statistical models and algorithms applied to large amounts of data [22-25]. Several studies refer to the capability of ML [26-28] to provide input for accurate decisions and to facilitate decision-making and problem-solving [29, 30]. This study examines the impact of ML capability on BP.

D. Artificial Intelligence

AI is described as a machine-based system which, for a given set of human-specified objectives, may make predictions, recommendations, or judgements that impact real or virtual environments [31]. It also refers to the automation of processes that are connected to human thought, such as learning, problem-solving, and decision-making [32]. AI will have a massive impact on society and experts suggest that the current time is the time for a rapidly changing and AI-powered economy [33]. AI is involved in all daily life activities and it is also involved in business for the purpose of automated decision making, which results in better performance [34]. This study examines the impact of AI capability on BP.

E. Technological Readiness

TR is characterized as the inclination to adopt and use new technologies in order to achieve a goal [35]. Organizations who intend to use new technology should evaluate and assess the current infrastructure and the readiness of their staff to utilize a new technology [36]. The TR is essential for an organization to successfully deploy a technology. Lack of readiness might cause resistance to change and failure of adopting technologies such as AI and ML, which will lead to a negative impact on the overall BP [37]. In this study, TR is predicted as a crucial mediating factor in the link between AI capability and ML capability with BP.

F. Data Quality

DQ is the sum of traits and properties of data that influence its capacity to fulfil a specific function [38]. The reliability of the collected data and their efficiency when being used in a system are critical for decision-making based on AI and ML, and impact the outcome of these decisions [11]. DQ is important for the effectiveness of ML and AI [39]. However, it has been indicated that while DQ has been largely acknowledged in business, it is ignored in the application of AI and ML [12]. Therefore, due to the lack of studies on DQ, this study intends to investigate the moderating effect of DQ.

G. Conceptual Framework and Hypotheses Development

Based on TOE and resource-based view as well as the balance scorecard, this research hypothesized that the ML capability and AI capability will have a positive influence on BP. The influence of ML capability and AI capability on BP is anticipated to be mediated by TR and moderated by DQ.

1) MLC and BP

MLC has been examined and linked to BP in some studies. MLC is able to predict the performance of companies [40] and helps in the coordination of organizational activities, which affects the overall BP [41]. Additionally, it can maintain a sustainable supply chain [42] and reduce risk by conducting an effective assessment of the latter and helps in decision-making that leads to better BP [9]. Therefore, it is anticipated that MLC will have a considerable favourable impact on BP in this research. So, the first research hypothesis is:

H1: ML capability has a positive impact on BP.

2) AI Capabilities and BP

Prior literature on the role of AI is derived from literature reviews and conceptual articles that attempt to operationalize or conceptualize the term and its link with the organizational outcome [7]. Recent research, however, has investigated the relationship between AIC and BP. For example, the AIC affected positively the BP in [6] and had a significant influence on the BP of China firms [43]. AIC strengthened the marketing and organizational capability, which resulted in a positive BP [44]. The positive effect of AIC on BP has also been found in the literature [45]. Accordingly, the following is hypothesized:

H2: AI Capability has a positive impact on BP.

3) Mediating Role of TR

TR is a critical predictor of using new technology. Most existing studies look into TR as a predictor or moderating variable. For instance, TR moderated the effect between predictors of using technology and acceptance of technology [46]. In addition, TR moderated the effect of self-service and technology acceptance [47]. Further, TR moderated the effect of innovation and gratification on virtual reality in the tourism sector [48]. Limited studies have examined the TR as a mediator. As an example, TR mediated the connection between digital financial literacy and inclusion [4]. In this research, the AIC and MLC cannot achieve their potential without having effective TR of organizations. Therefore, this study proposes TR as a mediator between AIC and MLC, and BP. Thus, the following are proposed:

H3: The effect of MLC on BP is mediated by TR.

H4: The effect of AIC on BP is mediated by TR.

