UNIVERSITY OF VAASA
FACULTY OF BUSINESS STUDIES
SCHOOL OF MANAGEMENT

Mashal Akram, 2403058

AI-Driven Social Media Analytics in Global Branding

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LIST OF TABLES & FIGURES

UNIVERSITY OF VAASA
Faculty of business studies

Author:	Mashal Akram
Topic of Thesis:	Strategic Management/Marketing
Name of supervisor:	Rumy Narayan
Degree:	Master’s degree in business studies
Department:	Department of Management
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ABSTRACT

The advent of social media and artificial intelligence (AI) has changed how B2B companies carry out their brands. This thesis examines how AI-based social media analytics could contribute to brand trust, global brand equity and sustainable brand positioning. Drawing on the Resource-Based View, Stakeholder Theory, and sustainability-oriented institutional approaches, the research develops a hypothesized framework that relates the use of analytics with value co-creation, alignment of stakeholders, and responsible brand management.

Quantitative cross-sectional survey was carried out among B2B professionals in marketing, branding, analytics and sustainability occupation fields. The SPSS and the PROCESS macro were used in analyzing the data to evaluate direct, mediating and moderating relationships. The model proposed value creation and stakeholder alignment as mediators, and institutional and cultural conditions as moderators.

The findings indicate that AI-driven analytics has only a modest and diffuse influence on branding outcomes. Direct relationships were weak and statistically non-significant, and neither mediation nor moderation effects were supported. Nevertheless, small directional tendencies appeared in relation to sustainability-oriented branding. These results suggest that analytics currently functions as an enabling tool rather than a strong driver of relational or strategic branding outcomes, offering implications for theoretical development, managerial practice, and future research.

KEYWORDS: B2B, branding, perceived value creation, sustainable brand positioning, Artificial Intelligence, stakeholder alignment, AI analytics, social media platforms

1. INTRODUCTION

The digitalization, globalization and AI have transformed the way the brands are constructed and managed in the recent years (Huang & Rust, 2020; Shen & Xie, 2024). Social media is becoming a multilayered space where the messages concerning brands are co-created, discussed, and formed by an algorithm (Pasquinelli & Eshuis, 2025). Within this digital context, AI helps companies to connect their social data into strategic information, build trust, and react more promptly to change, which is essential in companies that work in B2B settings (Johnston & Cortez, 2024). While consumer markets can sometimes be persuaded by intense emotions and impulse, B2B branding ultimately depends on trust, the perception of risk, and the credibility of the expertise of the company (Liu & Leach, 2001). With the ability to better process market signals through AI-driven social media analytics, the result is not only a better utilization of time and resources, but the potential to more effectively manage relationships in global markets.

From a managerial perspective, significance and interest in AI-driven social media analytics shows increasing demand for competitive resilience in volatile global environments (Chae et al., 2018; Wamba et al., 2017). While at the same time they adapt to the cultural, regulatory and institutional differences, firms are under constant pressure to maintain the brand consistency between the diverse markets (S.-C. Wang et al., 2015). The ability to perceive weak signals, define the shape of emerging trends and to constantly monitor feelings of their stakeholders in real-time can influence the degree of relevance and credibility that multinational B2B enterprises may maintain for their clients (Chae et al., 2018; Chalhoub, 2011). Meanwhile, AI-based branding has its set of difficulties. The issues of data privacy, bias in algorithms, and authenticity are now coming to the center of interest in judging the corporates legitimacy (Cagiza et al., 2025; Jaganathan et al., 2024). The businesses not only have tested their products and services but have been striving how responsible and transparent their use of the digital technologies has been. The change has led to a pressing concern among managers; what can firms do to use AI to enhance branding results without putting their reputation at risk?

The study of AI-driven social media analytics in B2B international branding is a timely and original study (Keegan et al., 2024). It is demonstrated in the existing literature that AI can be used to support segmentation, targeting, and interaction of consumer market, yet the B2B is still under-researched. Most contributions to date focus on operational advantage like efficiency and personalization but pay little attention to long-term results like brand equity, trust, and sustainable positioning (Fagundes et al., 2023). Most of the literature, however, to date remains dominated by business-to-consumer (B2C) markets, where the dynamics of branding are very different to B2B. The value of filling this gap is not based solely on the theoretical progress but also on the need to make sure that firms have research-based information on how to embrace AI in a manner that empowers them, not dilutes, their reputation globally (Huang & Rust, 2020).

The study of AI in marketing has accelerated in recent years, and researchers widely agree that AI creates a substantial value for branding (Cagiza et al., 2025; Huang & Rust, 2020). The available literature demonstrates that AI-based social media analytics appear efficient, enable instant decision making, and also aid large-scale personalized communication. Huang & Rust (2020) state that AI is not a continuation of automation, but a new paradigm, altering how marketing is performed as companies increasingly depend on the use of data to make the decisions. Also, as Paschen et al. (2019) state, AI-driven social media analytics enhances customer insight and responsiveness to campaigns. Applying to the B2B branding setting, it has been highlighted by scholars that these technologies can strengthen the credibility and enable long-term relationships through tracking the digital indicators of trust and expertise (Fagundes et al., 2023). The available literature has shown that AI-based social media analytics can be of strategic importance to branding both in the business and customer market.

Along with this technological advancement, the constraints are still there. To begin with, majority of the research remains centered on short term operational advantages like efficiency, segmentation and automation, with long term brand building results like trust, equity and sustainable positioning under explored. The researchers, Chintalapati & Pandey (2022) note that the existence of AI as an enabler of efficiency has been at the center of the current studies, and little has been done to examine its contribution to the formation of the enduring brand relationships. Secondly, most of the empirical research has focused on B2C segment and emotional appeal and consumer sentiment are the primary focus leaving B2B branding situations overlooked. According to Keegan et al. (2024), even though AI has become an integrated part of the business-to-consumer marketing approach, its implementation in business-to-business branding is still in its formative stages. Thirdly, little is known about how AI-driven analytics can lead to stakeholder alignment within highly complex B2B systems in which several actors, buyers, partners, regulators, and influence brand perceptions. This is highlighted by Kar & Kushwaha (2023), who say that the existence of various stakeholders with corresponding interests and motivation in an AI ecosystem has not been systematically studied.

Another area of gap is in ethical and sustainability aspects of AI in branding. The researchers say that although AI can magnify the sustainability discourses, it can also be a threat of greenwashing (Gündüzyeli, 2024). Hemker et al. (2021) also emphasize the fact that data-driven marketing can only be considered legitimate when an ethical perspective is applied, in which transparency and fairness are valued. These observations suggest the literature has failed to adequately examine the intersection of AI-based social media analytics and institutional forces, including Sustainable Development Goal 12 on responsible consumption and production, which is increasingly becoming part of the legitimacy of global brands (Greenland et al., 2023; Ibeama et al., 2025).

The gap in the research is the insufficient internalization of AI-oriented analytics into the sustainable brand-building and stakeholder confidence in global B2B. Although the existing body of work recognizes AI operational advantages, they do not provide answers on the question of how the technologies help create long-term value, align stakeholders, and achieve ethical legitimacy in various institutional contexts. By filling this gap, not only theoretical knowledge will be developed, but it will also offer useful advice to firms moving between the opposing demands of efficiency, trust, and sustainability in their branding strategies.

1.1. Research problem and theoretical contribution

The above-mentioned gaps indicate a rather evident necessity to comprehend how AI-based social media analytics can assist companies not only in becoming more efficient and responsive but also in establishing long-lasting brand trust, global brand equity, and real sustainability in global B2B markets. Although companies are becoming more dependent on these technologies to understand the sentiment of the stakeholders to make decisions, little evidence is available on whether the practices are building lasting value or just optimizing the short-term results. The main research problem of this thesis is thus:

How can global B2B firms leverage AI-driven social media analytics to create value, align with stakeholders, and build sustainable branding outcomes across diverse markets?

To address this problem, the study will investigate three research questions:

1. What are the ways that AI-based social media analytics can facilitate the creation of perceived value during branding in the B2B context?
2. What role do these analytics play in aligning the stakeholders in the global markets?
3. What is the moderating role of institutional and cultural contexts in the association between the use of analytics and branding results in the form of trust, equity, and sustainability positioning?

The thesis also contributes several theoretical and managerial implications by answering these questions. First in terms of theoretical contribution, it builds upon the Resource-Based View (RBV) by theorizing AI-based social media analytics as a strategic branding feature capable of bringing raw digital information to the value-generating insights (Deryl et al., 2023). Second, it contributes to the development of Stakeholder Theory by examining how algorithmic knowledge can help or impede the alignment of the expectations of various stakeholders in multi-faceted B2B ecosystems (Valentinov, 2022). Thirdly, it incorporates a sustainability-based approach, where applying AI to branding relates to the instability of the Sustainable Development Goal 12 (Greenland et al., 2023; Ibeama et al., 2025). The study's explicit association of the practices of analytics with such outcomes as sustainable brand positioning, environmental responsibility, and creation of long-term social and reputational values presents a more holistic perspective of how firms may leverage digital capabilities not only to create efficiency but also to create long-term social and reputational value.

Along with the theoretical contributions, there are also important managerial implications in the research. Within real-life setting particularly within multinational companies marketing managers are more likely to face a dilemma of to what extent they should depend on AI analytics when developing international campaigns. As an example, though predictive dashboards can optimize the use of media and the identification of the trends with customers, performance may be at risk of losing cultural awareness or trust in the insights due to overreliance on automated results. This study assists managers to make decisions on such dilemmas by demonstrating that AI-based social media analytics can be responsibly utilized to increase brand authenticity and assist sustainable brand positioning across markets. Therefore, to practitioners it offers evidence-based information on how AI-driven analytics can be deployed in a responsible way to promote global brand positioning (Stahl et al., 2022). Especially, the results will guide managers to understand how to find the balance between efficiency and authenticity, how to use the knowing of social media to connect with stakeholders working in different cultural and regulatory environments, and how to integrate sustainability into AI-driven branding processes. In this way, this thesis does not just provide a conceptual clarity, but also practical advice to managers who must find their way through two-sided pressures of competitiveness and legitimacy in more data-driven and ethically challenged business environment.

1.2. Thesis structure

This thesis is structured to guide the reader logically from identification of the research problem to presenting empirical results. The chapter 1 introduces the motivation for the study, outlines the research gap, and present the research problem, questions, and the intended theoretical and managerial contributions. The chapter 2 provides a literature review focused on evolution B2B branding in global markets, emergence of AI in social media analytics, AI driven analytics as value creating capability, social media as a branding platform, relational pathways in B2B branding, critical issues in branding and introduces the hypothesis against each presented literature. This review also forms a basis for the theoretical framework and presents hypothesized model based on empirical results. The chapter 3 reveals that how the research was carried out. It outlines the questionnaire, and how the data of respondents was gathered. It then summarizes the analytical methodology, introduce the sample, give descriptive statistics and appropriateness of the data to proceed further with the analysis. The chapter 4 gives the results in a clear, organized and descriptive manner. It provides the correlations between the main constructs, the direct impact of AI-driven analytics and the mediation processes via value creation and stakeholder alignment. It also analyses the sustainability as an integrative branding result and contextual moderation is tested. Lastly, the chapter ends by the interpretation of hypothesis by the observed trends. Finally, chapter 5 presents results in relation to theoretical framework and the academic contribution of the study, and practical implications to managers. It also recognizes the limitations of the study and provides recommendations on the way the research will be done in future.

2. THEORETICAL FOUNDATIONS OF AI-DRIVEN GLOBAL BRANDING AND HYPOTHESIS DEVELOPMENT

In the previous decade, social media analytics based on AI have been widely applied to global branding in the B2B context. The businesses utilizing such tools are taking the advantage of the vast quantities of data that the nature of such AI tools provides to better position themselves on the world stage in addition to enhancing their brand interactions. Social media analytics is an essential role in predicting the market trends through close monitoring of essential indicators like consumer sentiment, engagement, and any other analytical dimension, which is monitored and analyzed with the help of AI tools (Kumar et al., 2024; Labib, 2024). This leverage and ability to dynamically process vast amounts of information provides the B2B companies with the opportunity to modify their strategies to suit the market more appropriately and offer more value and satisfaction to the consumers (Hendrayati et al., 2024). Regarding business-to-business (B2B), the intertwining of artificial intelligence, social media, and branding has developed, and it is changing the methods of communication, interaction, and building trust in the global markets (Saheb et al., 2024). The main summary of the important previous studies using their scope, center, and the definite gaps in the research, which propose this thesis, is presented in Table 1.

Table 1: Prior Studies on AI and Branding: Focus, Findings, and Emerging Gaps

Study	Context	Focus / Method	Core Finding	What's Missing vs. This Thesis
(Davenport et al., 2020)	Mixed (B2B/B2C)	Conceptual review (AI in marketing)	AI enhances efficiency, targeting, decision speed	Doesn't test B2B **trust/equity/sustainability** outcomes or mediators
(Huang & Rust, 2020)	Mixed	Framework	AI reshapes marketing logic	No empirical B2B branding outcomes; no stakeholder legitimacy lens
(Paschen et al., 2019)	B2B	Conceptual	Social analytics improve market knowledge in B2B	Stops at knowledge; no test of branding outcomes
(Mikalef et al., 2023)	B2B	Empirical	AI competencies (capabilities view)	Not branding-specific; lacks stakeholder/sustainability outcomes
(Mikalef et al., 2021)	B2B	Conceptual	AI as enabler via dynamic capabilities	No empirical link to brand trust/equity; no sustainability

(Keegan et al., 2024)	B2B	Qualitative (activity theory)	How AI is implemented in practice	Adoption detail, but no branding outcomes/mediation
(Han et al., 2021)	B2B	Bibliometric	Maps AI in B2B marketing	Field overview; no causal mechanisms to brand outcomes
(Fagundes et al., 2023)	B2B	Empirical	Social media & brand equity links	Limited AI-analytics lens; no stakeholder mediation
(Koponen & Rytsy, 2020)	B2B	Empirical	Social presence satisfaction/trust	Not AI-specific; no analytics capability path
(Bonnin & Alfonso, 2019)	B2B	Qualitative	Narrative strategies in B2B branding	No analytics capability or sustainability linkage
(Srivastava et al., 2024)	B2B	Review	Customer engagement	Engagement focus; lacks AI, trust/equity/SDG paths
(Bag et al., 2024)	Mixed	Conceptual	AI for stakeholder engagement & social innovation	Not branding performance; no equity/trust tests
(Hemker et al., 2021)	Mixed	Perspective	Ethics of data collection	Governance lens; no branding outcomes
(Vinuesa et al., 2020)	Mixed	Perspective	AI & SDGs	Macro lens; no B2B branding model
(Gündüzyeli, 2024)	Mixed	Review	AI in digital marketing under sustainability	Flags greenwashing risk; not empirically linked to B2B outcomes
(Kumar et al., 2024; Labib, 2024)	Mixed	Reviews	Trend mapping of AI in marketing	Breadth, not mechanism-to-outcome tests
(Ziakis & Vlachopoulou, 2023)	Mixed	Review	Comprehensive AI-in-marketing synthesis	Limited B2B outcomes; no mediators
(Rusthollkarhu et al., 2022)	B2B	Framework	Managing B2B journeys with AI tools	Process detail; no trust/equity/sustainability outcomes
(Kar & Kushwaha, 2023)	Mixed	Big-data analysis	AI facilitators/barriers	Adoption factors; not branding outcomes
(Khandelwal et al., 2024)	Mixed	Bibliometric	AI in digital marketing	Trend mapping; lacks causal tests
(Luo et al., 2019)	B2C	Field experiments	Chatbot disclosure impacts purchases	Mechanism evidence but not B2B trust/equity
(Gao & Liang, 2025)	B2C	Empirical	AI try-on impulsive buying moderated by trust	B2C; signals optimization–ethics tension

2.1. Evolution of Global Branding in Digital Era

Branding in global markets has undergone significant transformation as digital channels, social media activity, and data-driven systems have become central to how firms communicate and build relationships. Most branding is being informed by the wider marketing technology environment where companies are using digital tools to design, implement and test their branding strategies rather than just relying on the creative messaging (Deryl et al., 2023). In this context, the Resource-Based View (RBV) could imply that the capacity to gather, process and interpret digital information is a significant strategic asset (Barney, 1991).

