

Examination of the Role of Ethics-Based Auditing in the Development of Trustworthy Artificial Intelligence (Case Study: Auditing Firms in Tehran)

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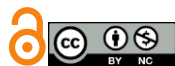
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ABSTRACT

Objective: The study aims to examine the role of ethics-based auditing in the development of trustworthy artificial intelligence (AI) within auditing firms based in Tehran.

Methodology: The research is applied in its objective and descriptive-survey in its execution. The study utilizes thematic content analysis to identify the necessity and importance of the research. A meta-analysis is conducted to review the literature. In-depth interviews with experts were carried out until theoretical saturation was achieved, followed by data coding. The model was tested using structural-interpretive equations and a questionnaire as tools to apply the research findings to the studied population. The sample includes managers of auditing firms in Tehran, selected using the snowball sampling method. Data were collected using both open and closed questionnaires and structured interviews.

Findings: The study identified 14 key indicators of ethics-based auditing influencing the development of trustworthy AI, including technical issues, organizational complexity, legal issues, increased transparency, reduced information asymmetry, stakeholder participation and cooperation, decentralization, ease of traceability, trustworthiness, infrastructure, real-time accounting, audit data security, flexibility, and cybersecurity. These indicators were categorized into four groups based on their influence power and dependency: independent, linkage, autonomous, and dependent variables.

Conclusion: The findings suggest that ethics-based auditing can significantly influence the development of trustworthy AI in auditing firms. From an agency theory perspective, blockchain technology and AI increase the difficulty of data manipulation and enhance process automation, improving transparency and reducing fraud. From a stakeholder theory perspective, blockchain technology promotes an open and inclusive environment, enhancing collaboration and business opportunities. The integration of blockchain and AI in accounting practices can meet the diverse needs of different users, improving trust and reliability in financial reporting.

1 Introduction

One tool for creating innovation in business models is the use of technology. Utilizing technology results in cost reduction, the creation of innovative revenue models, and more attractive value propositions. Additionally, with the emergence of new technologies, such as artificial intelligence, businesses now have more opportunities to develop innovative business models (Tan & Low, 2019). Artificial intelligence can be considered one of the most significant technologies humanity has achieved. AI refers to the science and engineering of creating intelligent machines through algorithms or a set of rules that enable a machine to mimic human cognitive functions like learning and problem-solving. AI systems have the potential to predict problems or address them as they arise, thereby acting intelligently and adaptively. The power of AI lies in its ability to learn and recognize patterns and relationships from large, multidimensional, and multi-modal datasets (Deloitte, 2018). Moreover, AI systems are dynamic and autonomous, learning and adapting as more data becomes available (Casino et al., 2019). As a scientific field, AI dates back to the 1950s. However, recent advances and innovations in information storage and processing have enabled a surge in the capabilities and potential of intelligent systems to transform industries, ranging from agriculture and finance to healthcare (Giboney et al., 2019).

Technology drives organizational change. Any research on the implications of technological change begins by describing the characteristics of the technology and the potential business model that can be used for effectively bringing the technology to market. AI is transforming organizations, impacting the innovation of business models on digital platforms, and this is happening rapidly. AI is developing business model innovation in industries including media, consumer products, financial services, healthcare, industrial, energy, and others (Warner & Wäger, 2019). Companies worldwide are experiencing disruptions in their industries due to new technologies leading to business model innovations. AI represents the most significant technological advancement. When companies utilize AI to create innovative business models, it disrupts industries and companies (Salah et al., 2019). Companies like Amazon, Uber, Tesla, Google, Alibaba, and UPS, along with many others, have reinvented their business models and enhanced their competitive advantages using AI. Senior managers must embrace an entrepreneurial and innovative

mindset and instill this mindset across their organizations using AI to remain competitive and sustainable (Hastig & Sodhi, 2020; Lumineau et al., 2020; Ziolkowski et al., 2020). AI enhances companies' ability to increase revenue in two distinct ways. First, AI's ability to detect very weak signals helps companies develop, refine, and produce numerous predictions (such as demand, supply, inventory, pricing, and logistics). Second, AI's operational speed allows companies to analyze large volumes of data for real-time decision-making. By improving prediction accuracy and enabling real-time decision-making, AI helps companies generate more revenue (Gomber et al., 2018).

