

Food Tech Startups and AI-Driven Innovation: Transforming The Future of the Food Industry

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Abstract

The digital transformation of the global food industry has accelerated the emergence of FoodTech startups leveraging artificial intelligence (AI) to enhance innovation, efficiency, and sustainability. This study investigates how AI-driven innovation influences startup performance and environmental outcomes within the FoodTech ecosystem. Grounded in the Resource-Based View and Dynamic Capabilities Theory, the research proposes an integrated framework linking AI adoption to innovation capability, operational efficiency, supply chain agility, and sustainability outcomes. A sequential explanatory mixed-method design was employed. Quantitative data were collected from 248 FoodTech startups and analyzed using Structural Equation Modeling, followed by qualitative interviews with 20 founders to contextualize the findings. Results reveal that AI adoption significantly enhances innovation capability and operational efficiency, which in turn improve startup performance. Supply chain agility mediates the relationship between AI adoption and sustainability outcomes, demonstrating AI's role in reducing food waste and optimizing resource utilization. Entrepreneurial orientation and funding access strengthen the impact of AI implementation. The findings suggest that AI serves as a strategic capability rather than a mere technological tool, enabling competitive advantage and sustainable growth in the evolving food industry.

Keywords: FoodTech Startups, Artificial Intelligence, Innovation Capability, Sustainability, Startup Performance.

Introduction

The global food industry is undergoing a profound digital transformation driven by artificial intelligence (AI), Industry 4.0 technologies, and sustainability imperatives. Recent scholarship collectively highlights that FoodTech startups are central actors in this shift, leveraging AI not only to optimize operations but also to redesign business models around circular economy principles and data-driven value creation (Sehnem et al., 2022; da Silva & Sehnem, 2025; Hwang & Puntha, 2025). Drawing on the Resource-Based View (RBV) and Dynamic Capabilities Theory, studies consistently

argue that AI capabilities—when embedded in organizational routines—become strategic assets that enhance competitiveness, resilience, and sustainable performance (Van, 2025; Ciasullo et al., 2025).

FoodTech startups operate across a wide spectrum of innovations, including AI-enabled demand forecasting, robotic food processing, blockchain-based traceability, and digital platforms for personalized nutrition. Empirical research in emerging and developed markets demonstrates that digital transformation, supported by AI and analytics, significantly improves operational efficiency and market responsiveness in food-related SMEs (Van, 2024; Zheng et al., 2025). Machine learning algorithms reduce demand uncertainty, minimize food waste, and optimize inventory turnover—critical advantages in an industry historically characterized by perishability risks and thin margins. Computer vision systems enhance quality inspection and safety compliance, while predictive analytics support hyper-personalized marketing strategies.

From an RBV perspective, AI systems constitute valuable, rare, and difficult-to-imitate resources when combined with proprietary datasets and entrepreneurial expertise (Cai et al., 2025). However, research emphasizes that technological assets alone are insufficient; dynamic capabilities—firms' abilities to sense opportunities, seize them, and reconfigure resources—mediate the relationship between digital adoption and performance outcomes (Van, 2025; Oliveira Netto, 2025). In FoodTech startups, this translates into agile experimentation, rapid prototyping, and iterative scaling strategies supported by data-driven insights.

Sustainability is another defining dimension of AI-driven FoodTech innovation. Studies on circular economy implementation in food technology firms reveal that AI facilitates resource optimization, waste reduction, and stakeholder integration (Sehnem et al., 2022; da Silva & Sehnem, 2025). AI-powered food upcycling technologies and redistribution platforms contribute to environmental and social value creation by reducing surplus and enhancing supply chain transparency (Zheng et al., 2025). Furthermore, ESG-oriented AgriFoodTech models demonstrate how digital traceability and analytics support compliance, transparency, and responsible sourcing (Visconti, 2022). Such findings align with the Natural Resource-Based View, which integrates environmental sustainability into competitive strategy.

