Review

ESG, Technology, and Financial Performance in Global E-Commerce: A Panel Study

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Review

ESG, Technology, and Financial Performance in Global E-Commerce: A Panel Study

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Abstract: This study investigates the factors influencing the stock excess returns of 13 leading global e-commerce firms between 2015 and 2023 using panel data regression. The analysis integrates financial asset pricing, ESG risk, cultural context, and technological adoption. Expanding the Fama-French framework, a hybrid model was estimated. Specification tests, including a significant Hausman test ($\chi 2 = 32.1$, $p<0.01$), supported the use of the Entity Fixed Effects model to control for firm-specific unobserved heterogeneity. Results indicate that standard Fama-French factors are significant predictors of excess returns. The direct impact of the aggregate ESG risk score was not statistically significant in the preferred model ($p=0.12$). However, a significant interaction in the pooled analysis ($p = 0.05$) suggests that improving ESG performance from a low risk level is associated with greater excess returns. While cultural distance and an AI adoption proxy were included, their direct or moderating effects on excess returns were not statistically robust in the preferred model. The findings emphasize that while systematic risks drive e-commerce financial performance, strategic ESG improvement, particularly from a lower baseline, may offer tangible financial benefits.

Keywords: E-commerce; ESG risk; fama-french model; excess returns; panel data regression; asset pricing; technology adoption; cultural distance

1. Introduction

International e-commerce continues to experience significant growth, fueled by increased global connectivity and evolving consumer behaviors (Petersen et al., 2022; Tam & Lung, 2025). In parallel, the digital marketing landscape is undergoing rapid transformation, offering substantial opportunities such as cost reductions and improved brand visibility, while simultaneously presenting challenges like managing online reputation and mitigating negative electronic word-of-mouth (Dwivedi et al., 2021; Perera et al., 2022). This complex environment is further influenced by the swift emergence of disruptive technologies, including Artificial Intelligence (AI), advanced forms often referred to as 'agentic AI', and Extended Reality (XR) technologies, notably the Metaverse (Ameen et al., 2022; Bamberger et al., 2025; Nalbant & Aydin, 2025).

These technologies can profoundly transform marketing practices, affecting everything from personalization and customer relationship management to immersive brand experiences (Al-Adwan et al., 2025). Successfully integrating these emergent technologies into international e-commerce marketing strategies involves understanding complex factors such as consumer and firm adoption processes, the influence of diverse cultural contexts on technology acceptance, how value is created and co-created in new digital spaces, and critical ethical considerations like data privacy, potential AI bias, and issues related to digital equity (Axcell & Ellis, 2023; Yu & Liu, 2024).

Existing scholarly work offers valuable insights into various facets of this domain, examining digital marketing trends, specific AI applications in marketing, or aspects of technology adoption (Ford et al., 2023; Vlačić et al., 2021). Theoretical frameworks such as UTAUT/UTAUT2, models of cross-cultural adaptation, and Service-Dominant (S-D) Logic provide foundational perspectives for analyzing technology acceptance, cultural influences, and value creation, respectively (Anwar et al., 2024; Axcell & Ellis, 2023; Tang & Yang, 2025). While valuable, there is a gap in the literature that comprehensively integrates these elements and empirically investigates specific relationships within this evolving landscape using quantitative methods. This study seeks to contribute to bridging this gap by exploring certain quantifiable relationships relevant to technology adoption and its outcomes

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in a cross-cultural e-commerce context, building upon the theoretical foundations identified in the literature review.

The overall aim of this research is to develop a theoretical framework based on a comprehensive literature review and empirically investigate specific relationships related to technology adoption within the context of international e-commerce, utilizing panel data analysis.

Specific objectives include: 1) To empirically examine the impact of factors influencing financial performance, including ESG risk ratings and Fama-French factors, on firm financial performance (stock excess returns) using panel data. 2) To explore how a categorical firm or market characteristic may moderate the relationship between ESG risk ratings and stock excess returns. 3) To assess these relationships while accounting for potential unobserved heterogeneity across entities and over time.

Based on the empirical objectives, the study is guided by the following Research Questions, specifically addressable by the panel data regression analysis:

RQ1: What is the direct impact of ESG risk ratings on stock excess returns in global e-commerce firms over time?

RQ2: How does a categorical firm or market characteristic variable moderate the relationship between ESG risk ratings and stock excess returns?

RQ3: How do these relationships change when accounting for unobserved firm-specific and time-specific effects?

This research offers several significant contributions. By integrating theoretical frameworks such as UTAUT2, insights from cross-cultural literature (informed by studies like Thompson & Brouthers, 2021), and S-D Logic through a comprehensive literature review, the study provides a more integrated understanding of technology, culture, and value in international e-commerce marketing (Abid et al., 2025; Gibson et al., 2024; Tang & Yang, 2025). The empirical component tests specific relationships within this domain, providing quantitative evidence to support or refine theoretical propositions regarding factors influencing stock excess returns in a panel setting.

The insights from both the literature review and the empirical findings offer actionable guidance for international marketers. The review provides a structured understanding of the technological landscape and relevant theories. The panel data results offer quantitative evidence regarding the impact of ESG risk ratings and the role of a categorical firm or market characteristic variable, informing strategic decisions aimed at improving stock excess returns in diverse international e-commerce contexts while considering the importance of controlling for unobserved effects.

For the structure of the Paper, following this introduction, Section 2 details the materials and methods used, describing both the literature review methodology and the approach to panel data regression analysis. Section 3 presents a comprehensive theoretical background and literature review, covering the international e-commerce and digital marketing landscape, emergent technologies (AI, Agentic AI, Metaverse/XR), implications for core marketing concepts, relevant theoretical frameworks and presents the empirical results, including descriptive statistics and regression output. Section 4 discusses the findings concerning the literature and theoretical frameworks, addressing the research questions. Finally, Section 5 concludes the paper, summarizing implications, acknowledging limitations, and suggesting future research directions.

2. Materials & Methods

This study employs a mixed-methods approach that integrates a systematic literature review with quantitative panel data regression analysis to investigate the relationship between ESG risk ratings, financial factors, including the Fama-French framework, and the stock performance, specifically excess returns, of leading global e-commerce firms, such as Amazon (AMZN), Alibaba (BABA), JD.com (JD), eBay (EBAY), Walmart (WMT), Sea Ltd. (SE), MercadoLibre (MELI), PDD Holdings (PDD), Etsy (ETSY), Zalando (ZAL.DE), Allegro (ALE.WA), Target (TGT), and Rakuten (4755.T). This section delineates the specific methodologies utilized in the empirical investigation.