This type of analytical insight can be invaluable, hard to replicate, and necessary to firms that want to remain competitive in fast-evolving markets. This change has also enhanced the contribution of dynamic capabilities. Companies need to detect new signals, decode change in the environment and redesign the branding responses (Eisenhardt & Martin, 2000; Ellström et al., 2022). Digital technologies enable brands to trace discussions, trends and make changes in time and across various markets. These functions are particularly applicable to international branding, where the companies should be able to shape their messages to the specific cultural and institutional environment without compromising the entire message. The capability to transform social information into meaningful insight thus comes into the forefront, because it enables firms to react swiftly, but intelligently to changes occurring in the external environment.

In the meantime, the digitalization has augmented the expectation of brands. Global consumers are increasingly carrying out more consideration on brands other than performance, to transparency, responsibility and authenticity. It means that the choices of the branding must be determined by the concerns of the stakeholders that influence or characterize the activities of the firm (Valentinov, 2022). With the increased exposure of branding and increased mediation by digital platforms, companies need to navigate relationships with an increasingly diverse portfolio of market actors. The mentioned circumstances reveal the increase in the relevance of structured data, the level of analytical ability and the possibility to interpret the numerous clues forming the brand perceptions.

2.2. Emergence of AI in Social Media Analytics

Artificial intelligence-based social media analytics has emerged as an essential part of decision making in international B2B branding. The development of social networks and online interaction has generated vast amounts of unstructured data which could provide an understanding of the market sentiment, stakeholder concerns and new trends. The AI systems can help companies keep track of such developments in a more organized way by recognizing patterns, assessing sentiment, and summarizing discussions in different digital space. In RBV terms, the capability of being able to process the scattered social information into a timely actionable information at the right moment is a valuable marketing skill that is difficult to emulate by other market players.

These tools of analysis are of particular importance to B2B firms that are global in their operations. They assist organizations to get information on the perceptions of their brand in various regions, industries and at different levels of stakeholders. Observing conversations, remarks and reactions, companies can also learn which elements of the value proposition resonate, and which might need to be changed (Güngör, 2020). This helps to have more consistent and relevant messaging across markets and therefore companies can adjust their message based on real-time feedback.

Even though AI has been a popular topic in the wider marketing literature, much of this literature focuses on how it can be used to enhance operations, including efficiency, automation, and campaign optimization (Rusthollkarhu et al., 2022). There has been less emphasis on how analytics can help in achieving the deeper relational outcomes like value creation or stakeholder coordination, especially in B2B. However, when companies incorporate analytics in their everyday branding processes, they can be more capable of targeting signals and reacting to stakeholder demands and stay consistent in the complex world of global markets.

2.3. AI-Driven Social Media Analytics as a Value-Creating Capability

In terms of capability, the AI-based social media analytics can be viewed as a strategic asset that allows companies to convert new amounts of scattered social data into marketable knowledge (Hemker et al., 2021). When the companies can recognize new trends, the stakeholder issues, and the moods in real-time, they can modify the branding messages, the product communication, and the relational strategies more efficiently. Such responsiveness produces perceived value to customers and partners since companies are more relevant, timely, and precise in their messages. Previous studies of digital capabilities indicate that the organizations, which are situated in a better capacity to sense and interpret external cues, tend to create more solid value propositions and enjoy elevated relationship satisfaction rates (Cao et al., 2022). Therefore, the perceived value creation in global B2B branding is likely to be increased through analytics capabilities that can lead to better environmental sensing and improved decision quality.

2.4. AI-Driven Analytics and Stakeholder Alignment in B2B Branding

B2B branding is experienced in multiple-actor complex ecosystems, including customers, distributors, regulators, and partners, with various expectations and informational requirements (Deryl et al., 2023). Companies can gain a better and more organized picture of these diffused stakeholder views through AI-driven social media analytics. Through tracking discussions, issues, and responses in diverse markets, the companies will be able to see where the stakeholder groups overlap and diverge and make changes to branding choices based on them (Peterson et al., 2023).

This enhances uniformity in the expectation of various stakeholders and what the brand conveys. Through this, analytics can serve as a form of coordination that assists companies to synchronise messaging, value propositions and relational practices in a variety of markets (Güngör, 2020). Once companies are able to align expectations, and to have coherent communication within the international stakeholder networks, there is a strong chance that stronger stakeholder alignment will emerge (Güngör, 2020; Valentinov, 2022). These observations suggest that AI-based social media analytics is a valuable feature that can drive improved value generation as well as stakeholder alignment in global B2B branding (Tantalo & Priem, 2016). Therefore, the hypothesis 1 is proposed as follows:

H1: AI-driven social media analytics positively enhance value creation and stakeholder alignment in global B2B branding.

2.5. Social Media as a Branding Platform

Social media has become a sophisticated branding platform that supports the visibility, interaction and long-term dedication (Agnihotri et al., 2023). It has changed the branding strategy where the company dictates the narrative to a process of co-creation with stakeholders (Bonnin & Alfonso, 2019). Viewed through the prism of the stakeholder theory, social media turns into the habitat where the meaning of the brand is co-produced, and legitimacy is negotiated with different audiences on a regular basis, in either B2B or B2C. B2B branding is based on a more strategic and knowledge-based approach on the LinkedIn, X (previously Twitter) and YouTube platforms. Such platforms are professional platforms where skills are combined with thought leadership and credibility, among other factors (Ring, 2020). RBV presents this social presence as a competence: the ability to derive, process, and respond to weak digital signals at a faster rate than competitors. Koponen & Rytsy (2020) believe that online B2B communications are strengthened regarding integrating social presence to transform an initial interest into a deeper level of interaction. Although technology may enhance efficiency, brand relevance in B2B environments continues to rely on the existence of a fruitful connection, trust and appreciation.

2.6. Relational Pathways in B2B Branding

B2B branding is fundamentally relational. Unlike consumer markets where emotional appeal and impulse may play a stronger role, B2B decisions depend heavily on credibility, competence and the ability of firms to deliver value consistently over time. In these settings, stakeholders evaluate brands based on the usefulness and relevance of the interactions they experience, the clarity of communication they receive, and the degree to which the firm demonstrates understanding of their needs and constraints (Jha & Verma, 2022; Valentinov, 2022). When companies manage to create this value, they tend to build a better level of trust and create perceptions of reliability, which are the foundation of brand equity and long-term relationship continuity in B2B relationships.

The other important aspect of B2B brand performance is the stakeholder alignment in markets. Due to the B2B involved transactions, there are various actors, such as customers, distributors, regulators, technical specialists and partners. The consistency of information and expectation of these groups is an aspect which is found to be a critical component of the perceived brand strength. As the stakeholders find uniformity in the claims, behaviors and relational practices by the firm, they are more likely to consider the brand as credible and legitimate (Peloza et al., 2012).

The alignment consequently minimizes uncertainty and facilitates better assessments of the brand trust, reputation and global brand equity, coupled with increasing the capacity of the brand to secure sustainable and responsible market status. The relational outcomes achieved by AI-based social media analytics relate to the fact that such applications can provide firms with a better understanding of the reactions, concerns, and expectations of different audiences in the marketplace. Messaging can be fine-tuned using analytics to detect and respond to

dispersed digital signals, rectifying discrepancies in the message, creating communication that communicates a better interpretation of stakeholder priorities (Bag et al., 2024).
These abilities do not directly generate trust or brand equity but instead, they impact the relational circumstances like perceived value and alignment of stakeholders that shape the way branding performance unfolds. According to this view, analytics influence their effects using internal processes which determine the relationships and legitimacy within markets. Building on these relational pathways, the hypothesis 2 is proposed as follows:
H2: Perceived value creation and stakeholder alignment positively affect branding outcomes and mediate the impact of AI-driven analytics.

2.7. Critical Issues in AI-Driven Branding

Although AI has become an essential component of digital branding, it brings a range of questionable ethical, operational, and strategic issues in the B2B context, where authenticity and trust are the main pillars of relations. The first among the leading liability is the dilemma between personalization and privacy (Wu, 2023). The ability of AI to simulate and analyze large volumes of behavioral and transactional data and provide hyper-personalized recommendations and content is its strength. However, this depth of knowledge can often be intrusive particularly when you are dealing with long time clients and a business premising on trust and confidentiality in a B2B business. Many B2B businesses rely on human trust-building. However, over-reliance on AI automation can sideline the human touch, potentially harming the brand’s image in the long run (Gündüzyeli, 2024; Shankar, 2024). Personal interactions, knowledge, and flexibility help in creating business relationships in B2B. Despite the rise of technology and heavy usage of AI, such applications are not capable of substituting human interaction required to support long-term high-end branding in B2B. As a stakeholder concern, the core of the matter is the legitimacy: transparent utilization of personal information forms the basis of trust, whereas obscure automation undermines it.
One more unresolved question is the conflict between optimization based on AI and sustainable branding goals. As AI systems strive to be the most visible, its proposed content forms and stories may encourage excessive consumption, superficial interactions or even be labeled as greenwashing, where sustainability messages are popularized and marketed only in the context of algorithms and not the practice itself (Lyon & Montgomery, 2015). Such contradictions damage the credibility and create ethical issues in B2B where long-term relationships and reputational capital are strategic resources (Stahl et al., 2022). Otherwise, companies are likely to lose the sustainability of brand loyalty to the temporary benefits of algorithms. Sustainability framework redefines optimization as only acceptable in the context

of straightforward socially responsible communication that builds long-term brand equity. The literature provides evidence that AI-based social media analytics can help companies to make global B2B branding more efficient, personalized, and responsive. However, most of the contributions are short-term and operationally based with an emphasis on the measures of engagement, campaign automation, and adoption barriers. The most crucial questions like construct validity (e.g. is sentiment the same as brand equity) are not tackled, platform and cultural biases, and alignment of AI with sustainable brand values over the long term are never addressed sufficiently. Few studies consider the interaction of the application of algorithmic tools with larger tasks (environmental stewardship, inclusivity, and trust-building in various markets).

2.8. Theoretical Framework

This thesis follows a multi-theoretical approach and is based on the Resource-Based View (RBV), the Stakeholder Theory, and the views on sustainability. The combination of these frameworks helps to study the impact of AI-based social media analytics on value-making, alignment of stakeholders, and brand validity in international B2B relationships. The interest of the mentioned perspectives has been proven by the previous literature review that has shown the role of both lenses in comprehending the strategic, relational, and ethical aspects of AI-enabled branding.

Some of the most crucial grounds that the Resource-Based View presents are that firms attain sustainable competitive advantage when they have valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). Nowadays, in the modern markets, these resources are not tangible but digital ones. The AI-driven social media analytics have become such a possibility since it allows firms to transform the unstructured and large-scale of information into the actionable insights needed to inform the branding strategy. By monitoring the consumer moods, detecting new trends, and analyzing the perceptions in cross-markets, the firms can restructure their branding messages in a timely and accurate manner (Homburg et al., 2015; Salampasis et al., 2013). This analytical skill provides B2B firms with an analytical strength as it improves responsiveness, builds credibility, and international position.

The AI-based social media analytics can be viewed in the context of the RBV as the expansion of marketing capabilities. They help the firms to identify their weak signals in the global markets and convert them into value-adding activities. This change is largely vital in the B2B environment where differentiation can be constrained, and brands are based on factors such as trust, and expertise as opposed to the emotional appeal. Therefore, the capability to create and utilize the findings of the social media data is a resource strategy that facilitates brand equity and sustainable customer relationships worldwide.

In contrast to the fact that RBV provides the explanation of the strategic capabilities of AI-based social media analytics, the Stakeholder Theory stresses that the achievement of branding can ultimately rely on the ability of the company to address the demands of different actors. According to Freeman (2010), stakeholders are any group or individual possible of influencing or influenced by an organization. In the business-to-business markets, these not only cover the buyers, but also the partners, the suppliers, the regulators, the employees, and the society broadly. Branding, then, is not merely positioning worth, but also about keeping legitimacy through a very broad web of relations of interdependence.

The social media analytics provided by AI can help align the stakeholders, enhancing the levels of transparency and offering personalized communication and the possibility to respond to the concerns in due time (Bag et al., 2024). As an example, the B2B constituents of decisions are becoming more dependent on the digital aspects of contacting such as LinkedIn or business networks to certify the credibility and competencies. The analytics can assist the firms to get to know that which stories resonate with groups in stakeholders, thus amplify the level of curbing. Simultaneously, there are also risks associated with relying on the analytics in case the stakeholders will see communication as intrusive, manipulative, or culturally insensitive (Bag et al., 2024). Therefore, strategic application of AI in the branding field implies a compromise between efficiency and legitimacy of the stakeholder.

The third theory lens can be explained by the growing significance of the sustainability and institutional demands. The international corporations are under mounting pressure to show an environmental concern, fairness and ethical behavior. The frameworks which reflect these pressures include the United Nations Sustainable Development goals, which are primarily, Goal 12, responsible consumption and production. The studies have already pointed out that AI applications in branding can both facilitate and compromise such goals (Ibeama et al., 2025; Vinuesa et al., 2020). On the one hand, AI-based social media analytics will be able to bring to the fore the sustainability activities, gauge the perception of corporate responsibility by the different stakeholders, and provide the ability to report transparently.

Conversely, visibility optimization may promote overconsumption, exaggerate superficial stories, or support the process of greenwashing when claims of sustainability are applied not to represent actual behaviors, but chiefly to draw attention. These contradictions are also strategically important to global B2B companies where trust and reputation are built over time. The framework thus does not see sustainability as a peripheral factor but as a moderating factor that can make or break AI-based analytics as a strength to or a liability of the brand. This may not succeed in one market as it would have in another. The way analytics may be used and the areas in which messages are decoded is influenced by regulations and platform policies, as well as cultural communication styles. It is also very natural that one would expect that the strength of such effects varies between institutional and cultural setting. With blend of these views, the framework situates AI-based social media analytics as a strategic branding capability which is empowering and limiting. According to the Resource-Based View, analytics is a source of competitive advantage as it turns social data into valuable information. Based on Stakeholder Theory, the results of branding will be based on the application of these insights to the alignment with various stakeholders at the global market levels. The sustainability of these practices, in the long term, will be based on their ethical foundation and role in supporting the goal of responsible branding. The integrated framework therefore suggests that AI-driven social media analytics influence three main branding outcomes in global B2B contexts: brand trust, global brand equity, and sustainable brand positioning. These outcomes are mediated by perceived value creation and stakeholder alignment, while institutional and cultural contexts moderate their effectiveness.