4) Moderating Role of Data Quality

DQ is essential for effective decision-making. Low data quality led to misleading knowledge and decisions which might lead to financial and market loss [49]. DQ is critical for all processes and organizational activities. However, it is more important when it comes to AI and ML [50], because AIC and MLC are more effective with high DQ. DQ affects the reliability of AI and ML [51] and enables their expansion [52]. The impact of digital accounting systems on the quality of decisions can be moderated by DQ [53]. To improve the efficiency of AIC and MLC on BP in this research, it is essential to collect and use high-quality data. Thus, the following are proposed:

H5: Data quality moderates the effect of MLC on BP.

H6: Data quality moderates the effect of AIC on BP.

II. RESEARCH METHODOLOGY

This research deploys quantitative methods. The data were collected via a survey. The research sample comprises CEOs and IT professionals from prominent Saudi IT enterprises. It uses convenience sampling based on snowballing and network recommendation to reach responders. The optimal sample size for structural equation modeling is 100–150 [54]. The G*power method requires 89 replies. This computation utilizes four predictors, 0.95 confidence, and 0.05 error margin. The questionnaire items were based on proven instruments. DQ was measured based on scales adopted from [55], while AIC was self-developed. However, the findings of [56, 57] were reviewed and utilized in the development of the measurement. Similar procedures were followed to measure MLC after reviewing [58, 59]. The measurement of BP was adopted from [60, 61]. TR was measured using the questionnaire presented in [47, 48]. Arabic is KSA's official language, hence the questionnaire was in Arabic. Bilingual Arabic-English specialists validated the measurement. Before collecting data, a preliminary investigation assessed measurement reliability. This approach yielded 197 responses. Three incomplete responses were deleted. A boxplot analysis revealed four outliers, which were deleted. 190 valid responses were retained for analysis. The values of skewness and kurtosis were below one, indicating a normal distribution. The tolerance value (should be larger than 0.20) and Variance Inflation Factor (VIF, should be less than 5) were within their acceptable ranges, indicating no issues of multicollinearity. Smart PLS version 4 was employed for the Measurement Model (MM) and the Structural Model (SM) to be analyzed and evaluated. Smart PLS 4 is efficient as the testing mediator and moderator [54].

III. FINDINGS

The findings of this study discuss the descriptive information of the respondents as well as the assessment of the MM and SM models.

A. Profile of Respondents

A total of 190 valid responses were collected. The respondents are males (79%), older than 40 years (63%), and holders of a bachelor's degree (71%) with working experience in a technological related field of more than 15 years (77%) and they are working as executives (35%) and heads of IT departments (41%).

B. Measurement Model

The measurement model was evaluated by Factor Loading (FL), validities, and reliabilities [54]. The FL for all items was checked. Accordingly, certain items were eliminated due to low FL. Items of AIC1 from AI capability, item MLC5 from MLC, and items BP5 and BP9 from BP were deleted due to low factor loading. After removing the items, Cronbach's Alpha (CA) as well as Composite Reliability (CR) values were improved. The convergent validity of the study is acceptable because the Extracted Average Variance (AVE) is larger than 0.50 for all the variables. Since the square root of AVE is more than the cross-loading of the variables, the findings for discriminant validity demonstrated that it is acceptable.

C. Structural Model

In the assessment of SM, there is a need to evaluate R-square (R^2), F-square (f^2), and path coefficient (B) [54]. The value of R^2, as shown in Figure 1, is 0.470, suggesting that 47% of BP can be explained by MLC, TR, DQ, and ALC. For the f^2, the acceptable value is 0.02. For all the paths, the f^2 is acceptable except for the DQ×MLC→BP. However, these values are low because the related hypotheses are rejected. Figure 1 displays the SM of this research, which includes the direct, mediation, and moderating hypotheses and paths.

D. Hypotheses Testing

The results of the hypotheses are evidenced in Table I. A total of six hypotheses were examined. The table demonstrates the direct effect, mediating and moderating hypotheses.

