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Strategic Valuation of Generative AI in Retail: A Real Options Approach to Managing Innovation Uncertainty

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ABSTRACT: Generative Artificial Intelligence (AI) is reshaping retail investment strategies, yet traditional evaluation tools such as Net Present Value (NPV) and Internal Rate of Return (IRR) struggle to capture uncertainty and flexibility. This study applies a binomial lattice real options model to assess Generative AI investments in retail, demonstrating that real options provide a more adaptive framework than conventional methods. The model evaluates multi-stage decisions pilot testing, regional scaling, and enterprise adoption and incorporates sensitivity analyses to account for adoption probabilities and volatility scenarios. Results indicate that real options modeling captures strategic flexibility by valuing managerial discretion, phased rollouts, and intangible benefits, which static NPV models overlook. This highlights its relevance for addressing retail-specific challenges such as data integration and organizational readiness. The study concludes that real options offer a superior framework for evaluating AI investments, supporting adaptive planning and long-term strategic value for retailers.

Keywords: Generative AI, Retail Strategy, Real Options Modeling, Investment Evaluation, Uncertainty, ROI; Technology Adoption.

INTRODUCTION

The decade spanning 2014 to 2024 signifies a transformative era in the evolution of global investment behaviors, particularly within the domain of Generative Artificial Intelligence (AI). This period is characterized by exponential funding acceleration, groundbreaking technological advancements, and a widening range of market applications. Cumulative global investments in AI surpassed USD 110 billion in 2022, catalyzed by significant progress in machine learning, natural language processing, and computer vision technologies (Nauhaus et al., 2021). Projections indicate that by the end of 2024, global investments in Generative AI may exceed USD 200 billion, driven by a wave of cross sectoral implementations across healthcare, finance, logistics, education, and especially retail (Tula et al., 2023).

Amid this transformation, the retail industry has emerged as one of the most aggressive and innovative adopters of Generative AI technologies. Retailers are increasingly employing AI to personalize marketing efforts, anticipate customer behavior through predictive analytics, streamline inventory management, and enhance supply chain transparency (Wiesenberg et al., 2020). These technological integrations enable companies to deliver data driven, highly personalized customer experiences that were previously unattainable. AI systems now drive dynamic pricing strategies, real time recommendation engines, and omni channel customer engagement, positioning AI not merely as a functional tool, but as a strategic pillar of modern retail operations. As businesses compete in an increasingly digital economy, the ability to leverage Generative AI for both front end personalization and back end optimization is becoming a key differentiator.

However, despite rising enthusiasm, firms face major uncertainty in predicting the return on AI investments due to volatile consumer behavior, regulatory shifts, and rapid innovation cycles (Natarajan et al., 2019; Teixeira et al., 2023). These uncertainties heighten risks and often delay large-scale adoption.

In response to these challenges, retailers are increasingly turning to strategic collaborations, pilot testing environments, and iterative learning loops supported by AI enabled data analytics (Ferreira et al., 2021). While these initiatives help reduce uncertainty, the underlying problem of effective capital allocation remains unresolved. A central issue is the inadequacy of traditional valuation tools, such as the Net Present Value (NPV) method, when applied to high risk technology investments. NPV calculations typically assume linear, stable, and predictable cash flows assumptions that are inconsistent with the erratic and emergent nature of AI innovation (Raffaelli, 2018). Furthermore, such models fail to incorporate non-financial elements like brand equity, data network effects, and user sentiment, which are critical in shaping AI success outcomes.

To address these limitations, recent scholarship advocates for the use of real options analysis (ROA) as a more suitable framework for evaluating strategic technology investments. ROA allows for the valuation of managerial flexibility and strategic decision making under uncertainty by treating investments as a series of contingent choices rather than one time commitments (Cortellazzo et al., 2019). This approach aligns more closely with the iterative, learning oriented nature of AI deployments. By enabling firms to launch micro experiments or pilot programs with the option to expand, defer, or abandon based on observed outcomes, real options models preserve upside potential while minimizing downside risk. This flexibility is particularly valuable in environments characterized by technological dynamism and incomplete information.