2.9. Sustainability Outcomes in AI-Driven Branding

Sustainability has become a defining expectation for global B2B brands, shaping how stakeholders evaluate credibility, responsibility and long-term value. In markets where buyers and partners prioritise environmentally and socially responsible practices, firms must demonstrate consistency between their sustainability claims and their actual behavior (Maignan & Ferrell, 2004). Stakeholder theory emphasises that brands earn legitimacy when diverse audiences perceive their actions as aligned with shared values, particularly transparency, fairness and long-term responsibility (Valentinov, 2022). AI-driven social media analytics can support this process by helping firms detect concerns, sustainability expectations and reputational risks at an early stage. When companies interpret these digital signals responsibly, they can refine their communication and ensure that sustainability narratives reflect genuine practices rather than algorithmic optimization.

However, the ability of AI-driven analytics to create sustainable branding outcomes depends largely on relational mechanisms. Trust is a central precursor to sustainable brand positioning. Stakeholders are more likely to believe and support sustainability initiatives when the brand is already perceived as reliable, transparent and consistent. Similarly, stakeholder alignment coherence between what different actors expect and what the brand communicates helps firms present a unified sustainability message across markets. When analytics help firms respond to concerns, correct inconsistencies and address the needs of multiple actors, they indirectly support the credibility of sustainability efforts by fostering higher trust and coordinated expectations.

In this sense, AI-driven analytics do not generate sustainable positioning automatically. Their influence emerges when insight generation enhances stakeholder trust and aligns sustainability communication across markets. Firms that use analytics effectively are therefore better able to demonstrate responsible behaviour, reduce the risk of perceived greenwashing and maintain a coherent sustainability narrative (Parguel & Guillaume, 2021; Vinuesa et al., 2020). These relational conditions create the foundation for stronger and more credible sustainable brand positioning. Hence, the hypothesis 3 is proposed as follows:

H3: AI-driven analytics enhance sustainable brand positioning through trust and stakeholder alignment.

2.10. Institutional and Cultural Moderators of AI-Driven Branding

An impact of AI-driven social media analytics on branding outcomes does not occur uniformly across markets. B2B firms operate in institutional environments that vary widely in terms of data governance, regulatory strictness, technological maturity and expectations for responsible digital behaviour. Institutional theory suggests that organisations must conform to local regulations, norms and societal expectations to maintain legitimacy. These contextual conditions shape how analytics can be applied, interpreted and accepted by stakeholders. For instance, stricter data privacy regimes or highly regulated communication environments may limit the extent to which insights can be used, while technologically advanced or open data environments may enable more effective deployment and interpretation of analytics outputs.

Cultural conditions also play an important moderating role in the effectiveness of analytics. Stakeholders across markets interpret digital communication differently due to divergences in communication style, risk tolerance, relational expectations and preferences for automation versus human interaction. In high-context cultures, trust is built through relational depth and personalised communication, while in low-context cultures data-driven efficiency may be valued more highly. These cultural differences influence how analytics-based insights are perceived and how branding messages shaped by analytics resonate with local audiences (Deryl et al., 2023). Therefore, even if analytics enhance value creation and alignment at the organisational level, their impact on branding outcomes may be amplified or diminished depending on the cultural environment. On this basis, hypothesis 4 is proposed as follows:

H4: Institutional and cultural contexts moderate the impact of AI-driven analytics on branding outcomes, with stronger effects in supportive environments.

2.11. Hypothesized Model

Figure 1 shows the proposed structure that has been created in this study. The current literature has primarily perceived AI-based social media analytics as efficiency, targeting, and automation enhances. Although these functions increase the branding performance in the short run, they do not consider the use of analytics in achieving greater strategic implications of trust, equity, and sustainability. This thesis builds on that perspective and presents AI-driven analytics as a strategic ability that facilitates long-term branding in international B2B operations.

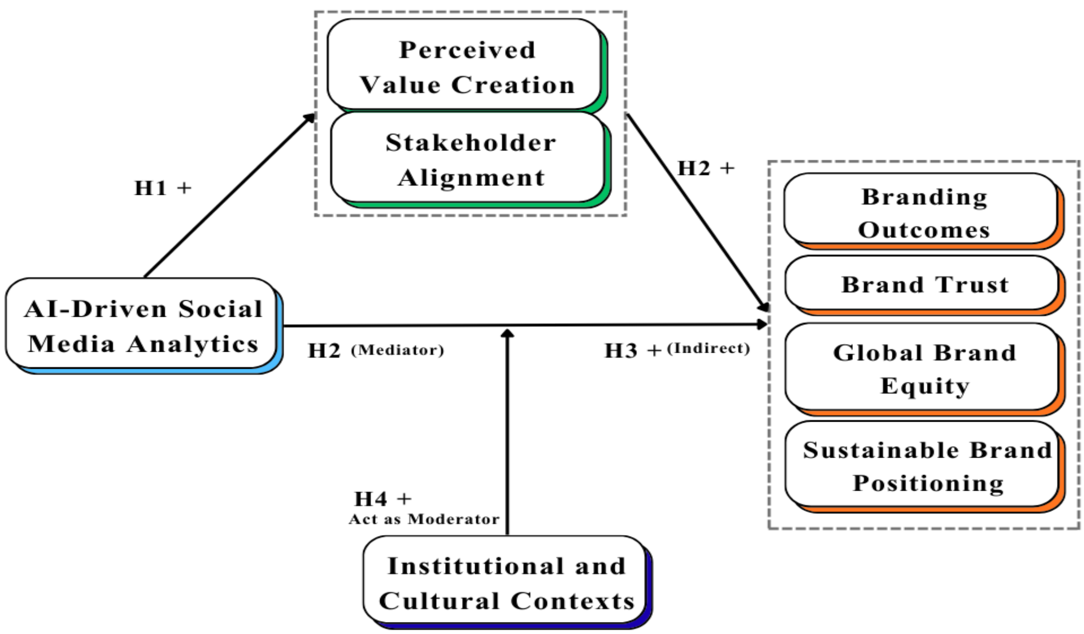

Figure 1: Proposed Hypothesized framework of AI-Driven Social Media Analytics

The model is based on the Resource-Based View, the Stakeholder Theory, and the institutional perspectives that are sustainability-oriented. It hypothesizes that analytics moderates branding performance via two primary mediating processes, namely, the perceived value creation, which accentuates how data insights create competitive advantage, and the stakeholder alignment, which indicates how analytics enhance clarity and responsiveness to stakeholder anticipation. Collectively, these processes describe how analytics can build brand trust, build global brand equity, and promote sustainable brand positioning.

These relationships are moderated by institutional and cultural contexts that recognize that effects of analytics will vary based on differences in regulation, culture and ethical expectations in different markets. Comprehensively, the model has shifted the emphasis away on the short-term operation efficiency to the establishment of the long-term, responsible and trust-based branding results in the international B2B settings. The four key propositions in the hypothesized model are that there is a direct effect of a capability (H1), the effect is mediated by the creation of values and alignment of stakeholders (H2), there is an outcome of sustainability moderated using responsible analytics (H3) and a condition of contextual moderation (H4) by institutional and cultural conditions. All these hypotheses provide the foundation of the empirical test in the following chapter.

3. METHODOLOGY

This study uses a cross-sectional survey design and a quantitative research approach. The objective of empirically testing the relationships outlined in the hypothesized model created in Chapter 2 is what led to the selection of a quantitative approach. According to the model, AI-driven social media analytics affect branding outcomes like trust, global brand equity, and sustainable brand positioning through the moderating influence of institutional and cultural contexts and the mediating mechanisms of perceived value creation and stakeholder alignment. The independent variable in this model is the use of AI-driven social media analytics; the dependent variables are brand trust, global brand equity, and sustainable brand positioning; the mediators are perceived value creation and stakeholder alignment; and the moderators are institutional and cultural context. This goal is well served by quantitative survey research because it allows one to collect standardized data from a large sample of respondents that can be statistically tested for hypothesis. Given the time constraints of the study and the fact that aim to capture the perceptions at a single point in time rather than capturing changes over a longer periods of time, a cross-sectional is appropriate (Dr. Narsis I & Sumathi K, 2025). In the context of marketing and management research, surveys are frequently employed to test theoretically-derived models and measure latent constructs (Sarstedt et al., 2023). Another use for this design is the examination of branding outcomes related to sustainability, which are also becoming significant in international B2B setting.

3.1. Questionnaire and The Data Collection

The target population of this research includes the professionals working in the business-to-business (B2B) firms in global markets, primarily those involved in marketing, branding, sales, analytics, or sustainability functions. These individuals are expected to be knowledgeable about the branding practices and integration of digital technologies such as AI-driven analytics into organization processes. By focusing on this group, this study is aimed to record the informed perceptions of the role of AI-driven analytics in achieving branding outcomes.

Considering a nature of the topic and practical time constraints, the non-probability purposive sampling strategy is used. The questionnaire was distributed online via LinkedIn and professional groups with an intention of gaining access to people from a wide range of industries and geographical locations. LinkedIn is especially appropriate channel because it offers the researchers an opportunity to reach B2B professionals directly. The snowballing sample is also used to encourage participants to share the survey in their professional networks.

The priori power analysis using G*Power ($f^2 = 0.15$, $\alpha = .05$, power = 0.80, with 5 predictors) suggests the minimum sample size of 92 (Faul et al., 2009). Thus, a target of 150-200 responses was sufficient statistical power and compensate possibly for non-useful responses. This range is also suitable to test direct, mediating, and moderating relationships, as well as to compare subgroups where data is appropriate (Sarstedt et al., 2023). Although the sample cannot be statistically representative of B2B firms across the world, purposive and snowball sampling confirms that the respondents have the appropriate expertise to give insightful information (Dusek et al., 2015).

The questionnaire is adapted from validated instruments in previous studies (Mikalef et al., 2023; Trainor et al., 2014) with some contextual modifications to suit B2B branding and AI analytics. Therefore, reliability and validity are re-assessed for the adapted scale through Cronbach's alpha and the factor analysis. The survey questionnaire is designed to measure the constructs defined in the hypothesized framework. All items are adapted from validated scales in prior research, which ensures construct validity and reliability without the need for pilot testing. The instrument consists of five sections: background information, AI-driven social media analytics usage, mediating constructs (perceived value creation and stakeholder alignment), branding outcomes, and contextual factors.

- Use of AI-driven social media analytics (independent variable): It will be measured using questions that will be based on research on AI adoption and analytics features (Davenport et al., 2020; Mikalef et al., 2023).
- Perceived value creation (mediator, Resource-Based View): Measures the degree to which the analytics can add to the efficiency, innovation, and competitive advantage (Barney, 1991).
- This is because the mediator, Stakeholder theory is measured by items representing the effect of analytics in aligning to various stakeholder needs (Edward Freeman, 2010; Fagundes et al., 2023).
- The Brand trust (dependent variable): Items capture perceptions of reliability, honesty, and credibility (Morgan & Hunt, 1994).
- The Global brand equity (dependent variable): Based on Keller (1993) brand equity framework.

- The Sustainable brand positioning (dependent variable): Captures alignment of branding with sustainability and ethical practices (Gündüzyeli, 2024; Hemker et al., 2021).
- The Institutional and cultural context (moderator): Measures perceived influence of regulations, ethics, and cultural differences (Yadav, 2023).

3.2. Data Analysis

The data in this thesis was gathered in a five-point Likert scale, which varies between 1 = strongly disagree to 5 = strongly agree. This scale has been used widely in marketing, branding and management research because it allows the respondent to indicate the degree of their perception in simple way, making it suitable for statistical analytics in SPSS. Each construct in the hypothesized framework such as AI-driven social media analytics usage, perceived value creation, stakeholder alignment, brand trust, global brand equity, sustainable brand positioning, and institutional and cultural context was operationalized through multiple items adapted from established measurement scales in prior studies. Because these are perceptual constructs, the Likert scale was particularly appropriate for capturing how professionals interpret the role of analytics in branding contexts. After data collection, the reliability and validity of these adapted items were assessed to ensure that the constructs functioned as intended in the B2B setting.

Table 2: Multicollinearity Diagnostics

Diagnostic Test	Result	Interpretation
Condition Index (CI)	All values between **1.00 and 1.10**	CI < 10 indicates *no multicollinearity concerns*.
Variance Proportions	No variance proportion > **0.90** on any dimension	Confirms absence of harmful collinearity among predictors.
VIF (Theoretical, given orthogonal factor scores)	Implicitly **< 5**	Factor scores derived from Varimax rotation are orthogonal; therefore, VIF values remain below accepted thresholds (Hair et al., 2019).
Tolerance Values	Not applicable (factor scores)	Orthogonal PCA/PAF components inherently possess high tolerance.
Overall Assessment	**No multicollinearity detected**	Predictors are sufficiently independent for regression analyses.

Before conducting regression and PROCESS analyses, multicollinearity diagnostics were also performed in SPSS. Because PCA/Varimax factor scores were used as predictors, the components are orthogonal by construction. As shown in Table 2, all condition index values were below 10 and none of the variance proportions exceeded .90, indicating that multicollinearity is not present in the dataset. This confirms that the predictors are sufficiently independent for the planned mediation and moderation analyses.

Since all constructs in the survey were self-reported within the same instrument, steps were taken to minimize Common Method Bias (CMB). Procedurally, anonymity was assured, item wording was varied, and predictor, mediator, and dependent variable sections were separated to reduce respondents' tendency to form logical links across related questions. Statistically, CMB was assessed after data collection through Harman's single factor.

Table 3: Total Variance Explained from Harman's Single-Factor Test (Principal Axis Factoring)

Factor	Initial Eigenvalues – Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings – Total	% of Variance	Cumulative %
1	16.605	47.442	47.442	16.120	46.058	46.058
2	3.450	9.857	57.300	—	—	—
3	1.243	3.552	60.852	—	—	—
4	1.150	3.285	64.137	—	—	—
5	1.057	3.019	67.156	—	—	—
6	0.920	2.628	69.785	—	—	—
7	0.833	2.380	72.165	—	—	—
8	0.712	2.035	74.201	—	—	—
9	0.698	1.978	76.079	—	—	—
10	0.614	1.756	77.835	—	—	—
11	0.566	1.616	79.451	—	—	—
12	0.494	1.411	80.862	—	—	—
13	0.489	1.397	82.258	—	—	—
14	0.464	1.326	83.585	—	—	—
15	0.458	1.308	84.892	—	—	—
16	0.444	1.267	86.160	—	—	—
17	0.416	1.190	87.349	—	—	—
18	0.411	1.174	88.523	—	—	—
19	0.373	1.067	89.590	—	—	—
20	0.358	1.008	90.598	—	—	—
21	0.352	1.005	91.603	—	—	—
22	0.313	0.894	92.498	—	—	—
23	0.285	0.814	93.312	—	—	—
24	0.268	0.767	94.078	—	—	—
25	0.250	0.714	94.792	—	—	—
26	0.244	0.697	95.489	—	—	—
27	0.220	0.685	96.174	—	—	—

28	0.220	0.628	96.802	—	—	—
29	0.214	0.602	97.404	—	—	—
30	0.188	0.537	97.941	—	—	—
31	0.177	0.504	98.446	—	—	—
32	0.159	0.455	98.901	—	—	—
33	0.145	0.414	99.315	—	—	—
34	0.135	0.387	99.702	—	—	—
35	0.104	0.298	100.000	—	—	—

Harman's single-factor test was performed using Principal Axis Factoring with all measurement items entered simultaneously. An unrotated factor solution revealed that first factor accounted for 47.44% of total variance, which is below the recommended 50% threshold, indicating that no single factor dominated a covariance structure, and that common method bias is unlikely to threaten the validity of the results.