For the first hypothesis, H1, MLC has a positive influence on BP (B=0.187, P<0.05). Thus, as indicated in Table I, H1 is supported. AIC has a substantial impact on BP for H2 (B=0.466, P<0.05). H2 is thus supported. Given that both the direct impact of MLC on BP and the indirect effect through TR are significant (B=0.171, P<0.05), H3 for the mediation effect hypothesis, is supported. Since both effects are significant, H3 is accepted and the mediation is only partial. Similarly, for H4, AIC has a favorable and considerable direct influence on BP. At a path coefficient of 0.049 and a p-value below 0.05, the indirect impact (AIC→TR→BP) is likewise significant and H4 is thus supported. Because the direct and indirect effects are substantial, the mediation is only partial. DQ does not significantly moderate the relationship between MLC and BP for H5. H5 is therefore rejected. H6, however, is supported since DQ, as illustrated in Table I, constructively moderated the impact of AIC on BP.

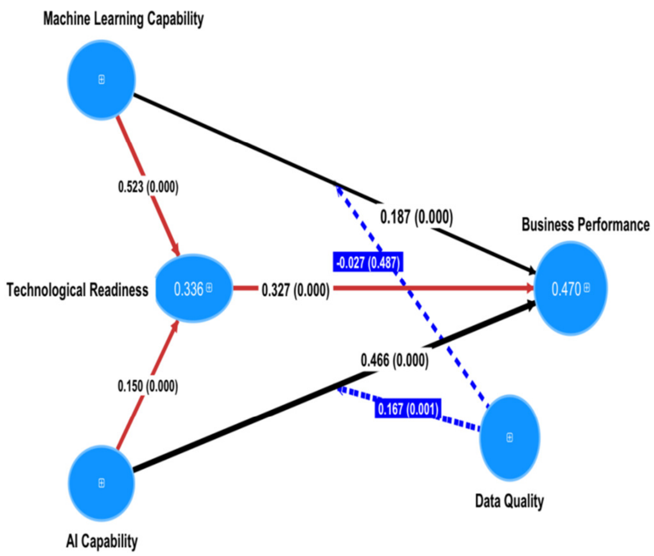

Fig. 1. Results of the structural model.

TABLE I. RESULTS OF HYPOTHESES TESTING

H	Path	B	Std.	T-values	P-Values
H1	MLC → BP	0.187	0.052	3.599	0.000
H2	AIC → BP	0.466	0.071	6.573	0.000
H3	MLC → TR	0.523	0.038	13.824	0.000
	MLC → TR → BP	0.171	0.028	6.221	0.000
H4	AIC → TR	0.150	0.042	3.567	0.000
	AIC → TR → BP	0.049	0.016	3.117	0.002
H5	DQ × MLC → BP	-0.027	0.039	0.695	0.487
H6	DQ × AIC → BP	0.167	0.049	3.426	0.001

IV. IMPLICATIONS

This research expands knowledge of corporate MLC and AIC usage. This research experimentally examines MLC and AIC's impacts, unlike prior studies that conceptualized and reviewed their potential. A large percentage of variation of BP was analyzed and explained with the TOE framework and RBV. The current study adds to developing economy literature, focusing on Saudi Arabia. The research supports Saudi Arabia's Vision 2030 by showing that MLC and AIC can help organizations increase performance and finally boost the country's GDP. Companies should emphasize AIC and MLC to improve performance. TR is necessary for efficient technology use. Effective TR levels are essential for MLC and AIC implementation because TR mediated partially the effect of MLC and AIC indicating that a significant part of the relationship between the variables is facilitated by TR. High-DQ enhances AIC's performance benefits. Thus, KSA tech businesses must develop strong data accuracy methods. Real-time data audits may discover and fix inaccuracies and misleading information. This research reveals how MLC and AIC affect KSA tech businesses' success. To maximize these potential, TR and DQ are crucial.