2.1. Review Methodology

A structured, three-stage process was implemented for the literature review to synthesize insights on technology adoption, cross-cultural marketing dynamics, and ESG performance within the e-commerce sector. Relevant scholarly articles were systematically searched across core databases, including Dimensions.ai, Scopus, and Web of Science, supplemented by specialized databases like the ACM Digital Library for technology-focused literature (AI/XR) and ABI/INFORM for marketing

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strategies. The search strategy employed key terms such as "e-commerce" or "digital retail" in combination with "ESG risk" or "sustainability performance," "Fama-French" or "asset pricing," and "technology adoption," "AI marketing," or "Metaverse CRM." This search was filtered to include peer-reviewed articles published between 2015 and 2024. The review specifically aimed to map how theoretical frameworks like UTAUT2 inform understanding of AI chatbot adoption in CRM, how Hofstede's dimensions can explain cultural moderation in the perception of ESG issues, and how Service-Dominant Logic illuminates value co-creation within AR/VR shopping environments. This comprehensive synthesis facilitated the identification of notable gaps in the existing literature, including limited integration of ESG metrics with technology-mediated consumer behavior models, regional biases in ESG-performance studies (particularly the underrepresentation of emerging markets), and a need to examine the temporal effects of initiatives like the UN Sustainable Development Goals (SDGs) on e-commerce stock returns.

2.1.1. Asset Pricing Model: Fama-French Five-Factor Model

This asset pricing study drew upon the Fama-French five-factor model (Fama & French, 2015), which extends the traditional Capital Asset Pricing Model (CAPM). This framework employs five specific factors to help explain observed divergences in asset returns.

2.1.2. ESG Risk Ratings Data Sources

ESG risk ratings, specifically including both composite scores and pillar-level (Environmental, Social, Governance) assessments, were primarily sourced utilizing the yesg Python library. These data were triangulated and validated against information obtained from reputable commercial ESG data providers, specifically referencing data available from MSCI (MSCI, 2024) and Morningstar-Sustainalytics (Morningstar-Sustainalytics, 2024)

2.2. Panel Data Regression Analysis

To empirically assess the factors driving the financial performance of leading global e-commerce firms, specifically measured by stock excess returns, a panel dataset was constructed. The dataset comprised 13 e-commerce firms worldwide, selected based on a market capitalization exceeding 10 billion, observed annually from 2015 through 2023. This time frame was chosen partly to align with the post-UN Sustainable Development Goals resolution period. The dependent variable was each firm's excess stock return (10 billion, observed annually from 2015 through 2023. This time frame was chosen partly to align with the post−UN Sustainable Development Goals resolution period. The dependent variable was each firm's excess stock return (Excess Return_it$) in period t, computed using the Capital Asset Pricing Model (CAPM). Independent variables included the standard Fama-French 5 factors (MKTit, SMBit, HMLit, RMWit, CMAit), which control for common systematic risks. ESG risk was a key independent variable, represented by both an aggregate composite score (ESG_Compositeit) and its Environmental, Social, and Governance components (e.g., metrics on carbon intensity, data privacy audits, AI ethics board presence). Control variables (Controljit) included firm size (log market cap), R&D expenditure (% of revenue), and cross-border transaction volume. The analysis also examined the moderating influence of cultural distance (Cultural_Distancei), derived from Hofstede dimension scores comparing the firm's primary market, on the ESG-excess return relationship. Additionally, a novel measure of AI adoption (AI_Adoption_Scoreit) was included, developed through NLP analysis of AI-related keyword density in firms' 10-K filings using transformer models.

The core empirical investigation involved estimating a hybrid asset-pricing model that extended the Fama-French framework to incorporate ESG performance, cultural distance, and technological adoption. The firm model i at time t was specified as:

Excess Returnit = β0 + β1(ESG_Compositeit) + β2(MKTit) + β3(SMBit) + β4(HMLit) + β5(RMWit) + β6(CMAit) + γ1(Cultural_Distancei × ESG_Compositeit) + γ2(AI_Adoption_Scoreit) + ∑j=1pθjControljit + αi + λt + ϵit$ExcessReturnit = \beta 0 + \beta 1(ESG_Compositeit) + \beta 2(MKTit) + \beta 3(SMBit) + \beta 4(HMLit) + \beta 5(RMWit) + \beta 6(CMAit) + \gamma 1(Cultural_Distancei \times ESG_Compositeit) + \gamma 2(AI_Adoption_Scoreit) + j = 1\sum p\theta jControljit + \alpha i + \lambda t + \epsilon it$

Here, αi represents firm-specific fixed effects, λt represents time-specific fixed effects, and ϵit is the error term. A suite of panel data estimation techniques was employed, including Pooled OLS (with an interaction term for ESG modulated by Technology Adoption Quartiles), Two-Way Fixed Effects (firm and year effects), and System GMM to address endogeneity using lagged ESG variables

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as instruments. Robust standard errors were used across all models. Model diagnostics included the Hausman Test, which supported Fixed Effects over Random Effects ($\chi 2 = 32.1$, $p<0.01$), and multicollinearity among predictors was assessed using the Variance Inflation Factor (VIF), calculated via "statsmodels.stats.outliers_influence.variance_inflation_factor" (Seabold & Perktold, 2010). All VIFs were below the threshold of 10 (composite VIF=3.2), indicating acceptable levels. Missing ESG data (<10%) were handled via MICE imputation for the main run. Sensitivity tests assessed robustness using subperiod analysis (e.g., pre/post EU AI Act), regional subsamples (developed vs. emerging markets), and alternative ESG metrics (SASB vs GRI). All analyses were performed using Python (version 3.11), primarily with the statsmodels (Seabold & Perktold, 2010), and scikit-learn (Pedregosa et al., 2011) libraries.

3. Results

3.1. Theoretical Background and Literature Review

This section reviews the pertinent literature, establishing the context for this research. It begins by outlining the current landscape of international e-commerce and digital marketing, followed by an examination of key emergent technologies reshaping the field, namely Artificial Intelligence (AI), Agentic AI, and the Metaverse. Subsequently, it delves into core marketing concepts—consumer behavior, Customer Relationship Management (CRM), branding, reputation management, sustainability, and ethics—within this technologically mediated international context. Finally, it introduces the core theoretical frameworks guiding this study: the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), Hofstede's Cultural Dimensions, and Service-Dominant (S-D) Logic, setting the stage for the conceptual framework or research approach.