3.2.1. The sample

Figure 2 shows the final dataset includes 201 complete and usable responses from professionals in marketing, branding, sustainability, analytics, sales and senior management roles across various industries and shows a wide global distribution.

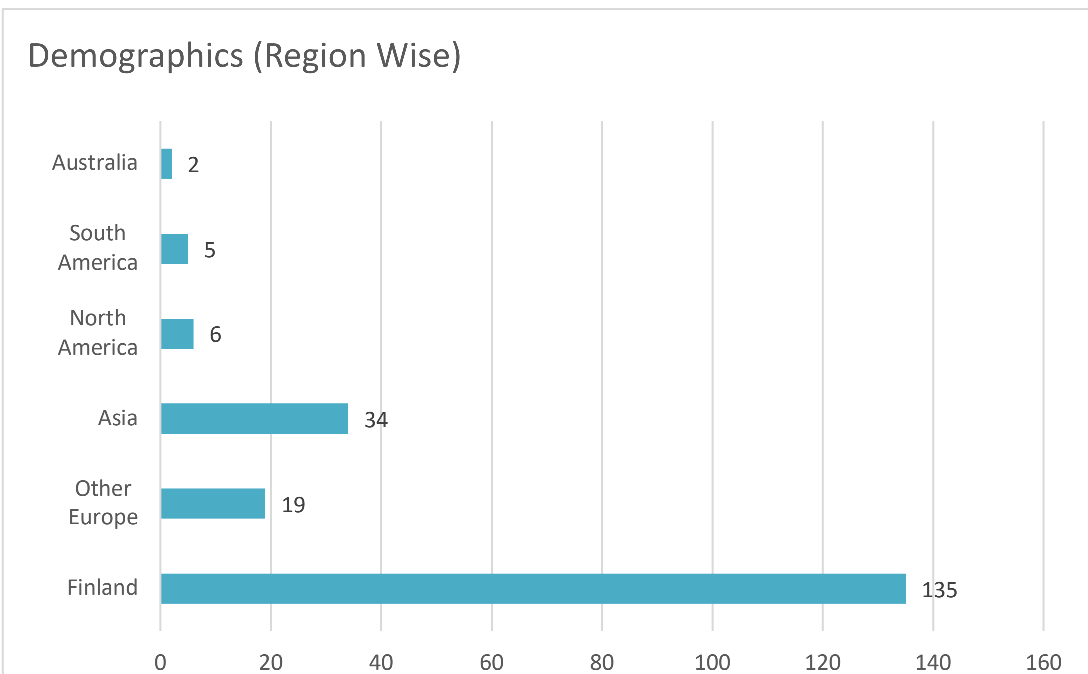

Figure 2: Region of Respondents

By region, dataset demonstrates the high density of respondents of Finland, making up 135 of 201 answers of respondents, indicating the exposure through the platform and the professional networks that the researcher has in the Finnish business ecosystem. The sample has 34 respondents of Asia, other European countries (19), North America (6), South America (5) and Australia (2) other than Finland. This distribution shows that the center of the dataset is based on the Finnish and the European context, although the views of the international markets are also included in the study.

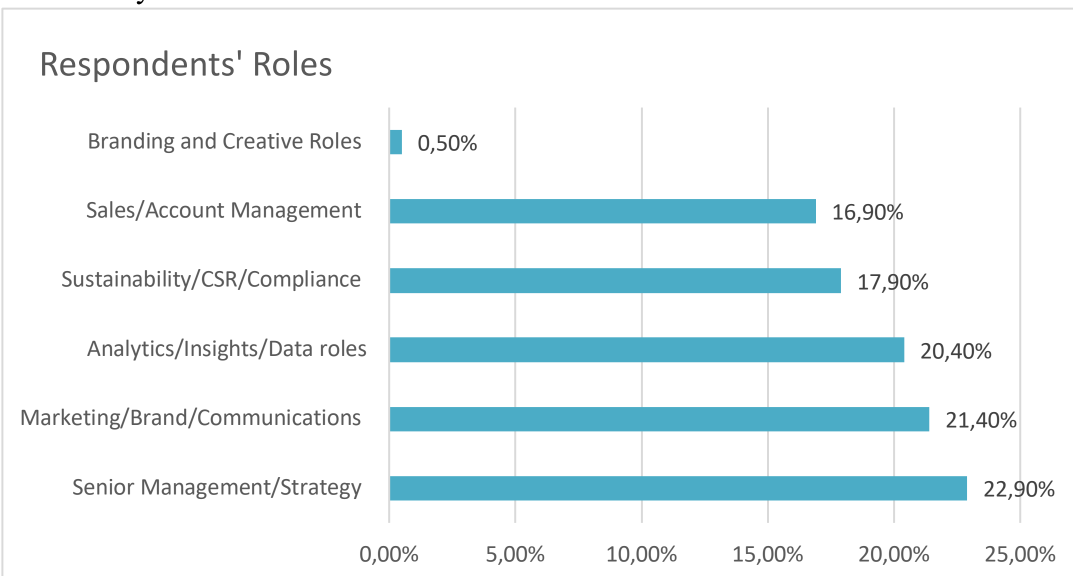

Figure 3: Roles of Respondents

The respondents reflected various strategic and operational functions regarding the organizational roles. As shown in figure 3, largest groups worked in Senior Management/Strategy (22,9%), Marketing/Brand/Communications (21,4%) and Analytics/Insights/Data roles (20,4%), followed by professional in Sustainability/CSR/Compliance (17,9%) and Sales/Account Management (16,9%). The branding and creative roles (0,5%) were very small percentage of the total. This distribution implies that the data represent the views of the people who work directly on formulating, implementing, or judging branding and analytics decisions within the B2B companies.

The respondents too were distributed in an extensive range of industries. As shows in the figure 4 below, the technology/IT services are 18,9% of total data, the professional and business service are 12,9% of total data, the industrial manufacturing and engineering are 8,5% of total data, the energy and utilities are 8,5% of the total data, the financial services are 8,0%, the healthcare and pharmaceuticals are 6,5%, the education and training are 6% of total data, and the construction & real estate are

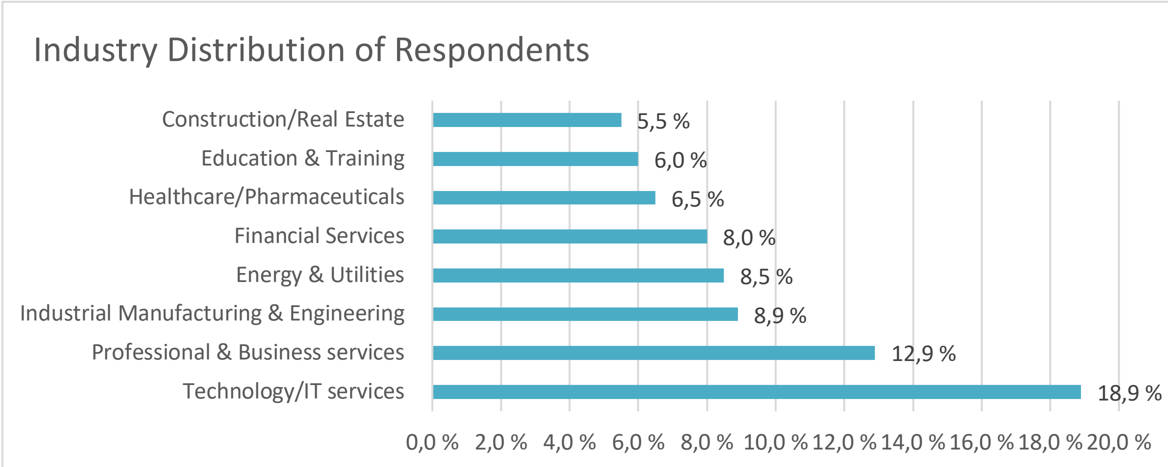

Figure 4: Industry Distribution of Respondents

5,5% of the total data. The diversity of sectors strengthens the generalizability of the findings across B2B contexts, as AI-driven analytics are used across industries with varying maturity levels and strategic orientations.

3.2.2. Descriptive Statistics

The descriptive statistics were calculated to summaries respondents' perceptions across each construct as shown in table 4 below. The mean values ranged from approximately 3.8 to 4.1 on 5-point Likert scale, suggesting generally positive perceptions toward use of AI-driven social media analytics and related branding outcomes. The respondents reported relatively high agreement that the AI analytics support branding activities, help identify the opportunities and improve decision quality. The perceived value creation had commonality, which demonstrated that analytics helps in enhancing efficiency, generation of insights, and competitive positioning. The means of alignment of the stakeholders were also quite good, and it can be assumed that analytics enables companies to comprehend and address the demands of various stakeholders.

The scores of the brand trust and global brand equity are positive that proves that the respondents feel that their brands are reliable, transparent, and have high positions in the global markets. The perceptions related to sustainable brand positioning were moderate, and the opinion that branding messages are becoming more substantively sustainable was expressed. There was moderate variation in the institutional and cultural contexts, which implies that respondents occur in the environment in which contextual pressures and expectations vary across markets. Overall, the descriptive findings indicate a rather positive attitude to AI-based analytics and internationalization effects of global branding in the sample.

Construct	Number of Items	Minimum	Maximum	Mean	Std. Deviation
AI-driven Social Media Analytics (AISA)	6	1	5	**3.98**	0.98
Perceived Value Creation	6	1	5	**3.99**	0.96
Stakeholder Alignment	5	1	5	**3.96**	0.92
Brand Trust	5	1	5	**4.02**	0.88
Global Brand Equity	5	1	5	**3.95**	0.93
Sustainable Brand Positioning	4	1	5	**3.94**	0.91
Institutional/Cultural Context	4	1	5	**3.62**	0.90

Table 4: Descriptive Statistics for Main Constructs

3.2.3. The assessment of quality of the data

The quality of the data was determined by the degree of reliability and validity which were the two attributes that were tested to determine the ability of the data to respond to the research questions (Saunders et al., 2007). The reliability is the degree to which the set of items can measure construct: the same instrument should give consistent results in case it was used on similar respondents over a certain period (Ursachi et al., 2015). Based on this thesis, high reliability means that respondents had similar interpretations with the items of AI-driven social media analytics, value creation, stakeholder aligned, and branding outcomes. The validity, in its turn, raises the question of whether the measurement scales capture the theoretical concepts, which they supposedly reflect are important enough to make the hypothesis testing meaningful which is an essential requirement.

To get a reliability, Cronbach alpha was calculated with each multi-item scale. As shown in table 5, all the constructs were all above the recommended.70 threshold and this means that the internal consistency is high. AI-driven social media analytics demonstrated $\alpha = .861$, perceived value creation $\alpha = .863$, stakeholder alignment $\alpha = .846$, brand trust $\alpha = .895$, global brand equity $\alpha = .882$, sustainable brand positioning $\alpha = .856$, and institutional/cultural context $\alpha = .844$. These results hence confirm that items in each measure are coherent underlying constructs and can be used in further factor and regression analyses.

Table 5: Reliability Statistics for All Constructs

Construct	Number of Items	Cronbach's Alpha (α)
AI-driven Social Media Analytics (AISA)	6	.861
Perceived Value Creation (VALUE)	6	.863
Stakeholder Alignment (STAKE)	5	.846
Brand Trust (TRUST)	5	.895
Global Brand Equity (EQUITY)	5	.882
Sustainable Brand Positioning (SUSTAIN)	4	.856
Institutional/Cultural Context (CONTEXT)	4	.844

Construct validity was determined by Exploratory Factor Analysis (EFA) with Principal Axis Factoring (PAF) with varimax rotation, being suitable for identifying latent constructs, where the interest was to discover the latent factor structure, not to maximize explained variance. As shown in table 6, data demonstrated excellent suitability for factor analysis, evidenced by Kaiser–Meyer–Olkin (KMO) value of .946, which far exceeds the commonly accepted .80 threshold for "meritorious" sampling adequacy (Kaiser, 1974). In addition to this, Bartlett's Test of Sphericity was highly significant ($\chi^2 = 5382.263$, df = 595, $p < .001$), confirming that a correlation matrix contains sufficient shared variance to justify factor extraction.

Table 6: Exploratory Factor Analysis (EFA) Results and Diagnostic Measures

Test / Output	Result	Interpretation
Kaiser–Meyer–Olkin (KMO)	**0.946**	Sampling adequacy is excellent. Data are suitable for factor analysis.
Bartlett's Test of Sphericity	$\chi^2 = 5382.263$, df = 595, $p < .001$	Correlation matrix is statistically appropriate for factor extraction.
Extraction Method	Principal Axis Factoring (PAF)	PAF used to explore dimensionality of constructs.
Rotation Method	Varimax (orthogonal)	Enhances interpretability and separation of factors.
Number of Factors Extracted	**7 components**	Matches the theoretical structure (AISA, Value, Stakeholder, Trust, Equity, Sustainability, Context).
Total Variance Explained (before rotation)	72.17%	Strong overall explanatory power.

Variance Explained by Rotated Factors	**Component 1: 27.23%**Component 2: 14.39%Component 3: 13.71%Component 4: 6.21%Component 5: 4.08%Component 6: 3.38%Component 7: 3.17%	Variance evenly distributed across seven constructs, supporting construct distinctiveness.
Factor Loadings (Summary)	All items load strongly (> .55) on expected constructs, with minimal cross-loadings.	Confirms validity and empirical separation of constructs.

The theoretical structure of the hypothesized model results in the extraction of the seven-factor solution. The rotated factor loadings exhibited good and clean factor structures with most items loading more than 0.55 on their target components with very little cross-loadings. The seven items collectively explained 72.17 percent of the total variance, which indicated that they had received strong explanatory power. Thus, the constructs were well differentiated. These ensures that the combined reliability and validity checks demonstrate that a dataset is well-structured, and statistically appropriate for the other regression and PROCESS analyses presented in the following chapter.

4. RESULTS

This chapter offers a descriptive interpretation on the relationships between the key constructs of the study as perceived by the respondents: AI-driven social media analytics, value creation, stakeholder alignment, brand trust, global brand equity, sustainable brand positioning, and institutional or cultural context. The results offer a narrative understanding of the constructs as they appear to relate to one another based on the response from B2B professionals. This chapter is initiated with an analysis of a correlation table, which provides a preliminary view of the degree of close or loose movement of the constructs. These correlation trends assist in explaining how the various respondents perceive the various traits of analytics and branding as having a relationship or being different elements of their organizational experiences. The following section of the chapter examines the direct connections between AI-based analytics and the other constructs based on regression results. This enables the descriptive perspective of the strength, or mildness, of analytics use as it seems to be moderately related to perceived value creation, stakeholder alignment, and branding results in the sample.