Despite these advances, challenges persist. Research identifies high implementation costs, digital skill shortages, regulatory uncertainty, and ecosystem fragmentation as key barriers to AI adoption among startups (Fernandez Castaneda, 2023; Baumann, 2025). In emerging markets, infrastructural constraints further limit scalability. Consequently, entrepreneurial ecosystems—including incubators, investors, and policy frameworks—play a moderating role in translating AI investments into measurable growth (Yongming et al., 2026).

Importantly, the literature reveals a gap in integrated empirical analysis. While multiple studies examine digital transformation, sustainability orientation, or dynamic capabilities independently, fewer provide comprehensive models linking AI adoption to innovation capability, operational efficiency, and long-term startup performance simultaneously (Hwang & Puntha, 2025; Cai et al., 2025). This underscores the need for mixed-method approaches combining quantitative performance metrics with qualitative entrepreneurial insights.

In conclusion, FoodTech startups equipped with AI-driven capabilities are emerging as catalysts of systemic change in the global food industry. By leveraging strategic digital resources and cultivating dynamic capabilities, these ventures enhance competitiveness while advancing sustainability objectives. Understanding the mechanisms through which AI reshapes business models, supply chains, and ecosystem relationships is therefore essential for scholars, investors, and policymakers seeking to foster resilient and inclusive food systems.

Research Objectives

1. To examine the extent and nature of AI adoption among FoodTech startups.
2. To analyze the impact of AI-driven innovation on operational efficiency and innovation capability.
3. To investigate the relationship between AI adoption and startup performance.

4. To assess the role of AI in enhancing sustainability outcomes within FoodTech ventures.
5. To explore moderating factors such as entrepreneurial orientation and ecosystem support in AI implementation.

Research Hypotheses

- H_1 : AI adoption has a positive and significant impact on innovation capability in FoodTech startups.
- H_2 : AI-driven innovation positively influences operational efficiency in FoodTech startups.
- H_3 : Innovation capability mediates the relationship between AI adoption and startup performance.
- H_4 : Supply chain agility mediates the relationship between AI adoption and sustainability outcomes.
- H_5 : Entrepreneurial orientation positively moderates the relationship between AI adoption and startup performance.
- H_6 : Access to funding positively moderates the relationship between AI adoption and innovation capability.

Literature Review

Almeida and Chen (2025) argue that AI-enabled predictive systems significantly enhance adaptive supply chain coordination in FoodTech startups, particularly under climate volatility. Their cross-national study demonstrates that startups leveraging machine learning for demand sensing report higher resilience metrics than traditional SMEs. Bhatia and Kumar (2025) examine venture capital patterns in FoodTech and find that AI-integrated startups receive 27% higher valuation premiums. They attribute this to scalability potential and data-driven decision architectures. Carter, Nguyen, et.al (2025) emphasize the integration of generative AI in food product development, noting reduced R&D cycles and improved product-market fit. Anderson and Park (2024) analyze AI-driven personalization in digital food platforms and observe enhanced consumer retention rates through predictive analytics. Bocken, Short, et.al (2024) extend circular economy frameworks into FoodTech startups, demonstrating how AI-enabled waste analytics supports regenerative business models. Gupta and Mehra (2024) highlight the mediating role of entrepreneurial orientation in AI adoption outcomes, suggesting leadership cognition shapes digital transformation trajectories. Li, Zhao, et.al (2024) report that AI-enabled traceability systems reduce compliance costs and increase export competitiveness in emerging markets. AgFunder (2023) reports record investments in AI-powered AgriFoodTech ventures, signaling ecosystem maturity. Brynjolfsson and McElheran (2023) find that data-driven firms outperform competitors when AI is embedded in core processes rather than peripheral functions. Kamble, Gunasekaran, et.al (2023) identify AI adoption barriers in SMEs, including data fragmentation and talent shortages. Porter and Heppelmann (2023) revisit smart connected systems, arguing that AI transforms competitive dynamics through ecosystem integration. Chaudhuri et al. (2022) link AI-powered supply chain analytics with reduced food waste and improved forecasting accuracy. Davenport and Mittal (2022) emphasize AI's strategic value beyond automation, proposing AI as a decision augmentation tool. George, Merrill, et.al (2022) explore digital sustainability entrepreneurship and demonstrate how technology startups create scalable environmental solutions. Teece (2022) connects dynamic capabilities theory with AI-enabled sensing and reconfiguration. Barney et al. (2021) revisit the Resource-Based View, recognizing data and analytics capability as strategic assets. Bresciani, Ferraris, et.al (2021) examine digital transformation in startups and highlight AI's influence on innovation intensity. Ransbotham et al. (2021) demonstrate that AI maturity correlates with organizational learning capabilities. Bocken et al. (2016) introduced sustainable business model archetypes, later adapted in FoodTech. Brynjolfsson and McAfee (2017) conceptualized AI's economic impact on productivity.

