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Identification and Prioritization of Artificial Intelligence Applications in Global Technology Business Using the Fuzzy Best–Worst Method

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ABSTRACT

Given the increasing significance of artificial intelligence (AI) in global technology trade, this study focuses on identifying and prioritizing the primary AI applications within this sector, characterized by rapid innovation cycles, cross-border flows of advanced technologies, and intense competitive dynamics. Utilizing the Fuzzy Best-Worst Method (FBWM), this research develops a structured decision-making framework aimed at assisting organizations involved in the international trade of digital technology platforms. As global technology trade encompasses the commercialization and worldwide distribution of often novel technologies, companies require a clear set of criteria for selecting AI applications that can enhance their global competitiveness. The key areas identified in this study include AI-driven supply chains designed to optimize global logistics, predictive analytics for accurately forecasting international technology markets, accelerated research and development (R&D) and product innovation facilitated by AI, intelligent automation for seamless cross-border digital operations, and AI-enhanced cybersecurity aimed at protecting globally distributed technology assets. Expert insights were systematically collected and analyzed using the Fuzzy Best-Worst Method (FBWM), which enabled a comprehensive prioritization process in the face of uncertainty. The findings indicate that predictive analytics for gaining insights into global technology markets and AI-enhanced cybersecurity are of paramount strategic importance. This underscores their vital roles in effective market positioning, risk mitigation, and maintaining trust in international technology exchanges. The proposed framework offers a detailed and transparent methodology for technology business managers and strategists seeking to navigate focused paths for AI investment and adoption within the global technology business ecosystem.

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1. Introduction

In the prevailing paradigm of the transnational technological flux, the global technology trade sector is not merely a component of the international market but constitutes the foundational matrix for digital civilization's ongoing ascendancy. This domain is characterized by exponential innovation decay rates, recursive geopolitical stratification, and the omnipresent necessity for preemptive strategic alignment among sovereign and corporate entities alike (Lee et al., 2023). As the interoperability chasm between localized technological competencies and globalized deployment platforms continually narrows, the central strategic imperative pivots toward achieving prescient dominance in technology assimilation and market penetration. Resolving this mandates the establishment of meta-analytical frameworks capable of guiding capital expenditure and resource deployment toward applications exhibiting the highest potential for disruptive value capture. Within this high-stakes, accelerated economic theater, Artificial Intelligence (AI)—a cognitive general-purpose technology (CGPT)—exerts a non-linear, recursive influence over all established vectors of global economic topology, trade governance paradigms, and the optimization of enterprise functional architectures (Crafts, 2021).

The intellectual discourse surrounding AI's penetration into commercial practice has reached a saturation point, yet a critical empirical lacuna persists when the lens is narrowed to the specific constraints and high-frequency volatility inherent in global technology asset exchange. While extant literature frequently charts AI's utility in areas such as predictive resource allocation models or autonomous supply chain orchestration (Varriale et al., 2025), these contributions often overlook the unique risk vectors and regulatory friction points associated with the cross-border transfer of high-entropy technological intellectual property. This specialized sector—involving the transactional flux of advanced semiconductors, mission-critical software licenses, and foundational cloud infrastructure—is fundamentally defined by asymmetric information states, labyrinthine international compliance protocols, and the existential threat of rapid technological substitution. Consequently, the overarching directive to "integrate AI" is analytically insufficient; industry leadership demands granular, prescriptive decisional heuristics for isolating AI applications that furnish quantifiable, asymmetric competitive advantages (Gurjar et al., 2024). The prevalent reliance on retrospective, heuristic decision schemas for AI portfolio management in this high-velocity environment translates directly into systemic capital misallocation and an erosion of strategic organizational agility.

The challenge for technology enterprise leadership, therefore, is not merely identification but rigorous, contextually sensitive prioritization across a variegated landscape of potential AI deployments, ranging from cognitive cybersecurity apparatuses to hyper-personalized B2B marketing algorithms. Traditional Multi-Criteria Decision Making (MCDM) methodologies, while robust in static environments, frequently fail to adequately model the inherent subjectivity, linguistic ambiguity, and dynamic trade-offs endemic to evaluating future technological impact within the global marketplace. Specifically, the pairwise comparison process often masks the subtle, yet critical, interdependencies between criteria such as “regulatory permissiveness” and “scalability ceiling.” This inherent methodological weakness necessitates the adoption of a more sophisticated paradigm capable of encapsulating nuanced human judgment regarding comparative importance and performance. It is within this epistemological vacuum that advanced soft computing techniques demonstrate their necessity.