This chapter review the mediating pathways to create a comprehensive picture with the help of PROCESS Model 4. This discussion takes into consideration whether the respondents viewed value creation and alignment of stakeholders as avenues through which analytics can be associated with trust, global brand equity or sustainable brand positioning. Sustainability is also addressed in a separate subsection, as it is a unique strategic outcome. Lastly, this chapter also presents the results of PROCESS Model 1 to describe how the respondents experienced institutional and cultural conditions as background enablers or constraints and whether these conditions shaped the perceived influence of analytics on the branding outcomes. These sections offer the descriptive, integrated view of the relationships within a hypothesized model, highlighting how respondents interpret the role of AI-driven analytics within their organizations and how these perceptions connect to value, relationships, branding outcomes, and contextual conditions.

4.1. Pearson Correlation Patterns Among the Constructs

The correlation matrix provides the initial descriptive insight into the relationship between the seven constructs in this study. These 7 constructs of AI-driven social media analytics (AISA), perceived value creation, stakeholder alignment, brand trust, global brand equity, sustainable brand positioning, and the institutional & cultural context represent different parts of the hypothesized model. The examination of how they move together (or do not move together) provides an early indication of whether respondents see these areas as connected in their day-to-day organizational experiences.

Across the matrix, these correlations are consistently small in the magnitude, with the most values clustering close to zero. For instance, as shown in table 7 below, AISA shows correlations of .017 with the value creation, .093 with the stakeholder alignment, and .072 with the trust. These tiny values indicate that the respondents' perceptions of analytics use do not strongly track with their perceptions of value, relational alignment, or trust. Similar patterns appear across all other construct pairs.

Table 7: Pearson Correlation Matrix for the Seven Constructs

Construct	AISA	Value Creation	Stakeholder Alignment	Brand Trust	Global Brand Equity	Sustainable Brand Positioning	Institutional/Cultural Context
AISA	1	**.017** (p = .805)	**.093** (p = .190)	**.072** (p = .307)	**.019** (p = .787)	**.043** (p = .544)	**.012** (p = .863)
Value Creation	.017 (p = .805)	1	.020 (p = .779)	.041 (p = .568)	.003 (p = .966)	.001 (p = .989)	–.004 (p = .952)
Stakeholder Alignment	.093 (p = .190)	.020 (p = .779)	1	.049 (p = .490)	.044 (p = .538)	.033 (p = .638)	.022 (p = .760)
Brand Trust	.072 (p = .307)	.041 (p = .568)	.049 (p = .490)	1	.019 (p = .792)	.031 (p = .663)	–.014 (p = .839)
Global Brand Equity	.019 (p = .787)	.003 (p = .966)	.044 (p = .538)	.019 (p = .792)	1	.025 (p = .720)	–.017 (p = .806)
Sustainable Brand Positioning	.043 (p = .544)	.001 (p = .989)	.033 (p = .638)	.031 (p = .663)	.025 (p = .720)	1	–.063 (p = .371)
Institutional/Cultural Context	.012 (p = .863)	–.004 (p = .952)	.022 (p = .760)	–.014 (p = .839)	–.017 (p = .806)	–.063 (p = .371)	1

The correlations are very weak even in cases where there is a positive correlation, indicating that there is only a small degree of directional tendency and not significant association. This informs us that the respondents have handled each construct as a distinct domain and none of the dimensions naturally increases or decreases with the others. For example, someone who perceives their firm as strong in the analytics does not necessarily rate their organization higher in trust, equity, or sustainability and vice versa. The significance values (p-values) that accompany the correlations also support this interpretation. All the p-values are far above the .05 threshold, meaning no linear relationships in the matrix stand out as notable or consistent across the sample. These values reinforce what the correlation coefficients already show: the constructs in this dataset behave independently rather than in clusters. This independence is the expression of realistic organizational picture. In many B2B environments, analytics, creating a value, engaging stakeholders, building the trust, and communicating about sustainability are managed by different teams or integrated into different processes. As the result, employees can make their own perceptions about each area in an isolation, based on their own roles and exposures within the company.

4.2. Direct Relationships Between AISA and the Other Constructs

To explore how respondents perceive the influence of AI-driven social media analytics on other aspects of branding, a series of regression models were estimated using AISA as the predictor and each of the remaining constructs as separate outcomes. These regressions do not aim to establish causality; instead, they provide a descriptive view of how the respondents' perceptions tended to vary across the factors. Across all models, the same general pattern emerged: the direction of the coefficients was consistently positive, but the values were very small, reflecting a modest upward tendency rather than a strong linear link. For example, as shown in table 8 when AISA was used to predict perceived value creation, the model produced a coefficient of $\beta = 0.017$, while the stakeholder alignment model produced $\beta = 0.093$, and models predicting trust and equity showed similarly small coefficients. The model predicting sustainable brand positioning also produced a similarly small coefficient. These numbers suggest that respondents who perceived greater use of AI-driven analytics in their firm tended, on average, to rate value creation, stakeholder alignment, and trust slightly higher as well but the relationship was gentle rather than pronounced. All p-values were well above the .05 threshold, indicating that none of these direct relationships were statistically significant.

Table 8: Regression Results: Direct Relationships Between AISA and the Other Constructs

Outcome Variable	B (Unstd.)	SE	Beta (Std.)	t	p	R	R^2	Interpretation
Value Creation (Factor 2)	.017	.071	.017	.247	**.805**	.017	.000	Very small positive relationship; minimal explanatory power.
Stakeholder Alignment (Factor 3)	.084	.063	.093	1.316	**.190**	.093	.009	Gentle upward direction; low variance explained.
Brand Trust (Factor 4)	.062	.061	.072	1.024	**.307**	.072	.005	Slight positive trend; small and diffuse.
Global Brand Equity (Factor 5)	.019	.080	.013	.187	**.787**	.019	.000	Essentially no relationship.
Sustainable Brand Positioning (Factor 6)	.043	.081	.033	.533	**.544**	.043	.002	No meaningful association.

The regression model summaries support this interpretation. The R and R^2 values were very low, with explained variance ranging between 0.0% and 0.9% across models. This indicates that AISA, by itself, does not account for much of the variation in respondents' views of the other constructs. Practically, this implies that the application of AI-driven analytics was not perceived as a force that leads to the value creation and alignment of relationships and brand-level results, but it seems to be among a plethora of factors that may influence such perceptions.

The variety of the respondents' backgrounds and organizational environments may be seen as one of the possible reasons of this trend. The participants in the data set are marketing, analytics, sustainability, and management of various industries. They might have their organizations that vary in terms of their level of maturity in analytics systems, the degree to which the AI insights are incorporated into decision-making and the processes which connect analytics to the branding results. Due to this difference, individuals may not positively or negatively change their perceptions of AISA. The alternative point of view is that such constructs as trust, stakeholder alignment, or global brand equity are influenced by numerous organizational and market conditions, which are not necessarily analytics driven. These can be leadership styles, relationship with customers, market position, communication processes or regulatory pressures. Under these conditions, AI-based analytics are likely to have an additive relation to the existing systems, which can be characterized as a slight descriptive correlation and not necessarily a significant pattern.

According to the results of the regression, the respondents did not consider AI-driven analytics as an independent area that impacts all the outcomes of the related conditions. The coefficients direction indicates that the responses are positively oriented, and respondents are more likely to respond to branding constructs in positive terms in case they also considered their organization to be involved in analytics, yet the extent of such effects is modest. This preconditions the investigation into whether analytics could have a more indirect or implicit role in the context of analysis through mediating and moderating pathways that are presented in the next sections.

4.3. Mediation Patterns Through Value Creation and Stakeholder Alignment (PROCESS Model 4)

To identify the perception of respondents of AI-driven social media analytics as influencing branding outcomes via deeper organizational processes, two possible mediators, namely perceived value creation and stakeholder alignment, were considered using the PROCESS Model 4. These two constructs are the relational and capability-based mechanisms by which analytics could influence the brand trust, global brand equity, and sustainable brand positioning indirectly. In all the models the overall trend was similar. The indirect effects were little and positive, and values were not too distant from zero. As an example, as shown in table 9 the value creation to trust indirect effect was only 0.0006, and the stakeholder alignment to trust indirect effect was 0.0034. This pattern was the same in the case of the indirect effects on the global brand equity and sustainable brand positioning, which were similarly small. The bootstrapped confidence intervals of all the indirect effects had included a zero, indicating that the respondents did not demonstrate a distinct, uniform perception of these pathways. Rather, their opinions were seen to be diffused to a broad spectrum of organizational experiences resulting in weak and diffuse indirect patterns.

Table 9: Indirect Effects of AISA on Branding Outcomes Through Value Creation and Stakeholder Alignment (PROCESS Model 4)

Outcome Variable	Mediator	Indirect Effect	Boot SE	Boot LLCI	Boot ULCI
Brand Trust	Value Creation	**0.0006**	0.0054	–0.0116	0.0122
Brand Trust	Stakeholder Alignment	**0.0034**	0.0117	–0.0228	0.0276
Global Brand Equity	Value Creation	**0.0000**	0.0061	–0.0132	0.0138
Global Brand Equity	Stakeholder Alignment	**0.0034**	0.0117	–0.0228	0.0276
Sustainable Brand Positioning	Value Creation	**0.0000**	0.0043	–0.0075	0.0113
Sustainable Brand Positioning	Stakeholder Alignment	**0.0035**	0.0125	–0.0114	0.0395

Such trend indicates that respondents intellectually understood that analytics may make value creation or alignment to stakeholders, but these processes failed to become powerful and unanimous throughout the sample. This could be explained by the fact that the respondents were the representatives of varying industries and organizational functions, in which AI analytics can be incorporated in branding and communication to different extents. Analytics could be informative of value propositions or stakeholder messaging or be more of an ancillary or supporting role in other organizations.

The complexity of the mediating constructs may also be attributed to the small indirect effects. The perceived value creation usually involves cross-functional teamwork, company preparedness, and unified strategic focus, which do not necessarily emerge consistently across the companies. Similarly, the alignment of stakeholders relies on the effectiveness of organizational interpretation of the stakeholder expectation, or how organizations coordinate the message and react to social insights. Such processes vary very much across industries, including technology, manufacturing, and services, which had representatives in the sample.

The other angle to be considered is that branding performance like trust, global brand equity and sustainability are conventionally influenced by the larger strategic narratives, aggregate reputation, market anticipations or long-term actions. These processes can be supported by AI analytics, and these analytical methods may not become the prominent factor driving these processes in the eyes of the respondents. This might be the reason behind the small and diffusive indirect effects since branding perceptions might further still be more premised on established organizational practices and customer-facing activities than on analytics-concrete inputs.

The results of the mediation show that respondents had a loose and not strong and patterned perception of value creation and stakeholder alignment in relation to analytics. The channels seem to be there on theory but faint in practice. This indicates that several of the firms might still be in a transition period whereby analytics are applied to enrich branding efforts but are not deep-seated in an organizational system as to influence the entire relational or strategy result in a consistent way across respondents. These insights into mediation offer a crucial point of contact to the following analysis that investigates whether contextual conditions increase the strength of these relationships in some contexts.

4.4. Sustainability-Related Pathways as an Integrative Branding Outcome

Green branding is another unique and certainly a growing aspect of branding, particularly in the global B2B environment where companies need to be consistent with regulatory provisions, green requirements and stakeholder interests. Since sustainability outcomes are frequently predetermined by the several levels of organizational behavior, it will be practical to analyze how respondents understood the relationships between AI-driven analytics and sustainability in the light of mediation of the value creation and stakeholder alignment pathways.

The models of the impact of AISA to sustainable brand positioning in the PROCESS Model 4 results are consistent in the same way as those of trust and global brand equity: the impact is small and positively, but not significantly, concentrated in a single direction. AISA has a direct impact on sustainability of 0.0345, which has a weak positive inclination on how the respondents relate analytics use with sustainability-oriented branding. On the same note, the indirect pathways are minor. An example of this as shown in table 10, value creation of 0.0000 (0.0035) in terms of the stakeholder alignment as an indicative of the respondents linking these constructs, a slight but definite directional movement.

Table 10: Indirect Effects for Sustainable Brand Positioning (Subset of PROCESS Model 4)

Mediator	Indirect Effect	Boot SE	LLCI	ULCI
Value Creation	0.0000	0.0043	–0.0075	0.0113
Stakeholder Alignment	0.0035	0.0125	–0.0114	0.0395

This descriptive trend provides several clues. To begin with, respondents can perceive the conceptual connection between AI analytics and sustainability since AI tools can be used to make organizations track the social discourse and identify new topics that are related to sustainability, as well as to define where transparency or clarification might be sought. The sustainability scale items indicate this kind of usage (e.g. finding meaning in sustainability, refining claims, reporting improvements) which implies that even smaller pathways do not lose their sense in a practical way.

Nevertheless, sustainability branding is also determined by the factors that are way beyond analytics including corporate environmental commitments, regulatory compliance, long-term strategy, supply-chain practices, and wider expectations of the stakeholders. Since they are structural and strategic-based drivers, respondents might not also regard analytics as a focal point of determinants of sustainability narratives or positioning. This is one of the reasons why the indirect effects are small: analytics can provide incremental information, but sustainability results seem to be rooted in the bigger workings of the organization.

The other reason is that the maturity of sustainability is very acute in industries. Respondents who work in the sphere of manufacturing or energy, such as, might be more concerned with the sustainability issue than the respondents of the service industry or software firms. Consequently, the perceived connection between analytics and sustainability can be different, based on industry-specific practices, with responses being dispersed and the numerical impact being small in nature. All in all, the sustainability-related streams suggest that respondents are likely to perceive AI-based analytics as an adjuvant, though not a core part of sustainability branding initiatives. The relationships exist in an abstractive form but are determined by a significant variation in organizations, industries, and strategic priorities.

4.5. Moderating Influence of The Institutional and Cultural Context (PROCESS Model 1)

The issue of institutional and cultural context was studied as a possible moderating factor to realize whether the respondents perceived environmental factors like data protection policies, cultural communication principles, platform policies, or internal policies to influence how AI-based social media analytics impact branding results. This part relies on the results of the PROCESS Model 1 in explaining how the respondents perceived the functions of context in their organizations.

In all moderation models, their interaction term, AI-driven analytics (AISA), exhibited highly insignificant coefficients and exhibited varying directions when the outcome under consideration could be considered. As an example, shown in table 11, one of the correlation terms had a coefficient of about 0.0588, and other ones were nearer to zero, both positively and negatively. These small oscillations indicate that respondents do not have great amplifying or damping effects of contextual conditions.