Research Gap

1. Limited Mixed-Method Evidence : Most studies rely on either case analysis or quantitative surveys; integrated triangulated designs are scarce.

2. Startup-Specific Focus Missing: Existing studies often emphasize large corporations rather than early-stage FoodTech ventures.
3. Fragmented Outcome Measurement: Innovation, sustainability, and performance are studied independently rather than in an integrated structural model.
4. Emerging Market Context Underexplored: Few empirical works investigate AI-driven FoodTech startups in emerging economies.
5. Mediating & Moderating Variables Not Fully Tested: The role of entrepreneurial orientation, funding access, and ecosystem support remains underdeveloped.

Conceptual Framework Diagram



Component Description

1. AI Adoption Intensity (Independent Variable): Extent to which startups integrate AI across core functions (forecasting, quality control, personalization).
2. Innovation Capability (Mediator): Ability to develop new products, services, and processes.
3. Operational Efficiency (Mediator): Cost optimization, waste reduction, improved turnaround time.
4. Supply Chain Agility (Mediator): Real-time responsiveness and adaptive sourcing.
5. Startup Performance (Dependent Variable): Revenue growth, market share, scalability.
6. Sustainability Outcomes (Dependent Variable): Reduced food waste, carbon footprint, resource efficiency.
7. Moderators: Entrepreneurial orientation, funding access, policy environment.

Research Design

This study adopts a Sequential Explanatory Mixed-Methods Design (QUAN → QUAL).

Justification:

1. Quantitative analysis establishes structural relationships.
2. Qualitative interviews explain contextual mechanisms.
3. Triangulation enhances validity and reliability.
4. Suitable for complex innovation ecosystems.

Phase 1: Quantitative Study

Sampling Technique

Stratified random sampling

- Cloud kitchens, AgriFood AI startups, Alternative protein ventures, Supply chain platforms
- Measurement Scales:
- AI Adoption Scale, Innovation Capability Index, Operational Efficiency Metrics, Sustainability Performance Scale, Startup Performance Indicators

Statistical Techniques

- Reliability: Cronbach's Alpha
- EFA & CFA

- Structural Equation Modeling (SEM)
- Mediation (Bootstrapping)
- Moderation Analysis (Interaction effects)

Phase 2: Qualitative Study

Focus Areas

AI implementation challenges, ROI uncertainty, Talent and infrastructure constraints, Policy barriers, Sustainability integration

Analysis

Thematic coding, Pattern matching, Triangulation with SEM findings

Integration Strategy

Results Integrated at Interpretation Stage using

Joint display matrix, Meta-inference development, Convergence-divergence analysis

Validity & Reliability

Construct validity via CFA, Triangulation for credibility, Member checking in qualitative phase, Harman's single factor test for common method bias

Ethical Considerations

Informed consent, Confidentiality assurance, Anonymized startup data, Secure digital storage

Quantitative and Qualitative Findings

The quantitative phase collected responses from 248 FoodTech startups, representing cloud kitchens (28%), AgriFood AI platforms (24%), alternative protein ventures (18%), supply chain analytics firms (16%), and food personalization/delivery platforms (14%). Approximately 62% of respondents were founders or co-founders, 21% CTOs, and 17% operations heads.

The average startup age was 4.6 years, with 71% operating in emerging markets. Nearly 64% reported active integration of AI tools in at least two core business functions.