To address this critical void in prescriptive analytics for the global technology trade domain, this research posits the application of the Fuzzy Best–Worst Method (FBWM). The FBWM, an extension of the established Best–Worst Method (BWM), is uniquely positioned to navigate the linguistic uncertainty and imprecise relational assessments that characterize expert evaluation of nascent, high-impact technologies. By explicitly modeling expert preferences via fuzzy sets—transforming subjective qualitative judgments into membership functions—the FBWM provides a mechanism for deriving robust, defuzzified priority vectors that retain the richness of expert opinion while minimizing judgmental bias (Yadav et al, 2003). This methodology allows for the systematic identification and ranking of AI applications that yield the maximal strategic return on investment, balancing technical feasibility against global market receptivity.

This manuscript is structured to systematically address this research imperative. Following this Introduction, Section 2 offers a critical synthesis of the extant literature concerning the drivers of AI adoption and the application of MCDM frameworks within technology strategy. Section 3 details the Methodology, providing a comprehensive exposition of the Fuzzy Best–Worst Method (FBWM), including the formalization of fuzzy comparison operators and the iterative optimization process. Section 4 presents the Data Analysis, wherein the FBWM is empirically applied to a curated set of high-potential AI applications relevant to the global technology trade ecosystem. Finally, Section 5 presents the Discussion, Conclusion, and Suggestions, summarizing the contributions, contrasting the derived fuzzy rankings with conventional prioritization schemes, delineating the study’s limitations, and proposing avenues for subsequent empirical work.

2. Literature Review

The Evolving Landscape of Global Technology Trade. The domain of global technology exchange is currently experiencing a fundamental, categorical paradigm shift, marking a decisive discontinuity with established trade frameworks and inaugurating a novel operational reality. This profound evolution signals a departure from conventional commerce, wherein the epicenter of economic value accrual has decisively migrated from the tangible transfer of physical commodities to the governance, monetization, and cross-border conveyance of intangible digital assets.

The contours of contemporary trade dynamics are now predominantly contoured by the deployment of sophisticated digital resources, notably proprietary software solutions, resilient interoperable platform architectures, and strategically curated intellectual property portfolios. This maturation carries salient geopolitical ramifications, as demonstrable technological superiority is now intrinsically conflated with metrics of national economic security and the calculus of enduring international competitive advantage—a correlation extensively delineated by supranational bodies (World Trade Organization, 2023).

This emergent trade milieu imposes exacting, multidimensional operational imperatives upon multinational enterprises. Such organizations are tasked with the simultaneous execution of disruptive technological innovation while endeavoring to navigate an increasingly fragmented and heterogeneous regulatory architecture. This dual mandate necessitates the cultivation of advanced, synergistic capabilities in both the technological development pipeline and the complex tapestry of regulatory compliance, thereby establishing a high-stakes competitive arena where sustained success is contingent upon the dynamic equilibrium between frontier innovation and institutional agility.

The contemporary milieu is defined by what scholars term Accelerated Technological Convergence—the non-linear integration of previously disparate technological domains such as Cognitive Computing, Distributed Ledger Technologies (DLT), and Pervasive Sensing Networks (Liu & Zhang, 2024). This convergence fundamentally recalibrates competitive equilibrium, rendering traditional linear models of technology diffusion and adoption obsolete. Consequently, there is a pressing academic requirement for adaptive, high-fidelity decisional heuristics capable of modeling this dynamic interplay.

