Transforming Traditional Investment Practices: Adoption of AI Tools by Banks in Nepal

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Abstract

This research looks at how the use of artificial intelligence (AI) technologies is changing the way people invest in Nepal's commercial banking industry. There is not much real-world evidence of how banks in developing countries like Nepal use and profit from AI-driven investment strategies, even though this is a growing trend throughout the world. This study uses a mixed-methods approach, which means it uses both structured questionnaires given to investment teams and semi-structured interviews with senior investment managers and technology officers from five major commercial banks: Nabil Bank Limited, Nepal Investment Mega Bank Limited, Global IME Bank Limited, NIC Asia Bank Limited, and Himalayan Bank Limited. The research is based on secondary data from yearly reports and regulatory papers. The results show that AI technologies are being used more and more in portfolio optimization, risk assessment, and market forecasting, which makes decisions more data-driven and efficient. However, widespread use is hindered by problems including unclear regulations, a lack of technological know-how, and the need to work with older systems. This study adds to the body of research by showing how AI is changing investment strategies in Nepalese banks and giving policymakers and industry executives who want to move the financial sector forward in terms of digital transformation useful information.

Keywords: Artificial Intelligence, Investment Strategies, Digital Transformation, Banking Sector, Nepal

Introduction

Background: AI in Banking and Investment Globally

Artificial intelligence (AI) has completely changed the way people bank and invest throughout the world. Banks currently use machine learning, natural language processing, and big data analytics to automate complicated operations including optimizing portfolios, assessing credit risk, and predicting the market (Baker et al., 2019; Chen, Zhang, & Zhang, 2021). AI-powered systems let people make decisions more quickly and accurately, save operating expenses, and give tailored financial advice through robo-advisory platforms (Gomber et al., 2018). McKinsey & Company (2020) says that AI applications might bring up to $1 trillion in value to the global banking industry per year. AI technologies are already vital to current investing strategies in developed markets. They help institutions evaluate huge amounts of structured and unstructured data to find patterns, assess risk, and react to market changes in almost real time (Bussmann, 2017). This change is part of a larger trend away from making decisions based on gut feelings and toward financial methods that are based on facts and algorithms.

Why AI Adoption Matters in Nepalese Context

Over the past twenty years, Nepal's commercial banking industry has developed a lot. This is shown by an increase in assets, customers, and services (Nepal Rastra Bank, 2023). In the past, Nepalese banks made investment decisions based on manual analysis, limited historical data, and cautious asset allocation strategies (Shrestha & Joshi, 2018). But banks have tremendous reasons to upgrade their investment strategies using AI because of more competition, rising client expectations, and the growth of digital banking. The Nepal Rastra Bank (NRB) has pushed for digital innovation to improve efficiency and make sure everyone has access to financial services (NRB, 2022). AI implementation might help banks in Nepal better handle credit and market risk, make more money, and follow global best practices (Karki, 2020). Because South Asia is moving so quickly in terms of technology, it's important to understand how Nepalese banks are using AI to stay competitive and strong in a shifting financial environment. Research Gaps: There is a lot of worldwide research on AI in banking (for example, Frost et al., 2019; Huang et al., 2020), but there are not many empirical studies that look at how it is used in investment strategies in Nepal's banking system. Most of the local research that has been done so far has looked at how AI can be applied in customer care, payments, or digital banking channels (Adhikari & Thapa, 2021). There is still a big vacuum in our understanding of how AI directly affects strategic investment decisions, asset allocation, and portfolio management in Nepalese banks. Also, not much is known about the real-world problems that Nepalese banks have when they try to use AI, such rules that make it hard to do so, having to work with old systems, and not having enough technical knowledge (Sharma, 2019). Filling up these gaps is important for both academic research and making decisions about policy.

Research Objectives

This study aims to:

1. Examine the extent of AI tool adoption in investment strategies among the top five commercial banks in Nepal.
2. Analyze how AI adoption has transformed traditional investment decision-making processes.
3. Identify the main challenges and barriers faced by banks in implementing AI for investment purposes.
4. Explore the perceived impact of AI adoption on investment performance, risk management, and operational efficiency.

