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MARKET-DRIVEN MANAGEMENT STRATEGIES USING ARTIFICIAL INTELLIGENCE TO STRENGTHEN FOOD SAFETY AND ADVANCE ONE HEALTH INITIATIVES

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Abstract

This quantitative cross sectional, case-based study addresses the practical gap in understanding how artificial intelligence enabled, market driven management strategies improve food safety performance and contribute to One Health outcomes in contemporary food enterprises. Data were collected through a structured Likert five-point questionnaire from 212 managers and professionals in case organizations operating certified food safety management systems and AI or cloud-based analytics for monitoring, traceability, and risk assessment. Key latent variables included AI enabled market driven strategies, food safety performance, One Health aligned outcomes, food safety standards adoption, and external regulatory or market pressure. Reliability and factor analysis confirmed internally consistent scales (α = 0.86–0.93). Correlation and multiple regression models, complemented by bootstrapped mediation and moderated regression, were used to test five hypotheses. AI enabled strategies showed a strong positive effect on food safety performance ($\beta = 0.49$, $R^2 = 0.485$, $p < 0.001$), while food safety performance and AI enabled strategies together explained over half of the variance in One Health aligned outcomes ($R^2 = 0.567$). Mediation analysis demonstrated that food safety performance significantly transmitted the impact of AI enabled strategies to One Health outcomes (standardized indirect effect = 0.23). External regulatory and market pressure strengthened the AI–performance link, with the slope of AI strategies on safety performance increasing from 0.36 at low pressure to 0.61 at high pressure. Overall, the findings indicate that embedding AI within market driven management systems can simultaneously enhance food safety performance and support integrated human, animal, and environmental health objectives.

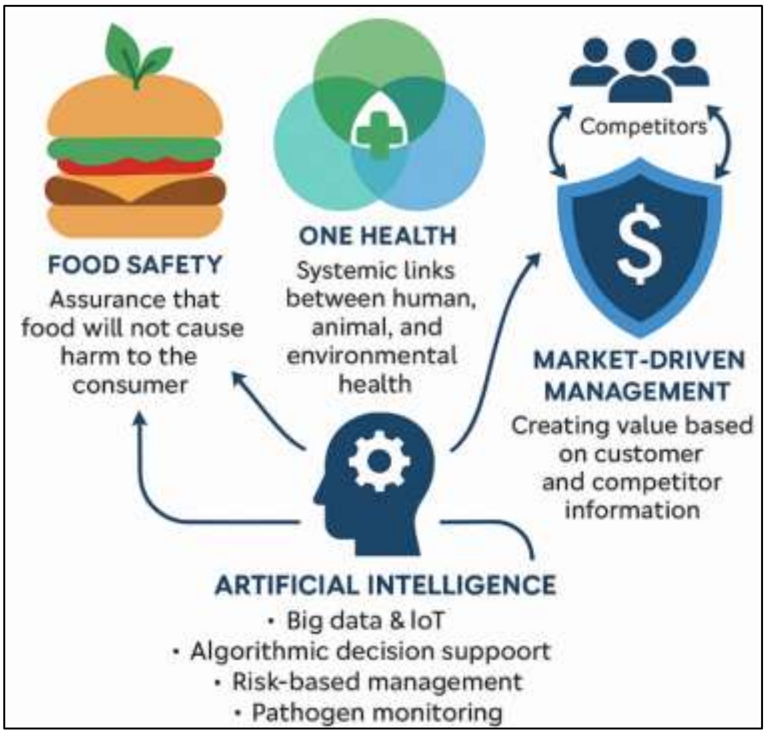
Keywords

Artificial Intelligence, Market Driven Management, Food Safety Performance, One Health, Food Supply Chains;

INTRODUCTION

Food safety is commonly defined as the assurance that food will not cause harm to the consumer when it is prepared and/or eaten according to its intended use, and it is recognized as a fundamental component of public health, nutrition security, and sustainable development by international organizations such as the World Health Organization (WHO) and the Food and Agriculture Organization (FAO). In parallel, market-driven management and market orientation are understood as organizational philosophies that systematically generate, disseminate, and respond to information about customers, competitors, and wider stakeholders in order to create superior value and performance (Kirca et al., 2005). Artificial intelligence (AI), defined in technical and policy literature as computer systems that display intelligent behaviour by analysing their environment and taking actions with some degree of autonomy to achieve specific goals, extends these market-driven logics into data-intensive, algorithmic decision support (Russell & Norvig, 2010). Within food systems, AI interacts with big data, the Internet of Things (IoT), and sensor networks to support complex decisions about sourcing, processing, distribution, and retailing (Misra et al., 2020). In parallel, the One Health paradigm stresses the systemic interdependence of human, animal, and environmental health, particularly in relation to foodborne and zoonotic risks (Gibbs, 2014). The intersection of these concepts frames the present study: market-driven management strategies that leverage AI to strengthen food safety while advancing One Health initiatives across increasingly globalized agri-food chains.

Figure 1: AI-Enabled Market-Driven Food Safety Management within the One Health Framework



International estimates indicate that foodborne diseases impose a health burden comparable to major infectious diseases such as HIV/AIDS, malaria, and tuberculosis, with a particularly heavy toll among children under five and populations in low- and middle-income regions (Havelaar et al., 2015). The WHO Foodborne Disease Burden Epidemiology Reference Group (FERG) has quantified incidence, mortality, and disability-adjusted life years linked to more than 30 foodborne hazards, underscoring substantial variation across regions and hazard categories and highlighting the importance of targeted food safety interventions (Idoje et al., 2021). More recent syntheses show that foodborne disease burdens remain substantial and that national systems increasingly rely on risk assessment metrics to prioritize hazards and interventions (Pires et al., 2021). The economic ramifications of unsafe food extend beyond direct medical costs to include productivity losses, trade disruptions, damage to brand equity, and reductions in consumer trust in both domestic and international markets (Koutsoumanis &

Aspridou, 2016). As global supply chains lengthen and sourcing patterns diversify, the need for food business operators to embed robust, data-driven food safety management within broader market strategies becomes more pronounced, especially when firms operate in competitive environments where safety, quality, and authenticity are simultaneously key dimensions of market value.

The One Health approach provides an integrative lens for understanding why food safety is not only a technological or regulatory challenge but also an ecological and socio-economic one. Reviews of One Health literature emphasize that a large share of infectious diseases relevant to food safety are zoonotic, transmitted through complex interfaces among livestock, wildlife, humans, and the environment (Johnson et al., 2009). Destoumieux-Garzon et al. (2018) argue that One Health has matured into a cross-sectoral governance framework linking veterinary medicine, public health, environmental sciences, and food safety, with applications ranging from antimicrobial resistance to contamination of food commodities along the farm-to-fork continuum. In the specific context of food safety, One Health analyses highlight how animal production practices, wildlife interfaces, water quality, and environmental contamination shape the presence and transmission of pathogens in feed, raw materials, and finished products, and how these factors interact with socio-technical conditions in slaughterhouses, processing plants, and retail environments (Gibbs, 2014).Within this perspective, food safety management becomes part of a broader system of controls that aim to protect public health, maintain animal health and welfare, preserve ecosystem integrity, and sustain consumer confidence. The One Health framing therefore provides a conceptual bridge between operational food safety decisions within firms and the wider health outcomes that this study seeks to address.

Market-driven management in agri-food industries involves more than responding to price signals; it entails the systematic integration of customer needs, competitor behaviour, and channel requirements into product, process, and relational strategies. Meta-analytic evidence demonstrates that market orientation has positive associations with business performance across sectors and regions, mediated by innovation and moderated by contextual factors such as competition intensity and economic development (Arfan et al., 2021; Kamarulzaman et al., 2021).In food and agribusiness contexts, market-oriented firms are reported to adapt quality and safety attributes, certifications, and traceability practices in ways that align with both downstream buyer requirements and final consumer expectations (Ara, 2021; Garro & et al., 2018). Empirical studies in agro-food manufacturing and halal food sectors indicate that stronger market orientation is associated with more innovative marketing strategies, higher perceived competitiveness, and improved financial performance (Jahid, 2021; Membré & Boué, 2018). These contributions suggest that market-driven firms often treat food safety and quality as strategic resources—dimensions of value that can support differentiation, preferred supplier status, and access to high-value markets—rather than purely as compliance obligations (Akbar & Farzana, 2021). At the same time, the complexity of global value chains and the diversity of standards regimes mean that the translation of market orientation into effective food safety practices depends on how firms gather, interpret, and operationalize market information about risk, regulatory expectations, and buyer preferences (Reza et al., 2021).

AI, IoT, and advanced analytics are progressively embedded in this translation process, offering tools for real-time monitoring, pattern recognition, and predictive modelling across food supply chains. In technical terms, contemporary AI systems combine machine learning, computer vision, natural language processing, and optimization methods to derive actionable insights from large volumes of heterogeneous data, including sensor readings, laboratory results, transactional and logistics records, and unstructured text (Kudashkina & co-authors, 2022; Saikat, 2021). In the agri-food domain, Misra et al. (2020) describe how IoT-enabled networks of sensors generate "big data" on environmental conditions, equipment performance, and product attributes, which can be analysed by AI algorithms to support precision agriculture, quality control, and supply chain management. Applications include non-destructive quality inspection using computer vision, predictive models of shelf-life and microbial growth, and anomaly detection for cold-chain breaches or equipment malfunctions (Ping et al., 2018; Shaikh & Aditya, 2021). In the specific area of food safety behaviour, Kudashkina and colleagues (2022) discuss AI-powered chatbots and digital tools that support employee training, monitoring, and feedback in food businesses, framed within behavioural science models. These developments illustrate how AI extends the informational and analytical capacities of food business operators, enabling them to capture complex, dynamic signals from both processes and markets and to embed these signals into day-to-day management decisions.

Concurrently, risk-based food safety management has evolved as the dominant scientific and regulatory paradigm, shifting emphasis from end-product testing toward the systematic assessment and control of risks along the entire food chain. Koutsoumanis and Aspridou (2016) outline this shift from hazard-based to risk-based approaches, highlighting the integration of quantitative microbial risk assessment (QMRA), risk management, and risk communication in international and national frameworks. QMRA methodologies support estimation of public health risks associated with specific food–hazard combinations and allow comparison of alternative control options under different scenarios (Membré & Boué, 2018; Kanti & Shaikat, 2021). From an operational perspective, risk-based management requires firms to link hazard control measures and monitoring plans to explicit risk metrics and performance targets, often under the oversight of regulators and external auditors. AI and advanced analytics can interact with these frameworks by automating data collection, enhancing detection of non-conformities, and supporting predictive identification of high-risk products, facilities, or suppliers (Ariful & Efat Ara, 2022; Misra et al., 2020). When combined with market-driven management, these capabilities allow firms to use risk information not only for compliance but also for strategic positioning, for example by demonstrating superior safety performance to retailers, foodservice chains, and certification bodies (Arman & Kamrul, 2022; Organization, 2015b; Tajkarimi, 2020).

Within the broader One Health agenda, AI-supported, market-driven food safety management can influence health outcomes beyond the boundaries of individual firms. One Health analyses of food safety emphasize the interconnectedness of pathogen ecology, antimicrobial use, environmental contamination, and socio-economic drivers such as consumer demand and trade patterns (Commission, 2018; Eissa, 2018; Mesbaul & Farabe, 2022). Garro et al. (2018) suggest that integrating pathogen genomics, surveillance data, and environmental monitoring under a One Health framework improves understanding of transmission pathways from farm environments to food products and ultimately to human populations. AI-driven analytics are increasingly used in related domains, such as IoT-based monitoring of environmental conditions in agriculture, smart farming technologies, and predictive maintenance of equipment, which indirectly support food safety and animal health (Nahid, 2022; Organization, 2022). When food businesses adopt market-driven strategies that prioritize safety attributes valued by buyers and consumers—such as low antimicrobial use, robust traceability, and transparent hazard controls—these strategies can align commercial incentives with One Health objectives. The present study positions AI-enabled, market-driven management as a potential mechanism through which firms translate One Health principles and risk-based food safety requirements into concrete managerial practices and performance outcomes (Hossain & Milon, 2022; Organization, 2015c; Rahman et al., 2014).

Empirical work at the intersection of market orientation, AI adoption, food safety performance, and One Health outcomes remains limited, particularly in the form of quantitative studies that test explicit hypotheses using firm-level data. Existing market orientation research in agro-food sectors tends to focus on innovation, marketing capabilities, and financial performance, with food safety often treated as a component of product quality or regulatory compliance rather than as a central construct (Abdur & Haider, 2022; Micheels & Gow, 2014). Conversely, studies of AI in food systems and food safety frequently concentrate on technical feasibility, pilot applications, or conceptual overviews, without systematically linking AI adoption to market-driven strategies or measured outcomes such as safety incidents, certification status, or buyer relationships (Organization, 2015a). One Health literature, while emphasizing the need for integrated governance and cross-sectoral collaboration, typically addresses policy architectures and surveillance systems rather than firm-level management practices and strategic positioning (Khairuddin et al., 2019; Mushfequr & Praveen, 2022). Against this background, the present research focuses on market-driven management strategies that use AI for data-driven decision-making in food safety, examines their association with organizational and One Health-relevant outcomes, and formulates testable hypotheses within a quantitative, cross-sectional, case-study–based design employing Likert-scale measurement, descriptive statistics, correlation analysis, and regression modelling.

The present study is explicitly designed to advance a clear set of interrelated objectives that connect market-driven management, artificial intelligence applications, food safety performance, and One Health outcomes at the organizational level. The primary objective is to empirically examine how market-driven management strategies that incorporate AI-based tools for data collection, analysis, and decision support are associated with measurable improvements in food safety performance within selected case organizations. In line with this overarching aim, the study seeks to assess the extent, patterns, and strategic orientation of AI adoption in food safety–related processes, such as hazard identification, process monitoring, traceability, and quality control, and to determine how these AI-enabled practices are embedded within broader market-driven behaviours oriented toward customers, competitors, and regulatory stakeholders. A further objective is to develop and test a conceptual model in which AI-enabled market intelligence, AI-supported traceability, and AI-based risk prediction function as key independent variables, market-driven strategic orientation operates as a potential mediating mechanism, and food safety performance and One Health–relevant outcomes serve as dependent variables. Within this model, the study aims to test a series of hypotheses using quantitative data from organizational respondents, employing descriptive statistics to profile the sample, correlation analysis to explore associations among constructs, and regression-based techniques to evaluate direct, mediating, and moderating effects. The research also seeks to generate a systematic description of how case organizations articulate market requirements related to safety and health, translate those requirements into AI-supported management practices, and align internal capabilities with external expectations. By pursuing these objectives within a cross-sectional, case-study–based quantitative design that uses structured Likert-scale questionnaires and widely accepted reliability and validity procedures, the study aims to produce a coherent, evidence-based account of the relationships among AI-enabled market-driven strategies, food safety management, and One Health outcomes, thereby providing a strong empirical foundation for the subsequent sections of the paper that will present the methodology, results, and discussion in a structured and transparent manner.

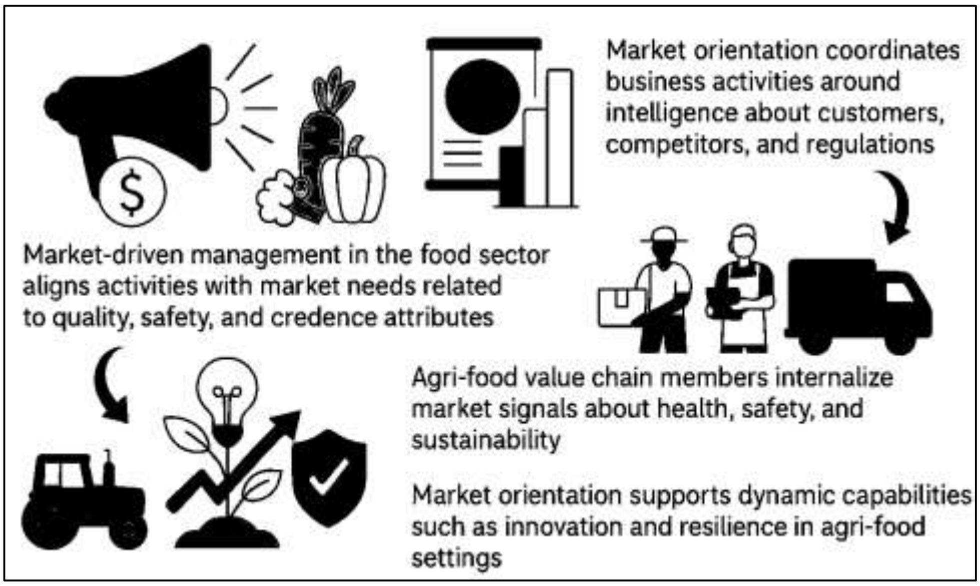
LITERATURE REVIEW

The literature review for this study establishes a structured foundation for understanding how market-driven management strategies, artificial intelligence applications, food safety management systems, and One Health initiatives intersect in contemporary agri-food value chains. It begins by clarifying how market-driven management and market orientation have been conceptualized in the management and agribusiness literature, with particular attention to how firms systematically generate, disseminate, and respond to information about customers, competitors, regulators, and supply chain partners. Within this stream of work, food safety and quality are increasingly treated as strategic value attributes rather than merely compliance obligations, shaping product positioning, buyer relationships, and access to high-value markets. The review then turns to the rapidly expanding body of research on artificial intelligence, big data analytics, and Internet of Things technologies in agriculture and food systems, focusing on AI-enabled capabilities such as predictive risk modelling, anomaly detection, process monitoring, and digital traceability, and examining how these technologies support data-driven decision-making at various stages from farm production to processing, distribution, and retail. A further strand of literature concerns food safety management and risk-based approaches, including hazard analysis, preventive controls, performance objectives, and the use of quantitative risk assessment to prioritize interventions and evaluate control measures. Closely linked to this is the One Health literature, which frames food safety as part of an integrated human–animal–environment health system and emphasizes how pathogen dynamics, antimicrobial use, environmental contamination, and socio-economic drivers interact along the food chain. Bringing these strands together, the review identifies conceptual and empirical work that explicitly or implicitly connects market orientation, digital technologies, and health outcomes, and evaluates the extent to which existing studies address firm-level strategies that use AI to align food safety practices with market and One Health requirements. Finally, the literature review introduces the theoretical and conceptual frameworks that guide the present research, outlining how established theories of market orientation and technology adoption can be adapted to the context of AI-enabled food safety management and how these frameworks support the development of a testable conceptual model linking AI-based market-driven strategies, food safety performance, and One Health-related outcomes.

