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Managing artificial intelligence in international business: Toward a research agenda on sustainable production and consumption

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Abstract

The collaboration between artificial intelligence (AI) and humans is reshaping international business (IB) management dynamics, aiming to achieve global sustainable development. Recent IB literature indicates that managing AI brings benefits such as better resource reconfiguration, reduced transaction costs, and global sustainable development. However, existing IB literature provides only meager knowledge about the characteristics of AI and how these characteristics can be employed for international expansion at the intersection of sustainable development. In response, our aim is to construct these characteristics by employing directed qualitative content analysis of empirical AI research. Based on our three constructed characteristics of AI, we contribute to current IB literature by providing a framework to balance economic and social goals and utilizing AI for global sustainable development. Further, we provide future IB research themes to guide IB and AI research toward achieving a sustainable production and consumption agenda.

KEYWORDS

artificial intelligence (AI), global sustainable development, international business, international expansion, sociotechnical theory

1 | INTRODUCTION

The role of artificial intelligence (AI)[1] is becoming an everyday phenomenon in the value creation of new business activities (Chalmers et al., 2021; Murray et al., 2021; Ratten, 2022). Even though AI is not a recent phenomenon in international business (IB) (Brouthers et al., 2009; Cavusgil et al., 1992; Hemphill & Kelley, 2021; Tatarinov et al., 2023; Veiga et al., 2000), there remains an uncertainty about whether AI will enable or hinder responsible consumption and production worldwide in line with the United Nations' (2023) Sustainable Development Goals (SDGs). This question aligns with the ethical guidelines for trustworthy AI that empowers human beings to make informed decisions and protect fundamental rights (European Commission, 2019). Such a question also relates to the Fifth Industrial Revolution that emphasizes advanced technologies, including AI, for human-centric and sustainable development (European Commission, 2022). This human-centric approach encompasses complementarity between humans and machines and aims to ensure the well-being of society, business, and end users.

For example, managing embedded AI in autonomous electric vehicles with a new business model to enable monthly subscriptions could combine public transport, and reduce car ownership costs and carbon footprint. Deploying virtual AI like avatars and human counterparts responsibly can also be used to protect end user privacy while improving service quality in healthcare. Aligning with these examples, a recent AI research project focusing on sustainable development found that while AI can accomplish targets across all the SDGs, it can also inhibit them (Vinuesa et al., 2020). Therefore, the research urges extending a systematic understanding of AI to the international context. This call motivated a focus on IB management in our study.

By taking firm-level management perspectives, we recognize the importance of extending AI research to IB literature. This urgency is paramount to achieving global development in balancing the three pillars of sustainable development—economic, societal, and environmental well-being. Against such a backdrop, recent IB literature on digitalization recognizes that firms need to balance their social, technological, and economic goals (Luo & Zahra, 2023; Verbeke & Hutzschenreuter, 2021). Similarly, IB scholars also point toward AI at the intersection of global sustainable development (Ciulli & Kolk, 2023; Tatarinov et al., 2023). However, IB literature contains only limited knowledge about the characteristics of AI and how managers can utilize those characteristics in their international expansion activities. On top of that, we know very little about AI in IB management at the intersection of sustainable development. We argue that AI can enable responsible consumption and production worldwide and help achieve SDGs but only if we have effective management strategies, policies, and institutions to support its use. Otherwise, there can be opposite, deleterious effects, hindering SDGs.

In response, our research focuses on SDG #12, which deals with sustainable consumption and production patterns in IB management (Chabowski et al., 2023; Montiel et al., 2021). To advance research in this domain, our study provides a new understanding that preliminarily builds on the management perspective of AI, which is developed mainly in information systems literature. We embrace a sociotechnical viewpoint of AI that aims to balance social and economic goals (Berente et al., 2021). The following research question is of particular interest in this study: *How does the existing empirical research on artificial intelligence relate to international business management?* To answer this question, we employ a qualitative content analysis method to analyze published empirical research on AI. We then construct three characteristics of AI and demonstrate how managers can utilize those characteristics in their international expansion activities at the intersection of SDG #12. Our study analyzes 85 empirical research papers on AI published in multiple disciplines with a critical realism view and a directed content analysis approach.

By doing so, our research contributes to the growing AI research in IB literature in four ways (Autio et al., 2021; Ciulli & Kolk, 2023; Del Giudice et al., 2023; Denicolai et al., 2021; Tatarinov et al., 2023). First, we construct three characteristics of AI–autonomy, learning, and combinative. Second, we show how managers can utilize those characteristics to achieve economic goals in international expansion activities. Third, we contribute to the open and multidisciplinary domain of AI research that focuses on global sustainable development (Jobin et al., 2019; Rahwan et al., 2019; Vinuesa et al., 2020). Fourth, we propose further research directions to initiate and guide research on AI in the context of sustainable production and consumption in IB that balance economic and social goals.

The paper is organized as follows. In the next section, we discuss the method of the study, which builds upon a directed content analytical approach. Then, we unpack the theoretical foundation of constructing the three characteristics of AI. Afterward, we explain the significant insights gained from our analysis. We also outline future IB research opportunities in AI related to the sustainable production and consumption agenda. Finally, we provide managerial implications and discuss the limitations of our study to guide future developments.