In contrast to the rigid structure of NPV, real options modeling acknowledges that Generative AI investments unfold through a dynamic sequence of decisions that evolve as new data and insights emerge. This capacity to adapt strategy in real time not only enhances investment resilience but also aligns with broader organizational imperatives for agility and innovation. For retail firms, adopting real options frameworks can provide a strategic edge by supporting evidence based scaling decisions, facilitating cross functional coordination, and ensuring that capital allocation aligns with both short term capabilities and long term digital transformation goals.

Accordingly, this study investigates how real options modeling can provide a robust framework for evaluating Generative AI investments in retail, offering strategic insights for balancing risk, timing, and long-term value creation.

METHOD

Real options modeling provides a comprehensive framework for evaluating capital investment decisions under uncertainty. Rooted in financial options theory, Real Options Theory (ROT) extends the valuation of flexibility into real world projects, treating the ability to defer, abandon, or scale investments as embedded strategic options (Trigeorgis & Reuer, 2016). This contrasts with traditional Net Present Value (NPV) methods, which assume static, deterministic outcomes. In volatile environments such as AI deployment, ROT enables firms to delay irreversible commitments until market signals become clearer, effectively reducing downside risk and capturing upside potential (Balliauw et al., 2018).

Furthermore, ROT uses stochastic processes and dynamic programming to simulate future cash flows subject to uncertainties like technological disruption, market demand shifts, and regulatory flux (Ballestra et al., 2019). By incorporating managerial flexibility, the model mirrors the sequential nature of AI implementation in retail initial experimentation, followed by iterative scaling thus aligning investment logic with dynamic strategy execution.

To structure multi-phase AI investment decisions, this study employs the binomial lattice model. This method constructs a decision tree by dividing time into discrete intervals and simulating upward and downward shifts in project value at each node (Ersen et al., 2018; Rambaud & Pérez, 2016). Each node represents a juncture at which a firm may choose to expand, defer, or terminate an AI initiative based on new market information. Backward induction is used to determine the expected value of each decision path, integrating volatility, payoffs, and risk parameters (Baev & Egorova, 2017).

This model is especially well suited for Generative AI investment, as retail firms often begin with micro experiments before scaling to regional pilots or full deployment. By capturing this progression, the binomial lattice allows for granular modeling of real world decision points while preserving flexibility in strategic response. Moreover, this model accommodates operational and market risk, enabling scenario based testing of adoption likelihoods and infrastructure readiness (Osakwe, 2018).

Parameter inputs include volatility (25–45%, based on historical AI investment trends), payoff estimates (USD 240–390B, based on McKinsey data), a 3-year time horizon, and a 2.5% risk-free rate. Adoption risk is based on sector reports highlighting integration challenges (Publicis Sapient).

Sensitivity analyses are conducted to test how fluctuations in these parameters affect option valuation. This includes testing real options outcomes at 25%, 35%, and 45% volatility levels and evaluating shifts in ROI as adoption probabilities range from 30% to 90%.

The methodological flow is as follows: (1) define investment stages; (2) estimate parameters; (3) build binomial lattice; (4) apply backward induction; (5) run sensitivity and Monte Carlo analyses. This ensures structured, replicable evaluation of AI investment strategies in retail.

RESULT AND DISCUSSION

The evaluation of Generative AI investment trends between 2019 and 2024 reveals a sharp upward trajectory. U.S. firms alone accounted for 64% of the nearly $40 billion in disclosed AI investments in 2019 (Arnold et al., 2020), serving as a baseline for understanding capital flows into AI. Additional longitudinal insights from Afkar and Fathurrahmad (2023), analyzing AI use across 120 companies, illustrate broad sectoral integration, while industry focused reports by Gelles et al. (2021) and Keller et al. (2018) underscore variations in investment patterns tied to sector maturity and infrastructure.