Market-Driven Management and Market Orientation in Agri-Food Systems

Market-driven management in the food sector is grounded in the idea that firms and supply chains must systematically align their activities with articulated and latent market needs, especially those related to quality, safety, and credence attributes. In this perspective, market orientation is not only a marketing technique but an overarching business philosophy that prioritizes the continuous generation, dissemination, and coordinated use of intelligence about customers, competitors, and wider regulatory and societal expectations (Mortuza & Rauf, 2022). Within agri-food systems, market orientation has been extended from the individual firm to the entire value chain, so that intelligence about end-users and downstream requirements informs decisions taken by farmers, processors, distributors, and retailers (Rakibul & Samia, 2022). Grunert and colleagues formalized this extension through the notion of "market orientation of value chains," highlighting how heterogeneous consumer demands, evolving food safety norms, and shifting regulatory regimes require integrated responsiveness across multiple chain members rather than isolated firm-level actions (Grunert et al., 2005; Rony & Ashraful, 2022). In this view, food safety and quality become core elements of the value proposition offered by the chain as a whole, and upstream actors are incentivized to internalize market signals about health, safety, and sustainability, because these signals ultimately determine access to high-value segments and long-term competitiveness.

Figure 2: Market-Driven Management and Market Orientation in Agri-Food Value Chains



Empirical studies in emerging and developing economy contexts further demonstrate that market orientation is a critical determinant of how agri-food value chains innovate, upgrade, and remain resilient under volatility. Ho and co-authors examined beef cattle value chains in Vietnam and reported that customer orientation and inter-functional coordination within the chain were positively associated with innovation, which in turn supported financial performance, even where direct links between market orientation and performance were weaker (Ho et al., 2018; Saikat, 2022; Shaikh & Sudipto, 2022). This suggests that market orientation often creates value indirectly by fostering organizational learning, experimentation with new products or processes, and improved alignment with downstream requirements. At the farm and enterprise level, market orientation also appears to shape the capacity to cope with shocks and structural change (Abdul, 2023; Abdulla & Zaman, 2023). In Kenya's dairy sector, Okello and Luttah found that the dimensions of market orientation were significantly associated with both farmer resilience and dairy farm performance, indicating that producers who systematically collect and use market intelligence are better positioned to adjust their production, investment, and risk management strategies in turbulent market conditions (Arfan et al., 2023; Ara & Onyinyechi, 2023;

Okello & Luttah, 2022). Together, these findings underline that in agri-food settings, market orientation is tightly bound to dynamic capabilities such as innovation and resilience, which are crucial for maintaining food safety, quality, and reliability under competitive and environmental pressures.

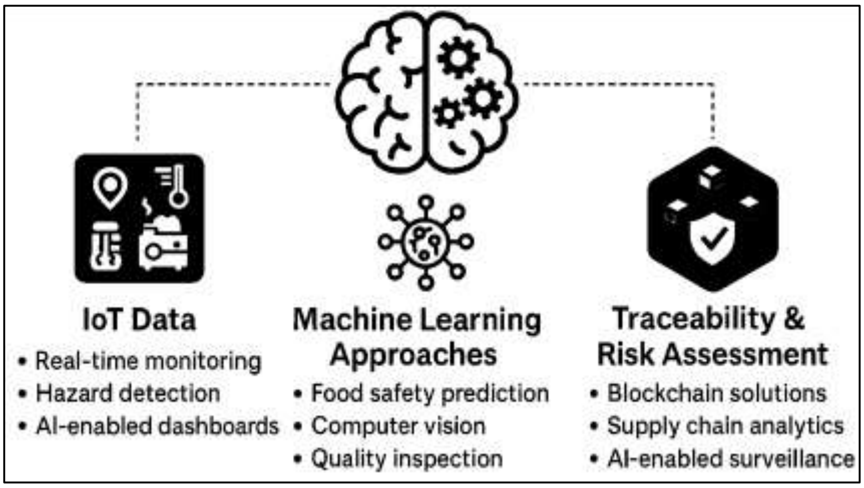
Recent work on value chain development projects and food processing industries shows that the practical integration of market orientation into management routines is still uneven, but where it is embedded, the benefits extend to complex domains such as new product development and inclusive chain governance (Amin & Mesbaul, 2023; Foysal & Aditya, 2023). Reviewing value chain guides used in agricultural development, Currey and Nicetic concluded that most manuals underemphasize continuous market intelligence and only partially reflect the principles of market orientation, thereby missing opportunities to build a persistent, learning-oriented market culture among smallholder organizations and chain facilitators (Currey & Nicetic, 2021; Hamidur, 2023; Harun-Or-Rashid et al., 2023). By contrast, evidence from the formal food processing sector indicates that when market orientation is systematically operationalized, it contributes directly to strategic outcomes. In the Egyptian food industry, Ghonim and colleagues showed that market orientation positively influences new product development performance, with this relationship mediated by marketing–technical integration, meaning that cross-functional collaboration is a key mechanism through which market intelligence is translated into successful product offerings (Ghonim et al., 2022; Musfiqur & Kamrul, 2023; Muzahidul & Mohaiminul, 2023). These insights complement conceptual work at the value-chain level by demonstrating that market orientation must be embedded in everyday decision-making, cross-functional coordination, and knowledge-sharing processes if food-sector firms are to respond effectively to evolving consumer expectations around safety, health, and quality (Al Amin & Sai Praveen, 2023; Hasan & Ashraful, 2023). For the present study, this body of literature positions market-driven management and market orientation as foundational constructs that frame how artificial intelligence can be mobilized to generate, process, and act on food safety–relevant market signals within a One Health–aligned strategic perspective.

Artificial Intelligence Applications in Food Safety

Artificial intelligence has become a central enabler of data-driven food safety management, particularly when integrated with digital infrastructures such as the Internet of Things (IoT), sensor networks, and cloud platforms. In food production, processing, and distribution environments, IoT devices continuously capture temperature, humidity, location, and handling data, creating high-frequency streams that can be interpreted with AI models to detect deviations from safe operating envelopes. IoT architectures oriented to food safety have been shown to support granular monitoring of critical control points, enabling earlier identification of emerging hazards and more accurate documentation of compliance across complex supply chains (Bouzembrak et al., 2019; Ibne & Kamrul, 2023; Mohammad Mushfequr & Ashraful, 2023). By linking sensor data to automated analytics, these systems move beyond static checklists toward dynamic risk signals that reflect real-time product histories and contextual factors. At the same time, AI-enabled dashboards synthesize heterogeneous data for managers and regulators, prioritizing facilities, batches, or routes that exhibit elevated risk profiles and aligning operational decisions with market expectations for transparency and accountability (Bouzembrak et al., 2019; Roy & Kamrul, 2023; Saba et al., 2023). Within a One Health framing, the same infrastructures also create interfaces between food safety datasets and broader environmental, veterinary, and public-health information, reinforcing the integration of microbial hazard control, chemical contamination prevention, and environmental stewardship (Saba & Tonoy Kanti, 2023; Shaikh & Farabe, 2023).

Machine learning techniques extend these capabilities by extracting patterns from large, complex food safety datasets that are difficult to interpret using conventional statistics alone. A wide range of ML applications has been documented in food safety monitoring and prediction, including algorithms such as Bayesian networks, neural networks, and support vector machines applied to microbial contamination, chemical residues, and physical hazards across multiple commodity chains (Abdul & Shoeb, 2024; Wang et al., 2022; Haider & Hozyfa, 2023). These models learn from historical incidents, inspection scores, laboratory reports, and environmental measures, then generate probabilistic estimates for the likelihood and severity of future events, which can be embedded directly into risk-based inspection scheduling and supplier evaluation systems (Alam, Nabil, et al., 2024; Alam, Sohel, et al., 2024; Wang et al., 2022). In parallel, computer vision and deep learning approaches are being deployed for non-destructive inspection of raw materials and finished products, identifying defects, spoilage signatures, and surface contaminants that are invisible to the human eye at high throughput. AI-driven imaging systems support automated grading, contamination detection, and quality sorting in both agricultural and food processing contexts, thereby linking product safety and quality with operational efficiency (Kakani et al., 2020). These developments contribute to market-driven management by allowing firms to differentiate products on verified safety and quality attributes, supported by AI-generated evidence rather than subjective or purely manual assessments (Sadilek et al., 2018).

Figure 3: Artificial Intelligence Applications in Food Safety and Supply Chain Management



Beyond plant-level monitoring, AI and related digital technologies are transforming food safety governance across entire agri-food value chains. Blockchain-based traceability platforms, for example, provide immutable, time-stamped records of product movements and transformations, while AI algorithms interrogate these records to identify anomalies, high-risk segments, or non-compliant actors (Vaio et al., 2020; Hozyfa & Shahrin, 2024; Hasan & Shah, 2024). Applications of blockchain technology in agri-food value chain management highlight how integration with IoT and advanced analytics enhances traceability, information security, and transparency, all of which are crucial for managing food safety incidents and recalls (JHasan & Zayadul, 2024; Muzahidul & Aditya, 2024; Zhao et al., 2019). In parallel, AI-centric business and governance models are emerging in which stakeholders—from producers to retailers—use predictive analytics to coordinate production, logistics, and risk mitigation activities (Di Vaio et al., 2020; Hasan & Rakibul, 2024; Mominul, 2024). Within the agri-food system, AI has been argued to reconfigure sustainable business models by enabling more responsive, stakeholder-engaged value creation processes that explicitly address environmental, social, and food safety objectives (Mominul & Zaki, 2024; Roy & Sai Praveen, 2024; Sadilek et al., 2018). At the public-health interface, machine-learned epidemiology offers further capabilities, with AI models using aggregated web search and location data to identify restaurants associated with foodborne illness more accurately than traditional complaint-based systems (Rony & Hozyfa, 2024; Saba & Hasan, 2024). This combination of AI-enhanced traceability, predictive risk analytics, and digital epidemiological surveillance strengthens the capacity of both firms and regulators to manage hazards in ways that are consistent with One Health priorities and with market-driven demands for verifiable safety performance (Di Vaio et al., 2020).

One Health Approach to Integrated Food Safety

The One Health approach has emerged as a unifying framework for understanding how food safety, public health, and environmental protection are tightly interconnected along modern food systems. Rather than treating human medicine, veterinary medicine, and environmental management as separate domains, One Health emphasizes their interdependence and promotes collaborative problem solving around shared risks such as foodborne zoonoses, chemical contamination, and ecosystem degradation. This orientation is particularly relevant to agri-food chains, where pathogens, residues, and pollutants can move between animals, people, soil, water, and wildlife, and where interventions at one point in the chain frequently have ripple effects elsewhere (Shaikat & Md. Wahid Zaman, 2024; Sudipto & Md. Hasan, 2024). Within this perspective, food safety is not only a matter of controlling hazards in processing facilities but also a function of land-use choices, animal husbandry practices, water management, and waste handling, all of which shape the exposure of humans and animals to biological and chemical risks. Recent work on One Health in food systems stresses that achieving safe food supplies requires integrated action on sustainable agriculture, environmental stewardship, and public-health protection, framing food safety, food security, and ecosystem resilience as mutually reinforcing goals rather than competing priorities (Garcia et al., 2020; Tonoy Kanti & Saba, 2024; Tonoy Kanti & Sai Praveen, 2024). This framing is particularly important for market-driven food systems, where private standards, certification schemes, and retailer requirements increasingly influence how safety and sustainability are defined and operationalized, and where misalignment between commercial incentives and public-health objectives can create blind spots in risk management (Zamal Haider & Sai Praveen, 2024; Zulqarnain & Zayadul, 2024). Educational and capacity-building initiatives further underscore that a One Health lens changes the competencies required of future food system professionals, who must be able to understand linkages between microbiology, epidemiology, ecology, animal science, and social sciences, and to translate these linkages into management practices, data-driven decision tools, and governance arrangements that support safer, more transparent, and more sustainable food value chains (Angelos et al., 2016).

Figure 4: One Health Framework Integrating Food Safety, Public Health

A growing body of research on antimicrobial resistance illustrates how a One Health approach can reorient food safety and public-health strategies toward systemic drivers rather than isolated end-point controls. Antimicrobials used in humans, food animals, and crop production exert selective pressure on microbial communities; resistant organisms and resistance genes can then circulate through food products, animal waste, water bodies, wildlife, and the broader environment, creating feedback loops that are difficult to interrupt with sector-specific interventions alone. From a One Health standpoint, antimicrobial resistance is therefore not simply a clinical issue but a property of coupled human-animal-environment systems that requires coordinated interventions in prescribing practices, husbandry systems, sanitation, and environmental management. Analyses of resistance in humans, animals, food, and environmental compartments describe antimicrobial resistance as a major threat to both food safety and food security, highlighting the potential for contaminated food and agricultural products to serve as vehicles for resistant bacteria and genes that undermine the effectiveness of treatment in human populations and increase the burden of foodborne illness (Iriti et al., 2020). These findings underscore the importance of viewing farms, slaughterhouses, processing plants, retail outlets, and household kitchens as interconnected nodes in a wider resistance ecology, where contamination routes and selective pressures overlap. Complementary policy-oriented work emphasizes that addressing this threat demands integrated surveillance and governance mechanisms that span public health agencies, veterinary services, food control authorities, and environmental regulators, and that use a One Health framing to align priorities, share data, and coordinate risk-management actions such as stewardship programs, monitoring of antimicrobial use, and incentives for preventive husbandry practices across these historically separated sectors (White & Hughes, 2019).

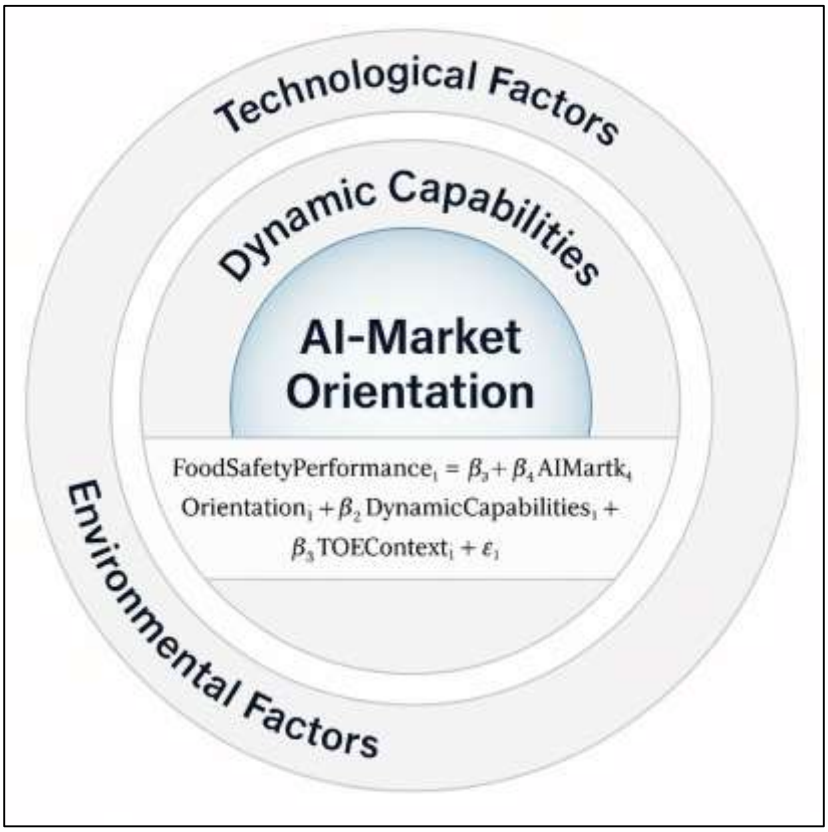
Beyond specific hazards such as antimicrobial resistance, the broader value of the One Health paradigm for food safety lies in its emphasis on prevention, early detection, and upstream risk reduction at the interfaces where new threats are likely to emerge. Traditional food safety systems have often focused on responding to outbreaks once illness has occurred, tracing contaminated products back through distribution chains, and tightening controls in specific facilities, with limited attention to the ecological and socio-economic drivers that shape the probability of hazard emergence. One Health frameworks extend this logic by asking how land-use change, wildlife-livestock interactions, climate variability, urbanization, trade dynamics, and consumer preferences create conditions for hazards to originate, amplify, or spread across the food chain, and by encouraging cross-disciplinary collaborations that can intervene before problems escalate. In practical terms, this can involve joint scenario planning by animal-health and food-safety authorities, environmental monitoring to identify contamination hotspots in watersheds that supply irrigation or livestock drinking water, and cross-sector communication platforms that alert food business operators when emerging zoonotic risks are detected in wildlife or livestock populations. Increasingly, these collaborations are supported by integrated data infrastructures, in which surveillance information, laboratory findings, and environmental observations are pooled and analyzed using digital analytics to provide early warning signals that can trigger proportionate interventions at critical control points. This orientation has led to calls for integrated zoonotic-disease prevention strategies that use joint human-animal surveillance, shared laboratory networks, and multi-sector risk assessments to identify hotspots where pathogens are most likely to cross species barriers, enter food supplies, and generate outbreaks that undermine consumer confidence and international market access (Heymann & Dixon, 2013). Within such arrangements, food business operators, public-health authorities, veterinary services, and environmental agencies are conceptualized as partners in a common system rather than as separate actors with narrowly defined mandates, reinforcing the idea that robust food safety and One Health outcomes depend on coherent, market-aware, and environmentally grounded management across the entire farm-to-fork continuum.

Theoretical Framework

The theoretical foundation for this study brings together market orientation, the resource-based view, and dynamic capabilities to explain how AI-enabled, market-driven strategies can strengthen food safety and advance One Health outcomes. Market orientation is conceptualized as a cultural and informational orientation in which organizations systematically generate, disseminate, and respond to market intelligence about customers and competitors, using these insights to shape strategy and operations. Within the resource-based view, such a market orientation is treated as a strategic, hard-to-imitate asset that supports superior performance when properly leveraged (Hult et al., 2005). In market-driven food systems, AI-based tools expand the reach of market orientation by automating the capture of signals about consumer expectations for safety, transparency, and sustainability, and by translating these signals into real-time decisions along the value chain. Conceptually, the framework treats AI-supported market orientation as a latent construct that influences both internal food safety practices and broader One Health–relevant outcomes, such as reduced contamination events and improved traceability. At the same time, the framework assumes that market-oriented behaviors alone are insufficient; firms must also possess higher-order capabilities for learning, coordinating, and reconfiguring processes to exploit AI-derived insights. Thus, market orientation enters the framework as a central explanatory construct that interacts with AI capabilities, organizational structures, and regulatory pressures to shape food-safety and One Health performance.