2 | DIRECTED CONTENT ANALYSIS OF PUBLISHED AI RESEARCH

Since the study embodies our knowledge, assumptions, beliefs, and value judgments about AI and responsible production and consumption patterns (SGD #12), we took a critical realism position (Bhaskar, 1978; Mingers, 2004). This philosophical stance allowed us the flexibility to conduct qualitative research using multiple criteria and procedures in IB beyond qualitative positivism and proceduralism (Welch & Piekkari, 2017). Consequently, our study embraced the inherent subjectivity in observations, transparency, and reflexivity to construct an understanding of AI in the context of IB management. Instead of using a methodological template, we employed our heuristics and imagination in the context-laden phenomenon, which is paramount for management and AI research (Furnari et al., 2021; Turing, 1950). Accordingly, we maintained that "a quality study results from the researcher's ability to reflect on how his or her field interactions, philosophical commitments, and theoretical preconceptions molded the interpretations and results" (Welch & Piekkari, 2017, p. 720). Reflecting on embodied value judgments about knowledge production, we took a pluralist approach to IB research and sociotechnical thinking that shaped our theoretical preconceptions. Hence, we aimed to advance the field concerning AI by taking an alternative method to investigate already published articles.

Instead of the systematic literature review method, which seems to embody qualitative positivism (see Evers et al., 2023, for an example), we employed a qualitative content analysis method. Our methodological approach aligns with our critical realism philosophical position and may be described as a directed qualitative content analysis method. Accordingly, we focused on the textual contents (as data) of empirical research at the intersection of AI and the international activities of firms. Within the qualitative content analysis methods (Hsieh & Shannon, 2005), we employed a directed content analysis approach to extend our current understanding of AI in IB management, which changes the dynamics of assessing the quality of our research (see Bonache, 2021; Welch & Piekkari, 2017). This approach is deemed the most appropriate to draw insights from extant scholarly works when little direct knowledge is available on the given phenomenon (Krippendorff, 2018). To achieve this, we used four subsequent stages—(1) developing the unit of analysis, (2) deciding on appropriate sampling, (3) constructing the dataset, and (4) analyzing data.

First, we developed a unit of analysis of our study that aligns with the research question. Given that we know little about AI in the international context in general and there is limited AI research in management and IB literature. Against this backdrop, our study is directed toward IB management that intersects with a sociotechnical viewpoint to manage AI (Berente et al., 2021). Put simply, we took insights from already published AI articles, molded those insights to construct characteristics of AI, and contextualized them into IB management to produce knowledge. We aimed to conceptually extend the current understanding of managing AI in IB operations toward achieving SDG #12, which balances economic and social goals. Consequently, the unit of analysis of our study is the characteristics of AI and managing those characteristics in IB to achieve responsible production and consumption. This allowed the construction of a fresh conceptual understanding of the given phenomenon based on empirical insights (Krippendorff, 2018; Welch et al., 2011).

Second, regarding directed content analysis, a central task of any textual analysis is to decide on the appropriate sample and which text to investigate. Our selection of published AI research followed qualitative relevance (purposive) sampling, which aims to select textual data in line with the unit of analysis (Krippendorff, 2018). Given that both AI[1] (See footnote 1) and IB as research domains capture multidisciplinary phenomena, we looked for articles in multiple disciplines, including IB, management, organizational studies, computer science, engineering, robotics, information systems, philosophy, and marketing. Consequently, this pluralistic approach allowed us to purposefully construct a dataset focused on existing AI research related to cross-border management in IB operations.

Third, we constructed a dataset.[2] Focusing on AI and IB, we initially used Google Search and Google Scholar to understand the phenomenon better. Accordingly, we aimed to include only quality scholarly works on AI with a predefined sampling procedure (see Figure 1). This sampling procedure guided us to develop relevant search strings and use advanced search functionalities in each database (see Appendix A). We limited our search to the English language and publishing dates from 1950 to 2023. Since we systematically know very little about AI in the international context, we wanted to cover an extensive period from the inception of intelligent machines (Turing, 1950) to recent developments in IB (Ciulli & Kolk, 2023; Tatarinov et al., 2023). We retrieved peer-reviewed journals listed in the Academic Journal Guide 2021 (levels 1–4*) and referred to CWTS Journal Indicators (www.journalindicators.com) for those not listed. Additionally, we took further precautions to exclude potential predatory and low-quality journals. To exclude low-quality journals, we excluded those listed as "0" or indicated as possible predatory journals. This cross-checking was complemented by two national journal rankings: the Finnish Publication Forum (level 1–3 journals) and the Norwegian Register for Scientific Journals, Series, and Publishers (level 1–2 journals). We then screened and constructed a dataset using Zotero referencing software to examine textual data.

Concerning which text to investigate to construct the dataset, we screened records based on content, including those focused mainly on AI, that must explicitly or implicitly relate to cross-border management perspectives. During this process, records in IB journals discussing AI as part of broader digitalization were considered. Additionally, we included technical papers that deal with developing new, or optimizing existing, AI models and methodological papers that deal with AI methods. However, we excluded technical and methodological papers that do not necessarily relate to firm-level management aspects. Furthermore, we included more records using cross-reference techniques. Hence, we developed our preliminary dataset comprising of 141 records with both non-empirical elements (conceptual, literature review, and technology explanation papers) and empirical elements as part of the broader research project. However, we finally constructed our dataset containing 85 records with only empirical elements. This includes methodological studies with empirical analysis (see Veiga et al., 2000), technical papers with empirical research (see Fish & Ruby, 2009), and traditional empirical papers (see Denicolai et al., 2021). After finalizing the dataset consisting of empirical AI research, we broadly sorted all empirical articles based on the emerging underlying characteristics of AI, inspired by both existing AI (Berente et al., 2021; Rahwan et al., 2019) and IB literature (Ojala et al., 2018, 2023; Tatarinov et al., 2023).