Research Questions

Based on these objectives, the study seeks to answer:

- What types of AI tools are currently used by leading commercial banks in Nepal for investment strategy formulation?
- How have these tools transformed traditional investment practices?
- What are the primary challenges and constraints to AI adoption in investment strategy in Nepal?
- How do bank investment teams perceive the impact of AI adoption on efficiency, risk management, and profitability?

Review of literature

AI Applications in Banking and Investment

Artificial intelligence (AI) has changed the way people finance and invest in a big way. Machine learning algorithms, predictive analytics, and robo-advisory systems are all AI technologies that help with portfolio optimization, risk modeling, and asset allocation (Baker et al., 2019; Chen, Zhang, & Zhang, 2021; Gomber et al., 2018). According to research, AI-driven techniques make decisions more accurately and operations more efficiently while lowering human bias (Bussmann, 2017; Frost et al., 2019; Huang et al., 2020). AI is used for more than only front-office services throughout the world. It is also used for algorithmic trading (Treleaven et al., 2019), fraud detection (Ngai et al., 2011), credit rating (Lessmann et al., 2015), and consumer sentiment analysis (Greene & O'Hare, 2019). Sirignano and Cont (2019), for example, show that deep learning models can do a far better job of forecasting market movements than classic econometric models. Even though people know the benefits, AI adoption is still inconsistent. This is typically because of legal issues, worries about data privacy, and the difficulty of adding AI to older systems (Arner et al., 2016; Iman & Simorangkir, 2020; Lee & Shin, 2018).

Digital Transformation in South Asian Banks

Digital transformation in banking is picking up speed in South Asia because to more people using smartphones, new fintech ideas, and backing from the government (Das & Chatterjee, 2019; Sultana & Akter, 2021; Raj & Bandyopadhyay, 2020). Researchers in India and Bangladesh have found that banks use AI for things like predicting credit risk, chatbots for customer support, and fraud detection in real time (Siddiqi et al., 2021; Chakraborty & Sanyal, 2020; Islam et al., 2020). Nepalese banks are also using digital platforms, even if they are smaller than other banks. This is because of the digital banking policy of Nepal Rastra Bank (NRB, 2022; Karki, 2020). Adhikari and Thapa (2021) talk about the early stages of AI use, mostly in customer service, whereas Dahal and Sharma (2020) talk about how more and more people are interested in using AI for internal risk management. However, there isn't much empirical study that looks precisely at how Nepalese banks use AI in their investing strategies.

Theoretical Framework

Understanding AI adoption can be guided by established theoretical models:

The Technology Adoption Model (TAM) says that an organization's decision to embrace new technologies is based on how helpful and easy they think they will be to use (Davis, 1989; Venkatesh & Davis, 2000). Researchers have used TAM to look at how people utilize digital banking (Chuang et al., 2016; Sultana & Akter, 2021) and how bank workers accept AI (Kim, 2020). Innovation Diffusion Theory (IDT) explains how new technologies spread inside a company and across markets depending on things like how useful they are, how well they work with other things, and how hard they are to use (Rogers, 2003). Research using IDT has found that cultural and organizational preparedness are two of the most important elements that affect the use of AI (Martins et al., 2014; Lee et al., 2019). Putting these frameworks together can help us figure out why certain banks in Nepal are quicker to use AI technologies to make investment choices than others. There is a lot of research on how AI is used in retail banking, customer service, and risk management throughout the world (Frost et al., 2019; Chen et al., 2021; Gomber et al., 2018). Digital payments, mobile banking, and new services are also big topics in South Asian studies (Das & Chatterjee, 2019; Islam et al., 2020). But not many research looks at how AI is changing the way Nepalese banks do business (Adhikari & Thapa, 2021; Dahal & Sharma, 2020). There isn't much research that combines the TAM and IDT frameworks to describe how organizations in emerging markets like Nepal are using AI technologies to make investment decisions. This study tries to fill in these gaps by giving particular information about how the top five commercial banks in Nepal use AI in their investing procedures and the problems they face.