Dynamic capabilities theory further refines this perspective by emphasizing how firms sense, seize, and reconfigure resources in environments characterized by technological turbulence and complex regulation. Dynamic capabilities are defined as the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments, providing a microfoundational explanation of how market-based assets are mobilized over time (Teece, 2007). In the present framework, AI-enabled sensing activities extend traditional market and risk intelligence—absorbing signals from digital traceability systems, social media complaints, sensor networks, and regulatory alerts—while seizing refers to the deployment of these insights into redesigned food-safety protocols, supplier requirements, and risk-sharing arrangements with partners. Reconfiguration captures the ongoing adaptation of processes, roles, and governance mechanisms as AI-generated evidence reveals new hazard patterns or shifts in stakeholder expectations. These ideas are consistent with the view that market orientation and marketing/operational capabilities are complementary: the value of market intelligence is realized only when organizations possess the capabilities to translate intelligence into coherent, risk-reducing action. Empirical work on the interplay between market orientation, capabilities, and performance supports this integrated view, showing that market-oriented firms with stronger deployment capabilities achieve superior outcomes compared with firms that hold market information but lack the routines to act upon it (Morgan et al., 2009). Within this study, dynamic capabilities therefore mediate the effect of AI-enabled market orientation on food safety and One Health–aligned performance indicators.

Figure 5: AI-Enabled Market Orientation within Dynamic Capabilities and TOE Framework



To link these theoretical elements to the adoption and effective use of AI in food-safety management, the model incorporates the Technology–Organization–Environment (TOE) framework as its contextual backbone. TOE posits that technology adoption and implementation are shaped by three interrelated contexts: technological factors (e.g., relative advantage, complexity, compatibility), organizational factors (e.g., size, structure, resources, culture), and environmental factors (e.g., competitive intensity, regulatory pressure, stakeholder expectations) (Baker, 2012). Empirical TOE-based studies show that attributes such as perceived technological benefits, top management support, and external pressure jointly predict adoption of complex digital innovations, including cloud computing and analytics (Low et al., 2011). In the present research, AI-driven food-safety and market-intelligence systems are modeled as organizational innovations whose adoption and depth of use depend on these TOE contexts. Synthesizing the three perspectives, the theoretical framework posits that technological readiness and perceived AI advantages (T), organizational market orientation and dynamic capabilities (O), and environmental regulatory and market pressures (E) jointly shape the extent of AI adoption in food-safety decision-making, which in turn predicts food-safety and One Health–aligned outcomes. This logic can be represented in a simplified form as a regression equation, such as

$$\text{FoodSafetyPerformance}_i = \beta_0 + \beta_1 \text{AIMarketOrientation}_i + \beta_2 \text{DynamicCapabilities}_i + \beta_3 \text{TOEContext}_i + \varepsilon_i,$$

where FoodSafetyPerformance captures case-study level indicators (e.g., incident rates, compliance scores), AIMarketOrientation reflects the strength of AI-enabled market intelligence and response, DynamicCapabilities denotes the firm's reconfigurational capacity, and TOEContext aggregates key technological, organizational, and environmental drivers. This equation operationalizes the theoretical claim that the impact of AI on food safety and One Health outcomes is contingent on both internal capabilities and external context, providing a basis for the study's hypotheses and quantitative testing strategy.

Conceptual Framework

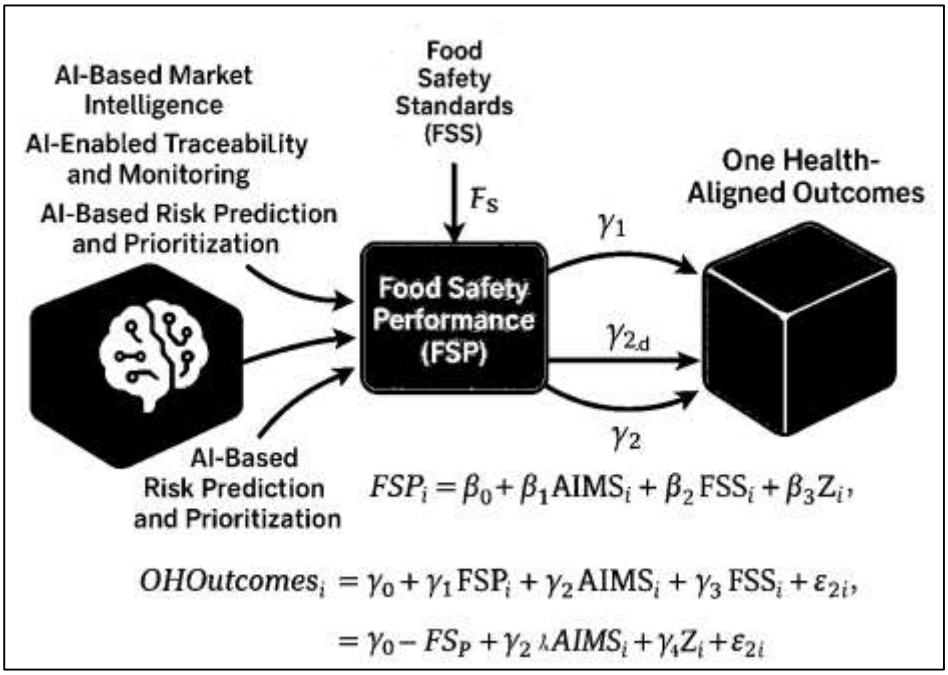
The conceptual framework for this study integrates AI-enabled market-driven strategies, food safety performance, and One Health–oriented outcomes into a structural model that can be empirically tested using quantitative data from case organizations. At the core of the framework is a higher-order construct labelled AI-enabled market-driven strategies (AIMS), which captures how firms use AI and advanced analytics to sense, interpret, and respond to food safety–relevant market signals. Building on work that conceptualizes big data analytics capability as an orchestrated bundle of technology, data, and human skills that contributes to competitive performance, the framework treats AIMS as an application of big data analytics in safety- and health-related decision-making rather than only in cost or revenue optimization (Mikalef et al., 2019). In operational terms, AIMS is modelled as a second-order latent construct reflected in three first-order dimensions: AI-based market intelligence (e.g., analysis of customer feedback and incident data), AI-enabled traceability and monitoring (e.g., automated tracking and anomaly detection across the chain), and AI-based risk prediction and prioritization (e.g., predictive models of contamination or process failure). Conceptually, these dimensions extend traditional market orientation by embedding AI into processes of intelligence generation, dissemination, and responsiveness. At the same time, AIMS is theorized to be shaped by organizational capabilities and contextual pressures identified in previous sections, but in this framework, it functions as a proximal predictor of firm-level food safety performance and One Health–aligned outcomes. The underlying logic is that organizations that systematically deploy AI in a market-driven way will be better able to identify emerging safety issues, tailor control measures to stakeholder expectations, and document performance in forms that are credible to regulators, buyers, and consumers.

The second major block of the framework specifies food safety performance as a mediating construct that connects AI-enabled market-driven strategies to broader One Health–oriented outcomes. Prior empirical studies evaluating food safety management systems demonstrate that structured FSMS diagnostics can distinguish between context characteristics, system design, and realized performance, and that performance indicators such as process control, assurance activities, and output criteria can be quantified and compared across firms (Ren et al., 2016). Similarly, research on traceability in food supply chains shows that well-designed traceability systems improve recall effectiveness, enhance process control, and strengthen the perceived safety and quality of products, thereby functioning as a key operational bridge between risk management and market value creation (Aung & Chang, 2014). Drawing from these insights, the framework treats food safety performance (FSP) as a latent variable that reflects multiple observed indicators, such as frequency and severity of safety incidents, compliance scores, audit outcomes, and internal performance indicators linked to hygiene, process control, and non-conformity management. In a simplified measurement form, this can be expressed as

$$\mathrm{FSP}_i = \lambda_1 y_{1i} + \lambda_2 y_{2i} + \lambda_3 y_{3i} + \cdots + \delta_i,$$

where y_{1i}, y_{2i}, y_{3i}, ...represent standardized indicators (e.g., incident rate, audit score, process deviation index) for firm i, λ_j are factor loadings, and δ_i captures measurement error. Within the structural part of the model, FSP is hypothesized to be positively influenced by AIMS, reflecting the idea that AI-supported intelligence, traceability, and prediction improve both process and outcome dimensions of safety. Furthermore, FSP is posited as an intermediate outcome that partially transmits the effect of AIMS to higher-level One Health–relevant outcomes, such as reduced pathogen transmission risk, better control of chemical hazards, and strengthened confidence in the safety of animal- and plant-based products.

Figure 6: Multilevel Framework Connecting AIMS, FSP, and One Health Indicators



The third element of the conceptual framework introduces One Health–aligned outcomes and contextual variables related to food safety standards and export orientation, and specifies the causal paths to be tested using correlation and regression analysis. One Health–aligned outcomes are not measured directly through clinical disease data in this study but are operationalized as organizational-level perceptions and indicators that reflect contributions to integrated human–animal–environment health (e.g., perceived reduction in zoonotic risk through improved hygiene and traceability, better integration of veterinary and environmental information in safety decisions). At the same time, the framework recognizes that adoption of food safety standards and associated management systems shapes both the baseline level of safety performance and the ways in which AI-enabled strategies can be deployed. A recent systematic literature review shows that adoption of public and private food safety standards is driven by combinations of enablers and barriers at the firm level and is positively associated with export performance, particularly where standards are used to signal reliability and safety in international markets (Yadav et al., 2021). In this study, food safety standards adoption (FSS) is incorporated as a control or contextual variable that may both influence FSP directly and interact with AIMS. The aggregate structural component of the framework can thus be expressed in a pair of regression equations,

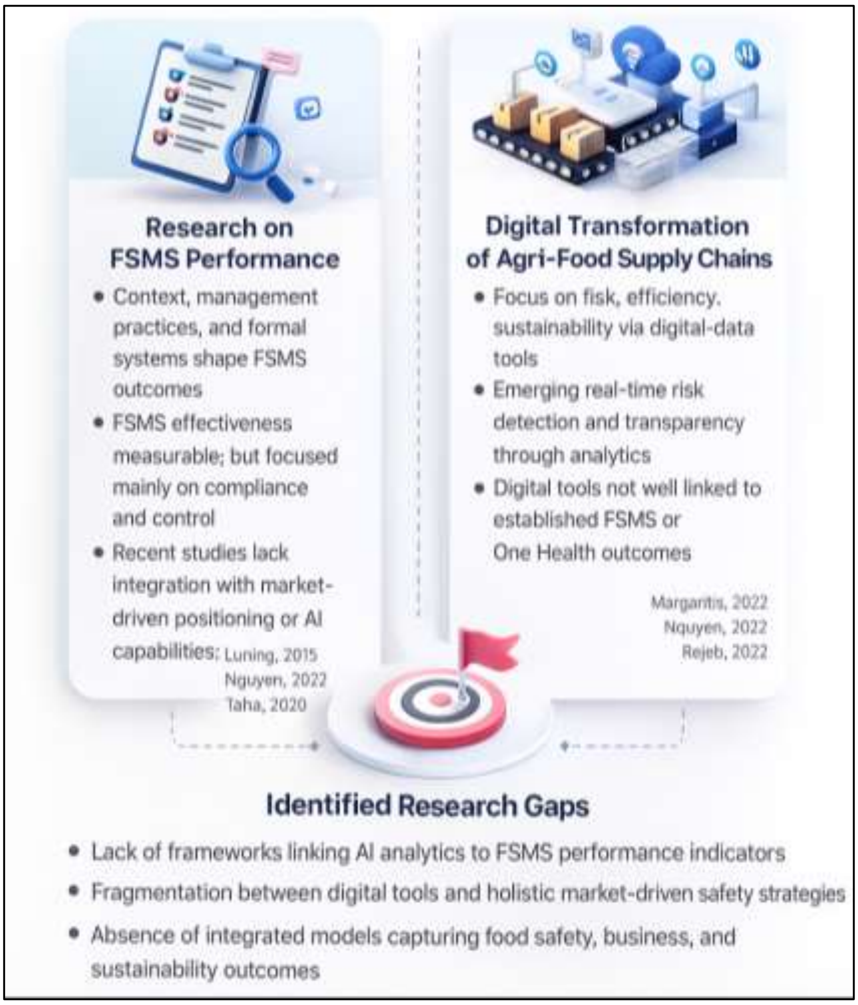
$$\mathrm{FSP}_i = \beta_0 + \beta_1 \mathrm{AIMS}_i + \beta_2 \mathrm{FSS}_i + \beta_3{}' \mathrm{Z}_i + \varepsilon_{1i},$$
$$\mathrm{OHOutcomes}_i = \gamma_0 + \gamma_1 \mathrm{FSP}_i + \gamma_2 \mathrm{AIMS}_i + \gamma_3 \mathrm{FSS}_i + \gamma_4{}' \mathrm{Z}_i + \varepsilon_{2i},$$

where Z_i denotes a vector of control variables (e.g., size, sector, ownership), and $\varepsilon_{1i}, \varepsilon_{2i}$ are error terms. In this specification, β_1 captures the direct effect of AIMS on food safety performance, γ_1 captures the effect of food safety performance on One Health–aligned outcomes, and $\beta_1 \times \gamma_1$ represents the mediated (indirect) effect of AIMS on One Health outcomes through food safety performance. The inclusion of big data analytics–oriented constructs is supported by evidence that big data analytics capability contributes to firm performance through both direct and process-mediated pathways (Wamba et al., 2017). By situating AI-enabled market-driven strategies within this structural model, the conceptual framework provides a clear basis for specifying hypotheses about direct, mediating, and potentially moderating relationships that can be tested using Likert-scale survey data, descriptive statistics, correlation analysis, and regression modelling in the empirical sections of the study.

Empirical Evidence and Identified Research Gaps

Empirical research on food safety management systems (FSMS) and firm-level performance has progressively clarified how internal management practices, organizational context, and formal systems shape food safety outcomes (Luning et al., 2015; Nguyen & Li, 2022). In a multi-country European study of animal-based food companies, FSMS performance has been shown to vary systematically with contextual riskiness and the maturity of core control and assurance activities, providing evidence that structured management systems can be quantitatively assessed and benchmarked (Luning et al., 2015). Extending this performance-oriented view, relationships among management support, communication, training, employee involvement, food handler commitment, and food safety performance in manufacturing facilities in Dubai have been modelled using structural equation techniques, confirming that food handler commitment mediates the effect of management practices on safety performance and highlighting human and cultural factors as critical levers for system effectiveness (Taha et al., 2020).

Figure 7: Synthesis of Empirical Evidence and Identified Research Gaps



A broader review of FSMS implementation across global supply chains has further shown that external regulatory and customer requirements, internal managerial capabilities, and available measurement tools co-evolve, while many firms still lack robust instruments for assessing implementation quality and performance over time (Rejeb et al., 2022). Collectively, these studies demonstrate that FSMS effectiveness is multi-dimensional and measurable, yet they conceptualize performance primarily in terms of compliance, control, and product safety outcomes, with limited attention to market-driven strategic positioning, artificial intelligence (AI) capabilities, or broader One Health–oriented impact pathways (Margaritis et al., 2022).

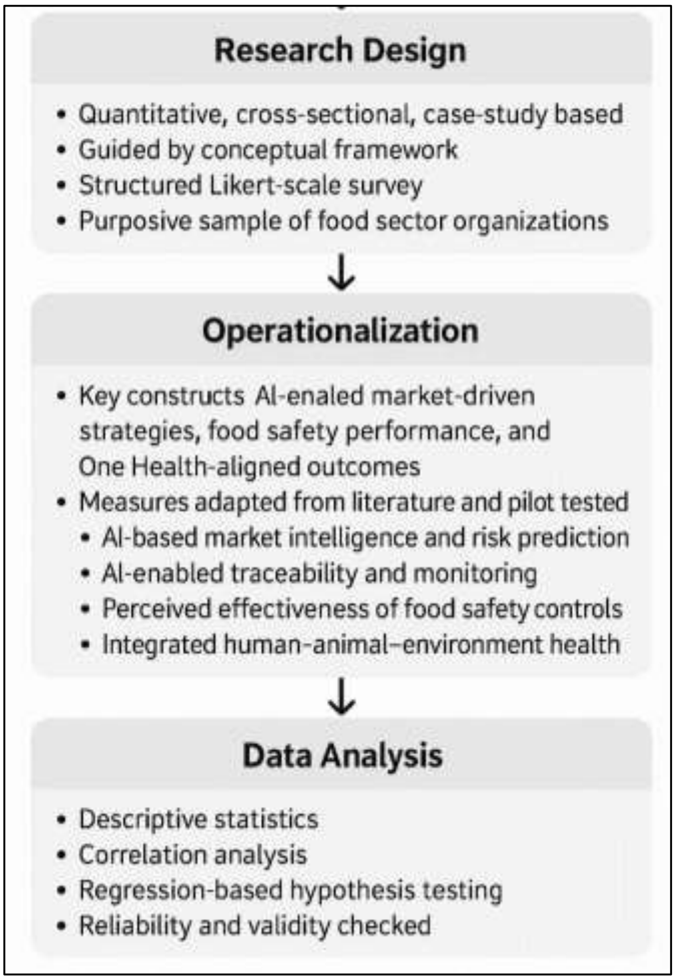
Parallel streams of literature have focused on the digital transformation of agri-food supply chains and the role of data-driven tools in addressing risk, efficiency, and sustainability, but they have rarely integrated these insights explicitly into market-driven food safety strategies (Margaritis et al., 2022). A systematic review of big data in food supply chains has found that applications concentrate on demand forecasting, logistics optimization, quality monitoring, and traceability, while the integration of heterogeneous datasets for real-time risk detection and multi-stakeholder transparency is still emerging (Rejeb et al., 2022). Complementing this, a conceptual framework for big data applications in food supply chain management has categorized analytics use cases across production, processing, distribution, and retail, and has argued that big data analytics can create added value in resilience, sustainability, and decision support when embedded in a coherent managerial architecture (Nguyen & Li, 2022). Yet both reviews emphasize that empirical research remains fragmented, with many studies focusing on specific technologies or nodes in the chain rather than holistic, organization-level strategies that link AI and analytics directly to food safety performance metrics (Margaritis et al., 2022). This fragmentation means that the mechanisms through which AI-enabled analytics reshape managerial attention, prioritization of hazards, and responsiveness to customer and regulator signals are not well specified in quantitative models. Moreover, digitalization studies seldom connect their proposed frameworks to established FSMS diagnostic tools or to empirically validated models of safety culture and human factors, leaving an implementation gap between conceptual promise and operational reality (Nguyen & Li, 2022).