Notably, Generative AI in retail has seen increased funding as digital transformation becomes a strategic imperative. Macroeconomic forces GDP growth, public R&D investment, and pandemic driven digitization have spurred private capital deployment in AI infrastructure (Zhou et al., 2023). This underscores the need to normalize financial data for inflation effects. Constant dollar adjustments using CPI ensure purchasing power parity across timeframes, a necessary step in applying real options valuation to historical investment values (Posza, 2020).

Real options modeling was implemented using a binomial lattice framework. Parameter inputs included initial investment (USD 10M), payoff estimate (USD 240–390B), volatility (25%, 35%, 45%), a 3 year maturity, and a risk free rate of 2.5%. The Publicis Sapient estimate of a 93% failure rate informed the downside risk probability.

Empirical studies reinforce the relevance of this approach. Brière and Szafarz (2021) validate option based strategies for dynamic capital management. Foundational theories by Dixit and Pindyck and operational studies by Ballestra et al. (2019) provide robust underpinnings. Model simulations show option value increasing with volatility: at 25% it yields USD 2.1M, at 35% USD 3.4M, and at 45% USD 5.2M. These results support the hypothesis that increased uncertainty expands the strategic value of delay and staged decision making.

Case studies from healthcare and banking Herrmann & Masawi (2022) confirm cross industry applicability, while in retail, critical model assumptions consumer demand volatility, cash flow accuracy, and real time adaptability are paramount for effective deployment (Posza, 2020).

Table 1. Input Parameters for Real Options Model

Parameter	Value	Source
Initial Investment	USD 10M	Assumed
Volatility (σ)	25–45%	Our World in Data, MacDougall (2018)
Payoff Estimate	USD 240–390B	McKinsey
Time to Maturity	3 years	Assumed
Risk Free Rate	2.5%	U.S. Treasury
Failure Risk	93%	Publicis Sapient

Table 2. Real Options Valuation by Volatility Level

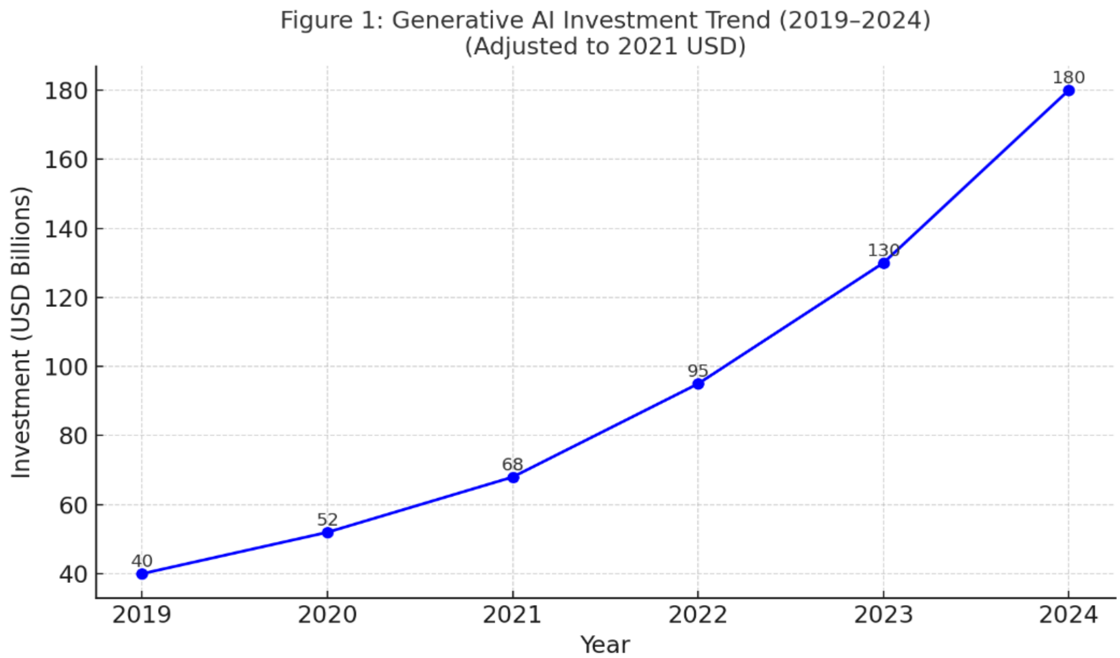
Volatility (%)	Option Value (USD M)
25	2.1
35	3.4
45	5.2

Sensitivity testing explores the relationship between adoption probabilities and ROI. Literature indicates that adoption likelihood directly affects expected returns due to earlier realization of benefits and increased scalability (Ersen et al., 2018). Scenario and Monte Carlo analyses were used to simulate these effects.