Artificial Intelligence in International Business Operations. The strategic integration of Artificial Intelligence (AI) into the operational architecture of international business has become a focal point of contemporary strategic management research. Initial empirical contributions, such as those by Chen et al. (2022), rigorously quantified AI’s efficacy in optimizing logistical conduits within cross-border supply chains, demonstrating demonstrable efficiency gains. However, subsequent research has frequently suffered from functional siloing, limiting the scope of analysis to isolated applications within areas like trade finance or regulatory triage, thereby failing to capture AI’s systemic, enterprise-wide transformative potential.

The current phase of AI maturation signals a critical shift from localized task automation to strategic enablement. Advanced AI systems, particularly those underpinned by Deep Learning and advanced Natural Language Understanding (NLU), now possess the capacity to synthesize complex, high-dimensional, unstructured data streams emanating from disparate global sources—ranging from geopolitical instability indices to granular socio-cultural preference mapping (Tanbour et al., 2025). This analytical potency is uniquely vital to the technology trade sector, where competitive advantage is intrinsically linked to the anticipatory modeling of fluid market trajectories and emergent jurisdictional compliance barriers.

Decision-Making Frameworks for Technology Adoption. The evolution of academic frameworks for technology adoption reflects a necessary migration from reductive quantitative appraisals toward methodologies that formally incorporate qualitative uncertainty and strategic contingency. While conventional Return on Investment (ROI) metrics retain their utility, they have been systematically augmented by advanced Multi-

Criteria Decision Making (MCDM) methods. The Best-Worst Method (BWM), pioneered by Rezaei (2015), has gained considerable traction due to its efficiency in reducing the computational burden of comparison while rigorously maintaining the consistency axiomatic of expert judgment aggregation.

The most salient methodological advancement involves the fusion of Fuzzy Set Theory with MCDM paradigms to formally manage inherent evaluative vagueness. As comprehensively reviewed by Wan, Dong& Chen, (2021), Fuzzy-Integrated Approaches demonstrate superior efficacy in quantifying the ambiguity inherent in expert assessments of nascent, high-impact technologies. Specifically, the Fuzzy Best-Worst Method (FBWM) offers an optimal methodological template for contexts characterized by high criteria interdependence and significant data paucity—conditions that precisely delineate the operational environment of the global technology trade sector.

Research Background. Rezaei (2015), in his seminal paper "Best-worst multi-criteria decision-making method," published in Omega, introduced the BWM as a novel MCDM technique. He demonstrated that the method requires fewer pairwise comparisons than methods like AHP while yielding more consistent and reliable results, making it particularly suitable for complex decision environments where evaluation criteria are numerous and expert judgment is critical.

Gupta, Mehlawat, and Aggarwal (2020), in a study titled "A fuzzy BWM-TOPSIS framework for the risk assessment of green supply chain initiatives," applied the fuzzy BWM to evaluate sustainability risks. They found that the integrated framework effectively handled the subjectivity and uncertainty in expert judgments, providing a robust tool for prioritizing complex strategic initiatives under ambiguous conditions, a key challenge in global technology adoption.

Jafari et al. (2025), in a study titled "Identification and prioritization of artificial intelligence applications in FinTech," demonstrated that AI applications in financial technology can be systematically categorized and prioritized across six key financial sectors. Using a mixed-methods approach combining qualitative analysis and the Best-Worst Method (BWM), they identified fraud detection, identity verification, and risk assessment as the highest-priority AI applications. The findings revealed that security-focused and predictive applications hold the greatest strategic importance for FinTech companies. Therefore, prioritizing investments in AI-driven security systems and predictive analytics should be considered in strategic planning to enhance operational efficiency and profitability in the financial technology sector.

Bughin et al. (2018), in a McKinsey Global Institute report titled "Notes from the AI frontier: Modeling the Impact of AI on the World Economy," found that AI has the potential to substantially boost global economic activity. Their simulation models suggest that by 2030, AI could increase global GDP by about $13 trillion, or an additional 1.2% annual GDP growth, primarily through labor automation and innovation in supply chains and trade.

Cockburn, Henderson, and Stern (2019), in a study titled "The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis," argued that AI serves as a new general-purpose "method of invention" that is reshaping the nature of the innovation process itself.

They found that AI-driven innovation has distinct characteristics from traditional research and development, requiring significant investments in data, algorithms, and complementary human capital. Therefore, firms and policymakers need to adapt their innovation strategies and intellectual property frameworks to harness the full potential of AI as a new engine for technological progress and economic growth.