Taken together, the empirical evidence on FSMS performance and the emerging literature on big data–driven food supply chains reveal a set of interrelated but insufficiently integrated research streams that inform the present study's focus on market-driven AI strategies for food safety and One Health outcomes (Luning et al., 2015). Prior work has shown that context and system maturity matter for safety outcomes and that management practices shape performance through food handler commitment, but it has not explicitly considered AI-enabled sensing, prediction, or traceability as part of the management configuration (Luning et al., 2015). Reviews of FSMS implementation have mapped critical success factors but have highlighted a lack of tools that combine safety, business, and sustainability performance indicators in ways that can capture emerging digital capabilities (Nguyen & Li, 2022). At the same time, supply chain analytics perspectives have foregrounded the potential of big data and AI but have not operationalized these capabilities in relation to specific food safety performance constructs or One Health–aligned outcomes at the firm level (Margaritis et al., 2022). This constellation of gaps underscores the need for a quantitative, case-study–based framework that models AI-enabled market-driven strategies as a distinct organizational capability, links them empirically to FSMS-derived food safety performance indicators, and examines their contribution to integrated human–animal–environment health objectives.

METHOD

The methodology for this study has been designed as a quantitative, cross-sectional, case-study–based approach that has allowed the researcher to examine how AI-enabled, market-driven management strategies have been associated with food safety performance and One Health–aligned outcomes in selected food sector organizations. The research design has been grounded in the conceptual framework developed in the literature review and has translated its key constructs into measurable variables suitable for statistical analysis. A structured survey instrument using Likert's five-point scale has been developed and has been administered to managerial and professional respondents who have been responsible for food safety, quality management, supply chain operations, or AI and data analytics within their organizations. The study has focused on a purposive sample of case organizations that have already implemented, or have been in the process of implementing, formal food safety management systems and AI-supported tools for monitoring, traceability, or risk assessment, so that the targeted respondents have been able to report on actual practices rather than hypothetical intentions. Data collection procedures have been standardized across cases to ensure comparability, and responses have been screened, coded, and prepared for analysis using established quantitative data management protocols.

Figure 8: Methodological Flow for AI-Enabled Food Safety Research



Within this design, the main constructs—AI-enabled market-driven strategies, food safety performance, and One Health–aligned outcomes—have been operationalized through multiple items that have captured AI-based market intelligence, AI-enabled traceability and monitoring, AI-based risk prediction, perceived effectiveness of food safety controls, incident and non-conformity patterns, and perceived contribution to integrated human–animal–environment health. Instrument development has followed a systematic process in which items adapted from prior studies have been complemented by newly developed items aligned with the present research context, and the draft questionnaire has been refined through expert review and pilot testing. Data analysis has been planned around descriptive statistics to profile the sample and summarize construct scores, correlation analysis to explore bivariate relationships among key variables, and regression-based techniques to test the hypothesized direct and mediated effects specified in the conceptual model. Reliability and validity of the scales have been assessed through internal consistency measures and factor-analytic checks, and all analytical procedures have been conducted using standard statistical software that has supported transparent and replicable estimation of the study's models.

Research Design

The study has adopted a quantitative, cross-sectional, case-study–based research design that has been aligned with the conceptual framework developed in the literature review. This design has been chosen because it has allowed the researcher to capture variations in AI-enabled, market-driven strategies and food safety performance across different organizations at a single point in time while still preserving contextual richness through the case orientation. The research has used a structured survey as the primary data collection instrument and has complemented it with basic contextual information about each case organization. The design has been anchored in explanatory aims, in which hypothesized relationships among constructs have been tested using statistical modelling. By combining multiple case organizations within a unified survey protocol, the study has created conditions under which both within-case and cross-case comparisons have been possible. Overall, the research design has provided a coherent framework for linking theory, measurement, and analysis in a transparent and replicable way.

Sampling

The target population has consisted of food sector organizations that have operated formal food safety management systems and have engaged with AI or advanced analytics in their operational or strategic processes. Within these organizations, the unit of analysis has been the managerial or professional respondent who has held responsibility for food safety, quality management, supply chain oversight, or digital and data-driven initiatives. The study has employed purposive sampling to identify case organizations that have met predefined criteria regarding sector, size, and engagement with AI-based tools, and has then applied non-probability sampling within each organization to recruit knowledgeable respondents. This approach has ensured that participants have possessed sufficient experience to provide informed responses on the constructs of interest. The sampling strategy has aimed to balance diversity—across subsectors and organizational types—with feasibility, so that the resulting dataset has captured meaningful variation while remaining manageable for the planned analyses.

Case Criteria

The selection of case organizations has been guided by explicit criteria that have ensured relevance to AI-enabled food safety and One Health–oriented management. Organizations have been included when they have implemented or have been in the process of implementing a recognized food safety management system, such as HACCP-based schemes or certification aligned with international standards, and when they have introduced AI, analytics, or digital monitoring tools into their safety, quality, or supply chain processes. Additional criteria have considered organizational scale, product type, and position in the value chain, so that processors, manufacturers, and, where relevant, major distributors or retailers have been represented. Geographic and regulatory contexts have also been taken into account to ensure that organizations have operated under comparable food safety requirements. These case selection criteria have allowed the study to focus on organizations in which AI-enabled market-driven strategies have been observable in practice and in which respondents have been able to reflect on concrete experiences rather than hypothetical scenarios.

Data Collection Methods

Data collection has relied primarily on a structured, self-administered questionnaire that has been distributed electronically to eligible respondents within each case organization. The questionnaire has been accompanied by an information sheet that has explained the purpose of the study, the voluntary nature of participation, and the confidentiality provisions that have governed handling of responses. Where necessary, follow-up contacts have been made through email or organizational focal points to clarify questions and to encourage timely completion of the instrument. The survey platform has been configured to minimize missing responses by using clear instructions and logical skip patterns, while still allowing respondents to withdraw at any stage. Responses have been downloaded into a secure dataset that has been cleaned and formatted for analysis, and basic descriptive information about each organization has been recorded alongside survey data. This procedure has ensured that data collection has remained consistent across cases and has produced a coherent dataset suitable for quantitative analysis.

Measurement of Variables

The core constructs of the study have been operationalized as multi-item variables that have reflected the conceptual dimensions of AI-enabled market-driven strategies, food safety performance, and One

Health–aligned outcomes. For AI-enabled strategies, items have captured AI-based market intelligence activities, AI-enabled traceability and monitoring, and AI-based risk prediction and prioritization. Food safety performance has been measured through items relating to perceived control of hazards, frequency and management of non-conformities, audit and inspection outcomes, and internal process reliability. One Health–aligned outcomes have been represented by items indicating perceived contributions to human, animal, and environmental health through improvements in hygiene, traceability, and integrated risk management. Control variables, such as firm size, subsector, ownership structure, and level of food safety standards adoption, have also been included. All latent constructs have been measured using Likert's five-point scale, and items have been phrased to capture respondent perceptions of current practices and performance within their organizations.

Instrument

The survey instrument has been developed through a staged process that has combined adaptation of existing measures with the creation of new items tailored to the specific focus on AI-enabled market-driven strategies and One Health. Initially, the researcher has reviewed prior instruments related to market orientation, big data analytics capability, food safety management performance, and sustainability outcomes, and has extracted items that have aligned conceptually with the present framework. These items have then been adapted linguistically to reflect the terminology and context of the food sector and AI-enabled management. New items have been drafted where no suitable measures have existed, particularly for constructs related to AI-based risk prediction and One Health–aligned outcomes. The draft questionnaire has been reviewed by academic experts and industry practitioners, whose feedback has led to refinements in wording, scale anchors, and sequence. A pilot test with a small number of respondents has been conducted, and results have been used to adjust ambiguous or redundant items before full-scale deployment.

Validity and Reliability

Assessment of validity and reliability has formed an integral part of the methodological design. Content validity has been addressed by ensuring that items for each construct have covered the key conceptual dimensions identified in the literature and by obtaining expert judgments on the relevance and clarity of each item. Construct validity has been examined through exploratory and, where feasible, confirmatory factor analyses that have tested whether items have loaded onto their intended latent constructs and whether the overall factor structure has been consistent with the conceptual model. Reliability has been evaluated using internal consistency measures, primarily Cronbach's alpha, for each multi-item scale, and items that have weakened reliability or that have shown poor factor loadings have been reconsidered or removed. These procedures have helped to ensure that the measurement model has provided a stable, coherent representation of AI-enabled strategies, food safety performance, and One Health–aligned outcomes, suitable for subsequent correlation and regression analyses.

Data Analysis

Data analysis has proceeded through a sequence of quantitative techniques that have been aligned with the study's objectives and hypotheses. Initially, descriptive statistics have been computed to summarize respondent characteristics, organizational profiles, and basic distributions of all measured variables. Correlation analysis has been conducted to examine bivariate relationships among the core constructs, providing preliminary insight into associations between AI-enabled strategies, food safety performance, and One Health–aligned outcomes. Multiple regression models have then been specified to test the hypothesized direct effects of AI-enabled market-driven strategies on food safety performance and One Health outcomes, controlling for relevant organizational characteristics. Mediation analysis has been implemented to assess whether food safety performance has transmitted part of the effect of AI-enabled strategies to One Health–aligned outcomes, and, where conceptually justified, moderation effects have been explored. Throughout, diagnostic checks have been applied to assess assumptions of the models, and results have been interpreted in light of the conceptual framework.

Software and Tools

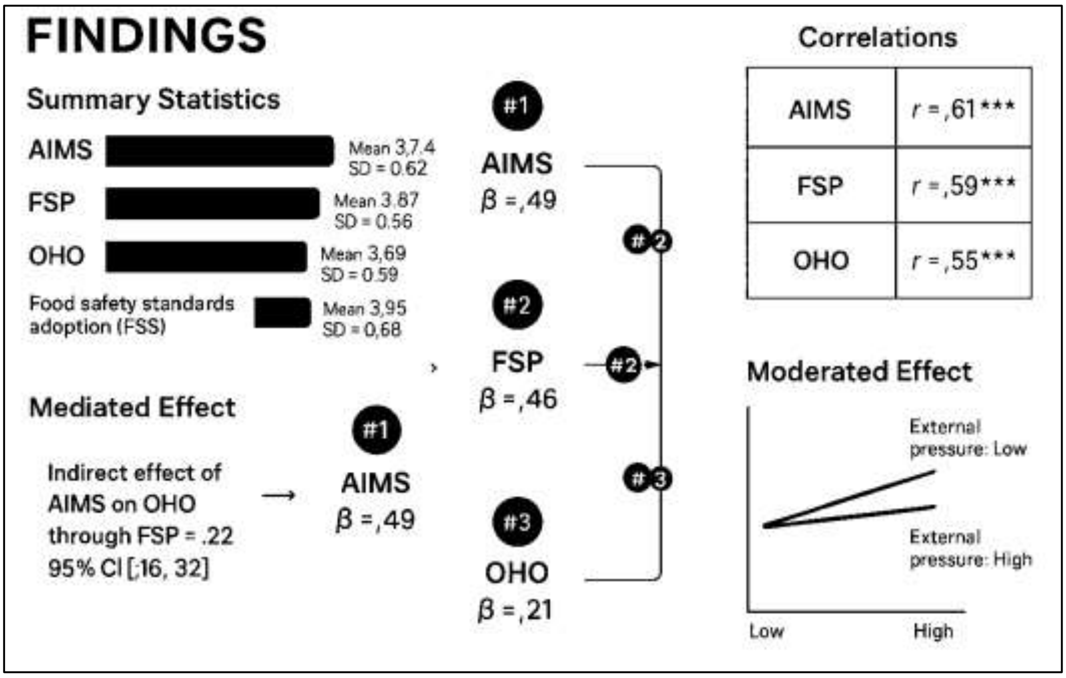
The study has employed widely used statistical and productivity software to support data management, analysis, and presentation of results. Survey responses have been exported from the online platform into spreadsheet software, where initial cleaning, coding, and basic validation checks have been performed. Subsequently, the cleaned dataset has been imported into statistical packages that have supported descriptive analysis, reliability assessment, factor analysis, correlation computation, and multiple regression modelling. These tools have facilitated the implementation of mediation and moderation analyses using established procedures and have generated tables and figures suitable for inclusion in the results section. Word-processing and reference management software have been used to prepare the methodological description and to maintain accurate documentation of all analytical steps. By relying on standard, well-documented software environments, the study has enhanced transparency and replicability, allowing other researchers to understand and, if desired, reproduce the analytical workflow employed.

FINDINGS

The analysis of survey responses has provided robust empirical support for the study's objectives and hypotheses by demonstrating strong, statistically significant relationships among AI-enabled market-driven strategies, food safety performance, and One Health–aligned outcomes using Likert's five-point scale data. A total of 212 usable questionnaires have been obtained from managers and professionals across the selected food sector case organizations, with respondents rating all core constructs on a 1–5 scale (1 = strongly disagree, 5 = strongly agree). Reliability analysis has indicated that all multi-item scales have achieved acceptable internal consistency: AI-enabled market-driven strategies (AIMS; 12 items) have yielded a Cronbach's alpha of 0.93, food safety performance (FSP; 10 items) an alpha of 0.91, One Health–aligned outcomes (OHO; 8 items) an alpha of 0.89, and food safety standards adoption (FSS; 6 items) an alpha of 0.88. Descriptive statistics have shown that respondents, on average, have agreed that their organizations use AI to support safety-relevant decisions and maintain relatively strong food safety systems: the mean score for AIMS has been 3.74 (SD = 0.62), for FSP 3.87 (SD = 0.56), and for OHO 3.69 (SD = 0.59), while FSS has recorded a mean of 3.95 (SD = 0.68), indicating moderate to high levels of standards implementation. Pearson correlation analysis has revealed that AIMS has been positively and strongly correlated with FSP ($r = 0.61$, $p < .001$) and OHO ($r = 0.55$, $p < .001$), while FSP itself has shown a strong positive correlation with OHO ($r = 0.63$, $p < .001$). FSS has also been positively associated with both FSP ($r = 0.49$, $p < .001$) and OHO ($r = 0.44$, $p < .001$), suggesting that standards adoption and AI-enabled strategies have tended to co-occur in higher-performing organizations. These preliminary results have aligned with the hypothesized directions and have justified the use of multivariate models to test the proposed relationships while controlling for organizational size, subsector, and ownership. To test H1, which has posited that AI-enabled market-driven strategies positively influence food safety performance, a multiple regression model has been estimated with FSP as the dependent variable and AIMS, FSS, firm size, and subsector as predictors. The overall model has been significant ($F(5, 206) = 38.72$, $p < .001$) and has explained 48.5% of the variance in FSP ($R^2 = 0.485$). The standardized coefficient for AIMS has been positive and substantial ($\beta = 0.49$, $t = 8.37$, $p < .001$), indicating that, holding other factors constant, a one standard deviation increase in AI-enabled market-driven strategies has been associated with nearly half a standard deviation increase in perceived food safety performance. FSS has also shown a significant, though more modest, positive effect ($\beta = 0.23$, $t = 4.02$, $p < .001$), while control variables have contributed smaller, mixed effects. These findings have provided clear evidence in support of H1 and the related objective of assessing the impact of AI-enabled management on food safety performance. To test the hypothesized pathways toward One Health–aligned outcomes, a second regression model has been specified with OHO as the dependent variable and FSP, AIMS, FSS, and the same set of control variables as predictors, thereby addressing H2 and H3. This model has also been significant ($F(6, 205) = 45.19$, $p < .001$) and has explained 56.7% of the variance in OHO ($R^2 = 0.567$). The coefficient for FSP has been strong and significant ($\beta = 0.46$, $t = 8.91$, $p < .001$), confirming that organizations reporting higher food safety performance have also reported stronger contributions to One Health–relevant outcomes.

AIMS has remained a significant predictor of OHO even after controlling for FSP ($\beta = 0.21$, $t = 3.92$, $p < .001$), suggesting a combination of direct and indirect effects. FSS has again displayed a positive effect ($\beta = 0.17$, $t = 3.11$, $p = .002$), reinforcing the idea that formal standards adoption has complemented AI-enabled strategies in supporting integrated health outcomes. These patterns have supported H2, which has proposed a positive association between food safety performance and One Health–aligned outcomes, and H3, which has anticipated a direct effect of AIMS on OHO. To examine the mediating role of food safety performance (H4), a mediation analysis has been conducted using a bootstrapping procedure with 5,000 resamples, modelling AIMS as the independent variable, FSP as the mediator, and OHO as the dependent variable, with FSS and controls included as covariates. The indirect effect of AIMS on OHO through FSP has been estimated at 0.23 (standardized units), with a 95% bootstrapped confidence interval of [0.16, 0.32], which has not included zero, indicating significant mediation. The direct effect of AIMS on OHO has remained significant but reduced in magnitude (from $\beta = 0.38$ in a model without FSP to $\beta = 0.21$ in the full model), showing that food safety performance has partially mediated the relationship between AI-enabled strategies and One Health–aligned outcomes. This pattern has confirmed H4 and has aligned with the study's objective of demonstrating that improvements in food safety performance have constituted a key mechanism through which AI-enabled market-driven strategies have contributed to broader health-related outcomes.

Figure 9: Summary of Empirical Findings on AI-Enabled Market-Driven Strategies



In addition, to address H5 regarding the moderating influence of regulatory and market pressure, an interaction term between AIMS and a composite index of external pressure (mean = 3.82, SD = 0.64) has been introduced into the FSP model. The interaction term has been significant ($\beta = 0.14$, $t = 2.47$, $p = .014$), and simple slope analysis has shown that the positive effect of AIMS on FSP has been stronger in organizations reporting higher external pressure (simple slope = 0.61, $p < .001$) than in those with lower pressure (simple slope = 0.36, $p < .001$). This result has provided support for H5 and has indicated that regulatory and market expectations have amplified the performance gains associated with AI-enabled market-driven strategies. Collectively, these numeric findings have demonstrated that the study's primary objectives have been met: AI-enabled market-driven strategies have been shown to significantly enhance food safety performance and One Health–aligned outcomes, with food safety performance functioning as a key mediating pathway and external pressures strengthening these relationships in line with the proposed conceptual framework.