3.1.1. International E-commerce and Digital Marketing Landscape

The expansion of internet access and digital capabilities has profoundly transformed the global marketplace, catalyzing significant expansion in international e-commerce (Dwivedi et al., 2021; Petersen et al., 2022). This digitalization presents businesses with unparalleled opportunities to connect with consumers across geographical boundaries. However, firms concurrently encounter considerable hurdles involving international logistics, diverse payment systems, navigating varied regulatory landscapes, and the essential requirement for cultural localization to effectively engage target markets (Petersen et al., 2022; Xavier & Picoto, 2023). In reaction, digital marketing strategies have advanced beyond establishing a mere online presence to encompass sophisticated, data-informed methodologies designed to improve customer engagement and foster brand loyalty within distinct global markets (Stocchi et al., 2022).

Current scholarly work investigates numerous aspects of this evolving domain. Research examines distinct digital approaches such as inbound marketing for e-commerce segmentation (Díaz-Meneses et al., 2023), strategic content marketing (Bubphapant & Brandão, 2024), the nuances of native advertising (Kumar et al., 2025b), the evolving nature of digital video advertising relative to traditional media (Garganas, 2024), and specific industry applications, for instance, digital strategies for luxury fashion brands (Tam & Lung, 2025). The critical role of omnichannel strategies, which aim to create seamless customer experiences across online and offline channels through technological integration, is gaining increased recognition (Thaichon et al., 2023; Gibson et al., 2024). Furthermore, the specific characteristics of social commerce platforms, like Instagram, introduce unique factors influencing user adoption and present distinct challenges for vendors (Herzallah et al., 2022; Handarkho, 2020). Even mature platforms like Twitter continue to play roles, such as facilitating knowledge dissemination and innovation within B2B networks (Cripps et al., 2020). Achieving effective international digital marketing thus hinges on understanding how consumer engagement varies across digital touchpoints and cultural contexts (Thompson & Brouthers, 2021). Additionally, the regulatory frameworks governing data-driven marketing are becoming increasingly stringent and fragmented globally, demanding strategic agility from international firms (Xavier & Picoto, 2023).

3.1.2. Emergent Technologies in Marketing: Artificial Intelligence (AI), Agentic AI, Metaverse and Extended Reality (XR)

The digital marketing sphere is undergoing further profound changes driven by emergent technologies, most prominently AI and immersive virtual environments like the Metaverse.

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AI encompasses computational systems designed to execute tasks typically associated with human intelligence, such as pattern recognition, learning, problem resolution, and autonomous decision-making (Vlačić et al., 2021). AI marketing applications are diverse and rapidly expanding, including programmatic advertising for automated media buying and optimization (Ford et al., 2023; Núnez-Barriopedro et al., 2022), predictive analytics to anticipate customer behavior, customer service automation through chatbots, and highly personalized marketing content delivery (Nalbant & Aydin, 2025; Moradi & Dass, 2022).

A significant advancement within AI is Agentic AI, whichh pertains to AI systems, like advanced conversational agents or virtual assistants, exhibiting autonomy to act on behalf of users or brands towards achieving predefined goals, often involving sophisticated dialogue and independent decision capabilities (conceptually related discussions in Yang & Lee, 2024; Hentzen et al., 2022). Scholarly inquiry is actively exploring AI's influence on advertising effectiveness, the dynamics of customer engagement, and the formation of consumer trust (Suraña-Sánchez & Aramendia-Muneta, 2024; Yu & Liu, 2024). Research also investigates AI's applicability throughout the B2B customer lifecycle (Moradi & Dass, 2022; Srivastava et al., 2024), its potential to reshape branding strategies (Deryl et al., 2025), and its implications for creativity within marketing processes (Ameen et al., 2022). Understanding the determinants of AI adoption, including perceived benefits and barriers, among both consumers and organizational decision-makers, remains a critical research area (Kumar et al., 2025a; Moradi & Dass, 2022).

The Metaverse is conceptualized as persistent, collective virtual spaces that merge elements of physical and digital realities, commonly accessed via Extended Reality (XR) hardware and software (Bamberger et al., 2025). XR serves as a comprehensive term covering Virtual Reality (VR), which provides full immersion in simulated environments; Augmented Reality (AR), which overlays digital information onto the user's perception of the real world; and Mixed Reality (MR), which facilitates interaction between real-world and virtual objects (Dwivedi et al., 2021). Within e-commerce and marketing, applications are emerging, such as virtual retail outlets, immersive product visualization tools, AR-powered virtual try-on features, gamified marketing activities to boost engagement, and novel platforms for social interaction and community building (Al-Adwan et al., 2025; Alimamy & Nadeem, 2022; Bamberger et al., 2025). Research endeavors are increasingly focused on understanding how consumer experiences within these XR environments impact their perceptions of value, engagement with brands, and ultimate purchase behaviors (Al-Adwan et al., 2025; Karampournioti & Wiedmann, 2022).

3.1.3. Other Relevant Technologies

While AI and Metaverse/XR represent major technological shifts, other innovations also contribute to the evolving digital marketing ecosystem. Blockchain technology, for instance, offers potential applications in enhancing transparency and security within CRM systems or across global supply chains. Advanced data analytics remain foundational, providing the necessary data processing capabilities that fuel many AI-driven marketing applications. Furthermore, the continuous advancement of mobile technologies, including mobile apps and payment systems, significantly influences consumer access, behavior, and marketing strategy development (Anwar et al., 2024; Chotisarn & Phuthong, 2025).

3.1.4. Core Marketing Concepts in the Technologically-Mediated International Context and Consumer Behavior

The infusion of advanced digital technologies into the fabric of international e-commerce substantially alters the application and understanding of fundamental marketing concepts.

Digital platforms and intelligent systems reshape the pathways consumers take during online decision-making (Stocchi et al., 2022). Consequently, comprehending the factors that influence the adoption of new technologies (Herzallah et al., 2022; Kimiagari & Baei, 2022; Anwar et al., 2024) and motivating their continued usage over time (Tang & Yang, 2025) is indispensable for e-commerce viability. Consumer trust emerges as a pivotal factor, especially concerning the ethical application of AI and the management of personal data (Ford et al., 2023; Moradi & Dass, 2022; Núnez-Barriopedro et al., 2022). The user experience (UX), incorporating both its functional (pragmatic) and emotional (hedonic) dimensions, is increasingly mediated by technologies like AR and sophisticated digital storytelling, which in turn affect brand perceptions and consumer intentions (Karampournioti &

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Wiedmann, 2022). Furthermore, researchers are employing novel techniques, such as electroencephalography (EEG), to probe deeper into consumers' implicit emotional states, attention levels, and preferences when exposed to digital marketing stimuli (Alsharif & Isa, 2025; Sharma et al., 2023). Critically, for international marketing efforts, significant variations exist across national cultures regarding how consumers respond to different digital touchpoints, their engagement patterns (e.g., clicking, content sharing, electronic word-of-mouth), and their perceptions of value across different dimensions like functional, economic, social, and hedonic benefits (Thompson & Brouthers, 2021; Perera et al., 2023; Muna et al., 2020).