Accounting organizations, the Chartered Accountants Association, the Institute of Management Accountants, the Institute of Chartered Accountants, and the International Federation of Accountants publish reports on their websites related to AI technology (O'Neal, 2019). Tan and Low (2019) argue that AI technology affects the database engine of accounting information systems (AIS) by digitizing paper-based validations. This technology can securely store accounting data such as accounts payable and accounts receivable (Dai & Vasarhelyi, 2017) and enhance transaction accounting efficiency (Hinings et al., 2018). Deloitte (2018) and McWaters et al. (2016) have identified ways in which AI technology addresses current accounting challenges. These methods can streamline operations, reduce transaction settlement time and counterparty risk, minimize fraud, and improve regulatory and capital liquidity (Deloitte, 2018; McWaters et al., 2016). The primary goal of using AI technology for maintaining accounting records is to create trust and a network of trust with or without an involved trusted person. Blockchain gathers credible pieces of information regarding the amount of a transaction and who is paying and being paid, hashes the block, and adds it to the existing chain (Fanning & Centers, 2016). The combination of AI algorithms, public and private keys, and decentralized ledgers is what makes AI powerful in modern internet use (Hughes et al., 2019) because its immutability, traceability, and visibility allow participants to view fully encrypted transactions (Cong et al., 2018). The distributed network, digital signature, and consensus validation rules make AI secure and trustworthy (Boillet, 2017). According to the Financial Reporting Council, the trust generated by AI occurs because records are resistant to manipulation and tampering due to their distribution and presentation. Hashes, like fingerprints, are unique, as any minor change when adding information causes the hash to change from one

unique identity to another, indicating the block is no longer the same. The consensus mechanism makes blockchain tamper-resistant. AI's unique feature is providing a source of trust for creating resilience (Casino et al., 2019). Furthermore, technology can lead to increased auditability of information and transparency. Given these points, the main research question is posed: What is the role of ethics-based auditing in the development of trustworthy AI in auditing firms based in Tehran?

2 Methods and Materials

The present research is applied in terms of its objective and descriptive-survey in terms of its execution method. This is because its expected results can be utilized by the research community and similar organizations. In such studies, the goal is to discover new knowledge that follows a specific application regarding a product or process in reality. More precisely, applied research attempts to address a scientific problem that exists in the real world. Through thematic content analysis, the necessity and importance of the research are identified. Then, the research background is reviewed using meta-analysis. The output questions are derived from in-depth interviews with experts until theoretical saturation is achieved, followed by data coding. Subsequently, the model is tested using structural-interpretive equations and a questionnaire as the tool to apply the research findings to the studied statistical population. The statistical population includes all related articles and theses in recent years, both in Persian (from 2011 onward) and English (from 2010 onward), which are examined and used in the section on structural-interpretive equations. The managers of auditing firms based in Tehran comprise the study's sample. In this research, the snowball sampling method is used to determine the number of analysis units. Given that a 5-year background is considered the basis, managers of auditing firms based in Tehran with at least 5 years of experience were selected as the research sample. The primary data on identifying ethics-based

auditing indicators for the development of trustworthy artificial intelligence are collected using both open and closed questionnaires completed by professors and managers. Additionally, in many instances, the researcher used structured interviews to advance the research objectives and obtain more precise and comprehensive information to acquire the exact data sought by the research through a specific list of interview questions. Furthermore, documents, records, and reports (secondary sources) were used to gather information related to ethics-based auditing for the development of trustworthy artificial intelligence. Overall, the current research employs both field and library methods for data collection, with interviews as the field method tool and articles, books, and theses as the library method tools. The study's reliability (stability index) and intra-subject agreement method were used to calculate the reliability of the conducted interviews. Additionally, to review and confirm the codes, three university faculty members and six job experts were consulted. Subordinate and main codes were provided to them, and after applying their comments, convergence in the results was achieved.

3 Findings and Results

First, the opinions of 15 experts on the relationship between the indicators are compared. For this purpose, the "mode" index is used so that among the four possible relationships between the indicators, the relationship with the highest frequency according to the experts is included in the final table. Based on this, the final structural self-interaction matrix (SSIM) is calculated as follows. To determine the types of relationships, it is suggested to use the opinions of experts and specialists based on various managerial techniques, including brainstorming and nominal group technique. Based on the analysis of related literature, the indicators associated with the role of ethics-based auditing in the development of trustworthy artificial intelligence are presented in Table 1.