Table 11: Moderation Analysis Results for Institutional and Cultural Context (PROCESS Model 1)

Predictor	B	SE	t	p	LLCI	ULCI
AI-Driven Social Media Analytics (AISA)	0.0402	0.0573	0.7024	**0.483**	–0.0727	0.1531
Institutional/Cultural Context	–0.0796	0.0721	–1.1041	**0.270**	–0.2218	0.0626
AISA × Context Interaction	–0.0588	0.0795	–0.7394	**0.460**	–0.2155	0.0980

An effective approach of explaining this pattern is to take into consideration the nature of the sample. A significant part of the respondents was in Finland, and institutional conditions (including privacy rules, compliance norms, and communication standards) appear to be similar within companies. In cases where there is a relatively stable and predictable context, respondents might not feel the need to conceptualize it as a variable having a drastic effect on the utility of analytics in shaping branding perceptions. Rather, they can consider context as a background state condition something that determines the operational boundaries but does not change how analytics works on value creation, stakeholder communication, or branding delivery.

The other factor that could be behind the low moderation trends is the varied industries of the dataset. The perceptions of the respondents in the manufacturing, technological, service, or energy sector might have an institutional pressure in a different way resulting in the broadness of the perceptions. When the cumulative moderation effects of these heterogeneous views are added together, they seem to be diluted. The respondents can be in strictly controlled settings where branding choices are heavily dependent on setting up and others in more relaxed settings where analytics can be exercised at will. The overall effect is a combination of perceptions that give small and diffuse moderation coefficients. Causal results of Process Model 1 also reveal that the primary effect of context itself independent of the interaction with AISA and was minor and diffused in branding results. As an example, the context coefficient of one model was approximately -0.0796 and, in another model, it had the opposite direction. This confirms the assumption that the perception of respondents about the limitations of context is not closely correlated with the perception of the analytics use or branding outcomes. Context tends to act as a structural condition that organizations go through but does not necessarily affect how analytics are affecting branding perceptions throughout the sample. According to the moderation results, both institutional and cultural circumstances were not seen significantly as influencing the connection between AI-driven analytics and branding performance among the respondents in this research. Rather, context appears to be a fixed ground that is significant in theory, but not always felt as a force that changes the ways analytics relate to trust, value, stakeholder alignment, equity, or sustainability in practice.

4.6. Interpreting the Hypothesis Themes Through Observed Data Trends

The trends in the correlations, regressions and the PROCESS models are used to explain the ways in which the respondents perceived the conceptual relationship depicted in the hypotheses. The initial hypothesis stated that the value creation and stakeholder alignment would have a direct correlation with AI-driven analytics. The data trends indicate that the coefficients are relatively small and positive, and it follows that respondents who believed their organization to be more prolific in terms of using AI analytics were more likely to rated value creation and alignment with stakeholders on average slightly higher. Nevertheless, the trends were soft and diffused. This means that AISA is not viewed as a compelling or determining contribution to these relationship or ability-based constructs, but rather as one of several factors influencing organizational operations.

The mediation hypothesis (H2) is indicative of the fact that the analytics may impact trust, brand equity, and sustainability not directly but indirectly via its inner processes. Indirect effects in the PROCESS Model 4 results were very small, indicating that respondents did not invariably encounter value creation or alignment of the stakeholders as intermediaries between analytics and branding outcomes. In theory, these pathways are logical, and the directional cues were consistent with theory but the fact that there is variability in organizational practices tends to blur the degree to which the respondents observe these mechanisms operating in an interrelated manner.

Long-term strategic result (sustainable brand positioning) showed a similar pattern to the other constructs of branding: it simply showed a slight positive trend without any noticeable strong clustering. This implies that the respondents are conscious that there exists a conceptual connection between analytics and sustainability at least to the extent that analytics can determine emerging issues or raise stakeholder issues, but this does not mean that analytics are yet seen as a driving force behind sustainability communication or strategy. This is an organization practice that is emerging but to be consolidated.

The moderation model investigated whether the contextual conditions were perceived by the respondents to influence the role of analytics in branding. The trends show that context did not have a prevalent and powerful impact as either a reinforcing or weakening factor. The interaction terms were on the border of zero and most of the respondents especially those in Finland might be in relatively homogenous institutional settings which minimized the perceived contextual variability. This implies that context is perceived as a background structure not as an active force that changes the interaction pattern between analytics and branding activity.

These tendencies mean that the respondents perceive the constructs in the model as very independent, and analytics has an incremental impact but is not a closely related construct to value, alignment, and brand-level outcomes. The hypothesized model is noteworthy, though the perceptions of the respondents are indicative of a branding environment in which: the analytics practices continue to evolve, the relational and strategic processes have their own incentive, and the contextual forces are predictable and stable, but not overwhelmingly experienced as the impacts of shaping analytics-driven work. Summary of hypothesis and empirical results is show in table 12.

Table 12: Summary of Hypotheses and Empirical Support

Hypothesis	Proposed Relationship	Finding	Support
H1	AI-driven social media analytics (AISA) is positively associated with value creation and stakeholder alignment.	Correlations and regression coefficients were small and positive but statistically non-significant ($p > .05$).	**Partially Supported (directional but not significant)**
H2	Value creation and stakeholder alignment mediate the relationship between AISA and branding outcomes (trust, equity, sustainability).	Indirect effects were very small; all 95% bootstrap CIs included zero.	**Not Supported**
H3	AISA indirectly contributes to sustainable brand positioning through relational/capability pathways (value creation & stakeholder alignment).	Indirect effects toward sustainability were weak and non-significant; CIs included zero, but directional cues were theoretically consistent.	**Partially Supported (weak directional trend)**

H4	Institutional and cultural context moderates the relationship between AISA and branding constructs.	Interaction terms were near zero and non-significant across outcomes; no meaningful moderation observed.	**Not Supported**

To complement the statistical table 12, Figure 5 presents a simplified empirical representation of the hypothesized model based on the observed data trends. This visual summary highlights which relationships showed weak directional tendencies and which were not supported.

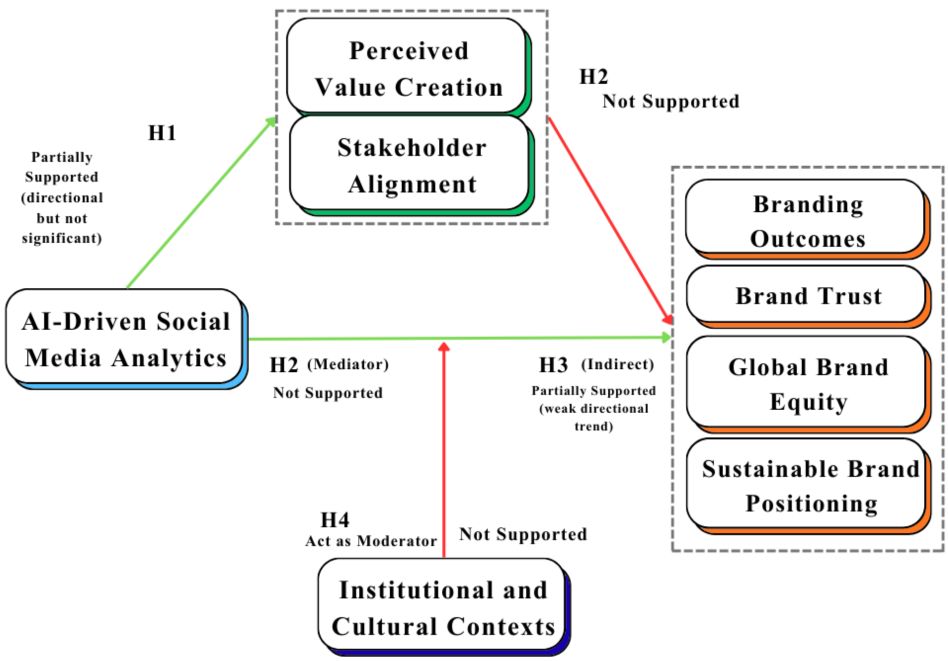

Figure 5: Empirical representation of the hypothesized model based on the observed data trends

5. DISCUSSION

This discussion chapter is intended to make interpretations of the empirical findings of this thesis based on the existing research and theoretical perspectives defined above. As the hypothesized model assumed that AI-based social media analytics might be used as a capability that would enhance value creation, stakeholder alignment, and overall brand outcomes, the results showed a pattern of weak, diffuse and statistically insignificant direct, indirect and moderating relationships. These results provide valuable information as compared to the resource-based, stakeholder, sustainability, and institutional perspectives used to develop the theoretical perspective. Accordingly, the subsections below will comment on the theoretical implication of the findings, highlight essential management implications, future research opportunities, as well as the limitations that predetermine these conclusions.

5.1. Theoretical implications

This thesis set out to address gaps in prior research that largely portrays AI-driven social media analytics as a powerful enabler of value creation, stakeholder alignment and sustainability-oriented branding, particularly through a Resource-Based View, Stakeholder Theory and sustainability & institutional lenses. Earlier studies frequently implied that once implemented, AI-based analytics would strengthen branding capabilities and relational outcomes in a relatively straightforward way (Bag et al., 2024; Davenport et al., 2020; Huang & Rust, 2020; Mikalef et al., 2021). In contrast, the empirical results of this thesis show weak, diffuse and statistically non-significant effects across direct, mediating and moderating relationships. The theoretical implications therefore lie less in confirming expected positive effects and more in qualifying and problematising these assumptions for global B2B branding.

First, the findings challenge the commonly assumed mediation logic between AI-driven analytics, value creation, stakeholder alignment and branding outcomes. Much of the prior literature suggests that analytics-derived insights should enhance internal sense-making and coordination, which in turn should translate into stronger relational constructs such as trust, equity and alignment (Mikalef et al., 2021; Morgan & Hunt, 1994; Palmatier et al., 2006). In this thesis, however, perceived value creation and stakeholder alignment did not significantly mediate the relationship between analytics use and branding outcomes. This implies that, in the examined B2B context, analytics is not yet deeply woven into the everyday routines that shape relational quality. Trust, equity and alignment still seem to be built primarily through accumulated interactions, shared norms and consistent organisational communication rather than through data flows alone. Theoretically, this tempers the expectation present in both RBV and stakeholder-based branding literature that analytics will automatically reinforce relational mechanisms in a measurable way. Instead, AI-driven analytics appear as a supporting layer whose effects remain weak unless organizational practices explicitly translate insights into relational behaviors (Böhmer & Schinnenburg, 2023; Deryl et al., 2023).

Second, the study refines sustainability-oriented branding arguments by showing that AI-driven analytics currently play a modest and indirect role in sustainable brand positioning. Earlier contributions argued that AI and social media analytics could help firms identify salient sustainability concerns, respond to stakeholder expectations and thus strengthen sustainability-related brand equity (Gündüzyeli, 2024; Ibeama et al., 2025; Vinuesa et al., 2020). At the same time, critical work warns about greenwashing and the gap between communicated and actual sustainability performance (Lyon & Montgomery, 2015; Parguel & Guillaume, 2021). The results of this thesis align more strongly with the latter concern. Respondents did not perceive analytics as a central driver of sustainability narratives; rather, sustainability outcomes remained relatively detached from analytics usage. Theoretically, this suggests that AI-driven analytics cannot substitute for material environmental and social actions. They may help to surface issues, refine messages or monitor reactions, but they do not, on their own, create credible sustainable positioning. This nuance adds to sustainability branding literature by emphasising that analytics should be conceptualised as a complementary capability that amplifies genuine sustainability practices instead of being treated as a primary mechanism for legitimacy building (Golob et al., 2022; Murad et al., 2023)

Third, from an RBV perspective, the findings cast doubt on whether AI-driven social media analytics currently function as a distinctive, value-creating capability in the studied B2B context. In Chapter 2, this thesis positioned analytics as a potential strategic asset that could meet VRIN criteria by turning dispersed social data into hard-to-imitate branding insights (Barney, 1991; Deryl et al., 2023). Empirically, however, the relationships between analytics usage and branding constructs were consistently small and non-significant. This pattern suggests that, for many firms in the sample, AI-based analytics are perceived less as a rare and inimitable capability and more as a generic tool that has not yet been fully integrated into branding architectures. This resonates with work showing that the strategic value of analytics depends on complementary routines such as cross-functional coordination, organisational learning and sense-making structures rather than on technology alone (Mikalef et al., 2021; Peterson et al., 2023; Teece, 2007). In RBV terms, the thesis therefore contributes by reframing AI-driven analytics from an assumed "strategic asset" to a potential capability-in-formation, whose impact on brand trust, equity and sustainability is contingent on broader capability systems that many firms have not yet fully developed.

Fourth, the absence of moderation by institutional and cultural context offers a more cautious view on how contextual forces operate in AI-enabled branding. Chapter 2 highlighted that institutional theory and cross-cultural perspectives suggest that data governance regimes, platform rules and cultural communication norms should meaningfully condition how analytics influence branding outcomes (Kostova & Roth, 2002; Yadav, 2023). In this study, the interaction terms between analytics and context were near zero and non-significant. One interpretation is that in relatively stable and predictable environments such as those that characterize much of the Finnish and wider European part of the sample context is experienced more as a baseline constraint than as a source of variation. Rather than actively amplifying or dampening analytics' branding effects, institutional and cultural conditions may be perceived as "taken-for-granted" boundaries within which all organizations must operate similarly (Weber & Glynn, 2006). Theoretically, this redirects attention away from context as a simple moderator and towards context as a structural backdrop that shapes capability development and sense-making over time (Mikalef & Krogstie, 2020). The findings thus reinforce broader arguments that analytics-oriented processes are embedded in multifaceted organisational and cultural systems and cannot be modelled as linear, technology-driven mechanisms (Chae et al., 2018; Wamba et al., 2017).

5.2. Managerial implications

The findings of this thesis offer several important implications for managers working in global B2B branding, particularly because they diverge from the optimistic assumptions commonly presented in practitioner literature and parts of academic research. Prior studies often recommend AI-driven social media analytics as a key mechanism for enhancing value creation, strengthening stakeholder relationships and enabling more credible sustainability communication (Davenport et al., 2020; Fagundes et al., 2023; Paschen et al., 2019). The empirical results of this study, however, suggest that managers should adopt a more grounded and capability-oriented perspective: analytics can be useful, but they rarely produce meaningful branding outcomes unless embedded within broader organisational routines, cultural practices and sustainability commitments.

First, managers should not assume that analytics will automatically generate relational benefits such as greater trust, improved stakeholder alignment or stronger brand equity. In theory, AI-based insights can help firms anticipate concerns, tailor messages and coordinate communication across markets (Trainor et al., 2014; Ziakis & Vlachopoulou, 2023). In practice, the respondents in this study did not experience analytics as a significant driver of these relational constructs. This underscores that trust and stakeholder alignment continue to arise primarily from human interaction, relational continuity and consistent organisational communication, rather than from automated insights alone (Barbour et al., 2018). For managers, this means analytics should be positioned as a supporting tool, not a substitute for relationship-building. To translate analytics into relational gains, firms must invest in internal processes cross-team interpretation sessions, message calibration routines, and shared sense-making that turn data patterns into coordinated relational actions (Barbour et al., 2018; Someh et al., 2023).