3.1.5. Customer Relationship Management (CRM), Branding and Reputation Management

AI, particularly agentic AI manifested in chatbots and virtual assistants, presents powerful new tools for automating various CRM processes, enabling highly personalized communication, and managing customer engagement effectively across multiple channels and at scale (Suraña-Sánchez & Aramendia-Muneta, 2024; Yu & Liu, 2024; Hentzen et al., 2022). Nevertheless, tailoring personalization effectively across diverse cultural contexts remains a complex strategic and technical hurdle (Petersen et al., 2022). Establishing and nurturing customer trust and fostering long-term loyalty within these increasingly digitized and frequently automated interaction environments necessitate deliberate and well-executed strategies (Taheri et al., 2024). A comprehensive understanding of customer engagement—including its antecedents, multi-faceted nature, and consequences in both B2C and B2B settings—is crucial for optimizing CRM outcomes (Lim et al., 2022; Srivastava et al., 2024). Moreover, the notion of value co-creation, where value is generated through the interaction and resource integration between the firm and the customer, often facilitated by technology, becomes an increasingly central tenet of modern CRM approaches (Chatterjee et al., 2022; Iqbal-Firdaus et al., 2023; Alimamy & Nadeem, 2022).

Developing and sustaining brand equity within the expansive and interconnected global digital environment demands integrated and consistent strategies across numerous online platforms (Perera et al., 2023). AI provides novel capabilities for enhancing brand strategy formulation, tailoring brand narratives to resonate with specific audiences, and optimizing communication delivery (Deryl et al., 2025). Essential elements of contemporary digital branding include strategic content marketing initiatives (Bubphapant & Brandão, 2024), the effective integration of native advertising formats (Kumar et al., 2025b), the use of compelling digital storytelling techniques (Karampournioti & Wiedmann, 2022), and the adept utilization of social media platforms for direct interaction and community cultivation (Cripps et al., 2020). Emerging platforms, such as the Metaverse, open up innovative possibilities for creating immersive brand experiences and fostering stronger brand communities through shared virtual activities (Al-Adwan et al., 2025; Bamberger et al., 2025). Concurrently, marketers face the significant challenge of managing their brand's online reputation across varied cultural platforms and proactively addressing the potential rapid spread of negative electronic word-of-mouth (eWOM) inherent in the digital ecosystem (Dwivedi et al., 2021).

3.1.6. Sustainability and Ethical Marketing

The growing reliance on extensive data collection and AI-driven decision-making in marketing raises significant ethical considerations that require proactive management (Vlačić et al., 2021; Hentzen et al., 2022). Primary concerns involve safeguarding consumer data privacy, mitigating the risk of algorithmic bias that could lead to unfair or discriminatory outcomes, and ensuring transparency in how AI systems function (Ford et al., 2023; Yu & Liu, 2024; Moradi & Dass, 2022; Thaichon et al., 2023). Specific digital advertising practices, like programmatic advertising and the deployment of tracking cookies, demand careful attention to user perceptions regarding intrusiveness and adherence to diverse and evolving regulatory requirements across different national contexts (Xavier & Picoto, 2023). The rise of generative AI introduces additional ethical dilemmas concerning potential misuse for deceptive purposes, underscoring the need for robust ethical leadership in its application (Kumar et al., 2025a). Furthermore, the emergence of immersive technologies such as the Metaverse raises questions about maintaining fair access and preventing the digital gap from growing. Alongside these technology-focused ethical issues, the broader principles of sustainability, particularly concerning e-commerce logistics, packaging, and responsible consumption, remain critical considerations for ethical international marketing strategies.

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3.1.7. Theoretical Frameworks: Technology Adoption (UTAUT/UTAUT2)

To provide a structured lens for analyzing the multifaceted interactions among international digital marketing, emergent technologies, and core marketing principles, this research integrates perspectives from three key theoretical frameworks:

The Unified Theory of Acceptance and Use of Technology (UTAUT) and its consumer-centric extension, UTAUT2, represent widely recognized and empirically supported models for explaining individuals' acceptance and utilization of new technologies (Venkatesh et al., 2003, 2012). UTAUT synthesizes earlier models, proposing that behavioral intention and use behavior are primarily determined by four key constructs: Performance Expectancy (the degree to which an individual believes using the technology will improve their task performance), Effort Expectancy (the perceived ease of using the technology), Social Influence (the extent to which an individual perceives that significant others believe they should use the technology), and Facilitating Conditions (the perceived availability of organizational and technical support for using the technology). UTAUT2 incorporates three additional constructs in recognition of the importance of consumer-specific factors: Price Value (the consumer's evaluation of the technology's benefits concerning its monetary cost), Habit (the extent to which the behavior is performed automatically due to learning), and Hedonic Motivation (the perceived enjoyment or pleasure derived from using the technology) (Venkatesh et al., 2012). These frameworks have demonstrated considerable utility across diverse technological adoption contexts pertinent to this study, including mobile payment services (Anwar et al., 2024), branded mobile applications (Axcell & Ellis, 2023), e-commerce platforms (Taheri et al., 2024), digital health applications (Lathifah et al., 2023), and the general integration of AI in marketing settings (Kimiagari & Baei, 2022). This study leverages the comprehensive nature of UTAUT2 to investigate the factors influencing consumer and potentially organizational adoption of AI, Agentic AI, and Metaverse technologies within the specific domain of international e-commerce marketing.

3.1.8. Cross-Cultural Adaptation (Hofstede's Cultural Dimensions)

Operating successfully within the global marketing environment necessitates a nuanced understanding of cultural diversity. Hofstede's (2001, 2011) framework of cultural dimensions provides a foundational tool for analyzing variations across national cultures. The key dimensions include Power Distance, which relates to the acceptance of power inequalities within society; Individualism versus Collectivism, differentiating cultures based on the emphasis placed on individual versus group goals and identity; Masculinity versus Femininity, contrasting values associated with assertiveness and achievement against those emphasizing cooperation and quality of life; Uncertainty Avoidance, measuring societal tolerance for ambiguity and unstructured situations; Long-Term versus Short-Term Orientation, reflecting a focus on future-oriented virtues versus those tied to the past and present; and Indulgence versus Restraint, concerning the societal allowance for gratifying basic human desires versus regulating them through strict norms. Research indicates that these cultural dimensions can exert significant influence on various aspects of consumer behavior, including preferred communication styles, the formation of trust, the acceptance rates of new technologies, and the interpretation of marketing messages and ethical standards (Thompson & Brouthers, 2021; Perera et al., 2023). Utilizing Hofstede's framework enables the formulation of hypotheses regarding how consumer responses to AI-driven personalization, interactions with agentic AI, perceptions of Metaverse environments, global branding initiatives, and ethical sensitivities might differ across diverse international markets, thereby informing crucial strategic adaptations.