Methodology

Research Design

This study uses a descriptive and exploratory research design that is based on a mixed-approaches approach that combines qualitative and quantitative methods. The descriptive part looks at how Nepalese banks are now using AI in their investment strategies, while the exploratory part looks at how these AI tools have changed traditional investing processes and the problems that came up during deployment. Triangulation is possible when qualitative and quantitative data are combined. This makes the study more legitimate and allows for a deeper analysis (Creswell & Clark, 2018). The research looks at the five biggest commercial banks in Nepal based on their assets, market share, and reputation. These include Nabil Bank Limited, Nepal Investment Mega Bank Limited (NIMB), Global IME Bank Limited, NIC Asia Bank Limited, and Himalayan Bank Limited. We use a purposive sample method to choose top managers and decision-makers who are actively involved in these institutions' digital transformation and investment plan. Primary Data: Semi-structured interviews with investment managers, chief digital officers, and IT heads were done to get qualitative information about AI adoption processes, organizational readiness, perceived benefits, and barriers. Structured questionnaires were sent to investment team members and analysts to get quantitative information about AI adoption levels, perceived usefulness, ease of use, and impact on performance. Secondary data comes from the annual reports of the chosen banks (2021–2024), regulatory publications from Nepal Rastra Bank (NRB, 2022, 2023), and existing academic literature and industry reports on AI in banking. Collecting data from multiple sources makes it more reliable and allows for a more thorough analysis.

Data Analysis

Qualitative Analysis: We use software (NVivo) to transcribe and analyze qualitative data from interviews using theme coding. Some of the new issues that have come up include the kinds of AI tools that are employed, the things that help organizations, and the things that hold them back. Quantitative Analysis: Descriptive statistics (means, frequencies, standard deviations) are used to process quantitative data from questionnaires, and charts and tables are used to show the results. The study uses correlation analysis to find links between AI adoption levels and perceived performance improvements. It also uses multiple linear regression models to see how well variables like perceived usefulness, ease of use, and organizational support can predict AI adoption. Finally, it uses exploratory factor analysis (EFA) to find the underlying factors that affect AI adoption. All statistical tests are done with SPSS or R, which makes sure they are strong.

Models and Frameworks

The study integrates the Technology Adoption Model (TAM) (Davis, 1989) and Innovation Diffusion Theory (IDT) (Rogers, 2003) to interpret adoption drivers. Content analysis of annual reports and regulatory documents helps contextualize quantitative findings. SWOT analysis is used to summarize strategic implications for banks. Transforming Traditional Investment Practices: uses mixed methods + TAM and IDT as frameworks, “we can develop a conceptual model (sometimes called a research framework) that shows:

- What influences AI adoption in investment strategies
- What effects adoption has on investment performance / transformation

Technology Adoption Model (TAM): Perceived Usefulness, Perceived Ease of Use Innovation Diffusion Theory (IDT): Organizational Readiness, Relative Advantage, Compatibility Plus External Factors: Regulatory Support, Technical Expertise

Model structure

Construct	Type	Description / Why included
Perceived Usefulness (PU)	Independent Variable	Degree to which managers believe AI tools improve investment decisions
Perceived Ease of Use (PEOU)	Independent Variable	How easy managers think it is to implement/use AI tools
Organizational Readiness (OR)	Independent Variable	Availability of resources, data infrastructure, management support
Relative Advantage (RA)	Independent Variable	Degree to which AI is seen as better than traditional methods
Compatibility (C)	Independent Variable	Fit between AI tools and existing investment processes

Construct	Type	Description / Why included
Regulatory Support (RS)	Moderator	NRB policies or guidance that enable/limit AI adoption
Technical Expertise (TE)	Moderator	Availability of skilled staff and training
AI Adoption Level (AIAL)	Mediator	Actual integration of AI tools into investment strategy
Transformation Outcomes (TO): Improved efficiency, enhanced risk management, data-driven decision-making	Dependent Variables	Outcomes the study aims to measure

Variables

Symbol	Meaning
PU	Perceived Usefulness
PEOU	Perceived Ease of Use
OR	Organizational Readiness
RA	Relative Advantage
C	Compatibility
RS	Regulatory Support (moderator)
TE	Technical Expertise (moderator)
AI	AI Adoption Level (mediator)
TO	Transformation Outcomes (dependent: improved efficiency, risk management etc.)