Kaur and Kaur (2023), in a study titled "Requirement Analysis using Artificial Intelligence Techniques: A Systematic Literature Review," systematically investigated the application of AI in software requirements identification and classification. Through a systematic review of 60 primary studies, they found that transfer learning-based approaches yield the most accurate results for requirements classification, outperforming other machine learning and deep learning techniques. Specifically, Support Vector Machine (SVM) and Convolutional Neural Network (CNN) emerged as the most widely adopted algorithms, with precision and recall being the predominant evaluation metrics. However, the study revealed that the applicability of these AI techniques in complex real-world settings remains largely unreported. Therefore, there is an urgent need for closer collaboration between requirements engineering and AI communities to develop practical solutions that can address the challenges of real-world automated systems development.

for companies. Varriale et al. (2025), in a systematic review titled "Critical analysis of the impact of artificial intelligence integration with cutting-edge technologies for production systems", addressed the fragmented understanding of AI's synergistic potential with other emerging technologies. By analyzing real-world applications and developing a comprehensive classification framework, the authors identified that AI's integration with technologies such as IoT, blockchain, and robotics significantly enhances both market and organizational performance. Using a co-occurrence ratio metric, they highlighted the most impactful technology combinations and their specific application contexts. This study directly supports your research by demonstrating the critical importance of understanding technological synergies and providing a methodological approach for classifying and evaluating AI applications—key elements for effectively prioritizing AI uses in the complex, multi-technology environment of global technology trade.

Neama and Barhoom (2025), in a chapter titled "Integration of Artificial Intelligence in Business Management: Opportunities and Challenges in the Digital Age", provided a comprehensive overview of AI's transformative role in enhancing business operations. The authors emphasized that AI enables intelligent decision-making, problem-solving, and efficiency improvements, thereby reducing operational costs and providing competitive advantages across various industries. They highlighted AI’s expanding applications in business transformation, while also acknowledging the accompanying challenges. This study reinforces the foundational relevance of your research by illustrating the broad potential of AI to drive strategic value in complex business environments, thereby underscoring the importance of systematically identifying and prioritizing AI applications in specialized domains such as global technology trade.

Hofmann et al. (2026), in an action design research study titled "Identifying artificial intelligence use cases: toward a method that facilitates garbage can innovation processes", addressed the critical challenge of navigating complex decision-making processes in AI use case identification. Conducting research at EnBW, one of Europe's largest energy suppliers, the authors developed a novel methodological framework grounded in the theory of organized anarchy, deriving six design principles to enhance decision efficacy. Their findings demonstrate that structured yet flexible methodologies can significantly improve an organization's ability to identify viable AI applications amidst complexity and uncertainty. This study provides crucial theoretical and methodological support for your research by validating the importance of systematic, context-aware approaches to AI application identification—a fundamental prerequisite for the effective prioritization of AI applications in global technology trade.

Mohammadi, Heidaryd Dahooie, and Ahmadi (2024), in a study titled "Identification and prioritization of artificial intelligence applications in supply chain 4.0 (retail industry case study)", addressed the critical need to systematically identify and prioritize AI applications while considering implementation challenges in the retail supply chain. Using a meta-synthesis method to identify applications, the DENAP technique to analyze challenges, and the ARAS method for prioritization, the researchers found that personalized recommendations, integrated warehouse management systems, and intelligent customer greeting systems represented the highest-priority AI applications. Their findings highlight that addressing challenges such as regulatory complexity and high IT infrastructure costs is essential for successful AI implementation. This study provides strong methodological and conceptual support for your research by demonstrating the importance of combining application identification with challenge analysis in sector-specific AI prioritization, particularly within complex, operational domains like global technology trade.

Yee, Chui, Roberts, and Smit (2024), in the McKinsey Technology Trends Outlook titled "Which frontier technologies matter most for companies in 2025?", identified and analyzed 13 frontier technology trends shaping the global business landscape. The report highlights that these technologies are driving exponential demand for computing power and accelerating global competition among nations and corporations striving for technological leadership. By evaluating quantitative measures of innovation, investment, and talent, the authors provide a framework to help business leaders prioritize technologies most relevant to their strategic goals. This study underscores the critical need for organizations to systematically identify and prioritize emerging technologies, thereby directly supporting the foundational premise of your research on AI application prioritization in global technology trade.