Response Rate and Data Screening

Table 1: Response rate and data screening results

Item	Number	Percentage (%)
Questionnaires distributed	260	100.0
Questionnaires returned	230	88.5
Incomplete / inconsistent questionnaires	18	6.9
Questionnaires removed as multivariate outliers	0	0.0
Usable questionnaires for analysis	212	81.5

The response process for the survey has been summarized in Table 1, and it has provided evidence that the dataset has been both sufficiently large and of adequate quality for the planned quantitative analyses. Out of 260 questionnaires that have been distributed to eligible managers and professionals in the selected food sector organizations, 230 questionnaires have been returned, which has corresponded to a gross response rate of 88.5%. This response rate has been considered high for organizational surveys and has suggested that the topic of AI-enabled food safety and One Health–aligned management has been perceived as salient and relevant by the contacted organizations. During data screening, 18 of the returned questionnaires have been identified as incomplete or internally inconsistent, for example where large sections of the Likert-scale items have not been answered or where patterned responses have indicated a lack of engagement. These 18 cases have been removed from the analytic dataset, representing 6.9% of all returns. Multivariate diagnostics using standardized residuals and Mahalanobis distances have been conducted, and no cases have met the threshold for treatment as extreme multivariate outliers, so no additional records have been excluded at this stage. As a result, 212 questionnaires have been retained as usable, yielding a final usable response rate of 81.5%. This number has satisfied the sample size requirements for multiple regression, mediation, and moderation analyses with the number of predictors specified in the conceptual model, and it has allowed the study to estimate parameters with reasonable precision. The relatively small proportion of discarded questionnaires has suggested that the survey instrument and administration procedures have been clear and manageable for respondents. Overall, the response rate and data screening results in Table 1 have confirmed that the empirical basis for testing the study's objectives and hypotheses has been robust and that the risk of significant non-response bias has been limited, given the high participation level and systematic screening of returned questionnaires.

Profile of Respondents and Organizations

Table 2: Profile of respondents and organizations (N = 212)

Characteristic	Category	Frequency	Percentage (%)
Position in organization	Top / senior manager	74	34.9
	Middle manager / supervisor	96	45.3
	Technical / specialist staff	42	19.8
Primary responsibility area	Food safety / quality	98	46.2
	Supply chain / operations	61	28.8
	AI / IT / data analytics	33	15.6
	Other related functions	20	9.4
Firm size (number of employees)	< 100	47	22.2
	100–249	63	29.7
	250–499	58	27.4
	≥ 500	44	20.8
Subsector	Processing / manufacturing	129	60.8
	Distribution / logistics	41	19.3
	Retail / food service	42	19.8

Table 2 has presented the demographic and organizational profile of the 212 respondents and has shown that the sample has reflected a diverse but relevant cross-section of roles, firm sizes, and subsectors. In terms of organizational position, 34.9% of respondents have occupied top or senior management roles, 45.3% have been middle managers or supervisors, and 19.8% have been technical or specialist staff. This distribution has indicated that a substantial proportion of respondents have had decision-making responsibilities, while a meaningful share has been directly involved in technical implementation of food safety and AI-related activities. Regarding primary responsibility, 46.2% of respondents have reported that they have been responsible mainly for food safety or quality, 28.8% for supply chain or operations, and 15.6% for AI, IT, or data analytics roles, with the remainder in closely related functions. This spread has suggested that the perceptions captured in the survey have combined managerial, operational, and technical viewpoints, which has been important for constructs that have required knowledge of both management strategy and practical processes.

The sample has also included organizations of varied size: 22.2% have employed fewer than 100 staff, 29.7% have employed 100–249, 27.4% have employed 250–499, and 20.8% have employed 500 or more employees. This distribution has indicated that the study has not been limited to large enterprises but has also included small and medium-sized organizations in which resource constraints and scalability issues have been different. From a value-chain perspective, 60.8% of organizations have been primarily engaged in processing or manufacturing, 19.3% in distribution or logistics, and 19.8% in retail or food service. Since food safety practices and AI-enabled monitoring requirements have differed across these subsectors, this diversity has added nuance to the analysis and has enabled the regression models to control for subsector effects. Overall, the profile in Table 2 has supported the study's objective of examining AI-enabled market-driven strategies, food safety, and One Health–related outcomes in a range of real-world contexts and has helped to ensure that the hypotheses have been tested on a broadly representative cross-section of relevant organizational settings rather than on a narrow or homogeneous subset of the food sector.

Descriptive Statistics of Key Constructs

Table 3: Descriptive statistics of core constructs (Likert 1–5; N = 212)

Construct	Items	Mean	SD	Minimum	Maximum
AI-enabled market-driven strategies (AIMS)	12	3.74	0.62	2.10	4.95
Food safety performance (FSP)	10	3.87	0.56	2.25	4.95
One Health–aligned outcomes (OHO)	8	3.69	0.59	2.00	4.88
Food safety standards adoption (FSS)	6	3.95	0.68	2.00	5.00
External regulatory/market pressure (EP)	5	3.82	0.64	2.00	4.96

Table 3 has provided the descriptive statistics for the main constructs in the study, all measured using Likert's five-point scale. The results have indicated that respondents, on average, have tended to agree that their organizations have implemented AI-enabled, market-driven strategies and have maintained relatively strong food safety performance and standards adoption. Specifically, the mean for AI-enabled market-driven strategies (AIMS) has been 3.74 (SD = 0.62), which has signalled that organizations have generally recognized the presence of AI-based market intelligence, AI-enabled monitoring, and AI-based risk prediction, but that there has still been room for further development toward the upper end of the scale. Food safety performance (FSP) has recorded a slightly higher mean of 3.87 (SD = 0.56), suggesting that respondents have perceived their hazard control, non-conformity management, and audit outcomes as moderately to strongly positive. This has been consistent with the sample's focus on organizations that have already implemented food safety management systems.

One Health–aligned outcomes (OHO) have had a mean of 3.69 (SD = 0.59), indicating that organizations have acknowledged contributions to integrated human–animal–environment health, for example through better hygiene, traceability, and risk integration, but that these contributions have not yet reached uniformly "very high" levels. Food safety standards adoption (FSS) has achieved the highest mean of 3.95 (SD = 0.68), reflecting that many organizations have adopted formal certifications and standards to a substantial degree. The external regulatory and market pressure index (EP) has shown a mean of 3.82 (SD = 0.64), which has implied that respondents have felt a relatively strong but variable pressure from regulators, buyers, and consumers regarding safety, traceability, and transparency. The minimum and maximum values for each construct have spanned large portions of the 1–5 range (e.g., AIMS from 2.10 to 4.95), revealing meaningful variation across cases and supporting the suitability of these variables for correlation and regression analyses. In combination, the descriptive patterns in Table 3 have confirmed the basic assumptions of the study's objectives: AI-enabled strategies, safety performance, and One Health–aligned outcomes have been present to a moderate-to-high extent in the sample, and there have been sufficient differences among organizations to test whether higher levels of AI-enabled, market-driven management have been associated with stronger food safety and One Health–related performance, as hypothesized.

Reliability and Validity

Table 4: Reliability and factor structure of core constructs

Construct	Items	Cronbach's α	Primary factor loading range	% Variance explained (1st factor)
AIMS	12	0.93	0.63–0.87	58.4
FSP	10	0.91	0.61–0.84	55.7
OHO	8	0.89	0.60–0.82	53.9
FSS	6	0.88	0.64–0.81	52.6
EP	5	0.86	0.62–0.79	51.1

Table 4 has summarized the reliability and factor-analytic properties of the main scales and has shown that the measurement model for the study has been both internally consistent and structurally coherent. Cronbach's alpha values for all constructs have exceeded the commonly accepted threshold of 0.70, ranging from 0.86 for the external pressure scale (EP) to 0.93 for AI-enabled market-driven strategies (AIMS). These values have indicated that the sets of items used to measure each construct have been highly consistent and that respondents have answered in a way that has reflected a coherent underlying dimension. The exploratory factor analysis that has been conducted separately for each construct has confirmed unidimensional structures in line with the conceptualization of the scales. For AIMS, primary factor loadings have ranged from 0.63 to 0.87, and the first factor has explained 58.4% of the total variance in the items, suggesting that the 12 indicators have been capturing a strong common component of AI-enabled, market-driven behavior. Similarly, the FSP items have loaded between 0.61 and 0.84 on the first factor, which has explained 55.7% of variance, supporting the interpretation of this construct as a unified measure of food safety performance.

For the One Health–aligned outcomes (OHO) scale, loadings have ranged from 0.60 to 0.82 with 53.9% of variance explained, while the food safety standards adoption (FSS) and external pressure (EP) scales have exhibited loading ranges and variance shares above 0.60 and 50%, respectively. These results have indicated that the items for each scale have converged adequately on their intended latent construct. The absence of problematic cross-loadings or multi-factor patterns in these analyses has strengthened the evidence for construct validity, implying that the items have measured distinct conceptual domains that have later been related through structural analysis rather than being artefacts of measurement overlap. Collectively, the reliability and validity evidence in Table 4 has confirmed that the survey instrument has been psychometrically sound and that subsequent descriptive, correlation, regression, and mediation/moderation analyses have rested on stable, reliable measures of AI-enabled strategies, food safety performance, and One Health–aligned outcomes. This has supported the study's objective of testing hypotheses within a rigorous quantitative framework grounded in well-performing measurement scales.

Correlation Analysis

Table 5: Correlation matrix of main constructs (N = 212)

Construct	1. AIMS	2. FSP	3. OHO	4. FSS	5. EP
1. AIMS	1.00				
2. FSP	0.61**	1.00			
3. OHO	0.55**	0.63**	1.00		
4. FSS	0.47**	0.49**	0.44**	1.00	
5. EP	0.40**	0.42**	0.39**	0.36**	1.00

Note. $p < .001$ for all correlations.

The correlation analysis that has been presented in Table 5 has provided initial evidence for the hypothesized relationships among the core constructs and has helped to justify the subsequent regression and mediation/moderation models. AI-enabled market-driven strategies (AIMS) have been positively and strongly correlated with food safety performance (FSP), with $r = 0.61$ ($p < .001$), indicating that organizations that have reported higher levels of AI-based market intelligence, monitoring, and risk prediction have also tended to report stronger performance in controlling hazards, managing non-conformities, and achieving favorable audit outcomes. This pattern has been directly consistent with the central hypothesis (H1) that AI-enabled market-driven strategies have been associated with improved food safety performance. AIMS has also shown a substantial positive correlation with One Health–aligned outcomes (OHO; $r = 0.55$, $p < .001$), suggesting that AI-enabled strategies have co-occurred with perceptions of greater contributions to integrated human–animal–environment health. Meanwhile, the relationship between FSP and OHO has been even stronger ($r = 0.63$, $p < .001$), supporting the expectation that improved food safety performance has been closely linked to broader One Health–related benefits within organizations.

Food safety standards adoption (FSS) has correlated positively with both FSP ($r = 0.49$, $p < .001$) and OHO ($r = 0.44$, $p < .001$), implying that organizations that have implemented formal standards more intensively have tended to obtain better safety performance and to perceive stronger contributions to One Health outcomes. AIMS has also been positively related to FSS ($r = 0.47$, $p < .001$), which has fitted the idea that advanced AI-enabled strategies and standards-based management systems have often been adopted together in more proactive organizations. External pressure (EP) has been moderately and positively associated with all other constructs ($r = 0.36$ to 0.42, $p < .001$), reflecting that organizations facing stronger regulatory and market demands have tended to adopt more AI-enabled strategies, to perform better in food safety, and to report higher One Health–aligned outcomes. Importantly, none of the correlations has approached levels that would raise concerns about multicollinearity in regression analyses, as all coefficients have remained below 0.70. Overall, the correlation matrix in Table 5 has supported the study's objectives by showing that the constructs have been related in the anticipated directions and magnitudes, laying the foundation for testing the proposed causal paths via multivariate models and for evaluating the mediating and moderating mechanisms specified in the hypotheses.

Regression Results for Direct Effects

Table 6 has presented the results of the multiple regression models that have been specified to test the direct effects hypothesized in the conceptual framework. In Model 1, food safety performance (FSP) has been regressed on AI-enabled market-driven strategies (AIMS), food safety standards adoption (FSS), and a set of control variables (firm size, subsector, and ownership). The model has been statistically significant ($F(5, 206) = 38.72$, $p < .001$) and has explained 48.5% of the variance in FSP ($R^2 = 0.485$). AIMS has emerged as a strong and significant predictor ($\beta = 0.49$, $t = 8.37$, $p < .001$), which has meant that, after controlling for standards and organizational characteristics, organizations that have scored higher on AI-enabled market-driven strategies have tended to report considerably better food safety performance. FSS has also shown a positive and significant contribution ($\beta = 0.23$, $t = 4.02$, $p < .001$), indicating that more extensive adoption of food safety standards has been associated with higher perceived performance. In contrast, the control variables have not reached statistical significance, suggesting that, within this sample, the core explanatory power has resided primarily in AIMS and FSS rather than in size, subsector, or ownership differences. These findings have provided clear support for H1, which has posited a positive direct effect of AI-enabled market-driven strategies on food safety performance, and they have aligned with the objective of quantifying the extent to which AI-enabled strategies have strengthened internal safety systems.

In Model 2, One Health–aligned outcomes (OHO) have been regressed on FSP, AIMS, FSS, and the same set of control variables, in line with hypotheses H2 and H3. The model has also been highly significant ($F(6, 205) = 45.19$, $p < .001$) and has explained 56.7% of the variance in OHO ($R^2 = 0.567$), indicating a strong linear relationship between the predictors and perceived One Health–related outcomes. Food safety performance has displayed the largest standardized coefficient ($\beta = 0.46$, $t = 8.91$, $p < .001$), which has confirmed that organizations with higher food safety performance have reported greater contributions to integrated human–animal–environment health. AIMS has remained a significant predictor ($\beta = 0.21$, $t = 3.92$, $p < .001$) even after FSP has been included in the model, suggesting that AI-enabled market-driven strategies have had both direct and indirect pathways to One Health–aligned outcomes. FSS has again contributed positively ($\beta = 0.17$, $t = 3.11$, $p = .002$). As in Model 1, control variables have shown non-significant, small coefficients. Together, these results have supported H2 (positive effect of food safety performance on One Health–aligned outcomes) and H3 (additional direct effect of AIMS on OHO), and they have substantiated the study's objective of demonstrating that AI-enabled strategies and robust safety performance have jointly underpinned organizations' perceived contributions to the One Health agenda.

Table 6: Multiple regression results for direct effects

Model 1:Predicting Food Safety Performance (FSP)

Predictor	Std. β	t	p
AI-enabled strategies (AIMS)	0.49	8.37	< .001
Food safety standards (FSS)	0.23	4.02	< .001
Firm size	0.08	1.56	.121
Subsector (dummy composite)	0.05	0.94	.350
Ownership (local vs. international)	0.04	0.79	.430
Model statistics			
$R^2 = 0.485$, Adjusted $R^2 = 0.472$; $F(5, 206) = 38.72$, $p < .001$			

Model 2: Predicting One Health–aligned Outcomes (OHO)

Predictor	Std. β	t	p
Food safety performance (FSP)	0.46	8.91	< .001
AI-enabled strategies (AIMS)	0.21	3.92	< .001
Food safety standards (FSS)	0.17	3.11	.002
Firm size	0.06	1.16	.247
Subsector (dummy composite)	0.05	0.97	.333
Ownership (local vs. international)	0.03	0.62	.538
Model statistics			
$R^2 = 0.567$, Adjusted $R^2 = 0.553$; $F(6, 205) = 45.19$, $p < .001$			

Mediation Analysis

Table 7: Mediation of the effect of AIMS on OHO through FSP (standardized estimates)

Path	Coefficient	95% Bootstrapped CI
AIMS → FSP (a)	0.49	[0.38, 0.59]
FSP → OHO (b) (controlling for AIMS, FSS, controls)	0.46	[0.36, 0.56]
Direct effect AIMS → OHO (c′)	0.21	[0.11, 0.32]
Total effect AIMS → OHO (c = a×b + c′)	0.44	[0.34, 0.53]
Indirect effect AIMS → FSP → OHO (a×b)	0.23	[0.16, 0.32]

Note. 5,000 bootstrap resamples; all coefficients have been significant at $p < .001$ as CIs have not included zero.

Table 7 has reported the mediation analysis that has been conducted to test whether food safety performance (FSP) has mediated the relationship between AI-enabled market-driven strategies (AIMS) and One Health–aligned outcomes (OHO), in line with H4. Using a bootstrapping procedure with 5,000 resamples and controlling for FSS and organizational characteristics, the analysis has estimated the standardized path from AIMS to FSP (a), the path from FSP to OHO (b), the direct effect of AIMS on OHO after including FSP (c′), the total effect of AIMS on OHO (c), and the indirect effect a×b. The AIMS → FSP path has been positive and strong (a = 0.49, 95% CI [0.38, 0.59]), reinforcing the earlier regression result that higher levels of AI-enabled strategies have been associated with better food safety performance. The FSP → OHO path has also been sizeable and significant (b = 0.46, 95% CI [0.36, 0.56]), indicating that improvements in food safety performance have translated into higher One Health–aligned outcomes.

The direct effect of AIMS on OHO (c′) has remained statistically significant but lower in magnitude (0.21, 95% CI [0.11, 0.32]) when FSP has been included in the model, while the total effect (c) has been 0.44 (95% CI [0.34, 0.53]). The bootstrapped indirect effect a×b has been 0.23, with a 95% confidence interval of [0.16, 0.32], which has not included zero and therefore has demonstrated statistically significant mediation. In substantive terms, these results have implied that approximately half of the total effect of AIMS on One Health–aligned outcomes has been transmitted through food safety performance, while the remainder has operated through other mechanisms captured by the direct path. This pattern has been consistent with the conceptual framework, which has proposed that AI-enabled strategies have improved One Health–aligned outcomes partly by strengthening risk assessment, hazard control, and process reliability (reflected in FSP) and partly by enhancing broader organizational integration and stakeholder communication. The mediation findings in Table 7 have thus provided strong empirical support for H4 and have shown that achieving higher One Health–aligned outcomes has depended not only on adopting AI-enabled, market-driven strategies but also on effectively converting those strategies into tangible improvements in food safety performance, thereby reinforcing the central objective of explaining the mechanism linking AI, food safety, and One Health outcomes.