Table 1

Identified Indicators of Ethics-Based Auditing for the Development of Trustworthy AIs

No.	Indicator	Symbol
1	Technical Issues	V1
2	Organizational Complexity	V2
3	Legal Issues	V3
4	Increased Transparency	V4
5	Reduced Information Asymmetry	V5
6	Stakeholder Participation and Cooperation	V6

7	Decentralization	V7
8	Ease of Traceability	V8
9	Trustworthiness	V9
10	Infrastructure	V10
11	Real-Time Accounting	V11
12	Audit Data Security	V12
13	Flexibility	V13
14	Cybersecurity	V14

The SSIM matrix must be prepared with expert opinions. For this purpose, with the opinions of 15 experts and using

the assumed relationships, the SSIM matrix is completed as follows.

Table 2

Structural Self-Interaction Matrix (SSIM) of Confirmed Indicators

Variable	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14
V1	A	V	X	A	X	A	A	A	V	A	A	X	A
V2		X	V	A	X	A	A	A	X	A	A	A	A
V3			A	A	A	X	A	X	A	A	A	A	X
V4				A	A	A	X	X	X	A	A	A	A
V5					A	A	A	A	A	A	A	A	A
V6						A	A	V	A	A	A	A	A
V7							V	X	V	A	A	A	X
V8								X	V	A	A	A	A
V9									X	X	A	A	X
V10										A	A	A	A
V11											X	A	X
V12												V	V
V13													V

The reachability matrix is obtained by replacing the symbols in the SSIM with the defined relationships,

effectively converting the symbols V, A, O, and X into a set of zeros and ones.

Table 3

Initial Reachability Matrix of the Research Indicators

Variable	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14
V1	-	0	1	1	0	1	0	0	0	1	0	0	1	0
V2	1	-	1	1	0	1	0	0	0	1	0	0	0	0
V3	0	1	-	0	0	0	1	0	1	0	0	0	0	1
V4	1	0	1	-	0	0	0	1	1	1	0	0	0	0
V5	1	1	1	1	-	0	0	0	0	0	0	0	0	0
V6	1	1	1	1	1	-	0	0	0	1	0	0	0	0
V7	1	1	1	1	1	1	-	1	1	1	0	0	0	1
V8	1	1	1	1	1	1	0	-	1	1	0	0	0	0
V9	1	1	1	1	1	1	1	1	-	1	1	0	0	1
V10	0	1	1	1	1	0	0	0	1	-	0	0	0	0
V11	1	1	1	1	1	1	1	1	1	1	-	1	0	1
V12	1	1	1	1	1	1	1	1	1	1	1	-	1	1
V13	1	1	1	1	1	1	1	1	1	1	1	0	-	1
V14	1	1	1	1	1	1	1	1	1	1	1	0	0	-

The Boolean rule was used to reconcile the reachability matrix, and the final reconciled reachability matrix is shown in Table 4.

Table 4

Reconciled Reachability Matrix

Variable	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	Influence Power
V1	1	0	1	1	0	1	0	0	0	1	0	0	1	0	6
V2	1	1	1	1	0	1	0	0	0	1	0	0	0	0	6
V3	0	1	1	0	0	0	1	0	1	0	0	0	0	1	5
V4	1	0	1	1	0	0	0	1	1	1	0	0	0	0	6
V5	0	1	1	1	1	0	0	0	1	1	0	0	0	0	6
V6	1	1	1	1	0	1	0	0	0	1	0	0	0	0	6
V7	1	1	1	1	0	1	1	1	1	1	0	0	0	1	10
V8	1	1	1	1	0	1	1	1	1	0	1	0	0	1	10
V9	1	1	1	1	0	1	1	1	1	1	1	0	0	1	11
V10	1	1	1	1	0	1	1	1	1	1	0	0	0	0	9
V11	1	1	1	1	0	1	0	1	0	1	1	0	0	0	8
V12	1	1	1	1	0	1	1	1	1	1	1	1	0	1	12
V13	1	1	1	1	0	1	1	1	1	1	1	0	1	1	12
V14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	14
Dependency Power	12	12	14	13	2	11	8	9	10	12	6	2	3	7	

At this stage, with the final reachability matrix obtained, we define the reachable set (output) and antecedent set (input) for determining the level of criteria. The reachable

set consists of criteria with a value of one in the row, and the antecedent set consists of criteria with a value of one in the column.