Finally, we analyzed the textual data. In proceeding with our analysis with a critical realism view and directed content analytical approach, our analytical process is neither untainted, inductive nor deductive (Krippendorff, 2018). Instead, in this directed approach, we constantly went back and forth in the literature (theory) while carefully reading and analyzing data in constructed datasets through successive iterations between theory and data (Bhaskar, 1978; Mingers, 2004). Put simply, our reports primarily relied on empirical insights from articles. However, we constantly directed those insights to existing AI and IB research through comparisons. After sorting the articles, we conducted a qualitative content comparison inspired by IB and management literature (Glikson & Woolley, 2020; Rana & Morgan, 2019; Welch et al., 2011). We read each article through carefully to understand the theoretical background, underlying assumptions, research strategy, findings, and discussion. However, we only focused on content that was derived from empirical insights (mainly the findings and discussion) to compare and relate to the focal unit of analysis. Therefore, we did not analyze other aspects of the articles such as conceptual background or hypothesis development. We then analyzed the texts through comparison to construct data-driven insights while embodying our value judgment, heuristics, and imagination.

We then categorized each paper based on the insights of textual data using Zotero's "Call Number" function to label relevant constructs, variables, or outcomes, which helped us to be systematic in constructing emerging themes and subthemes. We used an intra-content comparison to compare between parts of a text (e.g., paragraphs in the findings and discussion section of a single article) to recognize patterns for identifying similar and inconsistent themes. In addition, we compared different texts among articles and the textual content with a standard dimension (our emerging characteristics of AI and dimensions of IB management). As a result, the content comparison embodied our interpretation of relating repeated and irregular patterns to the extant theoretical assumptions in IB literature coupled with the sociotechnical thinking of managing AI in IB operations. In this process, we reflected on the following questions for each article to conduct the content analysis systematically and consistently

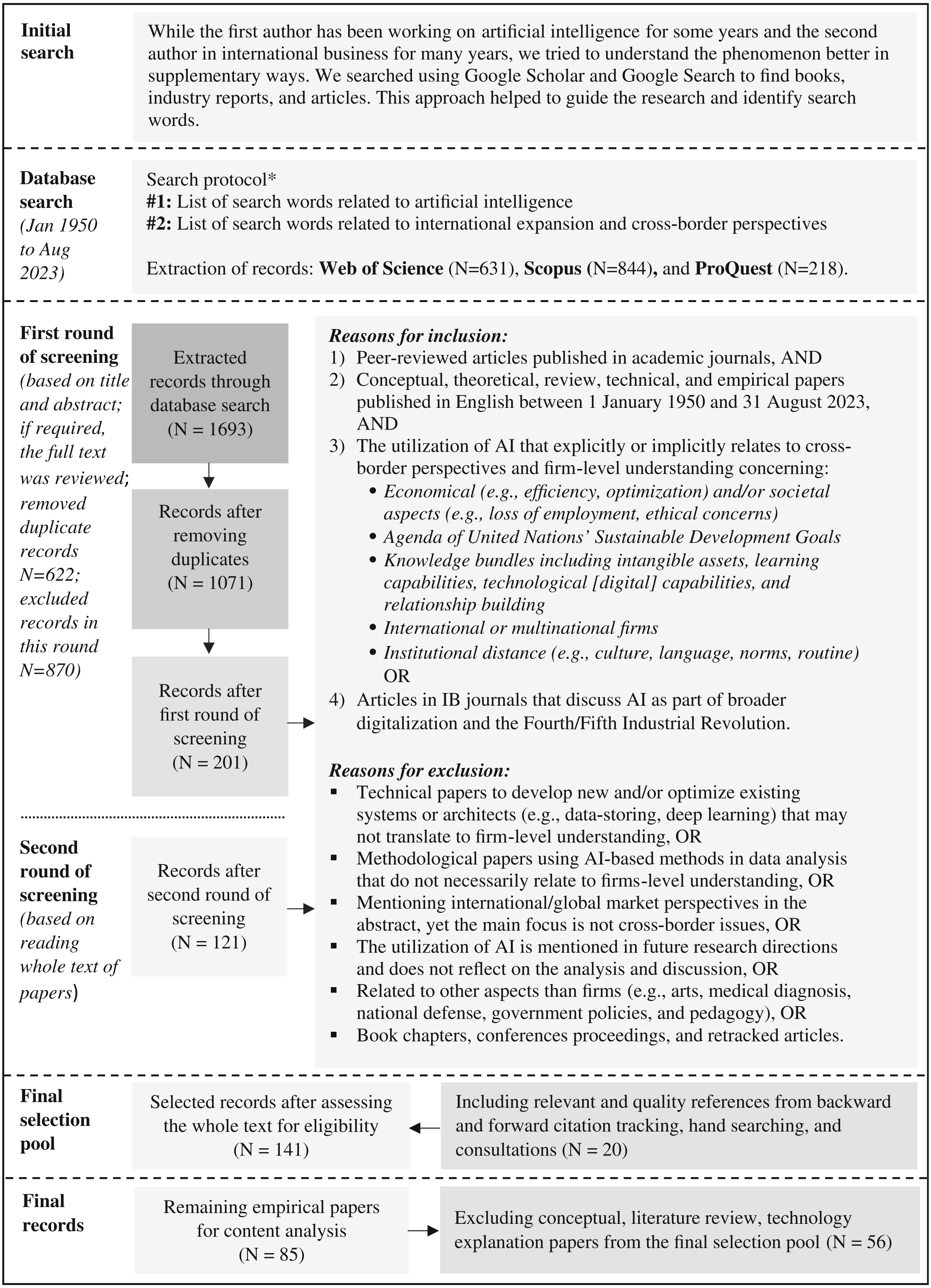

FIGURE 1 Construction of the dataset. *See Appendix A for a detailed account of the search protocol and search string/sets of keywords.

(Miles et al., 2014). How does the paper relate to IB management? Does it deal with any underlying characteristics of AI? If so, how does the characteristic impact IB management? Does it deal with sociotechnical issues of managing production and consumption in IB, and, if so, how? Does it inform future research directions in IB management, and if so, how?