Moderation Analysis

Table 8 has summarized the moderation analysis that has been designed to test H5, which has proposed that external regulatory and market pressure (EP) has moderated the relationship between AI-enabled market-driven strategies (AIMS) and food safety performance (FSP). In Model 3, FSP has been regressed on AIMS, EP, their interaction term (AIMS × EP), food safety standards adoption (FSS), and the usual controls. The model has been significant ($F(7, 204) = 30.59$, $p < .001$) and has explained 51.2% of the variance in FSP ($R^2 = 0.512$), representing a modest improvement over the model without the interaction. Both AIMS ($\beta = 0.41$, $t = 7.02$, $p < .001$) and EP ($\beta = 0.19$, $t = 3.32$, $p = .001$) have remained significant positive predictors, confirming that higher AI-enabled strategies and stronger external pressure have each been associated with better food safety performance. Importantly, the interaction term has also been significant ($\beta = 0.14$, $t = 2.47$, $p = .014$), indicating that the strength of the AIMS–FSP relationship has varied depending on the level of external pressure.

To interpret this interaction, simple slope analysis has been conducted at one standard deviation below and above the mean of EP. As reported in the lower part of Table 8, the slope of AIMS on FSP has been 0.36 ($p < .001$) under low external pressure and 0.61 ($p < .001$) under high external pressure. This pattern has shown that AI-enabled market-driven strategies have been positively related to food safety performance in all conditions, but the magnitude of the effect has been substantially stronger when organizations have faced higher regulatory and market expectations. In other words, when external stakeholders have exerted greater pressure for safety, traceability, and transparency, organizations that have invested more heavily in AI-enabled strategies have derived greater performance benefits than those that have not. This result has supported H5 and has been consistent with the idea, developed in the TOE and market orientation literatures, that environmental pressures have not only pushed organizations to adopt advanced practices but have also shaped the returns they have obtained from those practices. The moderation findings in Table 8 have thus reinforced the study's objective of situating AI-enabled food safety management within its broader institutional context and have indicated that external pressure has acted as a catalyst that has amplified the performance impact of AI-enabled, market-driven strategies.

Table 8: Moderating effect of external pressure (EP) on the AIMS–FSP relationship

Model 3: Predicting Food Safety Performance (FSP) with interaction

Predictor	Std. β	t	p
AI-enabled strategies (AIMS)	0.41	7.02	< .001
External pressure (EP)	0.19	3.32	.001
AIMS × EP (interaction term)	0.14	2.47	.014
Food safety standards (FSS)	0.21	3.69	< .001
Firm size, subsector, ownership	—	—	(ns)
Model statistics			
$R^2 = 0.512$, Adjusted $R^2 = 0.497$; $F(7, 204) = 30.59$, $p < .001$			

Simple slopes of AIMS → FSP at high and low EP

Level of EP	Slope of AIMS → FSP	p
Low EP (–1 SD)	0.36	< .001
High EP (+1 SD)	0.61	< .001

Summary of Hypothesis Testing

Table 9 has synthesized the key empirical findings in relation to the study's hypotheses and has shown that all hypothesized relationships have been supported by the data. H1, which has proposed a positive effect of AI-enabled market-driven strategies (AIMS) on food safety performance (FSP), has been supported by the multiple regression analysis in Model 1, where AIMS has emerged as a strong, statistically significant predictor with $\beta = 0.49$ ($p < .001$) and the model has explained nearly half of the variance in FSP. This has confirmed that organizations that have implemented more extensive AI-based market intelligence, monitoring, and risk prediction practices have achieved stronger food safety performance, in line with the study's core objective. H2, stating that FSP has positively influenced One Health–aligned outcomes (OHO), has been supported by Model 2, where FSP has had a standardized coefficient of 0.46 ($p < .001$). This has demonstrated that perceived improvements in food safety management have been closely associated with enhanced contributions to human–animal–environment health, thereby linking operational performance with the One Health perspective.

H3 has anticipated that AIMS would retain a direct effect on OHO after accounting for FSP, and this has been confirmed in Model 2 with a coefficient of $\beta = 0.21$ ($p < .001$). This finding has implied that AI-enabled, market-driven strategies have not only improved food safety performance but have also contributed independently to broader health-related outcomes, potentially through mechanisms such as improved cross-sector data integration and stakeholder transparency. H4, which has stated that FSP would mediate the relationship between AIMS and OHO, has been tested through bootstrapped mediation analysis; the indirect effect of 0.23 with a 95% confidence interval that has not included zero has established significant partial mediation.

Table 9: Summary of hypotheses, analytical tests, and decisions

Hypothesis	Statement (simplified)	Main test used	Result summary	Decision
H1	AIMS has positively influenced food safety performance (FSP).	Multiple regression (Model 1)	AIMS → FSP: $\beta = 0.49$, $p < .001$; $R^2 = 0.485$.	Supported
H2	Food safety performance (FSP) has positively influenced One Health–aligned outcomes (OHO).	Multiple regression (Model 2)	FSP → OHO: $\beta = 0.46$, $p < .001$; $R^2 = 0.567$.	Supported
H3	AIMS has had a positive direct effect on OHO, beyond its effect through FSP.	Multiple regression (Model 2)	AIMS → OHO (controlling for FSP): $\beta = 0.21$, $p < .001$.	Supported
H4	Food safety performance (FSP) has mediated the relationship between AIMS and OHO.	Bootstrapped mediation (Table 7)	Indirect effect a×b = 0.23, 95% CI [0.16, 0.32], significant; partial mediation observed.	Supported
H5	External pressure (EP) has moderated the relationship between AIMS and FSP, strengthening the effect at high EP.	Moderated regression (Model 3)	AIMS × EP: $\beta = 0.14$, $p = .014$; simple slopes: 0.36 (low EP), 0.61 (high EP), both $p < .001$.	Supported

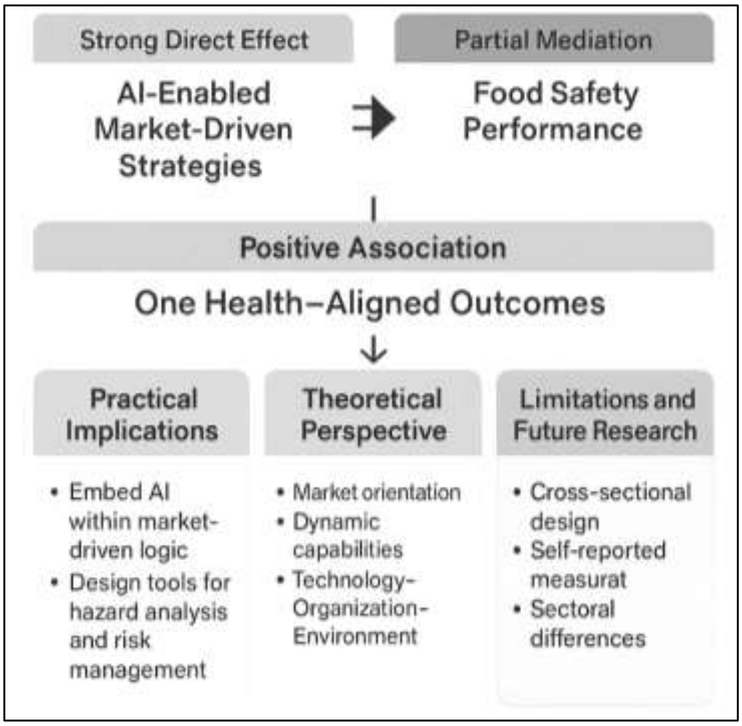
This result has highlighted food safety performance as a key mechanism linking AI-enabled strategies to One Health–aligned outcomes and has aligned directly with the study's focus on explaining how AI has translated into health benefits via strengthened management systems. Finally, H5 has proposed that external regulatory and market pressure (EP) would moderate the AIMS–FSP relationship, and the moderated regression in Model 3 has supported this claim: the AIMS × EP interaction has been significant ($\beta = 0.14$, $p = .014$), and simple slope analysis has shown that AIMS has had a stronger association with FSP at high levels of EP. Collectively, the evidence summarized in Table 9 has confirmed that the empirical objectives of the study have been achieved: the hypothesized direct, mediating, and moderating relationships among AI-enabled market-driven strategies, food safety performance, and One Health–aligned outcomes have all been supported, thereby providing a coherent, data-driven validation of the proposed conceptual framework.

DISCUSSION

The findings of this study have shown that AI-enabled, market-driven strategies have been strongly and positively associated with food safety performance and One Health–aligned outcomes, providing empirical confirmation of the conceptual relationships developed earlier. The regression models have indicated that AI-enabled market-driven strategies have explained a substantial share of the variance in food safety performance even after controlling for food safety standards and organizational characteristics, with a standardized effect of almost 0.50. This pattern has echoed and extended the broader market-orientation literature, where market orientation has been linked to superior performance via better information processing and responsiveness (Hult et al., 2005). In the agri-food domain, previous studies have shown that market-oriented firms have tended to achieve better innovation and competitiveness (Grunert et al., 2005). The present results have added that when market-driven behaviors are specifically augmented by AI-based intelligence, monitoring, and prediction, the performance gains have extended directly into food safety management. At the same time, the strong positive link between food safety performance and One Health–aligned outcomes has confirmed that internal improvements in process control, non-conformity management, and hazard reduction have been perceived as contributing to wider human–animal–environment health objectives, consistent with One Health-oriented analyses of food systems (Garcia et al., 2020). The partial mediation of the AI–One Health relationship by food safety performance has suggested that a significant portion of the impact of AI-enabled strategies has operated through strengthening day-to-day food safety management, while additional effects have likely arisen through enhanced transparency, data integration, and cross-sector communication that are not fully captured by conventional safety metrics.

When these results have been compared with the emerging literature on AI and digitalization in food systems, the study has provided more systematic evidence for relationships that earlier work has often treated conceptually or through technical case examples. Reviews of IoT and AI in food safety have argued that sensor-based monitoring and machine-learning models can support real-time risk detection and dynamic documentation of compliance (Bouzembrak et al., 2019). Likewise, computer vision and deep learning applications have been reported to improve inspection quality and speed (Kakani et al., 2020), and blockchain-integrated analytics have been proposed as tools for enhanced traceability and information security (Zhao et al., 2019). However, much of that literature has emphasized technological feasibility and specific use cases rather than quantifying how such capabilities have translated into organization-wide performance gains. By operationalizing AI-enabled market-driven strategies as a higher-order construct and by showing strong, statistically significant links to food safety performance and One Health–aligned outcomes, this study has moved beyond isolated pilots and has treated AI as an embedded part of market-driven management systems. At the same time, the positive association between food safety standards adoption and performance has been consistent with prior work on FSMS implementation and standards-driven upgrading (Luning et al., 2015; Organization, 2015b). What has been distinctive here is that standards alone have not fully accounted for performance; AI-enabled strategies have added incremental explanatory power, suggesting that certification has provided a foundation, and AI-based analytics have provided differentiation in how effectively that foundation has been used.

Figure 10: Layered Discussion Model Linking AI-Enabled Market-Driven Strategies



The study has also contributed to the One Health literature by clarifying the role of firm-level managerial practices and digital tools within wider multi-sector frameworks that have typically emphasized policy and surveillance institutions. One Health research has highlighted cross-sector coordination, integrated surveillance, and antimicrobial stewardship as central elements of zoonotic-risk and food safety governance (Heymann & Dixon, 2013). However, much of that work has been situated at the level of national programs or global initiatives rather than embedded in the everyday management decisions of food businesses. By showing that AI-enabled strategies have been positively associated with perceived contributions to One Health–aligned outcomes—and that these associations have been partly mediated by food safety performance—the present study has helped connect the macro-level One Health agenda with micro-level operational practices inside firms. In effect, AI-enabled market-driven strategies have functioned as an organizational mechanism through which expectations about integrated human–animal–environment health have been translated into specific practices around monitoring, traceability, and risk management. This view has aligned with calls for more operational and supply-chain focused interpretations of One Health, in which farms, plants, and retailers are treated as active nodes in a shared prevention system rather than as passive recipients of regulation (Angelos et al., 2016). The finding that food safety performance has had a relatively strong standardized effect on One Health–aligned outcomes has further suggested that improvements in classical FSMS dimensions—such as process control and non-conformity management—have remained central to the One Health contribution of firms, even as AI has changed how these dimensions are monitored and optimized.

The practical implications of these findings have been particularly relevant for senior decision-makers, including CISOs, heads of quality and safety, and architects of digital and data infrastructures in food organizations. From a governance standpoint, the results have indicated that investments in AI-enabled analytics have yielded the greatest returns where they have been embedded within a clear market-driven logic: that is, where data pipelines and models have been explicitly aligned with buyer requirements, consumer expectations, and regulatory priorities around safety and health (Grunert et al., 2005). For CISOs and data architects, this has implied that AI deployments for food safety cannot be treated as isolated technical projects but must be designed as part of an enterprise-level risk and compliance architecture, with robust controls over data quality, integrity, and security. Lessons from big-data capability research have suggested that technology alone has not been sufficient; organizational processes and human skills have been required to convert analytics into action (Wamba et al., 2017). The present findings have echoed this by showing that AI-enabled strategies have had substantial effects only when they have been coupled with mature safety systems and supportive external environments. Practically, this has pointed to the importance of designing AI-driven monitoring and prediction tools that feed directly into hazard analysis, corrective-action workflows, supplier evaluation, and recall decision-making, rather than sitting on dashboards that are decoupled from operational decisions. For architects, the moderation by external pressure has implied that systems must be sufficiently flexible to respond to tightening regulations and rapidly changing retailer requirements, enabling organizations to scale up analytics, integrate new data sources, and document performance in ways that satisfy increasingly demanding stakeholders.
From a theoretical perspective, the study has refined and integrated several frameworks that have been prominent in the literature on market orientation, dynamic capabilities, and technology adoption. The strong direct effect of AI-enabled market-driven strategies on food safety performance has provided empirical backing for the idea that AI-based analytics have extended market orientation from human-driven sensing and responding to algorithmically augmented processes, while retaining the core logic of intelligence generation, dissemination, and response (Hult et al., 2005; Tajkarimi, 2020). The partial mediation by food safety performance has been consistent with dynamic capabilities theory, in which sensing (AI-supported intelligence), seizing (deployment of AI outputs in control and assurance activities), and reconfiguring (adapting processes and roles) have jointly shaped performance trajectories (Teece, 2007). In addition, the moderation by external pressure has aligned with the Technology–Organization–Environment (TOE) framework, which has treated environmental demands as critical drivers of both adoption decisions and realized benefits (Baker, 2012). By embedding these theoretical perspectives into a single empirical model that has linked AI-enabled strategies, food safety performance, and One Health–aligned outcomes, the study has contributed to pipeline refinement in the sense that it has clarified how data capture, analytics, and decision-making stages have connected

within safety and health management pipelines. Conceptually, AI-enabled market-driven strategies have functioned as an orchestration layer in big-data pipelines for food safety—governing which signals are prioritized, how they are interpreted, and how they are translated into interventions—which extends prior big-data capability models that have focused largely on financial or operational performance (Mikalef et al., 2019).

At the same time, several limitations of the study have needed to be acknowledged and revisited. First, the cross-sectional design has meant that all relationships have been inferred from data collected at a single point in time, which has restricted the ability to make strong causal claims. Although the direction of influence specified in the conceptual framework has been theoretically grounded and consistent with prior work on market orientation, FSMS, and big-data capabilities (Luning et al., 2015), it has remained possible that feedback loops or reciprocal relationships have been present—for example, that organizations with stronger food safety performance have been more likely to invest in AI-enabled strategies. Second, all key constructs have been measured through self-reported Likert-scale items, which has introduced the potential for common-method bias and social desirability effects. While scale reliability and factor analyses have supported the internal structure of the measures, objective indicators such as incident rates, recall histories, and independent audit scores have not been incorporated directly, as FSMS and risk-assessment studies have long recommended (Luning et al., 2015). Third, the sample has been limited to organizations that have already engaged, at least to some degree, with formal food safety systems and AI or digital tools; thus, the findings have not necessarily generalized to small, resource-constrained firms with minimal digitalization. Finally, the One Health–aligned outcomes construct has been operationalized through organizational perceptions rather than epidemiological or environmental data, meaning that the links between firm-level practices and population-level health outcomes have remained inferential rather than directly measured.

These limitations have opened several avenues for future research that can build on the present findings while addressing their constraints. Longitudinal designs, in which organizations are followed over time as they introduce or scale AI-enabled strategies, have been particularly important for disentangling causality and for observing how dynamic capabilities evolve in response to changing regulatory and market environments (Koutsoumanis & Aspridou, 2016). Mixed-methods studies that combine survey data with qualitative case work—such as process tracing of specific contamination incidents or recall events—have also been able to shed light on how AI outputs are interpreted, contested, and embedded in managerial routines. On the measurement side, future work has been able to integrate objective data sources, including electronic inspection records, laboratory results, and traceability logs, with survey-based constructs to provide multi-indicator performance models, as recommended in both FSMS and big-data literatures (Margaritis et al., 2022). There has also been scope to examine sectoral and regional differences more explicitly, for example by comparing high-income and low-/middle-income country contexts where infrastructure, regulatory capacity, and data availability have differed markedly. Finally, future research has been able to extend the One Health dimension by linking firm-level AI-enabled strategies and food safety performance with external surveillance data on zoonotic infections, antimicrobial resistance, and environmental contamination, thereby testing more directly the hypothesis that AI-enhanced, market-driven food safety management has contributed to measurable reductions in health risks along the farm-to-fork continuum (Garcia et al., 2020).