Table 5

Determining the Level of Research Indicators

No.	Reachable Set	Antecedent Set	Common Set	Level
1	1, 3, 4, 6, 10, 13	1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	1, 4, 6, 13	Third
2	1, 2, 3, 4, 6, 10	1, 2, 5, 6, 7, 8, 9, 11, 12, 13, 14	1, 2, 6	Third
3	2, 3, 7, 9, 14	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	2, 3, 7, 9, 14	First
4	1, 3, 4, 8, 9, 10	1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	1, 4, 8, 9, 10	Second
5	2, 3, 4, 5, 9, 10	1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	2, 4, 5, 9, 10	Second
6	1, 2, 3, 4, 6, 10	2, 3, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	2, 3, 6, 10	Fourth
7	1, 2, 3, 4, 6, 7, 8, 9, 10, 14	3, 5, 7, 8, 9, 11, 12, 13, 14	3, 7, 9, 14	Sixth
8	1, 2, 3, 4, 6, 7, 8, 9, 11, 14	5, 7, 8, 9, 10, 11, 12, 13, 14	7, 8, 9, 11, 14	Sixth
9	1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 14	3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14	3, 4, 7, 8, 9, 10, 11, 14	Sixth
10	1, 2, 3, 4, 6, 7, 8, 9, 10	1, 2, 5, 9, 10, 11, 12, 13, 14	1, 2, 7, 8, 9, 10	Fourth
11	1, 2, 3, 4, 6, 8, 10, 11	2, 5, 7, 8, 9, 11, 12, 13, 14	2, 8, 11	Fifth
12	1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 14	5, 9, 11, 12, 13, 14	11, 12, 14	Seventh
13	1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 13, 14	3, 5, 6, 9, 11, 12, 13, 14	3, 11, 13, 14	Seventh
14	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	14	14	Eighth

Based on the existing relationships in the reachability matrix and the variable level information, the final graph of relationships between variables is obtained by eliminating cyclic relationships. The numbers are then replaced with the main research criteria.

We analyze the research variables using the MICMAC diagram. As shown in Figure 1, this diagram consists of a horizontal axis representing dependency and a vertical axis representing influence power. As shown, the research variables are categorized into four groups based on their influence power and dependency: independent, linkage,

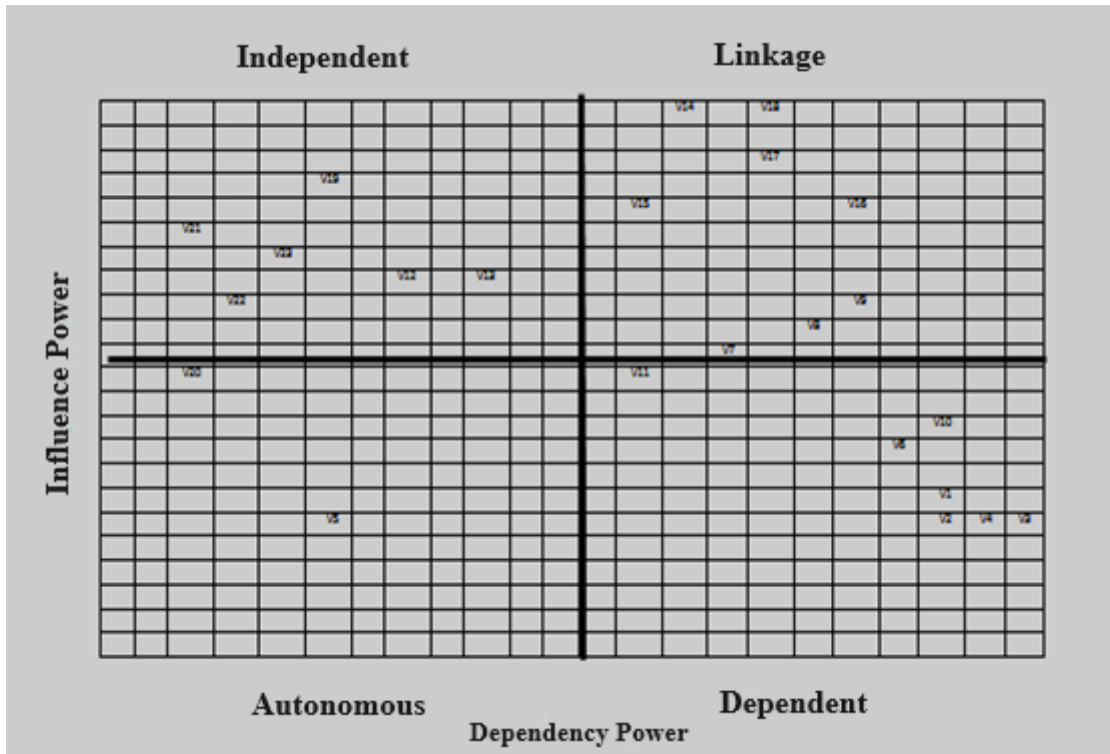
autonomous, and dependent variables. In this research, the components of technical issues (V1), organizational complexity (V2), legal issues (V3), increased transparency (V4), stakeholder participation and cooperation (V6), infrastructure (V10), and real-time accounting (V11) fall into the dependent variables group, indicating that the factors influencing the role of ethics-based auditing on the development of trustworthy AI have weak influence power but relatively high dependency. The component of reduced information asymmetry (V5) is in the autonomous variables group, indicating that the factors influencing the role of