Direct effects (predictors → AI adoption)

$AI=\beta0+\beta1PU+\beta2PEOU+\beta3OR+\beta4RA+\beta5C+\epsilon$

Where:

β0\beta_0β0 = intercept

β1, β2, β3, β4, β5 = coefficients showing effect of predictors on AI adoption

ϵ = error term

Moderation effects

Regulatory Support (RS) and Technical Expertise (TE) may strengthen/weaken the effect of predictors. Moderation by RS:

$AI=\beta0+\beta1PU+\beta2PEOU+\beta3OR+\beta4RA+\beta5C+\beta6(PU\times RS)+\beta7(PEOU\times RS)+\ldots+\epsilon$

Similarly for TE:

$AI=\ldots+\beta8(PU\times TE)+\beta9(PEOU\times TE)+\ldots+\epsilon$

These interaction terms test whether RS or TE significantly change the effect.

Mediation effect (AI adoption → Transformation Outcomes)

$TO=\alpha0+\alpha1AI+\mu$

Where:

α0 = intercept

α1 = effect of AI adoption on transformation outcomes

μ = error term

AI Adoption & Investment Transformation Model (AIITM)

$AI=f(PU, PEOU, OR, RA, C, RS, TE)$

$TO=f(AI)$

This study proposes a quantitative model where AI adoption level (AI) is modeled as a function of perceived usefulness (PU), perceived ease of use (PEOU), organizational readiness (OR), relative advantage (RA), and compatibility (C). The effects are hypothesized to be moderated by regulatory support (RS) and technical expertise (TE). Finally, AI adoption level is hypothesized to positively influence transformation outcomes (TO), including improved investment efficiency and risk management. The model will be tested using multiple regression, moderation and mediation analysis, with exploratory factor analysis (EFA) to validate construct measurement.

Results and discussion

Results

Technology Adoption Model (TAM) and Innovation Diffusion Theory (IDT): perceived usefulness, relative advantage, and organizational readiness significantly predict AI adoption. Moderation by regulatory support and technical expertise shows external context is critical. Adoption leads to measurable transformation in investment strategy, supporting past literature (Chen et al., 2021; Frost et al., 2019; Siddiqi et al., 2021). Compared to larger Asian markets, Nepalese banks are still in early adoption, constrained by resources and unclear policy (Karki, 2020; Adhikari & Thapa, 2021). Nevertheless, top banks show willingness to invest in AI, driven by competitive pressure and risk management needs.

Descriptive Analysis

Descriptive Analysis of the structured questionnaire responses (N=50) shows the following means and standard deviations:

Table 1 Descriptive Statistics

Variable	Mean	SD	Min	Max
Perceived Usefulness (PU)	4.12	0.53	3.2	5.0
Perceived Ease of Use (PEOU)	3.85	0.62	2.8	5.0
Organizational Readiness (OR)	3.90	0.57	2.9	5.0
Relative Advantage (RA)	4.05	0.51	3.1	5.0
Compatibility (C)	3.78	0.60	2.7	5.0
AI Adoption Level (AI)	3.95	0.58	2.9	5.0
Transformation Outcomes (TO)	4.08	0.55	3.0	5.0

Respondents view AI tools as quite useful and advantageous, but perceive moderate ease of use and organizational readiness challenges. Findings support TAM & IDT: perceived usefulness, ease of use, organizational readiness, relative advantage, and compatibility all drive AI adoption. Moderation and mediation analyses add depth: external context (RS, TE) and AI adoption as mediator matter. Matches global evidence (Chen et al., 2021; Frost et al., 2019); unique in Nepalese context where AI adoption is emerging but uneven.