V. CONCLUSION, LIMITATIONS, AND FUTURE WORK

This research examined how MLC and AIC affect BP. Conceptual and literature review research explored these issues. This research experimentally investigated these determinants in KSA technology businesses, providing new viewpoints. This research supports MLC and AIC's benefits, adding to the scientific debate. A key conclusion is that TR partially mediates the AIC-BP link. AIC can improve business performance depending on a company's TR. It was also found that DQ affects how AIC influences BP. This indicates that high-quality data can boost corporate success using AI. However, the results only apply to KSA technology businesses. Future studies should deploy random sampling to improve generalizability. Expanding the research to include listed, service, and manufacturing enterprises would improve its external validity.

Increasing the sample size can increase the generalizability of the findings. Adding variables can help to understand BP. Complex interactions between MLC and AIC might affect company success. The finding provides KSA technology firms with practical recommendations. This suggests that these organizations should prioritize AIC and MLC adoption to boost performance. Advanced AI technology and MLC are essential. Additionally, a company must be technologically ready and have high-quality data. This strategy helps organizations to be more competitive and increase BP.

REFERENCES

[1] H. Taherdoost and M. Madanchian, "Artificial Intelligence and Knowledge Management: Impacts, Benefits, and Implementation," *Computers*, vol. 12, no. 4, Apr. 2023, Art. no. 72, https://doi.org/10.3390/computers12040072.

[2] I. J. Ismail, "Speaking to the hearts of the customers! The mediating effect of customer loyalty on customer orientation, technology orientation and business performance," *Technological Sustainability*, vol. 2, no. 1, pp. 44–66, Jan. 2022, https://doi.org/10.1108/TECHS-03-2022-0016.

[3] R. J. Correia, J. G. Dias, M. S. Teixeira, and S. Campos, "Building competitive advantages and business success: the role of learning orientation, reward systems and entrepreneurial orientation," *European Business Review*, vol. 35, no. 1, pp. 92–119, Jan. 2022, https://doi.org/10.1108/EBR-03-2022-0051.

[4] A. K. Rizky, "The Role of Technology Readiness to Mediate the Impact of Digital Financial Literacy on Digital Financial Inclusion," in *10th*

Gadjah Mada International Conference on Economics and Business (GAMAICEB), Yogyakarta, Indonesia, Sep. 2022.

[5] M. Ghasedi, M. Sarfjoo, and I. Bargegol, "Prediction and Analysis of the Severity and Number of Suburban Accidents Using Logit Model, Factor Analysis and Machine Learning: A case study in a developing country," *SN Applied Sciences*, vol. 3, no. 1, Jan. 2021, Art. no. 13, https://doi.org/10.1007/s42452-020-04081-3.

[6] S.-L. Wamba-Taguimdje, S. Fosso Wamba, J. R. Kala Kamdjoug, and C. E. Tchatchouang Wanko, "Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects," *Business Process Management Journal*, vol. 26, no. 7, pp. 1893–1924, Jan. 2020, https://doi.org/10.1108/BPMJ-10-2019-0411.

[7] F. Kitsios and M. Kamariotou, "Artificial Intelligence and Business Strategy towards Digital Transformation: A Research Agenda," *Sustainability*, vol. 13, no. 4, Jan. 2021, Art. no. 2025, https://doi.org/10.3390/su13042025.

[8] X. Wang, X. Lin, and B. Shao, "How does artificial intelligence create business agility? Evidence from chatbots," *International Journal of Information Management*, vol. 66, Oct. 2022, Art. no. 102535, https://doi.org/10.1016/j.ijinfomgt.2022.102535.

[9] W. A. Khan, S. H. Chung, M. U. Awan, and X. Wen, "Machine learning facilitated business intelligence (Part I): Neural networks learning algorithms and applications," *Industrial Management & Data Systems*, vol. 120, no. 1, pp. 164–195, Jan. 2019, https://doi.org/10.1108/IMDS-07-2019-0361.