ethics-based auditing on the development of trustworthy AI have weak influence power and low dependency. The components of audit data security (V12) and flexibility (V13) fall into the independent variables group, indicating that the factors influencing the role of ethics-based auditing on the development of trustworthy AI have high influence power but relatively low dependency. The components of

decentralization (V7), ease of traceability (V8), trustworthiness (V9), and cybersecurity (V14) fall into the linkage variables group, indicating that the factors influencing the role of ethics-based auditing on the development of trustworthy AI have high influence power and high dependency.

Figure 1

MICMAC Model



4 Discussion and Conclusion

As technology improves access to real-time accounting data, blockchain creates research opportunities for event-based accounting approaches. Using blockchain technology for maintaining accounting records makes them traceable and visible, allowing all interested parties with the appropriate rights to view transaction data with less density in real-time according to their individual decision-making needs. For example, Sorter (1969) proposes an event-based approach to accounting theory by comparing it to the value approach in accounting. His example is an investor attempting to predict the company's value using two different approaches. He demonstrates that investors might predict the company's future values based on trends, size, and variability of current income or other aggregate values, which is more consistent with the value approach. Similarly,

investors might use accounting data to predict future sales, cost of sales, and taxes. The real difference between these two approaches is the degree of aggregation of accounting information. The event approach emphasizes using raw data and less dense information for decision-making, whereas the value approach uses aggregated information. The question of how to aggregate and share accounting information among different users has always challenged the accounting profession.

This study aimed to examine the role of ethics-based auditing in the development of trustworthy AI in auditing firms based in Tehran. The results showed that 14 indicators, including technical issues, organizational complexity, legal issues, increased transparency, reduced information asymmetry, stakeholder participation and cooperation, decentralization, ease of traceability, trustworthiness, infrastructure, real-time accounting, audit data security,

flexibility, and cybersecurity, are influential factors in ethics-based auditing for the development of trustworthy AI in auditing firms based in Tehran.

From an agency theory perspective, blockchain technology increases the difficulty for managers to manipulate accounting data because it provides smart contracts and accurately records data. Data recorded on the blockchain is validated through multi-party consensus, making data manipulation harder. Additionally, many processes can be automated. For example, a shared blockchain ledger in triple-entry accounting automates compliance. Invoice payment, expense reporting, audit sampling, and compliance processes can be automated using self-executing blockchain smart contracts. This technology makes it easier for organizations to control and monitor accounting information. Thus, when used alongside AI for anomaly detection, hiding financial fraud becomes harder. In theory, suspicious capital transfers can also be detected in real-time. However, this does not mean that using blockchain and AI in accounting can eliminate fraud. The claim of reducing agency problems by reducing information asymmetry assumes that people do not manipulate the source data on the blockchain. It is worth noting that if the potential benefits are large enough, there are still incentives for companies to commit fraud by falsifying source data.