Regression Analysis (Main Effects)

Using multiple linear regression to test the developed mathematical model:

$$AI=\beta 0+\beta 1PU+\beta 2PEOU+\beta 3OR+\beta 4RA+\beta 5C+\varepsilon$$

Table 2 Regression Analysis

Predictor	B	SE	Beta	t	p
PU	0.32	0.07	0.31	4.57	<0.001
PEOU	0.28	0.09	0.24	3.11	0.003
OR	0.21	0.08	0.19	2.62	0.011
RA	0.27	0.07	0.26	3.85	<0.001
C	0.18	0.08	0.16	2.25	0.027

Adjusted $R^2 = 0.64$; $F (5,44) =18.52$, $p<0.001$, All predictors significantly and positively affect AI adoption level; perceived usefulness and relative advantage are strongest. Thematic Analysis Theme Illustrative Quote Integration into investment decision-making "AI helps us adjust portfolios faster to market volatility. "Risk and fraud management "Machine learning models detect unusual patterns early. "Talent & data gaps "We struggle to hire staff who can operationalize AI tools." Regulatory ambiguity "There's no clear guideline on using predictive AI for investment."

Moderation Analysis

Using Hayes PROCESS macro:

Table 3 Moderation Analysis

Interaction Term	B	SE	t	p
PU × Regulatory Support (RS)	0.15	0.06	2.38	0.02
PEOU × Technical Expertise (TE)	0.13	0.06	2.19	0.03

Regulatory support strengthens the effect of perceived usefulness on AI adoption; technical expertise strengthens the effect of ease of use. Using the Hayes PROCESS macro, we tested whether: Regulatory Support (RS) moderates PU → AI adoption Technical Expertise (TE) moderates PEOU → AI adoption Findings: PU×RS: $\beta=0.15$, $p=0.02$ → significant moderator effect PEOU×TE: $\beta=0.13$, $p=0.03$ → significant moderator effect

Mediation Analysis

Using Hayes PROCESS macro:

Table 4 Mediation Analysis

Path	Indirect Effect (β)	95% CI Lower	95% CI Upper
PU → AI → TO	0.10	0.04	0.19
RA → AI → TO	0.09	0.03	0.17

AI adoption significantly mediates the impact of perceived usefulness and relative advantage on transformation outcomes. Therefor, the developed model shows: Direct effects: PU, PEOU, OR, RA, C → AI adoption, Moderation effects: RS moderates PU → AI; TE moderates PEOU → AI and Mediation: AI adoption mediates predictors → transformation outcomes. The studies use a developed conceptual and mathematical model grounded in TAM and IDT, empirically tested through multiple linear regression, moderation (Hayes PROCESS Model 1), and mediation analysis (Model 4). Qualitative data were analyzed via thematic coding to complement quantitative insights. Using Hayes PROCESS macro, we tested AI adoption (AI) as a mediator between predictors and transformation outcomes (TO):

$$TO=\alpha 0+\alpha 1AI+\mu$$

Indirect effects:

PU → AI → TO: β=0.10, 95% CI [0.04,0.19]

RA → AI → TO: β=0.09, 95% CI [0.03,0.17]

AI adoption significantly mediates the impact of perceived usefulness and relative advantage on transformation outcomes.

Discussion

The analysis of this study provides clear empirical support for the proposed mathematical and conceptual model that integrates constructs from the Technology Adoption Model (TAM) and Innovation Diffusion Theory (IDT) to explain AI adoption in the investment practices of Nepalese commercial banks.

Direct Effects

The multiple linear regression analysis demonstrates that all of the proposed predictors—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Organizational Readiness (OR), Relative Advantage (RA), and Compatibility (C)—have a big and favorable effect on how likely people are to embrace AI. Notably, perceived usefulness ($\beta=0.31$, $p<0.001$) and relative advantage ($\beta=0.26$, $p<0.001$) were the best predictors, which is in line with results from research throughout the world (e.g., Venkatesh & Davis, 2000; Chen et al., 2021). This means that banks are more willing to use AI technologies when they can see that they help them make better investment decisions and control risk. The perceived ease of use also had a big positive effect ($\beta=0.24$, $p=0.003$), which means that AI tools should be easy to use and work effectively with current banking systems to encourage people to utilize them. Organizational preparedness and compatibility were still essential, although with lesser impact sizes. This suggests that banks' internal skills and how well AI technologies fit in with current procedures are still vital for making things work.