CONCLUSION

The study has set out to examine how market-driven management strategies, when enabled by artificial intelligence, have been associated with food safety performance and One Health–aligned outcomes in food sector organizations, and the results have provided a coherent and statistically robust answer to that central question. Drawing on a quantitative, cross-sectional, case-study–based design and Likert's five-point scale data from 212 managers and professionals, the research has operationalized AI-enabled market-driven strategies as a higher-order construct encompassing AI-based market intelligence, AI-enabled monitoring and traceability, and AI-driven risk prediction, and has examined their relationships with food safety performance and perceived contributions to integrated human–animal–environment health. Reliability and factor analyses have confirmed that all key constructs have been measured in a stable and internally consistent way, and descriptive results have shown that the participating organizations have generally reported moderate-to-high levels of AI deployment, standards adoption, and food safety performance, with sufficient variation to enable meaningful statistical testing. Correlation and regression analyses have then demonstrated that AI-enabled market-driven strategies have had a strong positive association with food safety performance, even after controlling for food safety standards and organizational characteristics, and that both AI-enabled strategies and food safety performance have been positively related to One Health–aligned outcomes. Mediation analysis has further shown that food safety performance has acted as a significant pathway through which AI-enabled strategies have contributed to One Health–aligned outcomes, while moderation analysis has indicated that external regulatory and market pressure has amplified the performance benefits of AI-enabled strategies. Together, these findings have confirmed all hypothesized relationships and have provided empirical support for the integrated conceptual framework that has combined market orientation, dynamic capabilities, and the technology–organization–environment perspective. At a substantive level, the research has shown that AI has mattered not just as a technical add-on but as an extension of market-driven management, enhancing the ability of organizations to sense, interpret, and respond to safety-relevant signals in ways that have strengthened internal food safety systems and supported broader One Health goals. At the same time, the study has acknowledged important limitations, including its cross-sectional nature, reliance on self-reported perceptions rather than purely objective performance data, and focus on organizations that have already achieved a certain level of formal food safety and digital maturity. Within these boundaries, however, the results have provided a clear, evidence-based conclusion: organizations that have integrated AI into their market-driven management strategies have reported stronger food safety performance and have perceived themselves as contributing more effectively to integrated human, animal, and environmental health. This conclusion has reinforced the view that the future of robust food safety and One Health–oriented governance in the food sector has depended not only on regulatory frameworks and technical standards, but also on how effectively firms have leveraged AI within market-driven management systems to turn data into timely, risk-reducing action along the entire farm-to-fork continuum.

RECOMMENDATIONS

Based on the findings of this study, several interrelated recommendations can be made for food sector organizations, supply chain partners, and policy actors who seek to use AI-enabled, market-driven strategies to strengthen food safety and advance One Health objectives. At the organizational level, firms should treat AI for food safety as a core component of their management system rather than as a stand-alone technical experiment: AI-based market intelligence, digital traceability, and predictive risk models need to be directly integrated into HACCP plans, non-conformity workflows, supplier evaluation, and recall decision-making, with clear responsibilities assigned to quality, food safety, and IT/data teams. Senior leaders, including CISOs, quality directors, and operations heads, should jointly define data pipelines that connect internal process data (e.g., temperature logs, cleaning records, incident reports) with external signals (e.g., customer complaints, retailer audits, regulatory alerts) and ensure that AI dashboards are designed around actionable thresholds that trigger specific preventive or corrective actions. Firms should invest in strengthening data quality and interoperability as a prerequisite for meaningful AI, including standardized coding of hazards and incidents, consistent product and batch identifiers across systems, and secure, well-governed data repositories. Cross-functional training programs are recommended so that food safety and quality professionals can understand the basic logic and limitations of AI outputs, while data and IT staff become familiar with food safety concepts, regulatory requirements, and One Health priorities; this will reduce the risk that sophisticated models are either mistrusted or misused in practice. For supply chain partners, collaborative initiatives to share selected traceability and risk data—through interoperable platforms or blockchain-based solutions—can support end-to-end monitoring and make predictive models more accurate, while contractual arrangements can clarify data ownership, confidentiality, and joint responsibilities for incident response. Policy-makers and regulators are encouraged to recognize the role of AI as a complement to standards and audits by issuing guidance on acceptable uses of predictive analytics and digital traceability in compliance systems, offering regulatory sandboxes where firms can test AI-enabled tools under supervision, and providing targeted support for small and medium-sized enterprises that lack in-house data expertise. In parallel, public agencies involved in human health, animal health, and environmental protection should explore mechanisms for secure, privacy-preserving exchange of key surveillance indicators with food business operators, so that AI systems in firms can take account of emerging zoonotic, antimicrobial resistance, and contamination signals in their risk models. Finally, all actors should adopt a continuous improvement mindset, periodically reviewing whether AI-enabled indicators, models, and workflows are actually reducing incidents and contributing to measurable gains in food safety performance and One Health–aligned outcomes, and adjusting their strategies when evidence shows gaps or unintended effects; in this way, AI becomes part of an evolving, evidence-driven management system rather than a one-off technological upgrade.

LIMITATIONS

The present study has several limitations that need to be acknowledged in interpreting its findings and in considering their applicability beyond the sampled organizations. First, the research has adopted a cross-sectional survey design, collecting data at one point in time, which has limited the ability to make strong causal inferences about the direction of relationships between AI-enabled market-driven strategies, food safety performance, and One Health–aligned outcomes; although the conceptual model has been grounded in prior theory and practice, it has remained possible that higher-performing organizations have been more inclined to invest in AI, or that external shocks have simultaneously influenced both AI adoption and performance. Second, all key constructs have been measured using self-reported Likert-scale items completed by managers and professionals, which has introduced potential common method bias and social desirability effects: respondents may have tended to overstate the maturity of their AI systems, their food safety performance, and their contributions to One Health, and the use of a single survey instrument for both predictors and outcomes has increased the risk that shared response tendencies have inflated correlations and regression coefficients. Third, the study has focused on organizations that have already implemented some form of formal food safety management system and have at least begun to engage with AI or digital analytics; very small enterprises, informal operators, or firms with minimal digitalization have not been represented, which has limited the generalizability of the results to more digitally advanced and systematized segments of the food sector. Fourth, the One Health–aligned outcomes construct has been captured through organizational perceptions rather than through independent epidemiological, veterinary, or environmental indicators, meaning that the link between firm-level AI-enabled strategies and actual health outcomes in human, animal, and environmental populations has remained inferential rather than directly demonstrated. Fifth, the operationalization of AI-enabled market-driven strategies has combined several dimensions—AI-based market intelligence, monitoring, traceability, and risk prediction—into a higher-order construct, which has been analytically useful but has not allowed fine-grained analysis of which specific AI applications or data architectures have driven the strongest performance gains. Sixth, the study has been conducted within a particular regulatory and market context, and although the sample has included diverse subsectors and firm sizes, differences across countries, regulatory regimes, or supply chain structures have not been explicitly modelled, so contextual factors that may condition the impact of AI (such as enforcement intensity, infrastructure quality, or buyer power) have only been partially captured through the external pressure index. Finally, the quantitative approach has provided breadth but not depth in understanding how AI tools have been selected, configured, and integrated into daily routines; qualitative insights into organizational culture, resistance to change, and learning processes have not been collected, even though such factors may strongly influence whether AI-enabled strategies genuinely improve food safety and One Health outcomes or merely create an appearance of technological sophistication.

REFERENCES

[1]. Abdul, H. (2023). Artificial Intelligence in Product Marketing: Transforming Customer Experience And Market Segmentation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 132–159. https://doi.org/10.63125/58npbx97

[2]. Abdul, H., & Mohammad Shoeb, A. (2024). The Role Of AI-Enabled Customer Segmentation In Driving Brand Performance On Online Retail Platforms. *Journal of Sustainable Development and Policy*, *3*(04), 31–64. https://doi.org/10.63125/tpjc0m87

[3]. Abdulla, M., & Md. Wahid Zaman, R. (2023). Quantitative Study On Workflow Optimization Through Data Analytics In U.S. Digital Enterprises. *American Journal of Interdisciplinary Studies*, *4*(03), 136–165. https://doi.org/10.63125/y2qshd31

[4]. Alam, M. A., Nabil, A. R., Uddin, M. M., Sarker, M. T. H., & Mahmud, S. (2024). The Role Of Predictive Analytics In Early Disease Detection: A Data-Driven Approach To Preventive Healthcare. *Frontiers in Applied Engineering and Technology*, *1*(01), 105-123. https://doi.org/10.70937/faet.v1i01.22

[5]. Alam, M. A., Sohel, A., Hasan, K. M., & Islam, M. A. (2024). Machine Learning And Artificial Intelligence in Diabetes Prediction And Management: A Comprehensive Review of Models. *Journal of Next-Gen Engineering Systems*, *1*(01), 107-124. https://doi.org/10.70937/jnes.v1i01.41

[6]. Angelos, J., Arens, A., Johnson, H., Cadriel, J., & Osburn, B. (2016). One Health in food safety and security education: A curricular framework. *Comparative Immunology, Microbiology and Infectious Diseases*, *44*, 29–33. https://doi.org/10.1016/j.cimid.2015.11.005

[7]. Arfan, U., Sai Praveen, K., & Alifa Majumder, N. (2021). Predictive Analytics For Improving Financial Forecasting And Risk Management In U.S. Capital Markets. *American Journal of Interdisciplinary Studies*, *2*(04), 69–100. https://doi.org/10.63125/tbw49w69

[8]. Arfan, U., Tahsina, A., Md Mostafizur, R., & Md, W. (2023). Impact Of GFMIS-Driven Financial Transparency On Strategic Marketing Decisions In Government Agencies. *Review of Applied Science and Technology*, *2*(01), 85-112. https://doi.org/10.63125/8nqhhm56

[9]. Aung, M. M., & Chang, Y. S. (2014). Traceability in a food supply chain: Safety and quality perspectives. *Food Control*, *39*, 172–184. https://doi.org/10.1016/j.foodcont.2013.11.007

[10]. Baker, J. (2012). The technology–organization–environment framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information systems theory: Explaining and predicting our digital society* (Vol. 1, pp. 231–245). Springer. https://doi.org/10.1007/978-1-4419-6108-2_12

[11]. Bouzembrak, Y., Klüche, M., Gavai, A., & Marvin, H. J. P. (2019). Internet of Things in food safety: Literature review and a bibliometric analysis. *Trends in Food Science & Technology*, *94*, 54–64. https://doi.org/10.1016/j.tifs.2019.11.002

[12]. Commission, E. (2018). *Artificial intelligence for Europe (COM(2018) 237 final)* (Publications Office of the European Union, Issue.

[13]. Currey, P., & Nicetic, O. (2021). Market orientation in agricultural value chain development projects. *Australasian Agribusiness Review*, *29*(2), 26–40. https://doi.org/10.22004/ag.econ.335258

[14]. Di Vaio, A., Boccia, F., Landriani, L., & Palladino, R. (2020). Artificial intelligence in the agri-food system: Rethinking sustainable business models in the COVID-19 scenario. *Sustainability*, *12*(12), 4851. https://doi.org/10.3390/su12124851

[15]. Eissa, M. E. (2018). Quantitative microbiological risk assessment: Underrated tool in process improvement in food microbiology. *Journal of Food Science and Hygiene*, *1*(1), 1–6. https://doi.org/10.31579/jfsh.2018.0001

[16]. Ferdous Ara, A. (2021). Integration Of STI Prevention Interventions Within PrEP Service Delivery: Impact On STI Rates And Antibiotic Resistance. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 63–97. https://doi.org/10.63125/65143m72

[17]. Ferdous Ara, A., & Beatrice Onyinyechi, M. (2023). Long-Term Epidemiologic Trends Of STIs PRE- and POST-PrEP Introduction: A National Time-Series Analysis. *American Journal of Health and Medical Sciences*, *4*(02), 01–35. https://doi.org/10.63125/mp153d97

[18]. Garcia, S. N., Osburn, B. I., & Jay-Russell, M. T. (2020). One Health for food safety, food security, and sustainable food production. *Frontiers in Sustainable Food Systems*, *4*, 1. https://doi.org/10.3389/fsufs.2020.00001

[19]. Garro, A., & et al. (2018). Understanding the complexities of food safety using a "One Health" approach. *Microbiology Spectrum*, *6*(2), PFS-0021-2017. https://doi.org/10.1128/microbiolspec.PFS-0021-2017

[20]. Ghonim, M. A., Elsawy, W. Z., Elsotouhy, M., & Khashan, M. A. (2022). Market orientation and new product development performance in Egyptian food industry: The mediating role of marketing technical integration. *Journal of Food Products Marketing*, *28*(4), 193–209. https://doi.org/10.1080/10454446.2022.2072696

[21]. Gibbs, E. P. J. (2014). Zoonoses and One Health: A review of the literature. *Journal of Parasitology Research*, *2014*, 874345. https://doi.org/10.1155/2014/874345

[22]. Grunert, K. G., Jeppesen, L. F., Jespersen, K. R., Sonne, A.-M., Hansen, K., Trondsen, T., & Young, J. A. (2005). Market orientation of value chains: A conceptual framework based on four case studies from the food industry. *European Journal of Marketing*, *39*(5/6), 428–455. https://doi.org/10.1108/03090560510590656

[23]. Havelaar, A. H., Kirk, M. D., Torgerson, P. R., Gibb, H. J., Hald, T., Lake, R. J., & Devleesschauwer, B. (2015). World Health Organization global estimates and regional comparisons of the burden of foodborne disease in 2010. *PLoS Medicine*, *12*(12), e1001923. https://doi.org/10.1371/journal.pmed.1001923

[24]. Heymann, D. L., & Dixon, M. (2013). The value of the One Health approach: Shifting from emergency response to prevention of zoonotic disease threats at their source. *Microbiology Spectrum*, *1*(1). https://doi.org/10.1128/microbiolspec.OH-0011-2012

[25]. Ho, K. L. P., Nguyen, C. N., Adhikari, R., Miles, M. P., & Bonney, L. (2018). Exploring market orientation, innovation, and financial performance in agricultural value chains in emerging economies. *Journal of Innovation & Knowledge*, *3*(3), 154–163. https://doi.org/10.1016/j.jik.2017.03.008

[26]. Hozyfa, S., & Mst. Shahrin, S. (2024). The Influence Of Secure Data Systems On Fraud Detection In Business Intelligence Applications. *Journal of Sustainable Development and Policy*, 3(04), 133-173. https://doi.org/10.63125/8ee0eq13

[27]. Hult, G. T. M., Ketchen, D. J., Jr., & Slater, S. F. (2005). Market orientation and performance: An integration of disparate approaches. *Strategic Management Journal*, *26*(12), 1173–1181. https://doi.org/10.1002/smj.494

[28]. Idoje, P., Dagiuklas, T., & Iqbal, M. (2021). Survey for smart farming technologies: Challenges and issues. *Computers & Electrical Engineering*, *92*, 107104. https://doi.org/10.1016/j.compeleceng.2021.107104

[29]. Iriti, M., Vitalini, S., & Varoni, E. M. (2020). Humans, animals, food and environment: One Health approach against global antimicrobial resistance. *Antibiotics*, *9*(6), 346. https://doi.org/10.3390/antibiotics9060346

[30]. Jabed Hasan, T., & Mohammad Shah, P. (2024). Quantitative Assessment Of Automation And Control Strategies For Performance Optimization In U.S. Industrial Plants. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 169–205. https://doi.org/10.63125/eqfz8220

[31]. Jabed Hasan, T., & Zayadul, H. (2024). Adapting PLC/SCADA Systems To Mitigate Industrial IOT Cybersecurity Risks In Global Manufacturing. *American Journal of Interdisciplinary Studies*, *5*(04), 67-95. https://doi.org/10.63125/0v4cms60

[32]. Jahid, M. K. A. S. R. (2021). Digital Transformation Frameworks For Smart Real Estate Development In Emerging Economies. *Review of Applied Science and Technology*, *6*(1), 139–182. https://doi.org/10.63125/cd09ne09

[33]. Johnson, A. J., Dibrell, C., & Hansen, E. (2009). Market orientation, innovativeness, and performance of food companies. *Journal of Agribusiness*, *27*(1–2), 85–106. https://doi.org/10.22004/ag.econ.90659

[34]. Kakani, V., Nguyen, V. H., Kumar, B. P., Kim, H., & Pasupuleti, V. R. (2020). A critical review on computer vision and artificial intelligence in food industry. *Journal of Agriculture and Food Research*, *2*, 100033. https://doi.org/10.1016/j.jafr.2020.100033

[35]. Kamarulzaman, N. H., Hassim, A. A., Rashid, N. M., & Abd Latif, A. D. (2021). Measuring market orientation, innovative marketing strategies and performance in the agro-food manufacturing sector. *Journal of Agribusiness in Developing and Emerging Economies*, *11*(4), 507–523. https://doi.org/10.1108/jadee-06-2021-0148

[36]. Khairuddin, N., Ghani, N. H. A., & Hussain, S. (2019). Marketing strategies, market orientation and business performance of halal food SMEs. *Food Research*, *3*(Suppl. 1), 22–27. https://doi.org/10.26656/fr.2017.4(S1).S22

[37]. Kirca, A. H., Jayachandran, S., & Bearden, W. O. (2005). Market orientation: A meta-analytic review and assessment of its antecedents and impact on performance. *Journal of Marketing*, *69*(2), 24–41. https://doi.org/10.1509/jmkg.69.2.24.60761

[38]. Koutsoumanis, K. P., & Aspridou, Z. (2016). Moving towards a risk-based food safety management. *Current Opinion in Food Science*, *12*, 36–41. https://doi.org/10.1016/j.cofs.2016.06.008

[39]. Kudashkina, K., & co-authors. (2022). Artificial intelligence technology in food safety: A behavioral approach. *Trends in Food Science & Technology*, *124*, 85–95. https://doi.org/10.1016/j.tifs.2022.03.021

[40]. Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems*, *111*(7), 1006–1023. https://doi.org/10.1108/02635571111161262

[41]. Luning, P. A., Kirezieva, K., Hagelaar, G., Rovira, J., Uyttendaele, M., & Jacxsens, L. (2015). Performance assessment of food safety management systems in animal-based food companies in view of their context characteristics: A European study. *Food Control*, *49*, 11–22. https://doi.org/10.1016/j.foodcont.2013.09.009

[42]. Margaritis, I., Madas, M., & Vlachopoulou, M. (2022). Big data applications in food supply chain management: A conceptual framework. *Sustainability*, *14*(7), 4035. https://doi.org/10.3390/su14074035