[10] L. Ma and B. Sun, "Machine learning and AI in marketing – Connecting computing power to human insights," *International Journal of Research in Marketing*, vol. 37, no. 3, pp. 481–504, Sep. 2020, https://doi.org/10.1016/j.ijresmar.2020.04.005.

[11] H. Liu, F. Huang, H. Li, W. Liu, and T. Wang, "A Big Data Framework for Electric Power Data Quality Assessment," in *14th Web Information Systems and Applications Conference*, Liuzhou, China, Nov. 2017, pp. 289–292, https://doi.org/10.1109/WISA.2017.29.

[12] L. Ehrlinger, V. Haunschmid, D. Palazzini, and C. Lettner, "A DaQL to Monitor Data Quality in Machine Learning Applications," in *International Conference on Database and Expert Systems Applications*, Linz, Austria, Aug. 2019, pp. 227–237, https://doi.org/10.1007/978-3-030-27615-7_17.

[13] S. I. Khan, "Saudi Vision 2030: New Avenue of Tourism in Saudi Arabia," *Studies in Indian Place Names*, vol. 40, no. 75, pp. 2394–3114, 2020.

[14] L. G. Tornatzky and M. Fleischer, *The processes of technological innovation*. Lanham, MD, USA: Lexington Books, 1990.

[15] A. Alhamami, N. Hashim, R. Hamid, and S. Hamid, "The adoption of social media by small and medium enterprise: a systematic literature review," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 24, no. 2, pp. 1220–1227, Nov. 2021, https://doi.org/10.11591/ijeecs.v24.i2.pp1220-1227.

[16] H. H. Nuroglu, "Business Network Governance Structure and IT Capabilities," *Procedia - Social and Behavioral Sciences*, vol. 229, pp. 50–59, Aug. 2016, https://doi.org/10.1016/j.sbspro.2016.07.113.

[17] R. S. Kaplan and D. P. Norton, "Transforming the Balanced Scorecard from Performance Measurement to Strategic Management: Part II," *Accounting Horizons*, vol. 15, no. 2, pp. 147–160, Jun. 2001, https://doi.org/10.2308/acch.2001.15.2.147.

[18] A.-A. A. Sharabati and S. J. Fuqaha, "The Impact of Strategic Management on the Jordanian Pharmaceutical Manufacturing Organizations' Business Performance," *International Review of Management and Business Research*, vol. 3, no. 2, pp. 668–687, 2014.

[19] Y. Z. Shin, Y. G. Lee, and M. S. Park, "The use of non-financial performance measures in CEO compensation contracts and stock price crash risk," *Asia-Pacific Journal of Accounting & Economics*, vol. 30, no. 2, pp. 531–552, Mar. 2023, https://doi.org/10.1080/16081625.2020.1787850.

[20] A. R. Samanpour, A. Ruegenberg, and R. Ahlers, "The Future of Machine Learning and Predictive Analytics," in *Digital Marketplaces Unleashed*, C. Linnhoff-Popien, R. Schneider, and M. Zaddach, Eds. New York, NY, USA: Springer, 2018, pp. 297–309.

[21] M. A.Jabbar, S. Samreen, and R. Aluvalu, "The Future of Health care: Machine Learning," *International Journal of Engineering & Technology*, vol. 7, no. 4.6, pp. 23–25, Sep. 2018, https://doi.org/10.14419/ijet.v7i4.6.20226.

[22] M. F. Mubarak, F. A. Shaikh, M. Mubarik, K. A. Samo, and S. Mastoi, "The Impact of Digital Transformation on Business Performance: A Study of Pakistani SMEs," *Engineering, Technology & Applied Science Research*, vol. 9, no. 6, pp. 5056–5061, Dec. 2019, https://doi.org/10.48084/etasr.3201.