Having discussed the methodological stages of our research and the qualitative nature of our constructed dataset and analytical procedure, we now present the findings of our study. We first provide a definition of AI in IB management, followed by the theoretical support for our three constructed characteristics of AI from existing AI and IB literature. We then provide our empirical insights into the three characteristics of AI and outline future research opportunities to achieve sustainable production and consumption.

3 | CONSTRUCTING THE CHARACTERISTICS OF AI IN IB MANAGEMENT: THEORETICAL FOUNDATION

3.1 | What is AI in IB management?

IB research defines AI as the most important technological advancement that (a) learns patterns automatically from examples (Brynjolfsson et al., 2019), (b) makes autonomous decisions (Hemphill & Kelley, 2021), and (c) solves problems and achieve goals (Ferreira et al., 2023). Additionally, IB research went further to compare this technological advancement with humans to articulate that AI is composed of many computational capabilities that allow artificial systems to recognize patterns in a sophisticated way, similar to the human brain (Veiga et al., 2000), and perform functions that mimic or exceed human cognition (Ciulli & Kolk, 2023). However, recent IB research cautiously argues against such an assessment and for the importance of human knowledge in AI applications (Grant & Phene, 2022; Tatarinov et al., 2023).

This human-centrism is critical for successfully utilizing and managing AI in IB operations since AI is computationally constrained by the data it is trained on (Autio et al., 2021). Furthermore, AI's functions and decision-making behavior are also constrained by its operating environments and configurations of interactions like machine–machine and/or human–machine (Glikson & Woolley, 2020; Rahwan et al., 2019). Central to humans, the frontier of computational advancements must still uphold ethics and protect human rights across all economic activities (Berente et al., 2021). Consequently, we argue that AI works well in decision-making with human knowledge and experience. However, recent advances in computational capacity also make AI an evolving computation system that autonomously learns and makes decisions without human knowledge and experience (Lyytinen et al., 2021; Murray et al., 2021). We therefore maintain *AI as the frontier of computational advancements that address complex decision-making problems and can be engineered to learn, evolve, and develop with or without human intervention*. This article focuses only on narrow AI that performs narrowly defined or a singular task in IB operations. Throughout the paper, we use the term "AI" to refer to both complex and simple computational systems used to make decisions and reflect on their embodied representation, like robotic, virtual, and embeddedness (Glikson & Woolley, 2020; Rahwan et al., 2019).

3.2 | Characteristics of AI in IB management: Autonomy, learning, and combinative

Based on qualitative content analysis, we constructed three different characteristics of AI in IB management. The first characteristic of AI is autonomy, which covers its increasing capacity to act without human intervention and behave without human knowledge (Murray et al., 2021; Rahwan et al., 2019). Unlike past information technology and rule-based automation that required humans to codify and program tasks explicitly, AI is based on machine learning that is developed to detect patterns from data and reprogram itself automatically (Berente et al., 2021; Brynjolfsson et al., 2019). This self-development aspect allows AI to automate routine tasks and activities in extant cross-border business management. Recent IB literature suggests that such autonomous capabilities can be expanded across borders by feeding fine-grained data from diverse national contexts (Autio et al., 2021). With such proliferation within multinational settings, managing AI autonomy requires less monitoring, coordination, and transaction costs in IB operations (Cuypers et al., 2021). It also allows managers to combine autonomous machine intelligence with human intelligence in decision-making and knowledge transfer across borders (Grant & Phene, 2022).

The second characteristic of AI is learning, one of the central concepts from its inception (Turing, 1950). Learning refers to machines' "ability to inductively improve automatically through data and experience" (Berente et al., 2021, p. 1437). Machines can learn to recognize patterns through supervised and unsupervised learning techniques and other large-scale advanced computational methods, like deep or reinforcement learning or neural networks. For instance, the neural network model is inspired by the human brain with extensive interconnected units as neurons that connect a vast network to recognize complex patterns. Consequently, IB literature explains that these are modeled with many computational elements functioning in parallel and arranged similarly to biological neural nets (Veiga et al., 2000). Such learning functions enable machines to produce sophisticated outputs. These outputs of pattern recognition gradually improve and perhaps make machine intelligence, through data interpretation and experience iteration, similar to how the human brain routinely performs. Additionally, IB literature consistently argues the importance of learning about markets in firm internationalization (Johanson & Vahlne, 2009; Luostarinen, 1994). Recent AI developments provide excellent learning opportunities for managers in their internationalization process (Huo & Chaudhry, 2021).

The third characteristic of AI is combinative, one of the emerging concepts from recent development that involves hybrid interaction between machines and machines as well as humans and machines (Rahwan et al., 2019). Current IB literature posits that managers can utilize the combinative characteristics of AI to reconfigure the nature and structure of value-creating activities in the global marketplace (Tatarinov et al., 2023). This recombinant approach allows managers to develop dynamic capabilities that lead to firm-specific assets which include several functions of digital solutions (Banalieva & Dhanaraj, 2019; Lee et al., 2021). AI's modular property governs these interconnected yet separable functions (Autio et al., 2021; Nambisan & Luo, 2021). Modularity refers to the layered technological architecture of a solution to facilitate loose interconnectivity of given elements that can be recombined (Ojala et al., 2018). This combinative approach of AI helps managers to create entirely new functionality enabled by different configurations of new capabilities (as modules) to be added into the systems or architectures. A recent development on the characteristics of digital artifacts in IB argues that digital artifacts can be reprogrammed to facilitate dynamic capabilities in international expansion (Ojala et al., 2023). Similarly, AI literature indicates that each module of AI architecture can be modified or discrete if necessary to achieve its desired functionalities (Rahwan et al., 2019).

In this section, we have provided a theoretical foundation for the three constructed characteristics of AI. However, the question of how managers will utilize these characteristics in IB to achieve responsible production and consumption remains. In the following section, we thus present our empirical insights into AI related to each of the three characteristics and simultaneously develop possible future research agendas. However, we went beyond our dataset to develop a research agenda for managing AI in IB and achieving sustainable production and consumption. We complement the empirical insights with broader theoretical, conceptual, and empirical AI and IB research.