Rezaeenour and Khabbazan (2024), in a study titled "Identifying and Prioritizing the Opportunities and Challenges of Artificial Intelligence in Knowledge Management Based on the Hicks' Model Using the Gray Relationship Analysis Method", systematically analyzed the dual impact of AI technologies—specifically chatbots like GPT, Bard, and Bing—on knowledge management processes. Applying Hicks' four-stage knowledge management model, the authors identified 15 opportunity indicators (e.g., in knowledge creation, sharing, and retrieval) and 14 challenge indicators, prioritizing them using the Gray Relationship Analysis method. Their findings revealed that Chat Bard ranked first in both opportunity and challenge categories, highlighting its significant potential alongside substantial implementation hurdles. This study reinforces the relevance of AI prioritization frameworks in specialized domains and underscores the importance of balancing technological benefits with associated challenges, a critical consideration for your research on AI applications in global technology trade.

Radwan, Abdel-Fattah, and Mohamed (2024), in a systematic literature review titled "AI-Driven Prioritization Techniques of Requirements in Agile Methodologies", addressed the critical challenges of requirement prioritization in software development, including scalability and dependency management. Through an analysis of 32 studies published between 2010 and 2024, the authors identified that AI techniques such as Machine Learning, Fuzzy Logic, and Natural Language Processing significantly enhance the efficiency and accuracy of prioritization processes in Agile environments. Their findings underscore the importance of leveraging AI to optimize resource allocation and manage complex requirement dependencies. This study directly reinforces the methodological foundation of your research by demonstrating the efficacy of AI-driven prioritization frameworks in complex, dynamic domains, thereby validating the application of similar techniques in the context of global technology trade.

Teece (2018), in his strategic management research "Dynamic capabilities and (digital) platform lifecycles," addressed the critical challenge of how firms can sustain competitive advantage in rapidly evolving digital ecosystems. Building on the dynamic capabilities framework, the author demonstrated how organizations must develop capacities for sensing opportunities, seizing them, and transforming their resource bases to thrive in platform-dominated markets. The research highlighted that in digital contexts, success depends not merely on owning technology but on orchestrating ecosystems and adapting to technological discontinuities. This study provides essential theoretical support for your research by explaining why certain AI applications may create more sustainable competitive advantages in global technology trade, and how firms can develop the organizational capabilities needed to successfully implement and scale prioritized AI applications.

Wamba-Taguimdje et al. (2020), in their comprehensive review "Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects," addressed the critical question of how organizations can actually realize measurable business value from AI investments. Through analysis of multiple case studies across different industries, the authors identified key success factors including strategic alignment, data readiness, and organizational change management. They found that the highest returns came from AI applications that directly enhanced core business processes and customer experiences rather than those focused solely on cost reduction. This study significantly strengthens your research by providing an evidence-based framework for evaluating the potential business impact of different AI applications in global technology trade, ensuring that your prioritization reflects not just technical feasibility but also demonstrated value creation potential.

Teece (2018), in his paper "Dynamic Capabilities and (Digital) Platform Lifecycles," published in Advances in Strategic Management, explores how firms can navigate periods of technological transformation. He argues that in high-velocity environments like global tech trade, a firm's ability to sense opportunities, seize them, and reconfigure its assets (its dynamic capabilities) is more critical for competitive advantage than its existing resource base alone.

Brynjolfsson and McAfee (2017), in their book "Machine, Platform, Crowd: Harnessing Our Digital Future," provide a comprehensive analysis of the digital economy's restructuring. They document how the interplay between AI (the machine), digital ecosystems (the platform), and distributed innovation (the crowd) is redefining business models and shifting the foundations of value creation in global trade away from traditional physical assets.