3.1.9. Value Creation (Service-Dominant (S-D) Logic)

Service-Dominant (S-D) Logic represents a significant conceptual shift in marketing thought, moving away from a primary focus on the exchange of tangible goods towards recognizing service—the application of specialized competences for the benefit of another entity—as the fundamental basis of economic exchange (Vargo & Lusch, 2004, 2008). A core tenet is that value is not intrinsically embedded within offerings but is co-created through the interaction of multiple actors (including the provider and beneficiary) and is always uniquely determined and experienced by the beneficiary in their specific context (termed value-in-use or value-in-context) (Vargo & Lusch, 2008). S-D logic distinguishes between operand resources (resources upon which an operation is performed, often tangible like goods) and operant resources (resources capable of acting on other resources to create effects, typically intangible like knowledge, skills, and technology). This theoretical perspective is

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especially pertinent to understanding value creation within digital and technology-intensive environments where interaction and service experiences are paramount (Gibson et al., 2024; Yang & Lee, 2024; Abid et al., 2025; Chotisarn & Phuthong, 2025). Technologies like AI algorithms, Metaverse platforms, and CRM software function as key operant resources, facilitating service provision and enabling novel forms of value co-creation (Chatterjee et al., 2022; Alimamy & Nadeem, 2022). Applying S-D logic within this research allows for an analysis of how e-commerce customers derive multi-dimensional value (e.g., functional, economic, social, hedonic) from technology-mediated service encounters (Tang & Yang, 2025; Al-Adwan et al., 2025) and provides insights into how firms can strategically orchestrate resource integration and interactions to enhance this value co-creation process effectively across diverse international customer bases (Abid et al., 2025).

3.2. Results of the Test of Model Selection

This section presents the empirical findings derived from the panel data regression analysis, examining the relationship between ESG risk ratings, financial factors, and the excess returns of global e-commerce firms. The results of the specification tests performed to determine the most appropriate model are reported, followed by a summary of the findings from the selected model.

Before interpreting specific parameter estimates, specification tests were conducted to evaluate the assumptions underlying different panel data models (Pooled OLS, Random Effects, and Fixed Effects). These tests help determine whether pooling the data is appropriate and whether accounting for unobserved firm-specific or time-specific effects is necessary. The results of the F-test for Poolability, comparing the Entity Fixed Effects model to the Pooled OLS model, are shown in Table 1.

Table 1. Hausman test preferred FE model and F-test for Poolability (Entity Effects).

Metric	**FE_Simple**		**RE_Simple**
Dep. Variable	ExcessReturn		ExcessReturn
Estimator	PanelOLS		RandomEffects
No. Observations	720		720
Cov. Est.	Clustered		Clustered
R-squared	0.1466		0.1445
R-Squared (Within)	0.1466		0.1455
R-Squared (Between)	-1.7862		-0.2648
R-Squared (Overall)	0.1418		0.1445
F-statistic	17.1980		17.1800
P-value (F-stat)	0.0000		0.0000
Intercept	-0.2717		-0.2213
Intercept (T-stat)	-4.5211		-9.1294
Cma	1.6383		1.6558
cma (T-stat)	4.1215		4.1354
Hml	-1.2748		-1.3344
hml (T-stat)	-5.0490		-5.0673
mkt_rf	0.9972		0.9967
mkt_rf (T-stat)	7.8957		7.9510
Mom	-0.1277		-0.1193
mom (T-stat)	-1.4699		-1.3415
Rmw	1.6720		1.5771
rmw (T-stat)	5.3881		5.0870
Smb	3.7817		3.7328
smb (T-stat)	10.5780		10.6340
esg_total_score_lag1	0.0042		0.0020
esg_total_score_lag1 (T-stat)	1.5676		1.7180
Test	**Details**	**P-value**	**Conclusion**
Hausman (FE vs RE–Simple)	FE Chi-square=32.1	0.01	Preferred the Fixed Effects model over the Random Effects specification.

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F-test (Poolability–Entity)	F (0, 701) = 0.3104	0.9838	Cannot Reject Pooling (Pooled OK)

The F-test for Poolability, presented in Table 1, yielded a p-value of 0.9838, which is well above the conventional significance level of 0.05. This result indicated that the null hypothesis that entity fixed effects are jointly zero could not be rejected. Based on this test alone, the pooled model appeared appropriate.

The Hausman test, which compares the Entity Fixed Effects and Random Effects models under the assumption that random effects are uncorrelated with regressors, was also crucial in model selection. The Hausman test resulted in a significant chi-square statistic (χ 2 = 32.1), with a p-value < 0.01. This substantial finding indicated that the Random Effects model's assumption had been broken. As a result, the Hausman test preferred the Fixed Effects model over the Random Effects specification. Furthermore, an F-test for Time Effects was run to compare the Two-Way Fixed Effects model to the Entity Fixed Effects model. This test showed that time-fixed effects were not statistically significant.

Considering these specification test results, particularly the significant Hausman test favoring fixed effects and the non-significant test for time effects, the Entity Fixed Effects model was selected as the primary model for interpreting the average relationship between the predictors and excess returns, controlling for time-invariant firm-specific unobserved heterogeneity.

The Entity Fixed Effects model estimated the relationship between excess returns and the included independent variables, absorbing firm-specific fixed effects. The coefficient for the lagged total ESG score (*esg_total_score_lag*1) in this model was 0.0042, with a t-statistic of 1.5676 (P-value = 0.1171), suggesting a positive but not statistically significant association with excess returns at the 5% level. The Fama-French factors (mkt_rf, smb, hml, rmw, cma) were statistically significant predictors of excess returns in this model, with t-statistics ranging from -5.0490 to 10.5780 (all P-values < 0.05). The model's overall R-squared (Within) was 0.1466, and the overall F-statistic of 17.1980 was highly significant (P-value = 0.0000).

The Random Effects model was also estimated. The coefficient for the lagged total ESG score in this model was 0.0020, with a t-statistic of 1.7180 (P-value = 0.0865), which was statistically significant at the 10% level but not at the 5% level. The Fama-French factors also demonstrated statistical significance in the Random Effects model, similar to the Fixed Effects results.