[23] M. Ghobakhloo, S. Asadi, M. Iranmanesh, B. Foroughi, M. F. Mubarak, and E. Yadegaridehkordi, "Intelligent automation implementation and corporate sustainability performance: The enabling role of corporate social responsibility strategy," *Technology in Society*, vol. 74, Aug. 2023, Art. no. 102301, https://doi.org/10.1016/j.techsoc.2023.102301.

[24] M. F. Mubarak and M. Petraite, "Industry 4.0 technologies, digital trust and technological orientation: What matters in open innovation?," *Technological Forecasting and Social Change*, vol. 161, Dec. 2020, Art. no. 120332, https://doi.org/10.1016/j.techfore.2020.120332.

[25] A. Alrashedi and M. Abbod, "The Effect of Using Artificial Intelligence on Performance of Appraisal System: A Case Study for University of Jeddah Staff in Saudi Arabia," in *SAI Intelligent Systems Conference*, Amsterdam, Netherlands, Sep. 2021, pp. 145–154, https://doi.org/10.1007/978-3-030-55180-3_11.

[26] S. R. Gopi and M. Karthikeyan, "Effectiveness of Crop Recommendation and Yield Prediction using Hybrid Moth Flame Optimization with Machine Learning," *Engineering, Technology & Applied Science Research*, vol. 13, no. 4, pp. 11360–11365, Aug. 2023, https://doi.org/10.48084/etasr.6092.

[27] P. Ilius, M. Almuhaini, M. Javaid, and M. Abido, "A Machine Learning–Based Approach for Fault Detection in Power Systems," *Engineering, Technology & Applied Science Research*, vol. 13, no. 4, pp. 11216–11221, Aug. 2023, https://doi.org/10.48084/etasr.5995.

[28] N. A. Alsharif, S. Mishra, and M. Alshehri, "IDS in IoT using Machine Learning and Blockchain," *Engineering, Technology & Applied Science Research*, vol. 13, no. 4, pp. 11197–11203, Aug. 2023, https://doi.org/10.48084/etasr.5992.

[29] Y. Chen and Y. Zhou, "Machine learning based decision making for time varying systems: Parameter estimation and performance optimization," *Knowledge-Based Systems*, vol. 190, Feb. 2020, Art. no. 105479, https://doi.org/10.1016/j.knosys.2020.105479.

[30] N. Watson, S. Hendricks, T. Stewart, and I. Durbach, "Integrating machine learning and decision support in tactical decision-making in rugby union," *Journal of the Operational Research Society*, vol. 72, no. 10, pp. 2274–2285, Oct. 2021, https://doi.org/10.1080/01605682.2020.1779624.

[31] S. P. Phillips, S. Spithoff, and A. Simpson, "Artificial intelligence and predictive algorithms in medicine," *Canadian Family Physician*, vol. 68, no. 8, pp. 570–572, Aug. 2022, https://doi.org/10.46747/cfp.6808570.

[32] R. Kaswa, A. Nair, S. Murphy, and K. B. von Pressentin, "Artificial intelligence: A strategic opportunity for enhancing primary care in South Africa," *South African Family Practice*, vol. 64, no. 1, Sep. 2022, Art. no. 5596, https://doi.org/10.4102/safp.v64i1.5596.

[33] R. Williams, H. W. Park, and C. Breazeal, "A is for Artificial Intelligence: The Impact of Artificial Intelligence Activities on Young Children's Perceptions of Robots," in *CHI Conference on Human Factors in Computing Systems*, Glasgow, UK, Dec. 2019, pp. 1–11, https://doi.org/10.1145/3290605.3300677.

[34] K. Kim and B. Kim, "Decision-Making Model for Reinforcing Digital Transformation Strategies Based on Artificial Intelligence Technology," *Information*, vol. 13, no. 5, May 2022, Art. no. 253, https://doi.org/10.3390/info13050253.

[35] S. R. Cox, "The successful implementation of supply chain management technology initiatives: technological readiness as a key indicator," Ph.D. dissertation, Georgia Southern University, Statesboro, Georgia, 2015.