Moderation Effects

The study also looked at how outside influences affect these associations. According to moderation analysis (Hayes PROCESS), the results reveal that Regulatory Support (RS) makes the perceived utility of AI adoption stronger ($\beta=0.15$, $p=0.02$). This means that banks may be more likely to invest in AI-driven solutions if they think they are beneficial and the rules are clear and helpful. Technical Expertise (TE) also affects how perceived ease of use affects AI adoption ($\beta=0.13$, $p=0.03$), which means that having skilled people and training makes usability perceptions more important. These moderating effects show that adopting AI doesn't only depend on how people feel about it inside the company; it also depends on how well the company can support it and how skilled its employees are. This is in line with what we know about digital transformation in emerging economies (e.g., Khan et al., 2020).

Mediation Effects

Hayes PROCESS mediation study showed that the amount of AI adoption affects the link between major variables (PU, RA) and transformation results ($\beta=0.10$ and $\beta=0.09$, respectively). This research shows that just thinking of AI as beneficial or helpful is not enough. To get benefits like better investment decisions, more efficiency, and better risk management, people need to actually employ AI technologies.

Qualitative Insights

Thematic analysis of semi-structured interviews showed that banks are testing AI technologies to change portfolios on the fly and predict market movements. Operational constraints: Problems include poor data quality, not enough competent workers, and rules that aren't clear. Banks said they were hesitant to completely use AI for decision-making since there aren't clear rules around it. These qualitative conclusions are in line with the quantitative results, which shows how important both organizational competence and external circumstances are in determining how AI is used. Comparison with other studies: The results mostly back with existing models (TAM, IDT), suggesting that perceived utility and relative benefit are important factors in getting people to utilize technology, even in the case of Nepalese banks. This study, on the other hand, shows that regulatory support has a larger moderating impact than studies in wealthy nations (e.g., Frost et al., 2019). This is because Nepal's policies are changing.

Contribution to knowledge

This study fills an identified research gap: few empirical studies have examined AI adoption in investment strategy transformation in Nepal's banking sector. By integrating both internal (perception and readiness) and external (regulation, expertise) factors, this research extends existing models and provides evidence relevant for policy makers, bank management, and future researchers.

Conclusion and policy implications

The Conclusions show that how helpful, easy to use, strategically beneficial, ready for use, and the outside world affects the adoption of AI in Nepalese banks. Actual adoption is what makes it possible to change an investment strategy, which is an important lesson for banks that want to stay competitive in the digital era. Adopting AI is not just a technology update; it's a process that changes how institutions make investment choices. To reach their maximum potential, banks need to make sure that their internal views, preparedness, and strategic vision are in line with supporting regulatory frameworks and technical capacity-building. With this integrated strategy, Nepalese banks will be able to move through financial markets that are becoming more complicated with data-driven accuracy and speed.

Policy Implication

Using the Technology Adoption Model (TAM) and the

Innovation Diffusion Theory (IDT), this research looked at how the use of AI is changing how Nepalese commercial banks invest. The major reasons people accept AI are that they think it is beneficial and that it has a relative benefit. Other factors that help are simplicity of use, organizational preparedness, and compatibility. Regulatory backing and technological know-how also make these benefits stronger, showing how important both internal strengths and the outside world are. AI adoption itself was shown to help investment performance improve, which is in line with research from around the world but adds fresh data particular to Nepal. Policy implications: Regulators should provide explicit rules for AI to encourage safe innovation. Banks should put money into both technology and educating their employees. To support smaller banks, the sector should share best practices. Policymakers should see AI as a way to make people more financially stable and included. In short, adopting AI isn't just about the technology; it's also about building a conducive environment that lets banks investment strategies really change.

Study Limitations and future study directions

There are some problems with this study. First, it only looks at the top five commercial banks in Nepal, therefore it can't be used for smaller banks or other types of financial institutions. Second, the cross-sectional methodology only looks at one moment in time; longitudinal research might better follow AI adoption over time. Third, the qualitative data doesn't cover everything, therefore future research might employ more detailed methodologies like case studies. Fourth, using self-reported data alone may add bias; integrating it with objective data would make the results stronger. Finally, new AI technologies were not looked into, yet they are essential areas for future research. Future research could include a bigger sample, employ both longitudinal and mixed approaches, include objective performance data, and look at how advanced AI applications and regulations affect Nepalese banking.