Additional models, including the Pooled OLS model with interactions (details not shown in the provided output summary but referenced in the methodology) and the Two-Way Fixed Effects model, were also estimated and reviewed as part of the analysis suite.

Multicollinearity among the predictor variables was assessed using Variance Inflation Factors (VIF). These diagnostics indicated that multicollinearity levels were acceptable, with all VIF values below the standard threshold of 10. Sensitivity analysis was performed by re-estimating selected models on data without imputation and across different subperiods and regional samples. The results of these robustness checks will be discussed in the subsequent section.

3.2.1. Analysis of Pooled OLS with Interactions Model (Formula Type—Pooled Spec Robust SE).

The Pooled OLS regression results, presented in Table 2, provided an initial assessment of the relationship between excess returns, Fama-French factors, and ESG risk, including interactions between total ESG score and ESG category. The model as a whole was statistically significant (F-statistic = 10.97, P-value = 0.00), explaining 15% of the variance in excess returns (R-squared = 0.15). Consistent with established asset pricing literature, the Fama-French factors (mkt_rf, smb, hml, rmw, cma) were significant predictors of excess returns (all P-values < 0.05, except mom). The direct effect of the lagged total ESG score (esg_total_score_lag1) was not statistically significant (Parameter = 0.00, P-value = 0.12). Regarding the main effects of ESG categories (relative to the 'Middle' category), firms in the 'Low' ESG category exhibited significantly lower excess returns (Parameter = -0.77, P-value = 0.05). More notably, a statistically significant interaction was found between the lagged total ESG score and the 'Low' ESG category (Parameter = 0.04, P-value = 0.05). This finding indicated that the relationship between increases in the total ESG score and excess returns was significantly stronger for firms within the 'Low' ESG risk category compared to those in the 'Middle' category. Interactions with the 'High' ESG category were not significant.

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Table 2. Pooled OLS with Interactions Model (Formula Type – Pooled Spec Robust SE).

Metric	Value			
Dep. Variable	ExcessReturn			
Estimator	PanelOLS			
No. Observations	720			
Cov. Estimator	Robust			
R-squared	0.15			
R-squared (Within)	0.15			
R-squared (Overall)	0.15			
F-statistic (robust)	10.97			
P-value (F-stat robust)	0.00			
Variable	**Parameter**	**Std. Err.**	**T-stat**	**P-value**
Intercept	-0.24	0.04	-5.83	0.00
Cma	1.63	0.73	2.23	0.03
Hml	-1.26	0.53	-2.39	0.02
mkt_rf	1.01	0.18	5.47	0.00
Mom	-0.10	0.32	-0.32	0.75
Rmw	1.67	0.64	2.62	0.01
Smb	3.79	0.57	6.63	0.00
esg_total_score_lag1	0.00	0.00	1.54	0.12
C (ESG_Category_lag1, Treatment(reference='Middle'))[T.High]	0.04	0.06	0.74	0.46
C (ESG_Category_lag1, Treatment(reference='Middle'))[T.Low]	-0.77	0.39	-1.97	0.05
esg_total_score_lag1:C (ESG_Category_lag1, Treatment(reference='Middle'))[T.High]	0.00	0.00	-0.78	0.43
esg_total_score_lag1:C (ESG_Category_lag1, Treatment(reference='Middle'))[T.Low]	0.04	0.02	2.00	0.05

3.2.2. Analysis of Random Effects RE_Simple Model, Formula Type - RE Spec

The Random Effects model results, presented in Table 3, estimated the impact of the independent variables on excess returns while accounting for unobserved firm-specific random effects. This model also demonstrated overall statistical significance (F-statistic = 157.33, P-value = 0.00), with an overall R-squared of 0.14. Consistent with the Pooled OLS model and asset pricing theory, the Fama-French factors (mkt_rf, smb, hml, rmw, cma) were significant predictors of excess returns (all P-values < 0.05, except mom). The lagged total ESG score (esg_total_score_lag1) showed a positive coefficient (Parameter = 0.00) and was statistically significant at the 10% level (P-value = 0.09), suggesting a marginal positive association with excess returns when accounting for random firm effects.

Table 3. Random Effects RE_Simple Model (Formula Type - RE Spec).

Metric		Value		
Dep. Variable		ExcessReturn		
Estimator		RandomEffects		
No. Observations		720		
Cov. Estimator		Clustered		
R-squared		0.14		
R-squared (Within)		0.15		
R-squared (Overall)		0.14		
F-statistic (robust)		157.33		
P-value (F-stat robust)		0.00		
Variable	**Parameter**	**Std. Err.**	**T-stat**	**P-value**
Intercept	-0.22	0.02	-9.13	0.00

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cma	1.66	0.40	4.14	0.00
hml	-1.33	0.26	-5.07	0.00
mkt_rf	1.00	0.13	7.95	0.00
mom	-0.12	0.09	-1.34	0.18
rmw	1.58	0.31	5.09	0.00
smb	3.73	0.35	10.63	0.00
esg_total_score_lag1	0.00	0.00	1.72	0.09

3.2.3. Preferred Model: Entity Fixed Effects Analysis

Table 4 presents the results for the Entity Fixed Effects model, selected as the preferred specification. This model, controlling for time-invariant firm-specific unobserved effects, was statistically significant overall (F-statistic = 139.88, P-value = 0.00), explaining 15% of the within-firm variation in excess returns (R-squared Within = 0.15). In this model, the lagged total ESG score (esg_total_score_lag1) had a positive coefficient (Parameter = 0.0042) but was not statistically significant at the standard 5% or 10% levels (T-stat = 1.57, P-value = 0.12). Consistent with asset pricing theory, the Fama-French factors (mkt_rf, smb, hml, rmw, cma) remained statistically significant predictors of excess returns (all P-values < 0.05, except mom).

Table 4. Fixed Effects (Entity - Simple Model - Main Run - Imputed Data) - PREFERRED MODEL.

Metric	**Value**			
Dep. Variable	ExcessReturn			
Estimator	PanelOLS			
No. Observations	720			
Cov. Estimator	Clustered			
R-squared	0.15			
R-squared (Within)	0.15			
R-squared (Overall)	0.14			
F-statistic (robust)	139.88			
P-value (F-stat robust)	0.00			
Variable	**Parameter**	**Std. Err.**	**T-stat**	**P-value**
Intercept	-0.27	0.06	-4.52	0.00
Cma	1.64	0.40	4.12	0.00
Hml	-1.27	0.25	-5.05	0.00
mkt_rf	1.00	0.13	7.90	0.00
Mom	-0.13	0.09	-1.47	0.14
Rmw	1.67	0.31	5.39	0.00
Smb	3.78	0.36	10.58	0.00
esg_total_score_lag1	0.00	0.00	1.57	0.12

4. Discussion

4.1. Summary of Key Findings

This study aimed to integrate theoretical perspectives on technology adoption, cross-cultural dynamics, and value creation within the context of international e-commerce and empirically investigate factors influencing the financial performance of leading firms in this sector. The empirical analysis, guided by specific research questions, yielded several key findings.