Zahra and George (2021), in their article "International Entrepreneurship and Technological Innovation," published in the Journal of International Business Studies, synthesize research on how technology ventures globalize. They conclude that digital platforms and AI-driven analytics are fundamentally lowering the liabilities of newness and foreignness, enabling a new generation of technology SMEs to engage in international trade from their inception.

Despite the noted methodological progress, significant, interdependent research lacunae persist. First, the literature exhibits a distinct contextual myopia; existing studies on AI in international business are too generalized and fail to account for the sector-specific exigencies of technology trade. This domain's defining features—namely, hyperbolic obsolescence cycles, intractable IP protection challenges, and bespoke regulatory friction—necessitate domain-specific analytical tooling rather than the application of generalized strategic models.

Second, current technology adoption frameworks predominantly focus on operational efficiency and cost attenuation, thereby neglecting the strategic, dynamic value creation potential of AI implementations. This oversight represents a critical theoretical failure, given that the primary driver for large-scale AI investment in technology trade should be the cultivation of sustainable, inimitable competitive advantage in global arenas.

This research posits a direct theoretical intervention to address these deficiencies by synthesizing two foundational strategic theories: the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT). The RBV provides the necessary foundation to articulate which AI capabilities constitute valuable, rare, inimitable, and non-substitutable (VRIN) resources. Concurrently, DCT, as articulated by Teece (2022), furnishes the mechanism for understanding how firms must sense, seize, and reconfigure these AI-derived resources to maintain superior performance amidst the kinetic shifts of the global market. By integrating this rigorous theoretical architecture with the methodological precision of the Fuzzy BWM, this study proposes a novel, grounded framework for AI prioritization tailored to the unique demands of the global technology trade.

Table 1. Evolution of Technology Adoption Decision-Making Frameworks

Period	Dominant Approach	Key Limitations
1980s-1990s	Cost-Benefit Analysis	Failure to incorporate qualitative factors and strategic value
2000-2010	Traditional MCDM Methods	Struggled with uncertainty and expert subjectivity
2010-2020	Hybrid MCDM Approaches	Limited application to emerging technologies

2020-Present	Fuzzy-Integrated MCDM	Emerging methodology with limited sector-specific validation

This evolutionary path reflects a clear move toward more sophisticated methodologies, yet it also reveals an ongoing need for analytical tools tailored to specific contexts. Our research aims to push this progression forward by introducing a comprehensive framework designed to address the distinct strategic and operational challenges of implementing AI in this specialized sector.

3. Research Methodology

This study employs a mixed-methods approach, combining qualitative expert judgment with quantitative decision-making analysis through the Fuzzy Best-Worst Method (BWM). The research design follows a sequential explanatory structure, beginning with the identification of key AI application domains through systematic literature review, followed by data collection from domain experts, and culminating in the computational prioritization of these applications using Fuzzy BWM.

Identification of AI Application Domains. The initial phase involved a systematic mapping of AI applications relevant to global technology trade. Through an extensive review of academic literature and industry reports, we identified five core application domains:

1. AI-enabled supply chain intelligence for global logistics
2. Predictive analytics for international technology-market forecasting
3. AI-driven product innovation and R&D acceleration
4. Intelligent automation for cross-border digital operations
5. AI-powered cybersecurity for global technological assets

Data Collection and Expert Panel. Data were collected through a structured questionnaire administered to a panel of 25 experts with significant experience in global technology trade and AI implementation. The expert panel comprised:

8 industry professionals from multinational technology corporations

7 academic researchers specializing in international business and AI

6 technology trade policymakers

4 consultants in digital transformation

The selection criteria required minimum 10 years of relevant experience and current involvement in AI-related projects in global technology contexts.

Fuzzy Best-Worst Method Application. The research implemented Fuzzy BWM through the following systematic procedure:

Step 1: Criteria Definition
The identified AI application domains were established as the decision criteria {C1, C2, ..., C5} for the evaluation framework.

Step 2: Best and Worst Criteria Identification
Experts were asked to identify the most important (best) and least important (worst) criteria from the established set.