[36] O. Okuonghae, M. O. Igbinovia, and J. O. Adebayo, "Technological Readiness and Computer Self-efficacy as Predictors of E-learning Adoption by LIS Students in Nigeria," *Libri*, vol. 72, no. 1, pp. 13–25, Mar. 2022, https://doi.org/10.1515/libri-2020-0166.

[37] J. Kim and E. Kim, "Relationship between Self-Esteem and Technological Readiness: Mediation Effect of Readiness for Change and Moderated Mediation Effect of Gender in South Korean Teachers," *International Journal of Environmental Research and Public Health*, vol. 19, no. 14, Jan. 2022, Art. no. 8463, https://doi.org/10.3390/ijerph19148463.

[38] V. S. V. Pulla, C. Varol, and M. Al, "Open Source Data Quality Tools: Revisited," in *Information Technology: New Generations*, New York, NY, USA, 2016, pp. 893–902, https://doi.org/10.1007/978-3-319-32467-8_77.

[39] A. Jain *et al.*, "Overview and Importance of Data Quality for Machine Learning Tasks," in *26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, Jul. 2020, pp. 3561–3562, https://doi.org/10.1145/3394486.3406477.

[40] J. Pap, C. Mako, M. Illessy, N. Kis, and A. Mosavi, "Modeling Organizational Performance with Machine Learning," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 8, no. 4, Dec. 2022, Art. no. 177, https://doi.org/10.3390/joitmc8040177.

[41] T. Sturm *et al.*, "Coordinating Human and Machine Learning for Effective Organization Learning," *Management Information Systems Quarterly*, vol. 45, no. 3, pp. 1581–1602, Sep. 2021.

[42] D. Wang and Y. Zhang, "Implications for sustainability in supply chain management and the circular economy using machine learning model," *Information Systems and e-Business Management*, vol. 21, no. 1, pp. 1–1, Aug. 2023, https://doi.org/10.1007/s10257-020-00477-1.

[43] Y. Chen and Z. Lin, "Business Intelligence Capabilities and Firm Performance: A Study in China," *International Journal of Information Management*, vol. 57, Apr. 2021, Art. no. 102232, https://doi.org/10.1016/j.ijinfomgt.2020.102232.

[44] M. Nuseir and G. Refae, "The role of artificial intelligence, marketing strategies, and organizational capabilities in organizational performance: The moderating role of organizational behavior," *Uncertain Supply Chain Management*, vol. 10, no. 4, pp. 1457–1466, 2022.

[45] K. Bley, S. F. B. Fredriksen, M. E. Skjærvik, and I. O. Pappas, "The Role of Organizational Culture on Artificial Intelligence Capabilities and Organizational Performance," in *Conference on e-Business, e-Services and e-Society*, Newcastle upon Tyne, United Kingdom, Sep. 2022, pp. 13–24, https://doi.org/10.1007/978-3-031-15342-6_2.

[46] M. Tsourela and M. Roumeliotis, "The moderating role of technology readiness, gender, and sex in consumer acceptance and actual use of Technology-based services," *The Journal of High Technology Management Research*, vol. 26, no. 2, pp. 124–136, Jan. 2015, https://doi.org/10.1016/j.hitech.2015.09.003.

[47] J. C. Lin and H. Chang, "The role of technology readiness in self-service technology acceptance," *Managing Service Quality: An International Journal*, vol. 21, no. 4, pp. 424–444, Jan. 2011, https://doi.org/10.1108/09604521111146289.

[48] M. J. Kim, C.-K. Lee, and M. W. Preis, "The impact of innovation and gratification on authentic experience, subjective well-being, and behavioral intention in tourism virtual reality: The moderating role of technology readiness," *Telematics and Informatics*, vol. 49, Jun. 2020, Art. no. 101349, https://doi.org/10.1016/j.tele.2020.101349.