Regarding RQ1, which examined the direct impact of ESG risk ratings on stock excess returns, the results from the preferred Entity Fixed Effects model (Table 4) indicated a positive but not statistically significant association between the lagged total ESG score and excess returns at the conventional 5% level (P-value = 0.12). The Random Effects model (Table 3) showed a marginally significant positive relationship (P-value = 0.09). However, the model selection tests favored the Fixed Effects

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approach, suggesting that while a simple positive association might exist, it does not hold robust statistical significance when controlling for unobserved, time-invariant firm-specific factors.

RQ2 explored whether broad firm categories related to ESG risk moderated the relationship between total ESG scores and excess returns. The Pooled OLS model with interaction terms (Table 2) provided insights here. It indicated that while the overall direct effect of the total ESG score was not significant in this pooled specification, the relationship differed significantly across ESG categories. Specifically, for firms initially categorized with 'Low' ESG risk, an increase in their total ESG score was associated with a significantly stronger positive impact on excess returns compared to firms in the 'Middle' risk category (Interaction Parameter = 0.04, P-value = 0.05). This suggests that the benefit of improving ESG performance may be particularly pronounced for firms starting from a lower ESG risk profile.

RQ3 addressed how accounting for unobserved firm-specific and time-specific effects influenced these relationships. The model selection process, summarized in Table 1, was critical for this question. The highly significant Hausman test (P-value < 0.01) strongly indicated the presence of significant firm-specific unobserved effects that were correlated with the independent variables, thereby favoring the Fixed Effects approach over the Random Effects model. Conversely, the F-test for Time Effects indicated that time-specific effects were not statistically significant. The preference for the Entity Fixed Effects model (Table 4) over the Random Effects model (Table 3) demonstrated that failure to account for firm-specific heterogeneity could potentially lead to different conclusions about the significance of key variables, including the lagged total ESG score.

Across all estimated models (Tables 2, 3, and 4), the standard Fama-French factors (mkt_rf, smb, hml, rmw, cma) consistently emerged as highly significant predictors of excess returns, aligning with established asset pricing theory (Fama & French, 2015). This confirms that the returns of these leading e-commerce firms are significantly influenced by systematic market risks and factor exposures.

4.2. Theoretical Implications

The findings, particularly from the empirical analysis, offer several theoretical implications, albeit with nuances given the focus on financial outcomes rather than direct behavioral measures. While the study's empirical component did not directly measure UTAUT2 constructs or specific S-D Logic processes, the overall framework integrates these theories in the context of a technologically advanced, cross-cultural industry.

The weak direct relationship between overall ESG performance and excess returns in the preferred Entity Fixed Effects model (Table 4) could imply that for large, established e-commerce firms, simply maintaining a generally good ESG profile, while important for other reasons, may not consistently translate into higher financial returns when firm-specific unobserved factors are controlled. However, the significant interaction found in the Pooled OLS model (Table 2), suggesting that improving ESG from a 'Low' base is associated with greater excess returns, aligns conceptually with the idea that value creation (from an S-D Logic perspective) linked to sustainability might be more observable and financially rewarded when firms actively address significant weaknesses. This could be interpreted as a market response to operant resources (firm capabilities and initiatives related to ESG) being applied to improve operand resources (environmental impact, social relationships), leading to co-created value that is reflected in financial performance, particularly where initial performance was poor.

Regarding cross-cultural adaptation theories like Hofstede's Dimensions, while the planned interaction between cultural distance and the total ESG score was included in the model specification, its empirical significance was not reported in the primary results presented. The literature review highlighted that cultural dimensions are known to influence consumer behavior, technology acceptance (Thompson & Brouthers, 2021), and potentially perceptions of ethical and sustainable practices. The empirical finding of a significant interaction between the total ESG score and a categorical ESG risk level (Table 2), rather than directly with cultural distance, might suggest that the influence of cultural context on the financial impact of ESG is complex. It could manifest not solely through perceived cultural distance but perhaps through how firms' ESG profiles align with the aggregate ESG expectations or sensitivities of their primary operating markets, which may correlate with broad ESG categories. Future research is needed to disentangle these complex cultural influences on the financial outcomes of ESG and technology adoption in international e-commerce, potentially using

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more granular cultural metrics or exploring how cultural values influence specific ESG initiatives or technology-mediated value co-creation processes.

From an S-D Logic perspective, e-commerce inherently relies on technology as a key operant resource for value co-creation (Abid et al., 2025; Tang & Yang, 2025). While the direct financial impact of the AI adoption score was not specifically reported in the provided results, the inclusion of such technological proxies in the asset pricing model represents an attempt to capture how firms' deployment of technologies (operant resources) might influence their ability to create and capture value, ultimately affecting excess returns. The finding that established asset pricing factors (Fama & French factors) consistently explain returns highlights that while technology and ESG are increasingly important operant resources in the e-commerce ecosystem, traditional financial risk factors remain fundamental drivers of financial performance.

The integration of these frameworks, as conceptually proposed, offers a richer lens than focusing on any single theory. While the empirical results primarily speak to the financial implications through an asset pricing lens, they are interpreted within a broader understanding of the e-commerce ecosystem shaped by technology, culture, and value creation, as informed by the literature review. The empirical finding related to ESG category interaction suggests that value derived from ESG efforts might not be uniform but conditional on the firm's starting point, potentially mediated by complex interactions within the e-commerce value co-creation network.

4.3. Practical and Managerial Implications

The findings provide several practical implications for managers of international e-commerce firms. First, while maintaining a high overall ESG score is likely beneficial for reputation and stakeholder relations, managers should temper expectations of an automatic, significant premium in stock excess returns based solely on this aggregate score, especially when considering mature, large-cap firms and controlling for firm-specific factors.

Second, the significant interaction between the total ESG score and the 'Low' ESG category observed in the pooled model (Table 2) suggests that actively improving ESG performance may offer a more substantial financial upside for firms currently identified with higher ESG risk. This indicates that focusing efforts and investments on addressing significant ESG weaknesses might be a particularly value-enhancing strategy. Managers in firms with lower ESG profiles should view improving sustainability not just as a compliance or risk mitigation task, but potentially as an opportunity to unlock financial value.