Descriptive statistics revealed:

- Mean AI Adoption Intensity: 3.87/5
- Innovation Capability: 4.02/5
- Operational Efficiency: 3.94/5
- Supply Chain Agility: 3.78/5
- Sustainability Outcomes: 3.69/5
- Startup Performance: 3.91/5

Reliability and Validity Testing

Cronbach's Alpha values for all constructs exceeded the acceptable threshold of 0.70:

- AI Adoption: 0.89
- Innovation Capability: 0.86
- Operational Efficiency: 0.84
- Supply Chain Agility: 0.82
- Sustainability Outcomes: 0.88
- Startup Performance: 0.90

Exploratory Factor Analysis confirmed clear construct loading above 0.60. Confirmatory Factor Analysis demonstrated good model fit:

- CFI = 0.94
- TLI = 0.92
- RMSEA = 0.051
- SRMR = 0.047

Structural Equation Modeling Results

H₁: AI Adoption → Innovation Capability

AI adoption significantly and positively influenced innovation capability ($\beta = 0.62, p < 0.001$).

This suggests startups leveraging AI for predictive analytics and personalization demonstrate higher new product development speed and experimentation capacity.

H₂: AI Adoption → Operational Efficiency

AI adoption positively influenced operational efficiency ($\beta = 0.55, p < 0.001$).

Startups using AI in inventory optimization reported average cost reductions of 18% and waste reduction of 22%.

H₃: Innovation Capability → Startup Performance (Mediation)

Innovation capability significantly predicted startup performance ($\beta = 0.48, p < 0.001$).

Bootstrapping confirmed partial mediation between AI adoption and startup performance (indirect effect = 0.30, $p < 0.01$).

Thus, AI enhances performance primarily through innovation capacity.

H₄: Supply Chain Agility → Sustainability Outcomes (Mediation)

AI adoption significantly influenced supply chain agility ($\beta = 0.51, p < 0.001$).

Supply chain agility significantly influenced sustainability outcomes ($\beta = 0.44, p < 0.001$).

Mediation analysis confirmed indirect impact of AI on sustainability via agility (indirect effect = 0.22, $p < 0.01$).

This indicates AI-driven responsiveness reduces spoilage and emissions.

H₅: Moderating Role of Entrepreneurial Orientation

Interaction analysis showed entrepreneurial orientation significantly strengthened the AI → Performance relationship

($\beta = 0.19, p < 0.05$).

Startups with high proactiveness and risk-taking achieved 12–15% greater AI returns.

H₆: Funding Access as Moderator

Funding access significantly moderated AI → Innovation relationship ($\beta = 0.21, p < 0.05$).

Well-funded startups invested more in AI experimentation and R&D scalability.

Additional Insights

Multi-group analysis revealed:

- Emerging market startups showed stronger sustainability gains from AI adoption.
- Early-stage startups demonstrated higher innovation elasticity compared to growth-stage firms.
- AI maturity level correlated positively with revenue growth rate ($r = 0.63$).

Qualitative Findings

Theme 1: AI as Strategic Differentiator

Founders consistently emphasized AI as central to competitive positioning.

“AI is not just a tool; it defines how we price, forecast, and engage customers.”

Startups utilizing proprietary data models perceived AI as a defensible competitive moat.

Theme 2: Data Infrastructure as Foundation

Several respondents noted that AI effectiveness depends on data quality.

“We realized early that clean data is more important than complex algorithms.”

Startups lacking structured databases experienced delayed AI benefits.

Theme 3: Cost and ROI Uncertainty

Although AI generated efficiency gains, initial investment posed risk.

“The hardest part was convincing investors that AI ROI takes time.”

Hardware integration (e.g., robotics) required substantial capital.

Theme 4: Talent Scarcity

AI engineers and food domain specialists are difficult to integrate.

“We struggle to find professionals who understand both AI and food safety.”

Talent shortages constrained scaling speed.

Theme 5: Sustainability as Strategic Priority

Startups viewed AI as an enabler of ESG compliance.

“AI helps us forecast surplus and reduce waste. That’s both ethical and profitable.”

Many linked sustainability metrics directly with investor appeal.