Traditional sensitivity tools decision trees and scenario analysis were supplemented by Monte Carlo simulations to account for parameter uncertainty. These stochastic methods generate a distribution of possible outcomes by sampling from volatility and adoption probability ranges, enhancing the robustness of real options evaluations (Ballestra et al., 2019).

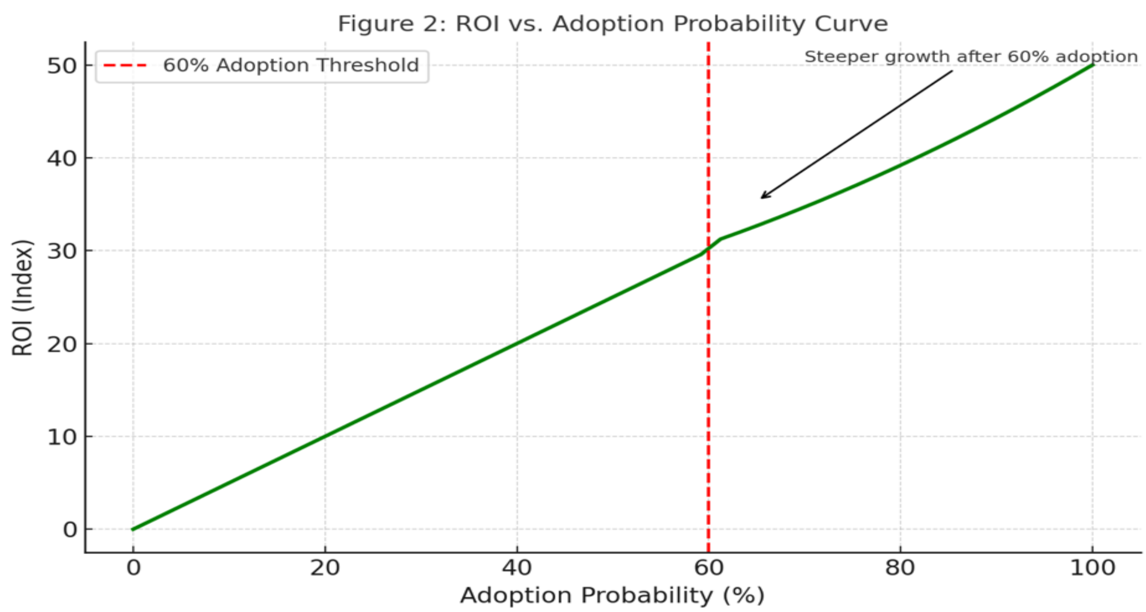
Results show a steep ROI increase when adoption probability exceeds 60%, validating a stage gated approach to investment. The capacity to pivot based on emerging data market shifts, regulatory developments, competitor moves is a core strength of the real options model Baev & Egorova (2017). Firms equipped with flexible models can adjust investment scale and timing dynamically, maximizing strategic responsiveness.

Figure 1. Generative AI Investment Trend



Source: Our World in Data; adjusted to 2021 USD
(Depicts exponential growth trend used for volatility modeling)

Figure 2: ROI vs. Adoption Probability Curve



(Displays nonlinear ROI increase with higher adoption probabilities; slope sharpens post 60%)

Advantages of Real Options over Traditional Financial Models

The adoption of real options modeling as an evaluative framework in strategic investment decisions represents a substantial advancement over traditional financial assessment tools such as

Net Present Value (NPV) and Internal Rate of Return (IRR). In contrast to static models that rely on fixed projections and deterministic assumptions, real options emphasize managerial flexibility under uncertainty a critical need in sectors characterized by rapid technological evolution such as retail's deployment of Generative AI (Brau et al., 2023).