4 | MANAGING AI IN IB: EMPIRICAL INSIGHTS AND TOWARD A RESEARCH AGENDA

4.1 | Autonomy as a characteristic of AI: Empirical foundation ($N = 18$)

4.1.1 | Managing autonomy in IB: Empirical insights

Autonomy aids decision-making to manage global value chains

Managers deal with uncertainty and risk factors in their everyday decisions managing their global value chains. Against such challenges, managers can deploy AI which can process information automatically to make near-optimal decisions (Chen & Du, 2022). For example, managers face uncertainty from risk factors emerging from commodity price shocks and fluctuations in global markets. In this case, managers can utilize AI models to make optimal decisions to hedge themselves against price uncertainty, reduce risk, and increase firm performance in global value chains (Ding et al., 2019).

Managers of firms that operate in global value chains also face risk factors related to multi-echelon supply networks, which refers to firms' inventories spanning multiple layers like sourcing, manufacturing plants, warehouses, and markets in different countries (Kumar et al., 2010). A firm in the automobile industry, like Volvo or Toyota, is an excellent example of such a global value chain. Managerial uncertainty in these firms emerges due to inherited risk factors cornering international coordination, material flows, and market demand. Risk factors may include late shipments, currency fluctuation, geopolitical shifts, customs delays, transport breakdowns, natural disasters, problems with quality control, and global healthcare crises. AI seems helpful for managers to automatically adjust supply chain design that can react to uncertainty arising from those risk factors, to some extent (Kumar et al., 2010). Doing so allows managers to make optimal decisions to manage inter-echelon quantity flow between suppliers' locations, warehouses, manufacturing plants, and distribution channels. Therefore, near-optimal decisions and automation optimize international operations and increase productivity and economic efficiency.

Autonomy optimizes international operations

Concerning productivity and economic efficiency with AI, managers can solve complex problems and enhance business processes that provide customized technological solutions for their global operations. This AI-driven automation increases productivity, reducing waste, labor cost, and workflow time, and increasing firm performance (Sharma & Kumar, 2023). Additionally, intelligence automation seems promising when it comes to improving profitability and labor productivity by reducing labor input costs, which enhances international competitiveness. To illustrate, managers in Chinese manufacturing firms use AI in product automation to increase efficiency. This management approach is central to upgrading their technological capabilities that complement a highly skilled labor force and enhance international competitiveness in the global value chain (Gao, 2023). To further demonstrate, a study on Spanish manufacturing firms revealed that AI-driven automation with robots enables higher labor productivity, leading to better financial performance through export sales to non-robotized firms (Ballestar et al., 2020).

Intelligence machines automatically crunch large amounts of real-time data to optimize production processes, integrating the effective coordination of complex value chains across borders (Kinkel et al., 2023). As an example, managers can deploy AI-enabled computer vision to detect production defects early and achieve real-time production adjustment. Furthermore, managers can equip assembly lines with AI to constantly monitor the production process and autonomously, which aids in reducing operational costs and automating product testing (Yu, Fletcher, & Buck, 2022; Yu, Liu, et al., 2022). Hence, managers can improve the quality of products and production, automating tasks and thereby driving firms to relocate production plants to their home countries (Kinkel et al., 2023; Stemmler, 2023). Similarly, managers of manufacturing firms may increase productivity with AI in just-in-time production systems.

In a just-in-time production system, goods must be delivered to customers on time while minimizing inventory-related costs by maintaining optimum inventory stock. In this case, selecting the right sourcing partners and evaluating supplier performance is paramount to scaling such a system to the entire value chain. Hence, managers can automate this selection and evaluation process with AI based on critical criteria such as product quality, delivery time, and location (Aksoy & Öztürk, 2011). Additionally, they can accommodate sustainability-related criteria like energy efficiency, social welfare investment, and cost reduction rate in the AI-based evaluation process (Wang, 2022). Therefore, managers in manufacturing firms can achieve economic goals while ensuring environmental and social well-being.

Concerning environmental well-being, AI helps to manage resources (e.g., energy, water, chemicals) efficiently during the production process to carry out tasks in a totally autonomous or semiautonomous way that maintains required outputs (Ferreira et al., 2023). Put simply, it allows managers to reduce carbon footprints while maintaining the quality and quantity of goods produced. Concerning social well-being, empirical insights indicate that managers can increase health and safety practices and improve factory workers' physical and mental health by improving working conditions and automating monotonous and routine tasks (Ferreira et al., 2023). However, AI-driven autonomous or semiautonomous manufacturing processes also raise the issue of replacing human labor with machines, which leads to loss of employment and job displacement (Stemmler, 2023).

4.1.2 | Toward a research agenda: Managing autonomy in IB to achieve sustainable production and consumption

Control problems in internationalization decision-making

As previously noted, the autonomy of AI leads to business processes being optimized and aids decision-making that efficiently helps to manage global value chains. However, extant research in information systems argues that managers' reliance on AI to automate tasks and routines makes them increasingly dependent on it (Berente et al., 2021). This adverse reliance effect may lead to control problems that could have deleterious consequences. The control problem refers to a human decision-maker's tendency to become complacent and overreliant on the output of a reliable, autonomous system (Zerilli et al., 2019). Such overreliance decreases unique human knowledge in human–machine collaborative decision-making settings (Fügener et al., 2021).