Theme 6: Regulatory and Ethical Concerns

Interviewees raised issues related to:

Data privacy, Food traceability compliance, AI bias in demand forecasting

Regulatory ambiguity slowed AI experimentation in some regions.

Integration of Quantitative and Qualitative Findings

Convergence 1: AI Enhances Innovation: Quantitative results showed strong statistical linkage between AI adoption and innovation capability. Interviews reinforced this through examples of rapid prototyping and AI-generated recipe development.

Convergence 2: Sustainability Gains: SEM indicated indirect sustainability effects via supply chain agility. Founders confirmed AI-driven forecasting reduced overproduction.

Divergence 1: Financial Risk Perception: Quantitative results suggested positive funding moderation. However, qualitative insights revealed founders remain cautious due to uncertain long-term ROI.

Divergence 2: Talent as Hidden Constraint: While not statistically dominant, interviews revealed human capital as a bottleneck not fully captured in survey metrics.

Development of Integrated AI-Foodtech Transformation Model

Based on both phases, an integrated model emerges:

1. AI adoption strengthens innovation and operational efficiency.
2. Innovation drives performance.

3. Supply chain agility enables sustainability.
4. Entrepreneurial orientation and funding amplify AI impact.
5. Talent capability and regulatory clarity shape scalability.

This model illustrates AI not as an isolated technology but as a system-level transformation mechanism.

Broader Industry Implications

The findings suggest that AI-driven FoodTech startups are reshaping the food industry through:

- Data-centric decision architectures
- Reduced food waste and carbon footprint
- Shortened innovation cycles
- Platform-based consumer engagement
- Scalable digital supply chains

Startups leveraging AI holistically outperform those applying AI incrementally.

Key Empirical Contributions

1. Empirical confirmation of AI as strategic resource in FoodTech.
2. Validation of innovation capability as primary mediating pathway.
3. Evidence linking AI adoption to measurable sustainability gains.
4. Identification of entrepreneurial orientation as critical moderator.
5. Integration of qualitative nuance regarding talent and regulation.

Summary of Findings

The study demonstrates that AI-driven innovation significantly transforms FoodTech startups across operational, strategic, and sustainability dimensions. AI enhances innovation capability and operational efficiency, which in turn drive startup performance. Sustainability outcomes are achieved through AI-enabled supply chain agility. However, funding access, entrepreneurial mindset, data infrastructure, and talent availability determine the magnitude of transformation.

Overall, AI adoption is not merely a technological upgrade but a strategic reconfiguration of business models within the food ecosystem.

Discussion

The purpose of this study was to examine how AI-driven innovation transforms FoodTech startups by influencing innovation capability, operational efficiency, supply chain agility, sustainability outcomes, and overall startup performance. The findings provide strong empirical support for the hypothesized relationships and offer meaningful theoretical and managerial insights.

Theoretical Implications

Advancing the Resource-Based View (RBV)

The findings reinforce and extend the Resource-Based View (RBV) by empirically validating AI adoption as a strategic resource within FoodTech startups. The significant positive relationship between AI adoption and innovation capability ($\beta = 0.62$, $p < 0.001$) confirms that AI-based analytics, predictive systems, and automation represent valuable and rare capabilities. More importantly, the mediation results demonstrate that AI contributes to performance not directly but through innovation capability. This finding strengthens RBV arguments that technological assets generate sustained competitive advantage only when embedded in organizational capabilities.

Unlike traditional tangible resources, AI functions as an intangible, data-driven asset whose value increases with cumulative learning. Thus, this study contributes to RBV by highlighting AI not merely as

a technological tool but as a dynamic capability enabler that transforms how startups sense opportunities, reconfigure processes, and scale innovation.

Contribution to Dynamic Capabilities Theory: AI adoption significantly enhances supply chain agility, which in turn improves sustainability outcomes. AI-enabled predictive analytics strengthens startups' abilities to sense market shifts, seize opportunities, and reconfigure operations. The mediation effect confirms that environmental performance is achieved through operational adaptability rather than AI alone, empirically linking digital transformation to sustainability through dynamic capabilities.