From a stakeholder theory perspective, blockchain technology can be an effective mechanism for promoting an open and inclusive environment. Stakeholders such as accountants, business partners, and investors can join blockchain ecosystems to view, update, or validate transactions based on their access rights and collaborate. Organizations can enhance stakeholder participation and expand business opportunities in blockchain networks. An event-based accounting approach with real-time data recorded on blockchains can meet the unique needs and goals of different accounting information users, who can then use AI to detect patterns and predict trends. Real-time accounting allows various users with access to the blockchain network to view transaction data as it occurs. Triple-entry accounting provides a unique shared ledger that authorized users can view as the sole source of truth. Continuous auditing offers greater assurance for improving trust. However, balancing stakeholder conflicts of interest is crucial. Companies must ensure that the design of the blockchain ecosystem maximizes their capacity to facilitate collaboration.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

References

- Boillet, J. (2017). Are auditors ready for blockchain? The audit profession is eyeing blockchain. *Accounting today*, 31(9), 34-34. <https://us.aicpa.org/content/dam/aicpa/interestareas/frc/assuranceadvisoryservices/downloadabledocuments/blockchain-technology-and-its-potential-impact-on-the-audit-and-assurance-profession.pdf>
- Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). A systematic literature review of blockchain-based applications: Current status, classification and open issues. *Telematics and Informatics*, 36, 55-81. <https://doi.org/10.1016/j.tele.2018.11.006>
- Cong, Y., Du, H., & Vasarhelyi, M. A. (2018). Technological Disruption in Accounting and Auditing. *Journal of Emerging Technologies in Accounting*, 15(2), 1-10. <https://doi.org/10.2308/jeta-10640>
- Dai, J., & Vasarhelyi, M. A. (2017). Toward Blockchain-Based Accounting and Assurance. *Journal of Information Systems*, 31(3), 5-21. <https://doi.org/10.2308/isis-51804>
- Deloitte, I. (2018). State of AI in the enterprise. Retrieved from www2.deloitte.com/content/dam/insights/us/articles/4780_State-of-AI-in-the-enterprise/AICognitiveSurvey2018_Infographic.pdf

<https://www.mckinsey.com/capabilities/quantumblack/our-insights/global-survey-the-state-of-ai-in-2020>

- Fanning, K., & Centers, D. P. (2016). Blockchain and Its Coming Impact on Financial Services. *Journal of Corporate Accounting & Finance*, 27(5), 53-57. <https://doi.org/10.1002/jcaf.22179>
- Giboney, J. S., Briggs, R., & Nunamaker, J. J. (2019). Special Section: Engineering Artifacts and Processes of Information Systems. *Journal of Management Information Systems*, 36(1), 11-13. <https://doi.org/10.1080/07421222.2018.1551763>
- Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *Journal of Management Information Systems*, 35(1), 220-265. <https://doi.org/10.1080/07421222.2018.1440766>
- Hastig, G. M., & Sodhi, M. S. (2020). Blockchain for Supply Chain Traceability: Business Requirements and Critical Success Factors. *Production and Operations Management*, 29(4), 935-954. <https://doi.org/10.1111/poms.13147>
- Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization*, 28(1), 52-61. <https://doi.org/10.1016/j.infoandorg.2018.02.004>
- Hughes, A., Park, A., Kietzmann, J., & Archer-Brown, C. (2019). Beyond Bitcoin: What blockchain and distributed ledger technologies mean for firms. *Business Horizons*, 62(3), 273-281. <https://doi.org/10.1016/j.bushor.2019.01.002>
- Lumineau, F., Wang, W., & Schilke, O. (2020). Blockchain Governance—A New Way of Organizing Collaborations? *Organization Science*, 32(2), 500-521. <https://doi.org/10.1287/orsc.2020.1379>
- McWaters, R. J., Galaski, R., & Chatterjee, S. (2016). The future of financial infrastructure: An ambitious look at how blockchain can reshape financial services. World Economic Forum,
- O'Neal, S. (2019). Big four and blockchain: are auditing giants adopting yet. In: Cointelegraph.
- Salah, K., Rehman, M. H. U., Nizamuddin, N., & Al-Fuqaha, A. (2019). Blockchain for AI: Review and Open Research Challenges. *IEEE Access*, 7, 10127-10149. <https://doi.org/10.1109/ACCESS.2018.2890507>
- Tan, B. S., & Low, K. Y. (2019). Blockchain as the Database Engine in the Accounting System. *Australian Accounting Review*, 29(2), 312-318. <https://doi.org/10.1111/auar.12278>
- Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3), 326-349. <https://doi.org/10.1016/j.lrp.2018.12.001>
- Ziolkowski, R., Miscione, G., & Schwabe, G. (2020). Decision Problems in Blockchain Governance: Old Wine in New Bottles or Walking in Someone Else's Shoes? *Journal of Management Information Systems*, 37(2), 316-348. <https://doi.org/10.1080/07421222.2020.1759974>