Management literature also demonstrates that such issues lead to over trusting in human–machine interaction (Glikson & Woolley, 2020). This evidence is consistent with an experimental study in which humans blindly follow an autonomous agent in a life-threatening situation (Robinette et al., 2016). Alarmingly, half of the participants even observed that the given autonomous agent was not functioning well during the experiment. This unexpected human behavior indicates that managers' overreliance on AI to optimize IB processes and decision-making without effective monitoring may reduce situational awareness. Such effects hinder the detection of potential system failures, thereby leading to disturbance in global value chains and negatively impacting customer experience. Consequently, how does machine autonomy alter human autonomy and negatively affect internationalization decision-making in global value chains? Why do some IB development managers (and not others) overly rely on AI in their internationalization decision-making?

Further IB research on AI's control problems in decision-making in the context of global value chains could add to ongoing debate on human autonomy being influenced by machine autonomy (Murray et al., 2021). More broadly, a fine-grained focus on the characteristics of AI autonomy and its negative impacts on internationalization decision-making could also be used in responsible decision-making to ensure global sustainable production and consumption patterns.

> **Future Research Theme 1.** *Addressing AI in internationalization decision-making in IB research could offer critical insights on managing the control problems that emerge from decision-makers' overreliance on AI and altering human autonomy to ensure sustainable production and consumption.*

Complexity to attribute responsibility and liability

Suppose that an accident happens when a fully autonomous vehicle is in control. Who would be held responsible or liable for the damage caused by AI in the absence of a human driver? This question also applies to AI which is increasingly used to automate decision-making or aid human decision-makers (Jobin et al., 2019). Furthermore, such a question is relevant to any context of IB operations in which a human decides or acts based on information provided by AI. The information could be dubious due to the data sets used in training, human bias inherent to the coding, and data encompassing discriminatory attributes like race, ethnicity, religion, or nationality (Greenstein, 2022). For example, an IB study demonstrates why managers stop international expansions of AI solutions to ensure human well-being due to an institutional void (absence of AI governance framework) in the host country (Tatarinov et al., 2023). On the contrary, managers intentionally or unintentionally develop and deploy AI solutions to increase user engagement and maximize economics of scale that may cause significant harm to society. To illustrate, some AI-powered social media platforms are notoriously debated for their deliberate system design to increase end-user engagement. Such AI-curated digital solutions lead to usage addiction, which has a negative impact on mental well-being and toxic behaviors (Crawford & Smith, 2023). Therefore, further IB research focusing on the institutional void in diverse multi-country contexts (e.g., Rana & Sørensen, 2021) could be useful for the heated debate on the emerging complexity of AI responsibility and liability (Bartneck et al., 2021). Consequently, to better understand this phenomenon, the following research questions are of particular interest. How do managers responsibly utilize AI in internationalization while balancing economic scale and end-user well-being? How do home-country institutions influence managers to maintain AI governance in the context of institutional voids in host countries? How do managers navigate legitimacy development during the internationalization of autonomous agents to minimize the complexity of responsibility and liability?

More broadly, the perspective of attributing responsibility to focus on AI autonomy that involves diverse actors (e.g., developers, manufacturers, government agencies, insurance companies, and consumers) could assist the management of AI governance in multinational corporations. This governance will also help with how to manage internationalization risks while fostering sustainable production and consumption in global markets.

> **Future Research Theme 2.** *Incorporating an institutional lens to attribute responsibility and liability in IB research could offer critical insights on managing AI governance in the context of diverse actors to ensure sustainable production and consumption when utilizing AI in global markets.*

Emerging international inequalities

Due to AI-driven changes in the global value chain, managers of manufacturing firms originating from developed countries may reconsider relocating their production from emerging countries to their home countries. This is due to routine and manual tasks being able to be automated with robotic AI, making backshoring a viable option (Ahi et al., 2022). The economic benefits of such backshoring initiatives are, for example, enabling firms to be closer to customers, increasing efficiency via shorter times to market, and reducing transportation costs (Bertulfo et al., 2022). Advanced technologies like robotic AI within the global value chain are negatively altering employability in manufacturing in several developing economies (Bertulfo et al., 2022). To provide concrete evidence, increasing managerial adoptions of AI-driven automation in exporting countries has led to reduced employment in manufacturing sectors in Brazil (Stemmler, 2023). Therefore, the adverse fear is that backshoring would reduce employment in developing countries, thereby increasing global income inequalities (Pinheiro et al., 2023; Studley, 2021). While there is relatively little knowledge on how to manage this problem from an international perspective (Kopalle et al., 2022), IB literature highlights the challenges along with recent global disruption and increased nationalist sentiments (Brakman et al., 2021; Del Giudice et al., 2023). Additionally, IB literature tends to focus on the economic benefits of backshoring initiatives (Ahi et al., 2022). However, managing negative social consequences is paramount to ensure global sustainable development.

Consequently, we urge IB scholars to examine questions such as: to what extent does AI autonomy lead to relocation strategies? What are the negative social consequences of AI-driven relocation strategies in developing countries? How can managers reduce income inequalities in host countries resulting from AI-driven reshoring of their manufacturing plants? Does AI autonomy lead to income inequalities within developed countries? Future IB research that focuses on AI autonomy and relocation at the intersection of emerging economic equalities could improve management practices in responsible manufacturing to maintain the economic benefits of host countries.

> **Future Research Theme 3.** *Incorporating relocation strategies and emerging economic inequalities to focus on the autonomous characteristics of AI in IB research could offer critical insights into managing sustainable production and consumption to ensure the economic benefits of host countries.*

4.2 | Learning as a characteristic of AI: Empirical foundation ($N = 36$)

4.2.1 | Managing learning in IB: Empirical insights

Learning aids internationalization decision-making processes

We see the value of AI-driven learning in firms through pattern recognition and assisting managers concerning location choice. Managers can use AI to augment decision-making in evaluating market attractiveness and the competitiveness of focal firms in overseas markets (Dikmen & Birgonul, 2004). Such AI models aid managers in collecting the most relevant data during international expansion and preparing priority lists during strategic planning. The insight from the models then informs managers about critical factors that increase the attractiveness of possible expansion—the availability of funds, market volume, economic prosperity, and country risk rating. However, not all managers necessarily have experiential learning as many have never operated in overseas markets.