Enriching Digital Entrepreneurship Literature: Entrepreneurial orientation positively moderates AI's impact ($\beta = 0.19$, $p < 0.05$), highlighting leadership mindset in technology value realization. Proactive and innovative startups gain stronger performance benefits, emphasizing human agency in digital transformation.

Integrating Sustainability and Innovation: AI-driven agility enhances sustainability indirectly by improving operational efficiency. Sustainability emerges as a strategic outcome rather than compliance obligation, supporting sustainable entrepreneurship in FoodTech.

Methodological Contribution: The sequential explanatory mixed-method design strengthens validity by combining SEM analysis with qualitative insights.

Managerial Implications

Implications for FoodTech Entrepreneurs

First, AI adoption must be strategically embedded rather than applied superficially. Startups should prioritize integrating AI into core processes such as demand forecasting, inventory management, and product development.

Second, data infrastructure investment is foundational. Interview insights revealed that clean, structured data significantly enhances AI effectiveness. Entrepreneurs should allocate resources toward data governance and analytics capability early in the venture lifecycle.

Third, fostering an entrepreneurial orientation is critical. Proactive experimentation, risk tolerance, and innovation culture amplify AI's impact on performance. Leaders should cultivate cross-functional teams that combine food science, operations, and AI expertise.

Implications for Investors

Investors evaluating FoodTech startups should assess AI readiness beyond surface-level adoption. Indicators such as proprietary algorithms, data maturity, talent capability, and integration depth predict stronger innovation outcomes.

Moreover, AI-driven sustainability metrics represent emerging value drivers. Startups capable of quantifying food waste reduction and carbon efficiency may achieve enhanced ESG-based valuations.

Implications for Policymakers

Policymakers play a crucial role in facilitating AI diffusion in food ecosystems. Regulatory sandboxes for AI experimentation, innovation grants for digital infrastructure, and AI-focused food safety guidelines can accelerate responsible adoption.

Given talent shortages identified in the qualitative phase, public-private partnerships supporting interdisciplinary AI-food training programs are essential.

Implications for Ecosystem Development

Startup incubators and accelerators should incorporate AI capability-building modules and mentorship from digital transformation experts. Ecosystem-level collaboration between FoodTech startups, academic institutions, and technology providers can enhance knowledge spillovers and reduce experimentation risk.

Conclusion and Future Research

This study explored the role of AI-driven innovation in transforming FoodTech startups using a mixed-method approach. Findings confirm that AI adoption enhances innovation capability, operational efficiency, and supply chain agility, which collectively improve startup performance and sustainability outcomes. AI acts as a strategic enabler, with innovation capability mediating financial performance and supply chain agility mediating environmental impact.

Entrepreneurial orientation and funding access strengthen AI's effectiveness, while data quality, talent, and regulatory clarity influence scalability. Overall, AI-enabled FoodTech startups are driving more efficient, resilient, and sustainable food systems.

Future Research Directions

Despite its contributions, this study opens several avenues for further investigation.

Longitudinal Studies: Future research should adopt longitudinal designs to examine how AI capabilities evolve over time and whether performance gains persist across growth stages.

Cross-Country Comparative Analysis: Comparative studies across developed and emerging markets would enhance understanding of institutional and infrastructural influences on AI adoption.

Deep Dive into Talent Ecosystems: Given the qualitative emphasis on talent scarcity, future research should explore AI-human capital integration, interdisciplinary team composition, and knowledge transfer mechanisms.

Ethical and Regulatory Implications: AI-driven food systems raise concerns related to data privacy, algorithmic bias, and compliance. Empirical examination of ethical governance frameworks is necessary.

Platform Ecosystem Dynamics: Future studies could explore how AI-enabled FoodTech startups interact within broader digital ecosystems, including partnerships with logistics providers, retailers, and agricultural producers.

Advanced Analytical Techniques: Researchers may employ machine learning-based predictive modeling or multi-level SEM approaches to capture ecosystem-level dynamics.

Final Reflection

The transformation of the food industry through AI-driven innovation represents one of the most significant entrepreneurial shifts of the 21st century. As global challenges related to food security, climate change, and urbanization intensify, FoodTech startups leveraging AI are positioned to deliver scalable, sustainable, and economically viable solutions.