[49] M. Abdallah, "Big Data Quality Challenges," in *International Conference on Big Data and Computational Intelligence*, Pointe aux Piments, Mauritius, Feb. 2019, pp. 1–3, https://doi.org/10.1109/ICBDCI.2019.8686099.

[50] J. G. Elmore and C. I. Lee, "Data Quality, Data Sharing, and Moving Artificial Intelligence Forward," *JAMA Network Open*, vol. 4, no. 8, Aug. 2021, Art. no. e2119345, https://doi.org/10.1001/jamanetworkopen.2021.19345.

[51] V. M. Alves *et al.*, "Curated Data In — Trustworthy In Silico Models Out: The Impact of Data Quality on the Reliability of Artificial Intelligence Models as Alternatives to Animal Testing," *Alternatives to Laboratory Animals*, vol. 49, no. 3, pp. 73–82, May 2021, https://doi.org/10.1177/02611929211029635.

[52] L. Bertossi and F. Geerts, "Data Quality and Explainable AI," *Journal of Data and Information Quality*, vol. 12, no. 2, Feb. 2020, Art. no. 11, https://doi.org/10.1145/3386687.

[53] M. Al-Okaily, R. Alghazzawi, A. F. Alkhwaldi, and A. Al-Okaily, "The effect of digital accounting systems on the decision-making quality in the banking industry sector: a mediated-moderated model," *Global Knowledge, Memory and Communication*, vol. 72, no. 8/9, pp. 882–901, Jan. 2022, https://doi.org/10.1108/GKMC-01-2022-0015.

[54] J. F. Hair, M. Sarstedt, C. M. Ringle, and S. P. Gudergan, *Advanced Issues in Partial Least Squares Structural Equation Modeling*. Thousand Oaks, CA, USA: SAGE, 2023.

[55] O. Enaizan, B. Eneizan, M. Almaaitah, A. T. Al-Radaideh, and A. M. Saleh, "Effects of privacy and security on the acceptance and usage of EMR: The mediating role of trust on the basis of multiple perspectives," *Informatics in Medicine Unlocked*, vol. 21, Jan. 2020, Art. no. 100450, https://doi.org/10.1016/j.imu.2020.100450.

[56] R. Pillai and B. Sivathanu, "Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations," *Benchmarking: An International Journal*, vol. 27, no. 9, pp. 2599–2629, Jan. 2020, https://doi.org/10.1108/BIJ-04-2020-0186.

[57] M. Stone *et al.*, "Artificial intelligence (AI) in strategic marketing decision-making: a research agenda," *The Bottom Line*, vol. 33, no. 2, pp. 183–200, Jan. 2020, https://doi.org/10.1108/BL-03-2020-0022.

[58] Y. Al-Anqoudi, A. Al-Hamdani, M. Al-Badawi, and R. Hedjam, "Using Machine Learning in Business Process Re-Engineering," *Big Data and Cognitive Computing*, vol. 5, no. 4, Dec. 2021, Art. no. 61, https://doi.org/10.3390/bdcc5040061.

[59] D. A. A. G. Singh, E. J. Leavline, S. Muthukrishnan, and R. Yuvaraj, "Machine Learning based Business Forecasting," *International Journal of Information Engineering and Electronic Business*, vol. 10, no. 6, pp. 40–51, Nov. 2018, https://doi.org/10.5815/ijieeb.2018.06.05.

[60] S.-M. Tseng, "The impact of knowledge management capabilities and supplier relationship management on corporate performance," *International Journal of Production Economics*, vol. 154, pp. 39–47, Aug. 2014, https://doi.org/10.1016/j.ijpe.2014.04.009.

[61] S.-M. Tseng and P.-S. Lee, "The effect of knowledge management capability and dynamic capability on organizational performance," *Journal of Enterprise Information Management*, vol. 27, no. 2, pp. 158–179, Feb. 2014, https://doi.org/10.1108/JEIM-05-2012-0025.