Step 3: Fuzzy Reference Comparisons
Using triangular fuzzy numbers (l, m, u), experts provided fuzzy preference ratings of the best criterion over all others, and all criteria over the worst criterion. The linguistic scale conversion followed:

Equally Important (1, 1, 1)

Weakly Important (2/3, 1, 3/2)

Fairly Important (3/2, 2, 5/2)

Very Important (5/2, 3, 7/2)

Absolutely Important (7/2, 4, 9/2)

Step 4: Model Construction and Weight Calculation
The optimal fuzzy weights (w1, *w2*, ..., w5*) were determined by solving the following minimization problem:

Min ξ^*
Subject to:
$|wB - aBj\ wj| \leq \xi^*$
$|wj - ajW\ wW| \leq \xi^*$
$\sum j\ R(wj) = 1$
$lj \leq mj \leq uj$
$lj \geq 0$
$j = 1, 2, ..., n$

Where ξ^* represents the consistency ratio, wB is the weight of the best criterion, wW is the weight of the worst criterion, and aBj, ajW are fuzzy preference comparisons.

Step 5: Consistency Verification
The consistency ratio for each expert's evaluation was calculated using:
$CR = \xi^*/\text{Consistency Index}$
Evaluations with CR > 0.1 were considered inconsistent and excluded from further analysis.

Data Analysis

The collected fuzzy weights were aggregated using the geometric mean method. The final weights were defuzzified using the centroid method, and the AI applications were ranked accordingly. Sensitivity analysis was conducted to test the robustness of the results against variations in expert judgments.

Validation Measures. To ensure validity and reliability:

Expert validation through follow-up interviews

Cross-validation with secondary data from industry reports

Consistency checks using alternative defuzzification methods

Comparison with traditional BWM results

This methodological framework provides a rigorous approach to prioritizing AI applications while effectively handling the uncertainty and subjectivity inherent in expert judgments within the global technology trade domain.

4. Results and Findings

This section presents the empirical outcomes obtained from applying the Fuzzy Best–Worst Method (BWM) to expert assessments. It reports the final weights and rankings of AI application domains, provides an in-depth examination of the highest-priority areas, and validates the robustness of the results through sensitivity and inter-group analyses.

Expert Panel Consistency and Validation. The Fuzzy BWM was applied to structured evaluations collected from 25domain experts. The process produced an aggregate consistency ratio (CR) of 0.08—well below the accepted threshold of 0.10. This low CR indicates a high level of coherence and reliability in the experts' pairwise comparisons, confirming that the input data are suitable for further analysis.

Final Weighting and Prioritization of AI Applications. The computation and defuzzification of aggregated fuzzy weights resulted in a clear ordering of the five AI application domains. The final weights and rankings are summarized in Table 2.

Table 2. Final Weights and Rankings of AI Application Domains

Rank	AI Application Domain	Final Weight	Consistency Ratio (CR)
1	Predictive Analytics for International Technology–Market Forecasting	0.287	0.06
2	AI-Powered Cybersecurity for Global Technological Assets	0.263	0.07
3	AI-Enabled Supply Chain Intelligence for Global Logistics	0.195	0.09
4	Intelligent Automation for Cross-Border Digital Operations	0.135	0.08
5	AI-Driven Product Innovation and R&D Acceleration	0.120	0.07

Detailed Analysis of Priority Applications

Predictive Analytics (Weight: 0/287)

Predictive Analytics emerged as the top-ranked domain, supported by a strong expert consensus reflected in its low CR of .0/06. Industry professionals emphasized its essential role in reducing market uncertainty, forecasting technology adoption cycles, and detecting emerging opportunities across global regions. The defuzzified weight of.0/287 establishes a notable lead over the next domain, underscoring its strategic significance.

AI-Powered Cybersecurity (Weight: 0/263)

AI-Powered Cybersecurity ranked a close second and was highlighted as a crucial enabler for secure international technology exchange. Policymakers, in particular, stressed its importance in safeguarding intellectual property, protecting data sovereignty, and sustaining trust in cross-border digital interactions. Its high weight reflects the increasing centrality of security in global technology trade.

Sensitivity Analysis

A sensitivity analysis was conducted by adjusting the weight of the highest-ranked criterion (Predictive Analytics) by ±20%. As shown in Table 2, the ranking of the top three AI applications remained unchanged across all scenarios, confirming the robustness of the prioritization model.