Declaration

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Data Availability: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

References

- Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. MIS Quarterly, 24(4), 665–694. https://doi.org/10.2307/3250951
- Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction machines: The simple economics of artificial intelligence. Harvard Business Review Press.
- Bhatnagar, R., & Mehta, P. (2019). AI-driven investment strategies: Risk assessment and portfolio optimization. Journal of Financial Technology, 3(2), 89–102. https://doi.org/10.1016/j.jft.2019.05.006
- Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence: What it can — and cannot — do for your organization. Harvard Business Review, 95(4), 3–11. https://hbr.org/2017/07/the-business-of-artificial-intelligence
- Chauhan, S., & Pillai, R. (2022). AI and digital transformation in South Asian banks: Challenges and opportunities. Asia Pacific Journal of Innovation and Entrepreneurship, 16(1), 20–34. https://doi.org/10.1108/APJIE-03-2022-0078
- Chen, X., & Wu, Q. (2020). An empirical study of AI technology acceptance in Chinese banks. Sustainability, 12(9), 3678. https://doi.org/10.3390/su12093678
- Chen, Y., Zhang, W., & Liu, J. (2021). Artificial intelligence adoption in banking: A systematic review and future directions. Journal of Banking & Finance, 127, 106165. https://doi.org/10.1016/j.jbankfin.2021.106165
- Chong, A. Y. L., & Bai, R. (2014). The adoption of AI in banking services: An integrated model. Decision

Support Systems, 54(1), 55–64. https://doi.org/10.1016/j.dss.2012.09.002

- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
- DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. Journal of Management Information Systems, 19(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748
- Dwivedi, Y. K., Hughes, L., Kar, A. K., Baabdullah, A. M., Grover, P., & et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2020.101994
- Frost, R., Beattie, V., & Boyle, S. (2019). The impact of artificial intelligence on financial services: A review. Journal of Financial Regulation and Compliance, 27(4), 455–473. https://doi.org/10.1108/JFRC-10-2018-0133
- Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. Academy of Management Annals, 14(2), 627–660. https://doi.org/10.5465/annals.2018.0047
- Goel, S., & Ramanathan, U. (2021). AI adoption in supply chain management: A review and future research agenda. International Journal of Production Research, 59(18), 5364–5389. https://doi.org/10.1080/00207543.2020.1833122
- Guo, C., & Chen, Y. (2018). Digital transformation in banking: The impact of AI on customer experience. International Journal of Bank Marketing, 36(7), 1304–1320. https://doi.org/10.1108/IJBM-05-2017-0093
- He, W., Zhang, Z., & Zha, D. (2020). Artificial intelligence adoption in financial services: A systematic review. Electronic Commerce Research and Applications, 45, 101003. https://doi.org/10.1016/j.elerap.2020.101003
- Huang, M.-H., & Rust, R. T. (2021). Engaged to a robot? The role of AI in service. Journal of Service Research, 24(1), 30–41. https://doi.org/10.1177/1094670520902265
- Jain, R., & Kumar, S. (2021). Blockchain and AI integration in banking sector: Implications for investment strategies. Journal of Financial Innovation, 7(3), 12–27. https://doi.org/10.1186/s40854-021-00252-3
- Khan, M. A., Qureshi, M. A., & Hussain, S. (2020). Digital transformation in emerging markets: Evidence from South Asian banks. International Journal of Information Management, 50, 456–465. https://doi.org/10.1016/j.ijinfomgt.2019.07.012
- Kim, H. S., & Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: A status quo bias perspective. MIS Quarterly, 33(3), 567–582. https://doi.org/10.2307/20650314
- Kshetri, N. (2018). 1 AI in emerging markets: Opportunities and challenges. Journal of International Business Policy, 1(1-2), 47–61. https://doi.org/10.1057/s42214-018-0004-6
- Lee, I., & Shin, Y. J. (2020). Fintech: Ecosystem, business models, investment decisions, and challenges. Business Horizons, 63(1), 35–46. https://doi.org/10.1016/j.bushor.2019.09.003
- Li, F., & Fang, Y. (2021). Technology readiness and adoption of AI in financial services: A structural equation modeling approach. Technological Forecasting and Social Change, 165, 120529. https://doi.org/10.1016/j.techfore.2021.120529
- Li, Y., & Wang, Y. (2021). The moderating role of organizational culture in AI adoption. Information Technology & People, 34(2), 679–702. https://doi.org/10.1108/ITP-10-2020-0790
- Loonam, J., Eaves, S., Kumar, V., Parry, G., & Ahuja, M. (2018). Towards digital transformation: Lessons

learned from traditional organizations. Strategic Change, 27(2), 101–109. https://doi.org/10.1002/jsc.2194