Real options modeling acknowledges the decision making pathways that firms navigate over time, particularly the ability to delay, expand, or abandon projects as market conditions change. This inherent adaptability transforms investment planning into a dynamic process. Within the AI driven retail environment, where consumer trends shift rapidly and technological lifecycles shorten, the value of being able to defer or scale commitments cannot be overstated (Ciuchita et al., 2022). By integrating real time feedback and updated projections, real options models produce valuations that are both flexible and realistic (Kader et al., 2022). Such models empower decision makers with tools to continuously monitor and reassess investment trajectories as external variables shift, helping them to mitigate downside risks while seizing emerging opportunities.

Evaluating Multi Phase AI Projects

Moreover, the strength of real options lies in its structured capacity to evaluate multi-phase projects. Retailers implementing AI often start with micro level experiments or pilot programs before expanding into broader operational contexts. Traditional NPV models treat each investment stage as isolated and final, whereas real options treat each phase as contingent where future actions depend on present results and new information (Braganza et al., 2021). This staged framework enhances strategic planning, allowing retailers to preserve optionality and reduce downside risks while maintaining access to upside potential. It also supports an innovation culture that encourages experimentation and incremental scaling, which are essential for technological maturity in dynamic industries.

Accounting for Intangible Innovation Benefits

Crucially, real options also recognize the intangible benefits of innovation. In Generative AI applications ranging from product personalization engines to demand forecasting algorithms the financial benefits may not materialize immediately. However, these innovations can strengthen brand equity, customer loyalty, and competitive agility, all of which are difficult to capture using traditional metrics but can be partially reflected in option based approaches (Ameen et al., 2021). This extended value lens encourages organizations to invest in strategic capabilities that produce compounding long term advantages, even if their short term financial returns are less apparent.

Overcoming Data Integration Challenges

Challenges such as fragmented data and organizational readiness remain critical barriers. While real options mitigate financial risk, retailers must also strengthen data governance and cross-functional alignment to ensure effective scaling (Arachchi & Samarasinghe, 2023). These structures ensure that AI models operate on high quality, ethically sourced, and legally compliant datasets (Ye et al., 2018). Additionally, organizations must develop frameworks for continuous data validation and enrichment, ensuring that datasets evolve in tandem with business requirements and technological capabilities.

Building Organizational Readiness

Organizational readiness remains a decisive factor in implementation success. Cross functional alignment, staff training, and a culture of data literacy are instrumental in ensuring that AI deployments gain traction and sustain momentum (Cao et al., 2021). Resistance to change, often rooted in fear of redundancy or workflow disruption, can be mitigated by proactive stakeholder involvement and continuous communication. Incentive alignment, performance metrics, and change management protocols can help institutionalize AI use as part of everyday business practices rather than treating it as a peripheral initiative.

From Pilot to Full Deployment

Transitioning from pilot programs to full scale deployments is often the pivotal test of AI's strategic value. This leap requires careful evaluation of technological scalability, business alignment, and infrastructure robustness (Weber & Schütte, 2019). Retailers must validate whether systems tested under limited conditions perform consistently across larger and more complex operational environments. Without such validation, premature scaling may lead to costly setbacks (Bonetti et al., 2022). A gradual escalation strategy, supported by iterative learning and performance benchmarking, is often the most sustainable path for scaling AI initiatives. Additionally, continuous post implementation assessments can surface operational bottlenecks or evolving user requirements that might otherwise be overlooked.