Second, the findings provide a cautionary message for managers seeking to use AI-driven analytics for sustainability branding. While the literature frequently highlights the promise of analytics for detecting sustainability issues, tracking stakeholder sentiment and refining sustainability narratives (Gündüzyeli, 2024; Vinuesa et al., 2020), respondents did not perceive analytics as having a major influence on sustainable brand positioning. This aligns with concerns about greenwashing and the communication performance gap: sustainability claims are credible only when rooted in substantive organizational behavior (Lyon & Montgomery, 2015; Parguel & Guillaume, 2021). Managers should therefore resist the temptation to rely on analytics to "signal" sustainability and instead focus on ensuring that sustainability communication is transparently linked to actual performance, measurable progress and verifiable initiatives. In practical terms, analytics can help identify what sustainability themes matter to stakeholders, but managers must ensure that responses are supported by organizational action not algorithmic optimization alone.

Third, managers should recognise that AI-driven social media analytics have not yet matured into a strategic capability in many organisations. Despite the enthusiasm around AI adoption, the study indicates that analytics is often perceived as a generic tool, not a source of differentiation. This suggests that firms may be investing in technology without simultaneously developing the complementary structures skills, routines, governance and cross-functional integration that make analytics strategically valuable (Mikalef et al., 2021; Teece, 2007). For managerial practice, the implication is clear: value does not come from possessing analytics but from institutionalising how analytics is used (Bumblauskas et al., 2017). Managers must prioritise capability-building over tool acquisition. Examples include establishing cross-functional analytics review forums, integrating analytics into strategic planning rather than tactical reporting, developing internal guidelines for interpreting AI outputs, and training teams to challenge, contextualize and responsibly use algorithmic insights (Bumblauskas et al., 2017; Cao et al., 2022). Only when these organizational routines exist can analytics become a genuine enhancer of branding outcomes.

Fourth, the absence of moderation effects by institutional and cultural context has implications for how managers structure global branding processes. Although theory suggests that different markets impose varying constraints on data use and communication norms (Kostova & Roth, 2002; Yadav, 2023), respondents in this study primarily operating in relatively stable regulatory environments did not perceive dramatic differences in how context shapes analytics-based branding. This suggests that for many B2B firms, context functions as a baseline compliance condition, not a dynamic strategic variable (Korherr et al., 2023; Lawal et al., 2022). Managers should therefore avoid assuming that analytics-based processes must be radically redesigned for each market. Instead, they should focus on building strong organisation-wide governance structures for ethical and compliant analytics use, while allowing local teams to tailor communication strategies according to cultural norms. Put differently, the strategic work lies not in radically different analytics systems per market, but in ensuring consistent internal governance and locally sensitive message interpretation (Joshi et al., 2022; Lawal et al., 2022).

Finally, the overall pattern of weak and dispersed effects highlights the importance of managing expectations within organisations. Many firms adopt AI technologies with the belief that analytics will rapidly transform branding outcomes. The results of this study suggest that such expectations are unrealistic. Managers should communicate internally that analytics is a long-term developmental capability, one that requires organizational learning, cultural adaptation and process integration before it can meaningfully influence trust, equity or sustainability outcomes. This reframing can help prevent disillusionment among employees, avoid overinvestment in isolated technical solutions, and encourage a more holistic approach to capability development (Bakonyi, 2024; Chowdhury et al., 2023).

5.3. Suggestions for future research

The implications of this thesis suggest some avenues for future research to further understand the impact of social media analytics fueled by artificial intelligence in the branding of businesses in the B2B setting. The first is in terms of expanding the model. The persistently weak relationships across correlations, regressions, mediation routes and moderation paths indicate that the constructs analyzed here may not adequately capture the mechanisms by which analytics becomes meaningful for branding (Agnihotri et al., 2023). Future studies should therefore consider the inclusion of additional organizational constructs such as data governance routines, cross-functional collaboration or analytics maturity levels. Including these elements may uncover more powerful indirect or contingent effects that were not apparent within the current set of variables (Bumblauskas et al., 2017; Carew et al., 2025; Y. Wang et al., 2021).

A second direction relates to methodological refinement. Since this study was conducted by using perceptual survey data and cross-sectional research design, longitudinal or multi-source research design could be useful for future studies. Longitudinal data would enable the researchers to analyze how the brand's impact on branding constructs increases over time when capabilities become more in-depth and organizational routines become more stabilized (Huynh et al., 2023). Multi-source data, such as combining survey with digital trace data or internal performance reports could also reduce perception bias and to provide a more robust assessment of how analytics is used within branding processes.

There is another recommendation regarding the relational constructs explored in the model. Value creation, stakeholder alignment, trust, equity and sustainability are complex and cumulative (Tantalo & Priem, 2016; Velter et al., 2020). They emerge through the repetition of interactions and embedded organizational practices. Future research should therefore investigate whether multi-level designs can be used to capture the interaction of analytics with relational dynamics at the team, departmental or organizational level. For example, analytics may increase alignment in a way that is only strengthened by having a shared set of norms for interpretation among employees or by the existence of routines for translating insights from analytics into coordinated action within the team. Multi-level approaches may therefore be able to reveal effects that aggregate perceptual models cannot detect.

The findings also suggest a need to examine variation among industries and institutional contexts. The sample in this thesis is of such a stable and homogenous environment where respondents may have similar interpretations of institutional norms and regulatory expectations. Replicating the model in more diverse and/or institutionally fragmented environments could reveal whether the model of analytics-driven branding processes is affected to greater extents by contextual pressures in environments of greater uncertainty or regulatory inconsistency. Comparative studies of more than one country or one industry would help explain why and when institutional context is a meaningful moderator.

Furthermore, sustainability branding emerged as an area where there was some conceptual relevance of analytics, but no strong empirical effect. This implies a need for further study to explore the role of analytics in the formation of credible sustainability strategies (Hazen et al., 2016). Researchers were able to investigate whether analytics plays a role in internal sustainability decision-making, assists firms in recognizing emerging environmental concerns, or if it aids in assessing stakeholder response to sustainability efforts. Such work would offer better insight into how sustainability-oriented capabilities interact with analytics and whether this relationship is strengthened as organizations embrace more transparent and purpose-driven approaches.

5.4. Limitations

Several limitations of this study should be recognized to put the results into perspective and to inform how to interpret the model. The first limitation is the cross-sectional nature of the data. The relationships between analytics, value creation, relational constructs and sustainability processes evolve over time and often need to have repeat organizational interactions before they are visible. A single wave of perceptual data cannot sufficiently capture the temporal dynamics of capability formation or relational development. As a result, the weak effects found in this study may reflect early stage or uneven adoption processes that a longitudinal design may be better able to find.

A second limitation has to do with the use of self-reported measures. Respondents rated their organization’s use of analytics as well as the branding constructs, leaving open the possibility of perceptual bias. Individuals may have varying perceptions of what analytics maturity, value creation, and sustainability communication mean based on their roles, experience and exposure to analytics initiatives. Although the dataset included respondents from a variety of functions, their assessments are still subjective. Objective indicators of analytics implementation, or external measures of branding outcomes, would add to the evidence base and help mitigate any bias arising from common perceptions.

The third limitation is the conceptual scope of the model. The constructs included in the analysis represent key aspects of relational branding and AI-enabled capability development, but they do not capture all the organizational factors that may have an impact on how analytics influences branding outcomes. Elements such as the structure of data governance, leadership commitment, skills of analysts, internal communication routines, and cross-functional integration were not measured. These factors may be required prerequisites for stronger direct or indirect effects and may help account for the fact that the hypothesized relationships were weak in the present study.

Another limitation refers to contextual homogeneity. Much of the sample represents organizational environments within similar institutional norms and cultural expectations. Where respondents operate under similar regulatory frameworks and organizational practices, perceptual variation in the degree to which context influences the use of analytics is likely to be limited. This helps explain why the moderation analyses did not show any significant contextual influences. A more diverse or internationally comparative sample could reveal stronger contextual patterns not discernible in this study.

Finally, the study involves perceived rather than observed outcomes. Perceptions of the effectiveness of analytics may differ greatly from actual patterns of use in the world. Some organizations might have analytics tools in place but not necessarily being used within branding activities, while others might use analytics informally in ways that are not captured through structured survey instruments. Future studies that include a combination of perceptual assessments and behavioral or system-level data could give a more complete understanding of how analytics interacts with organizational branding processes.

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APPENDICES

Appendix 1. Questionnaire

Study Title: AI-Driven Social Media Analytics in Global Branding

Purpose: This survey examines how AI-driven social media analytics relate to value creation, stakeholder alignment, branding outcomes in B2B Settings.

Eligibility: Professionals working in B2B Firms (marketing/sales/brands/sustainability)

Time: 7-10 minutes

Confidentiality: Responses are anonymous and reported in aggregate.

Consent: By proceeding you confirm you are 18+ and give informed consent to participate

(*I confirm I meet the eligibility criteria and consent to participate)*

Screening

1. Do you currently work in a **B2B** organization or a unit that primarily sells to other businesses?

   Yes/No → If no, (End Survey with Thank you)
2. Which best describes your role?
   a. Marketing/Brand/Communications
   b. Sales/Account Management
   c. Analytics/Insights/Data
   d. Sustainability/CSR/Compliance
   e. Senior Management/Strategy
   f. Other (please specify)
3. Background and controls
   a. Country/region you primarily work in (dropdown).
   b. In which industry do you currently work? (dropdown).
   c. Company size (employees): <50, 50–249, 250–999, 1,000–4,999, 5,000+.
   d. Seniority: Specialist, Manager, Director, VP/C-level, Other.
   e. Years in current role: 0–1, 2–4, 5–9, 10+.
   f. Extent of AI involvement in your role: None, Low, Moderate, High.

Scale notes for all construct items

Unless otherwise stated: **1 = Strongly disagree, 2 = Disagree, 3 = Neither, 4 = Agree, 5 = Strongly agree**.

A. AI-Driven Social Media Analytics Usage (Independent variable)

1. Our firm uses AI-based tools to monitor social media conversations relevant to our markets.
2. We apply AI to classify or summarize social media content at scale (e.g., topics, sentiment, themes).
3. AI outputs are regularly used to adjust brand messages or campaigns on social media.
4. Our team integrates AI-generated insights with CRM or other internal systems.
5. We review the quality and reliability of AI analytics before acting on them.
6. Decisions about social content are rarely informed by AI insights.

B. Perceived Value Creation (Mediator; RBV lens)

1. Insights from social media analytics help us identify opportunities earlier than competitors.
2. AI-based social analytics improve the efficiency of our branding activities.
3. These analytics support the development of new or refined value propositions.
4. Using AI-generated insights strengthens our competitive position in key markets.
5. AI-supported analysis improves the quality of branding decisions.
6. The value from AI-driven analytics is unclear in our organization.

C. Stakeholder Alignment (Mediator; Stakeholder Theory lens)

1. AI-driven insights help us understand the expectations of different stakeholder groups (e.g., buyers, partners).
2. We tailor branding messages to stakeholder needs identified through social analytics.

3. Analytics improve transparency in how we communicate with stakeholders.

4. Social media insights help us respond to stakeholder concerns in a timely manner.

5. Our branding choices reflect trade-offs between stakeholder groups identified through analytics.

D. Brand Trust (Outcome)

1. Stakeholders perceive our brand as reliable.

2. Our brand communicates honestly about performance and limitations.

3. We deliver on branding promises made in social channels.

4. Stakeholders can depend on our brand in high-stakes situations.

5. Our use of analytics supports credible, evidence-based brand communication.

E. Global Brand Equity (Outcome)

1. Our brand is widely recognized in our international target markets.

2. Perceptions of our brand are positive across different regions.

3. Our brand associations are consistent across countries.

4. Social media activities contribute meaningfully to our brand’s international standing.

5. Competitors view our brand as a strong player globally.

F. Sustainable Brand Positioning (Outcome; sustainability lens)

1. Our branding highlights sustainability initiatives that are substantive and verifiable.

2. AI-driven social media analytics help us identify sustainability topics that matter to stakeholders.

3. We correct or clarify sustainability claims if analytics indicate confusion or doubt.

4. Our brand avoids superficial “green” messages that lack evidence.

G. Institutional and Cultural Context (Moderator)

1. Data protection and privacy rules in our markets shape how we use AI in branding.

2. Cultural communication norms affect how we interpret social media analytics.

3. Platform policies and regulations influence our analytics practices.
4. Internal governance (ethics, compliance) constrains how AI outputs are applied.

H. Final page (thank you)

Thank you for participating. Your responses are anonymous and will be used for academic research only. If you would like a summary of results, you may share a contact email (optional).

Appendix 2. Reliability and Factor Analysis Diagnostics

2.1 Reliability Statistics (Cronbach's Alpha)

Scale: AISA

Case Processing Summary

		N	%
Cases	Valid	201	100.0
	Excluded[a]	0	.0
	Total	201	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.861	6

Scale: VALUE

Case Processing Summary

		N	%
Cases	Valid	201	100.0
	Excluded[a]	0	.0
	Total	201	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.863	6

Scale: TRUST

Case Processing Summary

		N	%
Cases	Valid	201	100.0
	Excluded[a]	0	.0
	Total	201	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.895	5

Scale: EQUITY

Case Processing Summary

		N	%
Cases	Valid	201	100.0
	Excluded[a]	0	.0
	Total	201	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.882	5

Scale: SUSTAIN

Case Processing Summary

		N	%
Cases	Valid	201	100.0
	Excluded[a]	0	.0
	Total	201	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.856	4

Scale: CONTEXT

Case Processing Summary

		N	%
Cases	Valid	201	100.0
	Excluded[a]	0	.0
	Total	201	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.844	4

Scale: STAKE

Case Processing Summary

		N	%
Cases	Valid	201	100.0
	Excluded[a]	0	.0
	Total	201	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.846	5

2.2 KMO and Bartlett's Test of Sphericity

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.946
Bartlett's Test of Sphericity	Approx. Chi-Square	5382.263
	df	595
	Sig.	<.001

2.3 Total Variance Explained (Before and After Rotation)

Total Variance Explained

Factor	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	16.261	46.460	46.460	11.256	32.161	32.161
2	3.108	8.880	55.340	4.967	14.191	46.352
3	.897	2.564	57.904	2.652	7.577	53.930
4	.773	2.208	60.111	1.758	5.022	58.952
5	.695	1.985	62.096	.821	2.345	61.297
6	.608	1.736	63.833	.701	2.002	63.299
7	.459	1.310	65.143	.645	1.844	65.143

Extraction Method: Principal Axis Factoring.