AI-based learning may complement a manager's lack of experiential learning in exploring international expansion possibilities and managers can use AI in their market screening efforts. For instance, AI can learn by crunching large amounts of data and generating insights from external databases to focus on potential countries' international trade at the intersection of focal firms' operating industries and product classifications (Fish & Ruby, 2009). Managers can also prioritize target locations, analyzing strategic country groups based on market attractiveness, firms' resources and capabilities, and customer-oriented approaches (Hsieh et al., 2022). Once managers can prioritize target countries or locations, AI-driven learning brings additional benefits to location-focused market selection (Tsilingeridis et al., 2023).

Learning about different locations can help managers to select suitable markets for international expansion. Existing literature concerning AI-based learning at the intersection of market-selection decisions focuses on two aspects. First, AI can help learn about internalization advantage patterns (concerned with reducing transaction costs) (Brouthers et al., 2009). It deals with the managers' location decisions in firms originating in developed countries, like Germany and the United Kingdom, and doing business in emerging markets, such as Eastern European countries. The AI provides a predictive solution to a managerial choice that embodies firm-specific resources (e.g., experience, proprietary knowledge), internalization advantages, and target country characteristics (e.g., market potential, market risk). AI-led learning via prediction solutions is an opportunity for better subsidiary performance. Second, AI can be useful in learning about the political risks of potential subsidiary locations in emerging markets (Herrero et al., 2011). It deals with managerial risk factors in emerging countries such as tax policy, security, and political stability, and the given location can be compared with different countries worldwide.

Learning about other critical aspects of location is also possible with AI.

AI learning helps decision-makers to evaluate international expansion location choices based on critical aspects such as financial leverage and geographical distance. For example, one study focusing on Chinese manufacturing firms revealed that financial leverage has a negative effect on location decisions (Huo & Chaudhry, 2021). Another study focused on Chinese renewable energy and showed that vegetation and distance to the power grid are the most important predictors of solar photovoltaic installation location (Sun et al., 2023). Such AI-driven priority lists of targets and strategic groupings of locations are helpful for managers to formulate relevant configurations in the context of limited resources and experiential learning. Besides market screening and selection, managers can use AI in market entry decisions.

To this end, AI can deal with the ambiguity of human knowledge conveyed through natural language to learn about political and social risks by integrating foreign exchange rates and trade balances. Accordingly, managers can deploy AI to assess country risk and assist with international market entry decisions (Levy & Yoon, 1995). Such learning can also be used in foreign direct investment decisions when evaluating a country's potential for greenfield investment (Alon et al., 2022).

Of particular note is that AI research on market entry decisions is rare. However, there is an indication that AI-based learning can augment managers' decision-making when determining entry mode selection (Li & Li, 2010; Rodgers et al., 2022). For example, managers can assess political risk during the internationalization decision-making process by using AI (Rios-Morales et al., 2009). Such AI offers relatively accurate and meaningful learning about target countries' political instability. This then assists managers in deciding on foreign direct investment.

Learning about the performance of entry mode choice

Learning about the performance of entry mode choice helps managers to survive and further expand in foreign markets. Although a meager amount of knowledge is available concerning the performance of entry mode choice, AI has excellent potential. To illustrate, the authors of a recent IB study suggest that AI-enabled learning may enhance export performance by identifying foreign markets and developing clientele (Neubert & Van der Krogt, 2018). Additionally, managers can utilize AI to learn about merger and acquisition performances in the operating industry. For instance, a study using an AI method in the telecommunication industry examined whether a multinational enterprise becomes a serial acquirer (Navío-Marco et al., 2020). Similarly, early IB research on AI also indicates that managers can accurately learn to predict post-merger performance (Veiga et al., 2000). Besides merger and acquisition performance, AI-based learning also aids managers in evaluating the success of international joint ventures.

Such evaluations can point to critical dimensions such as partner commitment, product characteristics, and control (Hu et al., 1999). Reflecting on foreign equity control, for instance, managers can use AI to construct relationships between factors related to transaction cost and ownership that lead to successful joint-venture performance. Factors may include the proprietary nature of assets, the host country's environment, and cultural differences between host and home countries (Hu et al., 2004). Similarly, managers can utilize AI to learn related and unrelated collaborative venture formation patterns based on the potential collaborating partners' industry groups and home country relatedness (Nair et al., 2007).

Learning leads to managerial capabilities

Managers can use AI-driven learning in predictive analytics which develops managerial capabilities. To illustrate, managers can utilize AI to predict firms' export potential to selected markets, focusing on product competitiveness (Yu, Fletcher, & Buck, 2022; Yu, Liu, et al., 2022). It is also possible to forecast export sales with higher accuracy by integrating nonlinear interrelationships between sales-related variables (Sohrabpour et al., 2021). Therefore, AI-driven learning helps managers to reduce transaction costs by optimizing supply chain and production management and provides insight into future sales, inventory control, and material flow. Besides export prediction, managerial capabilities include predicting their corporate competitiveness, resilience, and internationalization performance.

Initial research on multinational enterprises reveals that AI models can predict stock trends, thereby evaluating firms' corporate competitiveness (Zong & Wang, 2022). Similarly, AI models can predict corporate resilience, which may guide managers in developing dynamic capabilities to support their competitive advantage and create a portfolio of competencies to be used during a crisis (Bughin, 2023). Moreover, research on Finnish small and medium-sized firms has shown that AI models can predict the earliness of internationalization and international performance, thereby evaluating capability portfolios consisting of different firm resources such as managers' networking abilities, bricolage capabilities, and decision-making heuristics (Vuorio & Torkkeli, 2023). In addition to developing managerial capacity through prediction, managers can deploy AI to learn about distance and differences between markets.