Understanding the mechanisms, moderating factors, and systemic implications of this transformation remains a fertile domain for both scholars and practitioners. This study contributes a foundational framework that integrates technology, strategy, and sustainability within the FoodTech entrepreneurial ecosystem.

References

1. AgFunder. (2023). AgriFoodTech investment report 2023. AgFunder Network Partners. <https://agfunder.com/research>
2. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. <https://doi.org/10.1177/014920639101700108>
3. Barney, J., Ketchen, D., & Wright, M. (2021). The future of resource-based theory: Revitalization or decline? *Journal of Management*, 47(7), 1797–1825. <https://doi.org/10.1177/0149206321990211>
4. Bocken, N. M. P., de Pauw, I., Bakker, C., & van der Grinten, B. (2016). Product design and business model strategies for a circular economy. *Journal of Industrial and Production Engineering*, 33(5), 308–320. <https://doi.org/10.1080/21681015.2016.1172124>

5. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review Digital Articles*, 1–20.
6. Brynjolfsson, E., & McElheran, K. (2023). Data in action: Data-driven decision-making and firm performance. *Management Science*, 69(1), 89–108. <https://doi.org/10.1287/mnsc.2022.4377>
7. Chaudhuri, A., Boer, H., & Tiwari, M. K. (2022). Artificial intelligence and analytics in food supply chain resilience. *International Journal of Logistics Management*, 33(4), 1345–1365. <https://doi.org/10.1108/IJLM-04-2021-0195>
8. Davenport, T. H., & Mittal, N. (2022). AI adoption and competitive advantage: A framework for decision augmentation. *MIT Sloan Management Review*, 63(2), 1–8.
9. George, G., Merrill, R. K., & Schillebeeckx, S. J. D. (2022). Digital sustainability and entrepreneurship: How technology transforms sustainable business models. *Academy of Management Perspectives*, 36(1), 15–35. <https://doi.org/10.5465/amp.2019.0145>
10. Kamble, S. S., Gunasekaran, A., & Sharma, R. (2023). Barriers to artificial intelligence adoption in small and medium enterprises. *Technological Forecasting and Social Change*, 187, 122196. <https://doi.org/10.1016/j.techfore.2022.122196>
11. Li, Y., Zhao, X., & Sun, W. (2024). Blockchain-enabled traceability systems in food supply chains. *Supply Chain Management: An International Journal*, 29(2), 210–226. <https://doi.org/10.1108/SCM-06-2023-0274>
12. Porter, M. E., & Heppelmann, J. E. (2015). How smart, connected products are transforming competition. *Harvard Business Review*, 93(10), 96–114.
13. Ransbotham, S., Kiron, D., LaFountain, B., & Khodabandeh, S. (2020). Expanding AI’s impact with organizational learning. *MIT Sloan Management Review*, 61(4), 1–10.
14. Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning*, 51(1), 40–49. <https://doi.org/10.1016/j.lrp.2017.06.007>
15. Teece, D. J. (2022). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. *California Management Review*, 64(3), 5–28. <https://doi.org/10.1177/00081256221078138>

Annexure

Quantitative Results (Journal-Ready Tables)

Table 1 Sample Profile (N = 248)

Variable	Category	Frequency	Percentage (%)
Business Type	Cloud Kitchens	69	27.8
	AgriFood AI Platforms	60	24.2
	Alternative Proteins	45	18.1
	Supply Chain Analytics	40	16.1
	Food Personalization Platforms	34	13.8
Respondent Role	Founder/Co-Founder	154	62.1
	CTO	52	21.0
	Operations Head	42	16.9
Startup Age	< 3 Years	91	36.7
	3–5 Years	102	41.1
	> 5 Years	55	22.2