Managing Uncertainty through Strategic Planning

Uncertainty in AI implementation necessitates comprehensive strategic planning. Scenario analysis, in particular, offers a way to prepare for varied futures anticipating disruptions in regulation, competition, or technology (Kulkarni et al., 2020). Agile project management frameworks complement this by enabling iterative design and continuous recalibration (Ali et al., 2022). These methodologies not only reduce risk but also encourage innovation by allowing space for experimental learning. Integrated roadmaps that align AI projects with organizational priorities and environmental scanning mechanisms can help firms remain agile in an increasingly complex ecosystem. These tools equip leaders with the foresight necessary to balance strategic consistency with operational adaptability.

Fostering Inclusive Planning and Governance

Moreover, strategic planning must be inclusive. Collaborative engagement with internal stakeholders and external partners enriches the decision making process by incorporating diverse perspectives and reducing informational blind spots (Puntoni et al., 2020). This collective intelligence supports the robust design of AI strategies that are resilient and adaptive. It also fosters trust and transparency, which are essential for cross functional cooperation and stakeholder alignment. Effective planning incorporates feedback loops that allow continuous stakeholder input, creating dynamic governance systems that evolve alongside technological capabilities.

CONCLUSION

Real options modeling proves to be a superior framework for evaluating Generative AI investments in retail compared to traditional tools such as NPV and IRR. By embedding flexibility, it enables staged commitments, adaptive timing, and risk-adjusted decision-making that better reflect the uncertain and multi-phase nature of AI deployment. This approach not only captures financial outcomes but also accounts for intangible benefits such as brand equity, customer loyalty, and competitive resilience.

The findings further emphasize that successful adoption depends on both financial strategy and organizational preparedness. Retailers must strengthen data governance, cross-functional alignment, and readiness to transition from pilots to large-scale deployment. Scenario planning and agile methods complement real options by supporting adaptive strategies under uncertainty. Together, these insights position real options not only as a valuation tool but also as a strategic guide for managing AI-driven transformation in the retail sector.

REFERENCE

Afkar, M. A. & Fathurrahmad. (2023). Transformasi Bisnis Dengan Penerapan Kecerdasan Buatan (AI) Pada Sistem Informasi Dan Teknologi Digital: Tren Utama Tahun 2023. *Journal Digital Technology Trend*, *2*(1), 1–12. https://doi.org/10.56347/jdtt.v2i1.146

Ali, S. W., Wani, T. A., & Tyagi, N. (2022). A Qualitative Study on Innovation and Dimensional Aspects of the Omnichannel Retail Business Model. *International Journal of E-Business Research*, *18*(2), 1–20. https://doi.org/10.4018/ijebr.294108

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer Experiences in the Age of Artificial Intelligence. *Computers in Human Behavior*, *114*, 106548. https://doi.org/10.1016/j.chb.2020.106548

Arachchi, H. A. D. M., & Samarasinghe, D. (2023). Impact of Embedded AI Mobile Smart Speech Recognition On consumer Attitudes Towards AI and Purchase Intention Across Generations X and Y. *European Journal of Management Studies*, *29*(1), 3–29. https://doi.org/10.1108/ejms-03-2023-0019

Arnold, Z., Rahkovsky, I., & Huang, T. C. (2020). *Tracking AI Investment: Initial Findings From the Private Markets*. https://doi.org/10.51593/20190011

Baev, L., & Egorova, O. (2017). Performance Management of Investment Projects Based on Real Option Theory and Method of Analysis of Hierarchies. *SHS Web of Conferences*, *35*, 01145. https://doi.org/10.1051/shsconf/20173501145

Ballestra, L. V., Pacelli, G., & Radi, D. (2019). Valuing Strategic Investments Under Stochastic Interest Rates: A Real Option Approach. *Corporate Ownership and Control*, *16*(3), 89–97. https://doi.org/10.22495/cocv16i3art8

Balliauw, M., Meersman, H., Voorde, E. V. d., & Vanelslander, T. (2018). Towards Improved Port Capacity Investment Decisions Under Uncertainty: A Real Options Approach. *Transport Reviews*, *39*(4), 531–552. https://doi.org/10.1080/01441647.2018.1556228