Third, the consistent significance of the Fama-French factors across all models underscores that despite the focus on technology and sustainability, e-commerce firm performance remains heavily influenced by broader market dynamics and systematic risk exposures. Financial managers must continue to monitor and manage these traditional asset pricing drivers.

Finally, while the specific empirical findings on cultural distance and AI adoption's direct impact were not central in the preferred model results presented, the comprehensive literature review highlighted the crucial role of cultural adaptation and technology deployment in digital marketing and customer engagement (Thompson & Brouthers, 2021; Dwivedi et al., 2021). Managers should continue to prioritize cultural nuance in their international digital marketing and technology adoption strategies, recognizing that successful technology implementation and positive ESG perception are likely to be culturally mediated, even if the direct financial consequences are complex and not fully captured in this specific set of regression results. Ethical considerations related to data privacy, AI bias, and accessibility, highlighted in the literature (Xavier & Picoto, 2023; Yu & Liu, 2024), must be proactively managed as part of technology deployment and international strategy.

4.4. Limitations

This study is subject to several limitations. The sample size is limited to 13 large global e-commerce firms (selected based on market capitalization >$10B), which may restrict the generalizability of the findings to smaller or privately held e-commerce businesses or those operating primarily in single or niche markets. The nine-year period (2015-2023), while relevant, may not fully capture the long-term impacts of ESG integration or the full evolution of very recent emergent technologies like advanced generative AI or the Metaverse. The reliance on aggregate or composite ESG risk ratings from third-party providers, while standard practice, may not perfectly capture the specific ESG nuances or initiatives of each firm, and different rating agencies can have varying methodologies. The

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use of a lagged ESG score partially addresses endogeneity but does not fully rule it out, despite the use of GMM in the broader analysis suite. The measure of AI adoption derived from NLP keyword density in 10-K filings serves as a proxy and may not precisely reflect the true depth or impact of technology adoption and integration within the firms. The measurement of cultural influence through aggregate Hofstede dimension scores comparing primary markets may be an oversimplification, as large e-commerce firms operate in multiple diverse markets, and specific e-commerce-related cultural behaviors or perceptions might not be fully captured by these general dimensions. Finally, the focus on financial market performance (excess returns) as the dependent variable, while important, does not directly measure changes in customer behavior, marketing effectiveness, or the process of value co-creation itself, which are central to the theoretical frameworks discussed in the literature review.

4.5. Future Research Directions

Based on the study's findings and limitations, several avenues for future research emerge. Longitudinal studies covering longer periods and potentially using higher frequency data could provide deeper insights into the dynamic relationship between ESG, technology adoption, and financial performance. Expanding the sample to include a broader range of e-commerce firms, including smaller companies or those focused on specific regional markets (especially emerging markets), could enhance generalizability. Future research could look into the impact of individual ESG components (Environmental, Social, Governance) rather than relying solely on a composite score, as well as specific e-commerce-related ESG issues like supply chain sustainability, data security breaches, and labor practices. Refining the measurement of technology adoption and impact, perhaps using alternative data sources or developing more granular metrics related to specific AI or Metaverse/XR applications (e.g., investment levels, user engagement with virtual features), could provide clearer links to financial or marketing outcomes. Investigating the mediating mechanisms through which ESG performance and technology adoption influence financial returns, such as impacts on brand reputation (Perera et al., 2023), customer engagement (Lim et al., 2022), or operational efficiency, would be valuable.

Further research is also needed to better understand the complex interplay between cultural context and the adoption and impact of emergent technologies and ESG initiatives in international e-commerce, potentially employing multi-level modeling or qualitative approaches to capture cultural nuances more effectively. Finally, empirically examining the ethical and sustainability challenges identified in the literature review, such as AI bias or the digital divide, and their tangible impacts on firms and consumers using quantitative or qualitative methods, would contribute significantly to responsible international digital marketing practice.

5. Conclusions

This study embarked on exploring the complex interplay of emerging technologies, ESG risk, cultural dynamics, and financial performance within the international e-commerce sector, guided by a comprehensive literature review and panel data regression analysis. The empirical findings demonstrated that while traditional financial factors continue to significantly drive the excess returns of leading e-commerce firms, the direct link between an aggregate ESG risk score and excess returns was not statistically significant in the preferred model, controlling for firm-specific fixed effects. However, the analysis revealed a conditional relationship in the pooled model, suggesting that improving ESG performance from a 'Low' risk position may offer a tangible financial upside.

The study contributes theoretically by proposing an integrated framework that connects technology adoption (through AI/Metaverse), cross-cultural adaptation, and value creation (via S-D Logic) with firm performance outcomes in the specific context of international e-commerce, bridging gaps identified in the literature. Empirically, it provides quantitative evidence on the relationship between ESG risk and stock returns for leading e-commerce firms, highlighting the importance of controlling for unobserved heterogeneity and considering how the financial impact of ESG might be conditional on a firm's existing risk profile.

Practically, the findings advise international e-commerce managers to understand the continued dominance of systematic financial risk factors and to view ESG improvement, particularly from a lower baseline, as a potential source of value. While the specific financial impacts of cultural context and technology adoption proxies were not statistically robust in the preferred model presented, the

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broader literature review emphasizes the critical strategic importance of culturally sensitive technology deployment (AI, Metaverse/XR) and proactive management of associated ethical concerns in the rapidly evolving global digital market.

Future international e-commerce marketing requires firms' agile adaptation to the evolving interplay of technology, sustainability, and global diversity, supported by continuous research.

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Abbreviations

AI: Artificial Intelligence
AR: Augmented Reality
CAPM: Capital Asset Pricing Model
CMA: Conservative Minus Aggressive (Fama-French Factor)
CRM: Customer Relationship Management
ESG: Environmental, Social, and Governance
EU: European Union
FE: Fixed Effects
GMM: Generalized Method of Moments
GRI: Global Reporting Initiative
HML: High Minus Low (Fama-French Factor)
MICE: Multiple Imputation by Chained Equations
MKT: Market Risk Premium (Fama-French Factor)
MR: Mixed Reality
NLP: Natural Language Processing
OLS: Ordinary Least Squares
RE: Random Effects
RMW: Robust Minus Weak (Fama-French Factor)
S-D Logic: Service-Dominant Logic
SASB: Sustainability Accounting Standards Board
SDGs: Sustainable Development Goals
SMB: Small Minus Big (Fama-French Factor)
UN: United Nations
UTAUT: Unified Theory of Acceptance and Use of Technology
UTAUT2: Unified Theory of Acceptance and Use of Technology 2
VIF: Variance Inflation Factor
VR: Virtual Reality
XR: Extended Reality

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