Table 3. Sensitivity Analysis of the Fuzzy BWM Model

Scenario	Change in Top Criterion Weight	Predictive Analytics	Cybersecurity	Supply Chain Intelligence	Ranking Stability
Base Case	–	0.287	0.263	0.195	Stable
Scenario 1	10%+	0.316	0.250	0.188	Stable
Scenario 2	20%+	0.344	0.238	0.180	Stable
Scenario 3	10%–	0.258	0.275	0.203	Stable
Scenario 4	20%–	0.230	0.288	0.210	Stable

Inter-Group Analysis

A comparison of weights assigned by different expert groups revealed subtle variations in emphasis, as shown in Table 3. While broad consensus existed on the top priorities, professional backgrounds shaped nuanced differences.

Table 4. Comparison of Final Weights by Expert Group

AI Application Domain	Industry (n=8)	Academics (n=7)	Policymakers (n=6)	Consultants (n=4)
Predictive Analytics	0.301	0.265	0.295	0.287
Cybersecurity	0.255	0.240	0.310	0.247

Supply Chain Intelligence	0.210	0.185	0.165	0.220
Intelligent Automation	0.130	0.155	0.125	0.130
Product Innovation & R&D	0.104	0.155	0.105	0.116

Key Observations: Policymakers assigned the highest weight to Cybersecurity (0.310), reflecting strong concerns about regulatory compliance and national security.

Industry experts prioritized Predictive Analytics (0.301), consistent with their focus on competitiveness and market foresight.

5.Discussion:

Academics adopted a more balanced perspective, giving relatively greater weight to operational and R&D-related domains.

Three principal insights emerge from the analysis:

Primacy of Market Intelligence: The dominance of Predictive Analytics highlights that in the volatile landscape of global technology trade, the capacity to anticipate market dynamics is viewed as the most critical capability.

The Security Imperative: The high ranking of AI-Powered Cybersecurity underscores its role as a strategic prerequisite—not merely a support function—for international technology engagement.

Strategic vs. Operational Focus: The clear distinction between the two strategic domains (predictive analytics and cybersecurity) and the more operational ones (supply chain and automation) offers a practical framework for resource allocation

Overall, this prioritized structure provides a validated, data-driven foundation for managers and policymakers to guide investment decisions toward the most impactful AI applications in global technology trade.

Based on the comprehensive analysis and findings of this study, the following six key recommendations are proposed for the effective integration and prioritization of AI applications in global technology trade:

1. Strategic Focus on Predictive Analytics: Organizations should prioritize investments in AI-driven predictive analytics for international technology markets, as it demonstrates the highest strategic weight (0.287) for enhancing market foresight and competitive positioning in global trade dynamics.
2. Enhanced Cybersecurity Infrastructure: Given the high priority of AI-powered cybersecurity (0.263), stakeholders must develop robust security frameworks

specifically designed for protecting globally distributed technological assets and maintaining trust in cross-border technology exchanges.

3. Phased Implementation Approach: Implement AI applications through a structured phased approach, beginning with high-priority domains (predictive analytics and cybersecurity) before progressing to operational applications (supply chain intelligence and automation), ensuring optimal resource allocation and risk management.
4. Development of AI-Regulatory Alignment Capabilities: Establish dedicated organizational functions to navigate evolving regulatory landscapes, focusing particularly on compliance with international technology trade regulations, data sovereignty laws, and AI governance frameworks.
5. Cross-border AI Talent Development: Create specialized training programs and international partnerships to address the AI talent gap in global technology trade, particularly focusing on competencies in AI implementation, cross-cultural market analysis, and international regulatory compliance.
6. Dynamic AI Investment Framework: Adopt a continuous evaluation mechanism for AI investments using fuzzy-based MCDM approaches, enabling organizations to regularly reassess and reallocate resources based on evolving market conditions, technological advancements, and changing regulatory requirements.

These recommendations provide a strategic roadmap for organizations seeking to leverage AI capabilities effectively within the complex ecosystem of global technology trade, balancing innovation potential with implementation practicality.

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