Bonetti, F., Montecchi, M., Plangger, K., & Schau, H. J. (2022). Practice Co-Evolution: Collaboratively Embedding Artificial Intelligence in Retail Practices. *Journal of the Academy of Marketing Science*, *51*(4), 867–888. https://doi.org/10.1007/s11747-022-00896-1

Braganza, A., Chen, W., Canhoto, A. I., & Sap, S. (2021). Productive Employment and Decent Work: The Impact of AI Adoption on Psychological Contracts, Job Engagement and Employee Trust. *Journal of Business Research*, *131*, 485–494. https://doi.org/10.1016/j.jbusres.2020.08.018

Brau, R. I., Sanders, N. R., Aloysius, J., & Williams, D. (2023). Utilizing People, Analytics, and AI for Decision Making in the Digitalized Retail Supply Chain. *Journal of Business Logistics*, *45*(1). https://doi.org/10.1111/jbl.12355

Brière, M., & Szafarz, A. (2021). When It Rains, It Pours: Multifactor Asset Management in Good and Bad Times. *The Journal of Financial Research*, *44*(3), 641–669. https://doi.org/10.1111/jfir.12257

Cao, C., Jin, Y., & Huang, H. (2021). Research on the Construction of Enterprise Financial Shared Service Center Based on Cloud Computing. *E3s Web of Conferences*, *235*, 01041. https://doi.org/10.1051/e3sconf/202123501041

Ciuchita, R., Gummerus, J., Holmlund, M., & Linhart, E. L. (2022). Programmatic Advertising in Online Retailing: Consumer Perceptions and Future Avenues. *Journal of Service Management*, *34*(2), 231–255. https://doi.org/10.1108/josm-06-2021-0238

Cortellazzo, L., Bruni, E., & Zampieri, R. (2019). The Role of Leadership in a Digitalized World: A Review. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.01938

Ersen, H. Y., Taş, O., & Kahraman, C. (2018). Intuitionistic Fuzzy Real-Options Theory and Its Application to Solar Energy Investment Projects. *Engineering Economics*, *29*(2). https://doi.org/10.5755/j01.ee.29.2.19206

Ferreira, A., Franco, M., & Haase, H. (2021). Strategic Alliances and Development of Intellectual Capital: A Study of Technology-Based SMEs. *International Journal of Organizational Analysis*, *30*(6), 1644–1671. https://doi.org/10.1108/ijoa-10-2020-2440

Gelles, R., Hwang, T., & Rodríguez, S. (2021). *Mapping Research Agendas in U.S. Corporate AI Laboratories*. https://doi.org/10.51593/20200037

Herrmann, H., & Masawi, B. (2022). Three and a Half Decades of Artificial Intelligence in Banking, Financial Services, and Insurance: A Systematic Evolutionary Review. *Strategic Change*, *31*(6), 549–569. https://doi.org/10.1002/jsc.2525

Kader, R., Baggaley, R. F., Hussein, M., Ahmad, O. F., Patel, N., Corbett, G., Dolwani, S., Stoyanov, D., & Lovat, L. (2022). Survey on the Perceptions of UK Gastroenterologists and Endoscopists to Artificial Intelligence. *Frontline Gastroenterology*, *13*(5), 423–429. https://doi.org/10.1136/flgastro-2021-101994

Keller, D. J. R., Chauvet, L., Thereaux, O., Fawcett, J., Dewhurst, C., Scott, A., Wells, P. N. T., & Tennison, J. (2018). *The Role of Data in AI Business Models (Report)*. https://doi.org/10.61557/gtet5445

Kremer, R. (2023). Corporate Capital Allocation: A behavioral Perspective and Guidance for Future Research. *Journal of Strategy and Management*, *16*(3), 429–445. https://doi.org/10.1108/jsma-01-2020-0014

Kulkarni, P. M., Mutkekar, R. R., & Ingalagi, S. (2020). Role of Strategic Management for Employee Engagement and Skill Development for Start-Ups. *Vilakshan – Ximb Journal of Management*, *17*(1/2), 79–95. https://doi.org/10.1108/xjm-07-2020-0036