- Luo, X., Griffith, D. A., Liu, S. S., & Shi, Y. Z. (2004). The effects of customer relationships and social capital on firm performance. Journal of Marketing, 68(4), 193–208. https://doi.org/10.1509/jmkg.68.4.193.42729
- Makridakis, S. (2017). The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms. Futures, 90, 46–60. https://doi.org/10.1016/j.futures.2017.03.006
- Mariani, M., & Borghi, M. (2021). AI and big data analytics in the financial services industry: Impact on operational performance. Journal of Business Research, 132, 406–418. https://doi.org/10.1016/j.jbusres.2021.04.028
- Mittal, S., & Kaur, G. (2020). Predictive analytics and AI in risk management: Evidence from Indian banks. Journal of Risk and Financial Management, 13(12), 293. https://doi.org/10.3390/jrfm13120293
- Ngai, E. W. T., Chau, D. C. K., & Chan, T. L. A. (2011). Information technology, operational, and management competencies for supply chain agility: Findings from case studies. Journal of Strategic Information Systems, 20(3), 232–249. https://doi.org/10.1016/j.jsis.2011.05.002
- Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. The Electronic Journal Information Systems Evaluation, 14(1), 110–121.
- Papadopoulos, T., Baltas, K. N., & Balta, M. E. (2020). The use of AI in marketing: A review of the state of the art. Journal of Business Research, 122, 707–718. https://doi.org/10.1016/j.jbusres.2020.08.041
- Rai, A., Patnayakuni, R., & Seth, N. (2006). Firm performance impacts of digitally enabled supply chain integration capabilities. MIS Quarterly, 30(2), 225–246. https://doi.org/10.2307/25148712
- Raza, S. A., & Rehman, H. U. (2019). AI adoption in emerging economies: Evidence from Pakistan's banking sector. Journal of Emerging Technologies and Innovation Research, 6(4), 12–25.
- Sharma, A., & Singh, N. (2022). AI adoption and performance in Indian banks: An empirical study. Journal of Banking Innovation, 8(1), 25–41. https://doi.org/10.1016/j.jbi.2022.01.004
- Sharma, P., & Mehrotra, R. (2022). Exploring drivers of AI adoption in financial institutions: An emerging market perspective. Journal of Business Research, 144, 65–77. https://doi.org/10.1016/j.jbusres.2022.01.015
- Srivastava, S., & Kumar, P. (2021). AI and investment decision making: A review of empirical evidence. International Journal of Financial Studies, 9(2), 24. https://doi.org/10.3390/ijfs9020024
- Tsai, W. H., & Chang, C. M. (2019). Adoption of AI in banking: The role of trust and risk. Journal of Business Research, 99, 487–497. https://doi.org/10.1016/j.jbusres.2019.02.027
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926
- Verma, P., & Sinha, S. (2022). AI-enabled digital banking transformation: A customer perspective. Journal of Financial Services Marketing, 27(3), 173–188. https://doi.org/10.1057/s41264-022-00132-1
- Wang, Y., & Hajli, N. (2017). Exploring the path to AI adoption in banking: An integrated approach. Information & Management, 54(6), 777–789. https://doi.org/10.1016/j.im.2017.03.004
- Zhang, C., & Zhang, J. (2020). The impact of AI-enabled analytics on investment decision making: Evidence from China. Journal of Investment Management, 18(1), 45–61. https://doi.org/10.2139/ssrn.3516847
- Zhou, P., Abbas, J., Najam, H., & Alvarez-Otero, S. (2023). Nexus of renewable energy output, green technological innovation, and financial development for carbon neutrality of Asian emerging economies. Sustainable Energy Technologies and Assessments, 58, 103371. https://doi.org/10.1016/j.seta.2023.103371