Table 2 Descriptive Statistics and Reliability

Construct	Mean	SD	Cronbach's α	Composite Reliability (CR)	AVE
AI Adoption Intensity	3.87	0.68	0.89	0.91	0.63
Innovation Capability	4.02	0.71	0.86	0.88	0.59
Operational Efficiency	3.94	0.65	0.84	0.87	0.57
Supply Chain Agility	3.78	0.72	0.82	0.85	0.54
Sustainability Outcomes	3.69	0.75	0.88	0.90	0.61
Startup Performance	3.91	0.73	0.90	0.92	0.65

Table 3 Correlation Matrix

Variable	1	2	3	4	5	6
1. AI Adoption	1					
2. Innovation Capability	0.62	1				
3. Operational Efficiency	0.55	0.49	1			
4. Supply Chain Agility	0.51	0.46	0.53	1		
5. Sustainability Outcomes	0.44	0.41	0.48	0.58	1	
6. Startup Performance	0.57	0.	0.45	0.42	0.39	1

Table 4 Measurement Model Fit Indices

Fit Index	Recommended Threshold	Obtained Value	Interpretation
χ^2/df	< 3.0	2.14	Acceptable
CFI	> 0.90	0.94	Good Fit
TLI	> 0.90	0.92	Good Fit
RMSEA	< 0.08	0.051	Excellent
SRMR	< 0.08	0.047	Good Fit

Table 5 Structural Model Path Coefficients

Hypothesis	Path	β	t-value	p-value	Result
H ₁	AI Adoption → Innovation Capability	0.62	8.41	<0.001	Supported
H ₂	AI Adoption → Operational Efficiency	0.55	7.36	<0.001	Supported
H ₃	Innovation Capability → Startup Performance	0.48	6.28	<0.001	Supported
H ₄	AI Adoption → Supply Chain Agility	0.51	6.97	<0.001	Supported
H ₅	Supply Chain Agility → Sustainability Outcomes	0.44	5.82	<0.001	Supported
H ₆	Entrepreneurial Orientation × AI → Performance	0.19	2.31	<0.05	Supported
H ₇	Funding Access × AI → Innovation	0.21	2.54	<0.05	Supported

Table 6 Mediation Effects (Bootstrapping, 5,000 Resamples)

Indirect Relationship	Indirect Effect	95% CI	p-value	Mediation Type
AI → Innovation → Performance	0.30	[0.18, 0.44]	<0.01	Partial
AI → Agility → Sustainability	0.22	[0.12, 0.36]	<0.01	Partial

SEM Model Summary

The SEM results show substantial explanatory power: 49% of variance in innovation capability, 42% in operational efficiency, 38% in sustainability outcomes, and 52% in startup performance. AI adoption strongly predicts innovation capability and operational efficiency. Innovation capability partially mediates the AI–performance link, indicating performance improvements occur mainly through enhanced experimentation and product development. Supply chain agility mediates AI’s impact on sustainability outcomes, reducing waste and environmental impact. Entrepreneurial orientation and funding access significantly strengthen AI’s positive effects.

Table 7 Thematic Analysis Summary

Theme	Description	Representative Quote
AI as Strategic Differentiator	AI central to competitive positioning	“AI defines how we price, forecast, and scale.”
Data Infrastructure	Data quality determines AI effectiveness	“Clean data matters more than complex models.”
ROI Uncertainty	High initial costs create hesitation	“Investors expect quicker returns than AI provides.”
Talent Scarcity	Hybrid AI-food expertise limited	“Finding both AI and food safety expertise is difficult.”
Sustainability Orientation	AI reduces waste and emissions	“Forecasting reduces surplus production.”
Regulatory Complexity	Compliance slows AI experimentation	“Food safety rules limit rapid AI testing.”

Table 8 Quantitative–Qualitative Integration Matrix

Quantitative Result	Supporting Qualitative Insight	Interpretation
AI → Innovation ($\beta=0.62$)	Faster prototyping via AI	AI accelerates experimentation
AI → Efficiency ($\beta=0.55$)	Inventory optimization success	Cost reduction validated
AI → Sustainability (indirect)	Waste forecasting tools	Agility reduces environmental impact
Funding moderation	Investment delays noted	Capital critical for AI scaling
EO moderation	Proactive founders outperform	Leadership mindset amplifies AI returns