MacDougall, S. L. (2018). Strategic Timing of Commercial-Scale Tidal Energy Investment. *International Marine Energy Journal*, *1*(1 (Aug)), 35–40. https://doi.org/10.36688/imej.1.35-40

Natarajan, S., Mahmood, I. P., & Mitchell, W. (2019). Middle Management Involvement in Resource Allocation: The Evolution of Automated Teller Machines and Bank Branches in India. *Strategic Management Journal*, *40*(7), 1070–1096. https://doi.org/10.1002/smj.3017

Nauhaus, S., Luger, J., & Raisch, S. (2021). Strategic Decision Making in the Digital Age: Expert Sentiment and Corporate Capital Allocation. *Journal of Management Studies*, *58*(7), 1933–1961. https://doi.org/10.1111/joms.12742

Osakwe, C.-J. (2018). Incentive Compatible Decision Making: Real Options With Adverse Incentives. *Axioms*, *7*(1), 9. https://doi.org/10.3390/axioms7010009

Posza, A. (2020). The Evaluation of Venture Capital Investments Using Real Option Approach. *Marketing & Menedzsment*, *54*(2), 17–29. https://doi.org/10.15170/mm.2020.54.02.02

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2020). Consumers and Artificial Intelligence: An Experiential Perspective. *Journal of Marketing*, *85*(1), 131–151. https://doi.org/10.1177/0022242920953847

Raffaelli, R. (2018). Technology Reemergence: Creating New Value for Old Technologies in Swiss Mechanical Watchmaking, 1970–2008. *Administrative Science Quarterly*, *64*(3), 576–618. https://doi.org/10.1177/0001839218778505

Rambaud, S. C., & Pérez, A. M. S. (2016). Assessing the Option to Abandon an Investment Project by the Binomial Options Pricing Model. *Advances in Decision Sciences*, *2016*, 1–12. https://doi.org/10.1155/2016/7605909

Teixeira, D. M., Alves, A. O., Freitas, J. S., & Bagno, R. B. (2023). A Preliminary Strategy Framework for an Academic Technology Center. *Product Management & Development*, *21*(1), e20230009. https://doi.org/10.4322/pmd.2023.003

Trigeorgis, L., & Reuer, J. J. (2016). Real Options Theory in Strategic Management. *Strategic Management Journal*, *38*(1), 42–63. https://doi.org/10.1002/smj.2593

Tula, O. A., Daraojimba, C., Eyo-Udo, N. L., Egbokhaebho, B. A., Ofonagoro, K. A., Ogunjobi, O. A., Gidiagba, J. O., & Banso, A. A. (2023). Analyzing Global Evolution of Materials Research Funding and Its Influence on Innovation Landscape: A Case Study of U.S. Investment Strategies. *Engineering Science & Technology Journal*, *4*(3), 120–139. https://doi.org/10.51594/estj.v4i3.556

Weber, F., & Schütte, R. (2019). A Domain-Oriented Analysis of the Impact of Machine Learning—The Case of Retailing. *Big Data and Cognitive Computing*, *3*(1), 11. https://doi.org/10.3390/bdcc3010011

Wiesenberg, M., Godulla, A., Tengler, K., Noelle, I.-M., Kloss, J., Klein, N., & Eeckhout, D. (2020). Key Challenges in Strategic Start-Up Communication. *Journal of Communication Management*, *24*(1), 49–64. https://doi.org/10.1108/jcom-10-2019-0129

Ye, Y., Lau, K. H., & Teo, L. K. Y. (2018). Drivers and Barriers of Omni-Channel Retailing in China. *International Journal of Retail & Distribution Management*, *46*(7), 657–689. https://doi.org/10.1108/ijrdm-04-2017-0062

Zhou, L., Liu, B., Li, Y., Wang, M., Sun, C., Zhang, X., Liu, G., & SIUZANNA, N. (2023). Cost-Effectiveness of Pit and Fissure Sealing at Schools for Caries Prevention in China: A

Markov Modeling Analysis. *Caries Research*, *57*(4), 516–523. https://doi.org/10.1159/000530377