Appendix 3. Rotated Component Matrix

Rotated Factor Matrix[a]

	Factor 1	2	3	4	5	6	Factor 7
We review the quality and reliability of AI analytics before acting on them.	.809						
Using AI-generated insights strengthens our competitive position in key markets.	.794						
AI-supported analysis improves the quality of branding decisions.	.766						
AI-based social analytics improve the efficiency of our branding activities.	.744						
These analytics support the development of new or refined value propositions.	.713			.318			
Social media insights help us respond to stakeholder concerns in a timely manner.	.708						
We tailor branding messages to stakeholder needs identified through social analytics.	.696						
Our firm uses AI-based tools to monitor social media conversations relevant to our markets.	.696						.315
AI-driven insights help us understand the expectations of different stakeholder groups (e.g., buyers, partners).	.691						
AI outputs are regularly used to adjust brand messages or campaigns on social media.	.683						
Insights from social media analytics help us identify opportunities earlier than competitors.	.678				.480		
Our brand communicates honestly about performance and limitations.	.671		.361				
Stakeholders perceive our brand as reliable.	.663						

Rotated Factor Matrix[a]

	Factor						Factor
	1	2	3	4	5	6	7
Perceptions of our brand are positive across different regions.	.661						
We apply AI to classify or summarise social media content at scale (e.g., topics, sentiment, themes).	.646						
Our team integrates AI-generated insights with CRM or other internal systems.	.642				.350		
Social media activities contribute meaningfully to our brand's international standing.	.621		.338				
Analytics improve transparency in how we communicate with stakeholders.	.593			.327			
We deliver on branding promises made in social channels.	.583		.445				
Our use of analytics supports credible, evidence-based brand communication.	.582		.469				
Our brand associations are consistent across countries.	.582		.448				
Our brand is widely recognised in our international target markets.	.558		.534				
Our branding choices reflect trade-offs between stakeholder groups identified through analytics.	.496					.480	
AI-driven social media analytics help us identify sustainability topics that matter to stakeholders.		.776					
Social media insights inform improvements to our sustainability practices or reporting.		.734					
Our branding highlights sustainability initiatives that are substantive and verifiable.		.729					

Rotated Factor Matrix[a]

	Factor						Factor
	1	2	3	4	5	6	7
Internal governance (ethics, compliance) constrains how AI outputs are applied.	.318	.722					
Data protection and privacy rules in our markets shape how we use AI in branding.		.721					
Cultural communication norms affect how we interpret social media analytics.		.713					-.306
Platform policies and regulations influence our analytics practices.		.665					
We correct or clarify sustainability claims if analytics indicate confusion or doubt.		.626					
Stakeholders can depend on our brand in high-stakes situations.	.538		.610				
Competitors view our brand as a strong player globally.	.443		.519				
The value from AI-driven analytics is unclear in our organization.				.669			
Decisions about social content are rarely informed by AI insights.	.380			.585			

Appendix 4. Multicollinearity and Correlation Diagnostics

4.1 Pearson Correlation Matrix for the seven constructs

Correlations

		REGR factor score 1 for analysis 1	REGR factor score 2 for analysis 1	REGR factor score 3 for analysis 1	REGR factor score 4 for analysis 1	REGR factor score 5 for analysis 1	REGR factor score 6 for analysis 1	REGR factor score 7 for analysis 1
REGR factor score 1 for analysis 1	Pearson Correlation	1	.017	.093	.072	.019	.043	.012
	Sig. (2-tailed)		.805	.190	.307	.787	.544	.863
	N	201	201	201	201	201	201	201
REGR factor score 2 for analysis 1	Pearson Correlation	.017	1	.020	.041	.003	.001	-.004
	Sig. (2-tailed)	.805		.779	.568	.966	.989	.952
	N	201	201	201	201	201	201	201
REGR factor score 3 for analysis 1	Pearson Correlation	.093	.020	1	.049	.044	.033	.022
	Sig. (2-tailed)	.190	.779		.490	.538	.638	.760
	N	201	201	201	201	201	201	201
REGR factor score 4 for analysis 1	Pearson Correlation	.072	.041	.049	1	.019	.031	-.014
	Sig. (2-tailed)	.307	.568	.490		.792	.663	.839
	N	201	201	201	201	201	201	201
REGR factor score 5 for analysis 1	Pearson Correlation	.019	.003	.044	.019	1	.025	-.017
	Sig. (2-tailed)	.787	.966	.538	.792		.720	.806
	N	201	201	201	201	201	201	201
REGR factor score 6 for analysis 1	Pearson Correlation	.043	.001	.033	.031	.025	1	-.063
	Sig. (2-tailed)	.544	.989	.638	.663	.720		.371
	N	201	201	201	201	201	201	201
REGR factor score 7 for analysis 1	Pearson Correlation	.012	-.004	.022	-.014	-.017	-.063	1
	Sig. (2-tailed)	.863	.952	.760	.839	.806	.371	
	N	201	201	201	201	201	201	201

4.2 Collinearity Diagnostics (Condition Index & Variance Proportions

Collinearity Diagnostics[a]

				Variance Proportions						
Model	Dimension	Eigenvalue	Condition Index	(Constant)	REGR factor score 2 for analysis 1	REGR factor score 3 for analysis 1	REGR factor score 4 for analysis 1	REGR factor score 5 for analysis 1	REGR factor score 6 for analysis 1	REGR factor score 7 for analysis 1
1	1	1.122	1.000	.00	.06	.19	.21	.14	.21	.08
	2	1.046	1.035	.00	.10	.17	.06	.00	.18	.44
	3	1.007	1.055	.00	.44	.11	.09	.30	.00	.05
	4	1.000	1.059	1.00	.00	.00	.00	.00	.00	.00
	5	.968	1.077	.00	.22	.09	.08	.48	.12	.04
	6	.944	1.090	.00	.17	.12	.53	.04	.18	.02
	7	.913	1.109	.00	.01	.33	.02	.05	.31	.38

Appendix 5. Regression Results

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.017[a]	.000	-.005	.95637072

a. Predictors: (Constant), REGR factor score 1 for analysis 1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.056	1	.056	.061	.805[b]
	Residual	182.014	199	.915		
	Total	182.070	200			

a. Dependent Variable: REGR factor score 2 for analysis 1

b. Predictors: (Constant), REGR factor score 1 for analysis 1

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t
1	(Constant)	-7.875E-17	.067		.000
	REGR factor score 1 for analysis 1	.017	.071	.017	.247

Coefficients[a]

Model		Sig.
1	(Constant)	1.000
	REGR factor score 1 for analysis 1	.805

a. Dependent Variable: REGR factor score 2 for analysis 1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.093[a]	.009	.004	.85951472

a. Predictors: (Constant), REGR factor score 1 for analysis

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.280	1	1.280	1.732	.190[b]
	Residual	147.014	199	.739		
	Total	148.294	200			

a. Dependent Variable: REGR factor score 3 for analysis 1

b. Predictors: (Constant), REGR factor score 1 for analysis 1

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t
1	(Constant)	-1.781E-16	.061		.000
	REGR factor score 1 for analysis 1	.084	.063	.093	1.316

Coefficients[a]

Model		Sig.
1	(Constant)	1.000
	REGR factor score 1 for analysis 1	.190

a. Dependent Variable: REGR factor score 3 for analysis 1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.072[a]	.005	.000	.82124181

a. Predictors: (Constant), REGR factor score 1 for analysis 1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.707	1	.707	1.048	.307[b]
	Residual	134.213	199	.674		
	Total	134.920	200			

a. Dependent Variable: REGR factor score 4 for analysis 1

b. Predictors: (Constant), REGR factor score 1 for analysis 1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	2.361E-17	.058		.000
	REGR factor score 1 for analysis 1	.062	.061	.072	1.024

Coefficients[a]

Model		Sig.
1	(Constant)	1.000
	REGR factor score 1 for analysis 1	.307

a. Dependent Variable: REGR factor score 4 for analysis 1

Appendix 6. Process Model 4: Mediation Analysis

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : TRUST
    X  : AISA
    M  : VALUE

Sample
Size:  201

**************************************************************************
OUTCOME VARIABLE:
 VALUE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0175      .0003      .9146      .0609     1.0000   199.0000      .8054

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0675      .0000     1.0000     -.1330      .1330
AISA          .0174      .0706      .2467      .8054     -.1219      .1567

**************************************************************************
OUTCOME VARIABLE:
 TRUST

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0824      .0068      .6768      .6763     2.0000   198.0000      .5097

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0580      .0000     1.0000     -.1144      .1144
AISA          .0615      .0608     1.0123      .3126     -.0583      .1813
VALUE         .0338      .0610      .5548      .5797     -.0864      .1541


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .0615      .0608     1.0123      .3126     -.0583      .1813

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
VALUE      .0006      .0054     -.0116      .0122

*********************** ANALYSIS NOTES AND ERRORS ************************
```

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : EQUITY
    X  : AISA
    M  : VALUE

Sample
Size:  201

**************************************************************************
OUTCOME VARIABLE:
 VALUE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0175      .0003      .9146      .0609     1.0000   199.0000      .8054

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0675      .0000     1.0000     -.1330      .1330
AISA          .0174      .0706      .2467      .8054     -.1219      .1567

**************************************************************************
OUTCOME VARIABLE:
 EQUITY

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0194      .0004      .7288      .0372     2.0000   198.0000      .9635

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0602      .0000     1.0000     -.1187      .1187
AISA          .0170      .0631      .2694      .7879     -.1074      .1413
VALUE         .0024      .0633      .0378      .9699     -.1224      .1272


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .0170      .0631      .2694      .7879     -.1074      .1413

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
VALUE      .0000      .0061     -.0132      .0138

*********************** ANALYSIS NOTES AND ERRORS ************************
```

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : SUSTAIN
    X  : AISA
    M  : VALUE

Sample
Size:  201

**************************************************************************
OUTCOME VARIABLE:
 VALUE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0175      .0003      .9146      .0609     1.0000   199.0000      .8054

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0675      .0000     1.0000     -.1330      .1330
AISA          .0174      .0706      .2467      .8054     -.1219      .1567

**************************************************************************
OUTCOME VARIABLE:
 SUSTAIN

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0431      .0019      .5934      .1839     2.0000   198.0000      .8321

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0543      .0000     1.0000     -.1071      .1071
AISA          .0345      .0569      .6063      .5450     -.0777      .1467
VALUE         .0002      .0571      .0036      .9971     -.1124      .1128


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .0345      .0569      .6063      .5450     -.0777      .1467

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
VALUE      .0000      .0043     -.0075      .0113

*********************** ANALYSIS NOTES AND ERRORS ************************
```

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : TRUST
    X  : AISA
    M  : STAKE

Sample
Size:  201

**************************************************************************
OUTCOME VARIABLE:
 STAKE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0929      .0086      .7388     1.7321     1.0000   199.0000      .1897

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0606      .0000     1.0000     -.1196      .1196
AISA          .0835      .0635     1.3161      .1897     -.0416      .2087

**************************************************************************
OUTCOME VARIABLE:
 TRUST

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0839      .0070      .6766      .7016     2.0000   198.0000      .4970

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0580      .0000     1.0000     -.1144      .1144
AISA          .0587      .0610      .9623      .3371     -.0616      .1790
STAKE         .0406      .0678      .5985      .5502     -.0932      .1744


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .0587      .0610      .9623      .3371     -.0616      .1790

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
STAKE      .0034      .0117     -.0228      .0276

*********************** ANALYSIS NOTES AND ERRORS ************************
```

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : EQUITY
    X  : AISA
    M  : STAKE

Sample
Size:  201

**************************************************************************
OUTCOME VARIABLE:
 STAKE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0929      .0086      .7388     1.7321     1.0000   199.0000      .1897

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0606      .0000     1.0000     -.1196      .1196
AISA          .0835      .0635     1.3161      .1897     -.0416      .2087

**************************************************************************
OUTCOME VARIABLE:
 EQUITY

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0462      .0021      .7276      .2121     2.0000   198.0000      .8090

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0602      .0000     1.0000     -.1186      .1186
AISA          .0135      .0633      .2141      .8307     -.1112      .1383
STAKE         .0417      .0703      .5926      .5541     -.0970      .1804


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .0135      .0633      .2141      .8307     -.1112      .1383

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
STAKE      .0035      .0125     -.0114      .0395

********************** ANALYSIS NOTES AND ERRORS ************************
```

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : SUSTAIN
    X  : AISA
    M  : STAKE

Sample
Size:  201

**************************************************************************
OUTCOME VARIABLE:
 STAKE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0929      .0086      .7388     1.7321     1.0000   199.0000      .1897

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0606      .0000     1.0000     -.1196      .1196
AISA          .0835      .0635     1.3161      .1897     -.0416      .2087

**************************************************************************
OUTCOME VARIABLE:
 SUSTAIN

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0522      .0027      .5929      .2704     2.0000   198.0000      .7634

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0000      .0543      .0000     1.0000     -.1071      .1071
AISA          .0323      .0571      .5655      .5723     -.0803      .1449
STAKE         .0264      .0635      .4155      .6782     -.0988      .1516


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .0323      .0571      .5655      .5723     -.0803      .1449

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
STAKE      .0022      .0101     -.0184      .0252

*********************** ANALYSIS NOTES AND ERRORS ************************
```

Appendix 7. Process Model 1: Moderation Analysis

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : TRUST
    X  : AISA
    W  : CONTEXT

Sample
Size:  201

**************************************************************************
OUTCOME VARIABLE:
 TRUST

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1816      .0330      .6623     2.2388     3.0000   197.0000      .0850

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0019      .0574      .0326      .9740     -.1113      .1151
AISA          .0795      .0605     1.3125      .1909     -.0399      .1989
CONTEXT      -.0786      .0762    -1.0316      .3035     -.2290      .0717
Int_1        -.1989      .0840    -2.3667      .0189     -.3646     -.0332

Product terms key:
 Int_1    :        AISA     x        CONTEXT

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0275     5.6012     1.0000   197.0000      .0189
----------
    Focal predict: AISA     (X)
          Mod var: CONTEXT  (W)

Conditional effects of the focal predictor at values of the moderator(s):

    CONTEXT     Effect         se          t          p       LLCI       ULCI
     -.5678      .1924      .0815     2.3617      .0192      .0317      .3530
     -.0390      .0872      .0610     1.4293      .1545     -.0331      .2076
      .6362     -.0471      .0758     -.6209      .5354     -.1966      .1024

********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.
```

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : EQUITY
    X  : AISA
    W  : CONTEXT

Sample
Size:  201

**************************************************************************
OUTCOME VARIABLE:
 EQUITY

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2161      .0467      .6986     3.2166     3.0000   197.0000      .0239

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0025      .0590      .0425      .9662     -.1138      .1188
AISA          .0402      .0622      .6471      .5183     -.0824      .1629
CONTEXT      -.1030      .0783    -1.3158      .1898     -.2574      .0514
Int_1        -.2662      .0863    -3.0837      .0023     -.4364     -.0959

Product terms key:
 Int_1    :        AISA     x        CONTEXT

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0460     9.5093     1.0000   197.0000      .0023
----------
    Focal predict: AISA     (X)
          Mod var: CONTEXT  (W)

Conditional effects of the focal predictor at values of the moderator(s):

    CONTEXT     Effect         se          t          p       LLCI       ULCI
     -.5678      .1914      .0837     2.2872      .0232      .0264      .3563
     -.0390      .0506      .0627      .8076      .4203     -.0730      .1742
      .6362     -.1291      .0779    -1.6580      .0989     -.2826      .0245

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.
```

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : SUSTAIN
    X  : AISA
    W  : CONTEXT

Sample
Size:  201

**************************************************************************
OUTCOME VARIABLE:
 SUSTAIN

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0933      .0087      .5923      .5767     3.0000   197.0000      .6310

Model
              coeff         se          t          p       LLCI       ULCI
constant      .0006      .0543      .0102      .9919     -.1065      .1076
AISA          .0402      .0573      .7024      .4833     -.0727      .1531
CONTEXT      -.0796      .0721    -1.1041      .2709     -.2218      .0626
Int_1        -.0588      .0795     -.7394      .4605     -.2155      .0980

Product terms key:
 Int_1    :        AISA     x        CONTEXT

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0028      .5468     1.0000   197.0000      .4605

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```