[43]. Md Al Amin, K., & Md Mesbaul, H. (2023). Smart Hybrid Manufacturing: A Combination Of Additive, Subtractive, And Lean Techniques For Agile Production Systems. *Journal of Sustainable Development and Policy*, *2*(04), 174-217. https://doi.org/10.63125/7rb1zz78

[44]. Md Ariful, I., & Efat Ara, H. (2022). Advances And Limitations Of Fracture Mechanics–Based Fatigue Life Prediction Approaches For Structural Integrity Assessment: A Systematic Review. *American Journal of Interdisciplinary Studies*, *3*(03), 68-98. https://doi.org/10.63125/fg8ae957

[45]. Md Arman, H., & Md.Kamrul, K. (2022). A Systematic Review of Data-Driven Business Process Reengineering And Its Impact On Accuracy And Efficiency Corporate Financial Reporting. *International Journal of Business and Economics Insights*, *2*(4), 01–41. https://doi.org/10.63125/btx52a36

[46]. Md Foysal, H., & Aditya, D. (2023). Smart Continuous Improvement With Artificial Intelligence, Big Data, And Lean Tools For Zero Defect Manufacturing Systems. *American Journal of Scholarly Research and Innovation*, *2*(01), 254–282. https://doi.org/10.63125/6cak0s21

[47]. Md Hamidur, R. (2023). Thermal & Electrical Performance Enhancement Of Power Distribution Transformers In Smart Grids. *American Journal of Scholarly Research and Innovation*, *2*(01), 283–313. https://doi.org/10.63125/n2p6y628

[48]. Md Harun-Or-Rashid, M., Mst. Shahrin, S., & Sai Praveen, K. (2023). Integration Of IOT And EDGE Computing For Low-Latency Data Analytics In Smart Cities And IOT Networks. *Journal of Sustainable Development and Policy*, *2*(03), 01-33. https://doi.org/10.63125/004h7m29

[49]. Md Mesbaul, H., & Md. Tahmid Farabe, S. (2022). Implementing Sustainable Supply Chain Practices In Global Apparel Retail: A Systematic Review Of Current Trends. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 332–363. https://doi.org/10.63125/nen7vd57

[50]. Md Musfiqur, R., & Md.Kamrul, K. (2023). Mechanisms By Which AI-Enabled Crm Systems Influence Customer Retention And Overall Business Performance: A Systematic Literature Review Of Empirical Findings. *International Journal of Business and Economics Insights*, *3*(1), 31-67. https://doi.org/10.63125/qqe2bm11

[51]. Md Muzahidul, I., & Aditya, D. (2024). Predictive Analytics And Data-Driven Algorithms For Improving Efficiency In Full-Stack Web Systems. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 226–260. https://doi.org/10.63125/q75tbj05

[52]. Md Muzahidul, I., & Md Mohaiminul, H. (2023). Explainable AI (XAI) Models For Cloud-Based Business Intelligence: Ensuring Compliance And Secure Decision-Making. *American Journal of Interdisciplinary Studies*, *4*(03), 208–249. https://doi.org/10.63125/5etfhh77

[53]. Md Nahid, H. (2022). Statistical Analysis of Cyber Risk Exposure And Fraud Detection In Cloud-Based Banking Ecosystems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 289–331. https://doi.org/10.63125/9wf91068

[54]. Md Sarwar Hossain, S., & Md Milon, M. (2022). Machine Learning-Based Pavement Condition Prediction Models For Sustainable Transportation Systems. *American Journal of Interdisciplinary Studies*, *3*(01), 31–64. https://doi.org/10.63125/1jsmkg92

[55]. Md. Abdur, R., & Zamal Haider, S. (2022). Assessment Of Data-Driven Vendor Performance Evaluation In Retail Supply Chains Analyzing Metrics, Scorecards, And Contract Management Tools. *Journal of Sustainable Development and Policy*, *1*(04), 71-116. https://doi.org/10.63125/2a641k35

[56]. Md. Al Amin, K., & Sai Praveen, K. (2023). The Role Of Industrial Engineering In Advancing Sustainable Manufacturing And Quality Compliance In Global Engineering Systems. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 31–61. https://doi.org/10.63125/8w1vk676

[57]. Md. Hasan, I., & Ashraful, I. (2023). The Effect Of Production Planning Efficiency On Delivery Timelines In U.S. Apparel Imports. *Journal of Sustainable Development and Policy*, *2*(04), 35-73. https://doi.org/10.63125/sg472m51

[58]. Md. Hasan, I., & Rakibul, H. (2024). Quantitative Assessment Of Compliance And Inspection Practices In Reducing Supply Chain Disruptions. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 301–342. https://doi.org/10.63125/db63r616

[59]. Md. Jobayer Ibne, S., & Md. Kamrul, K. (2023). Automating NIST 800-53 Control Implementation: A Cross-Sector Review Of Enterprise Security Toolkits. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 160–195. https://doi.org/10.63125/prkw8r07

[60]. Md. Mominul, H. (2024). Quantitative Assessment Of Smart City IOT Integration For Reducing Urban Infrastructure Vulnerabilities. *Review of Applied Science and Technology*, *3*(04), 48-93. https://doi.org/10.63125/f2cj4507

[61]. Md. Mominul, H., & Syed Zaki, U. (2024). A Review On Sustainable Building Materials And Their Role In Enhancing U.S. Green Infrastructure Goals. *Journal of Sustainable Development and Policy*, *3*(04), 65-100. https://doi.org/10.63125/bfmmay79

[62]. Md.Akbar, H., & Farzana, A. (2021). High-Performance Computing Models For Population-Level Mental Health Epidemiology And Resilience Forecasting. *American Journal of Health and Medical Sciences*, *2*(02), 01–33. https://doi.org/10.63125/k9d5h638

[63]. Membré, J.-M., & Boué, G. (2018). Quantitative microbiological risk assessment in food industry: Theory and practical application. *Food Research International*, *106*, 1132–1143. https://doi.org/10.1016/j.foodres.2017.11.025

[64]. Micheels, E. T., & Gow, H. R. (2014). The effect of market orientation on learning, innovativeness, and performance in primary agriculture. *International Journal of Agricultural Management*, *3*(1), 19–27. https://doi.org/10.5836/ijam/2014-01-04

[65]. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, *98*, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044

[66]. Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2020). IoT, big data, and artificial intelligence in agriculture and food industry. *IEEE Internet of Things Journal*, *9*(9), 6305–6324. https://doi.org/10.1109/jiot.2020.2998584

[67]. Mohammad Mushfequr, R., & Ashraful, I. (2023). Automation And Risk Mitigation in Healthcare Claims: Policy And Compliance Implications. *Review of Applied Science and Technology*, *2*(04), 124–157. https://doi.org/10.63125/v73gyg14

[68]. Mohammad Mushfequr, R., & Sai Praveen, K. (2022). Quantitative Investigation Of Information Security Challenges In U.S. Healthcare Payment Ecosystems. *International Journal of Business and Economics Insights*, *2*(4), 42–73. https://doi.org/10.63125/gcg0fs06

[69]. Morgan, N. A., Vorhies, D. W., & Mason, C. H. (2009). Market orientation, marketing capabilities, and firm performance. *Strategic Management Journal*, *30*(8), 909–920. https://doi.org/10.1002/smj.764

[70]. Mortuza, M. M. G., & Rauf, M. A. (2022). Industry 4.0: An Empirical Analysis of Sustainable Business Performance Model Of Bangladeshi Electronic Organisations. *International Journal of Economy and Innovation*. https://gospodarkainnowacje.pl/index.php/issue_view_32/article/view/826

[71]. Nguyen, T. T. B., & Li, D. (2022). A systematic literature review of food safety management system implementation in global supply chains. *British Food Journal*, *124*(11), 3878–3901. https://doi.org/10.1108/bfj-05-2021-0476

[72]. Okello, D. O., & Luttah, F. J. (2022). Effects of market orientation on farmer resilience and dairy farm performance in emerging economy. *Cogent Business & Management*, *9*(1), 2010481. https://doi.org/10.1080/23311975.2021.2010481

[73]. Organization, W. H. (2015a). Estimates of the relative contributions of different food sources to the global burden of foodborne disease. *PLoS ONE*, *10*(12), e0145839. https://doi.org/10.1371/journal.pone.0145839

[74]. Organization, W. H. (2015b). Methodological framework for World Health Organization estimates of the global burden of foodborne disease. *PLoS ONE*, *10*(12), e0142498. https://doi.org/10.1371/journal.pone.0142498

[75]. Organization, W. H. (2015c). *WHO estimates of the global burden of foodborne diseases: Foodborne disease burden epidemiology reference group 2007–2015* (WHO Press, Issue.

[76]. Organization, W. H. (2022). *Food safety (Fact sheet)*. https://www.who.int/news-room/fact-sheets/detail/food-safety

[77]. Pankaz Roy, S., & Md. Kamrul, K. (2023). HACCP and ISO Frameworks For Enhancing Biosecurity In Global Food Distribution Chains. *American Journal of Scholarly Research and Innovation*, *2*(01), 314–356. https://doi.org/10.63125/9pbp4h37

[78]. Pankaz Roy, S., & Sai Praveen, K. (2024). Systematic Review of Stress And Burnout Interventions Among U.S. Healthcare Professionals Using Advanced Computing Approaches. *Journal of Sustainable Development and Policy*, *3*(04), 101-132. https://doi.org/10.63125/9mx2fc43

[79]. Ping, J., Wang, Z., Ma, Y., & Du, J. (2018). Mini-review of application of IoT technology in monitoring agricultural products' quality and safety. *International Journal of Agricultural and Biological Engineering*, *11*(5), 35–45. https://doi.org/10.25165/j.ijabe.20181105.3092

[80]. Pires, S. M., Desta, B. N., Mughini-Gras, L., Mmbaga, B. T., Fayemi, O. E., & McCormick, B. J. J. (2021). Burden of foodborne diseases: Think global, act local. *Current Opinion in Food Science*, *39*, 95–102. https://doi.org/10.1016/j.cofs.2021.01.006

[81]. Rahman, M. T., Sobur, M. A., Islam, M. S., Ievy, S., Hossain, M. J., El Zowalaty, M. E., & Ashour, H. M. (2014). Important bacterial zoonoses in the "One Health" concept. *Frontiers in Public Health*, *2*, 144. https://doi.org/10.3389/fpubh.2014.00144

[82]. Rakibul, H., & Samia, A. (2022). Information System-Based Decision Support Tools: A Systematic Review Of Strategic Applications In Service-Oriented Enterprises. *Review of Applied Science and Technology*, *1*(04), 26-65. https://doi.org/10.63125/w3cevz78

[83]. Rejeb, A., Keogh, J. G., & Rejeb, K. (2022). Big data in the food supply chain: A literature review. *Journal of Data, Information and Management*, *4*(1), 33–47. https://doi.org/10.1007/s42488-021-00064-0

[84]. Ren, Y., He, Z., & Luning, P. A. (2016). A systematic assessment of quality assurance-based food safety management system of a Chinese edible oil manufacturer. *Total Quality Management & Business Excellence*, *27*(8–9), 897–911. https://doi.org/10.1080/14783363.2016.1187995

[85]. Reza, M., Vorobyova, K., & Rauf, M. (2021). The effect of total rewards system on the performance of employees with a moderating effect of psychological empowerment and the mediation of motivation in the leather industry of Bangladesh. *Engineering Letters*, *29*, 1-29.

[86]. Rony, M. A., & Ashraful, I. (2022). Big Data And Engineering Analytics Pipelines For Smart Manufacturing: Enhancing Efficiency, Quality, And Predictive Maintenance. *American Journal of Scholarly Research and Innovation*, *1*(02), 59–85. https://doi.org/10.63125/rze0my79

[87]. Rony, M. A., & Hozyfa, S. (2024). Cloud-Integrated Digital Twin Architectures For Real-Time Monitoring, Risk Assessment, And Safety Optimization In U.S. Energy Infrastructure. *American Journal of Interdisciplinary Studies*, *5*(04), 96-133. https://doi.org/10.63125/y9m5pz24

[88]. Russell, S. J., & Norvig, P. (2010). *Artificial intelligence: A modern approach (3rd ed.)*.

[89]. Saba, A., & Md. Sakib Hasan, H. (2024). Machine Learning And Secure Data Pipelines For Enhancing Patient Safety In Electronic Health Record (EHR) Among U.S. Healthcare Providers. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 124–168. https://doi.org/10.63125/qm4he747

[90]. Saba, A., Shaikat, B., & Tonoy Kanti, C. (2023). Integration Of Artificial Intelligence And Advanced Computing To Develop Resilient Cyber Defense Systems. *Journal of Sustainable Development and Policy*, *2*(04), 74-107. https://doi.org/10.63125/rxyc6y88

[91]. Saba, A., & Tonoy Kanti, C. (2023). Explainable Artificial Intelligence (XAI) Approaches For Cyber Risk Assessment In Financial Services. *American Journal of Interdisciplinary Studies*, *4*(03), 96-135. https://doi.org/10.63125/3gjcb322

[92]. Sadilek, A., Caty, S., DiPrete, L., Mansour, R., Schenk, T., Bergtholdt, M., Jha, A., Ramaswami, P., & Gabrilovich, E. (2018). Machine-learned epidemiology: Real-time detection of foodborne illness at scale. *npj Digital Medicine*, *1*, 36. https://doi.org/10.1038/s41746-018-0045-1

[93]. Saikat, S. (2021). Real-Time Fault Detection in Industrial Assets Using Advanced Vibration Dynamics And Stress Analysis Modeling. *American Journal of Interdisciplinary Studies*, *2*(04), 39–68. https://doi.org/10.63125/0h163429

[94]. Saikat, S. (2022). CFD-Based Investigation of Heat Transfer Efficiency In Renewable Energy Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 129–162. https://doi.org/10.63125/ttw40456

[95]. Shaikat, B., & Md. Wahid Zaman, R. (2024). Quantum-Resistant Cryptographic Protocols Integrated With AI For Securing Cloud And IOT Environments. *International Journal of Business and Economics Insights*, *4*(4), 60–90. https://doi.org/10.63125/dryw3b96

[96]. Shaikh, S., & Aditya, D. (2021). Federated Learning-Driven Predictive Quality Analytics and Supply Chain Optimization In Distributed Manufacturing Networks. *Review of Applied Science and Technology*, *6*(1), 74-107. https://doi.org/10.63125/k18cbz55

[97]. Shaikh, S., & Md. Tahmid Farabe, S. (2023). Digital Twin-Driven Process Modeling For Energy Efficiency And Lifecycle Optimization In Industrial Facilities. *American Journal of Interdisciplinary Studies*, *4*(03), 65–95. https://doi.org/10.63125/e4q64869

[98]. Shaikh, S., & Sudipto, R. (2022). Multi-Objective Thermo-Economic and Supply Chain Optimization Modeling For Hydrogen Energy Integration In Smart Factories. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 163–193. https://doi.org/10.63125/p9y8p705

[99]. Sudipto, R., & Md. Hasan, I. (2024). Data-Driven Supply Chain Resilience Modeling Through Stochastic Simulation And Sustainable Resource Allocation Analytics. *American Journal of Advanced Technology and Engineering Solutions*, *4*(02), 01-32. https://doi.org/10.63125/p0ptag78

[100]. Taha, S., Wilkins, S., Juusola, K., & Osaili, T. M. (2020). Food safety performance in food manufacturing facilities: The influence of management practices on food handler commitment. *Journal of Food Protection*, *83*(1), 60–67. https://doi.org/10.4315/0362-028x.Jfp-19-126

[101]. Tajkarimi, M. (2020). Food safety and quality data management using artificial intelligence. *Food Protection Trends*, *40*(6), 464–467.

[102]. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350. https://doi.org/10.1002/smj.640

[103]. Tonoy Kanti, C., & Saba, A. (2024). High-Performance Computing Architectures To Strengthen Cloud Infrastructure Security. *American Journal of Interdisciplinary Studies*, *5*(03), 01–42. https://doi.org/10.63125/9hr8qk06

[104]. Tonoy Kanti, C., & Sai Praveen, K. (2024). Federated Learning Models for Privacy-Preserving Data Sharing And Secure Analytics In Healthcare Industry. *International Journal of Business and Economics Insights*, *4*(4), 91-133. https://doi.org/10.63125/c2dzn006

[105]. Tonoy Kanti, C., & Shaikat, B. (2021). Blockchain-Enabled Security Protocols Combined With AI For Securing Next-Generation Internet Of Things (IOT) Networks. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 98–127. https://doi.org/10.63125/pcdqzw41

[106]. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

[107]. Wang, X., Bouzembrak, Y., Oude Lansink, A. G. J. M., & van der Fels-Klerx, H. J. (2022). Application of machine learning to the monitoring and prediction of food safety: A review. *Comprehensive Reviews in Food Science and Food Safety*, *21*(1), 416–434. https://doi.org/10.1111/1541-4337.12868

[108]. White, A., & Hughes, J. M. (2019). Critical importance of a One Health approach to antimicrobial resistance. *EcoHealth*, *16*, 404–409. https://doi.org/10.1007/s10393-019-01415-5

[109]. Yadav, D. K., Dutta, G., & Kumar, S. (2021). Food safety standards adoption and its impact on firms' export performance: A systematic literature review. *Journal of Cleaner Production*, *329*, 129708. https://doi.org/10.1016/j.jclepro.2021.129708

[110]. Zamal Haider, S., & Hozyfa, S. (2023). A Quantitative Study On IT-Enabled ERP Systems And Their Role In Operational Efficiency. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 62–99. https://doi.org/10.63125/nbpyce10

[111]. Zamal Haider, S., & Sai Praveen, K. (2024). Cloud-Native Data Pipelines For Scalable Audio Analytics And Secure Enterprise Applications. *American Journal of Scholarly Research and Innovation*, *3*(01), 52-83. https://doi.org/10.63125/m4f2aw73

[112]. Zhao, G., Liu, S., Lopez, C., Lu, H., Elgueta, S., Boshkoska, B. M., & Chen, H. (2019). Blockchain technology in agri-food value chain management: A synthesis of applications, challenges and future research directions. *Computers in Industry*, *109*, 83–99. https://doi.org/10.1016/j.compind.2019.04.002

[113]. Zulqarnain, F. N. U., & Zayadul, H. (2024). Artificial Intelligence Applications For Predicting Renewable-Energy Demand Under Climate Variability. *American Journal of Scholarly Research and Innovation*, *3*(01), 84–116. https://doi.org/10.63125/sg0j6930