Learning about distance and differences

Managers can deploy AI as exploratory tools to understand distance and differences in firms' international expansion activities. Research demonstrates that AI can unearth the underlying pattern of national culture in a narrowly constructed interconnectivity such as cultural compatibility in post-merger performance (Veiga et al., 2000), and multicultural factors to understand customer requirements (Yan et al., 2001). While national culture is a multifaced construct, its differences may not be adequately captured by any single trace or generalized label like "individualism" or "collectivism." Additionally, nations comprise of an almost infinite number of properties or patterns—some of them are culturally universal (etic), and others are culturally specific (emic) (Veiga et al., 2000). In this case, IB studies demonstrate that managers can deploy AI to learn about cultural heterogeneity within nations, focusing on individuals to draw on country-level differences (Messner, 2022c). As an example, AI models can learn to trace cultural distance by crunching data on individuals' values embodying societal and cultural beliefs and behaviors, even emotional brain systems (Messner, 2022a, 2022b). Such learning enables managers to identify similar cultural subgroups across counties and isolate nations with notable cultural similarities. Besides learning about national cultures, AI can be helpful to learn about differences within countries.

Managers can use AI to learn about micro-market segments within subgroups (Ali & Rao, 2001). Such AI can compare and contrast market segmentation structures in different countries using small samples to foster relationship marketing. This learning about differences implies managing internationalization strategies via identifying consumption patterns in foreign markets and detecting purchase intention patterns within subgroups (Messner, 2022a; Migdał-Najman et al., 2020; Sharma et al., 2022). For instance, small- and medium-sized exporting firms may only target the same cultural subgroups within heterogeneous nations that align with their product features or functionality.

Given the proliferation of unstructured user-generated data on social media, managers can deploy AI models to learn about potential differences in consumer behaviors within countries and subcultural groups. A study on Korean beauty products belonging to the K-beauty subcultural group revealed that consumers have different behaviors and consumption patterns (e.g., attractiveness vs. avoidance) within a homogenous (based on religion) country group, like Indonesia and Malaysia (Jung et al., 2023). Another study based on millions of tweets collected from X (formerly known as Twitter) on a given topic shows how consumer sentiments and emotions substantially differ across countries (Schlegelmilch et al., 2023).

4.2.2 | Toward a research agenda: Managing learning in IB to achieve sustainable production and consumption

Privacy protection

As mentioned previously, AI needs data to learn. The widespread usage of digital technologies enables firms to collect digital trace data for learning. Unlike past information technologies, AI not only learns from proprietary or internal data sources but also from other or external data sources within and beyond organizations. Learning, therefore, confronts managerial issues like privacy violations (Berente et al., 2021; Kopalle et al., 2022). For example, Clearview's image recognition AI is notorious for using billions of images from social media services across the globe without users' consent (Hill, 2020). Such privacy violations are costly for end users and firms alike, which leads to negative consequences. For end users, the loss of privacy may lead to feelings of uneasiness and powerlessness, loss of resources such as time or money, a negative change in an individual's social relationships, and restricted freedom of opinion and behavior (Karwatzki et al., 2022). For firms, it may lead to a loss of customer trust and pose reputational risk in foreign markets (Madan et al., 2023). The intersection of privacy concerns and trust is becoming a global issue with the rise of pervasive digital technologies, particularly for firms minimizing risk and end users protecting their privacy (Luo, 2022). While there has been minimal research on AI and privacy in international contexts, early IB literature shows that managing privacy during the internationalization of digital solutions is paramount (Tatarinov et al., 2023).

Consequently, we propose that the following research questions are particularly important to address in future studies. How do managers ensure privacy protection during the international expansion of AI solutions? How do national and cultural attributes shape the perception of end users' privacy concerns about AI-enabled products? How do managers comply with strong institutions (presence of tight AI regulatory framework) in their home country to ensure privacy protection in host countries with weak institutions? How do the managers of digital platforms legitimize privacy violations by utilizing pervasive AI in foreign markets? To what extent does having privacy protection by default affect the legitimacy of AI solutions during international expansion activities?

> **Future Research Theme 4.** *Incorporating privacy concerns into AI learning in the various contexts of international expansions in IB research could offer critical insights on managing risk and end users' well-being that ensure responsible production and consumption across borders.*

Algorithmic inscrutability in decision-making

Previously, we argued that learning augments managerial decision-making to demonstrate the economic value of AI in internationalization. However, there is growing concern about broader managerial and social implications, including negative consequences like undetected biases that shape machine behavior (Asatiani et al., 2021; Rahwan et al., 2019). However, AI is becoming increasingly complex due to voluminous data being fed into algorithms and advanced computational techniques used in learning. Consequently, AI is increasingly inscrutable in its decision-making, which refers to opacity and unexplainable aspects of AI systems (Asatiani et al., 2021; Berente et al., 2021). Put simply, as AI learns more and grows in complexity, it becomes harder for humans to interpret and explain its output. The problem of algorithmic inscrutability affects not only naive end users but also experts. Management literature provides evidence of how experts' biases are transferred to machines via incomplete data and coding (Sobolev, 2023). Although examining the inscrutability of AI learning is gaining traction in other management domains (Lebovitz et al., 2021; Rai, 2020), IB literature also suggests its importance to achieve global sustainable development (Ciulli & Kolk, 2023). Interestingly, empirical research in IB studies also echoes such "black box" issues of AI learning (Veiga et al., 2000). We, therefore, call for a further understanding of the phenomena from a cross-border management perspective.

> **Future Research Theme 5.** *Incorporating algorithmic inscrutability to focus on AI learning in IB research could offer critical insights into managing transparency to optimize business processes in IB operations and ensure sustainable production and consumption.*

4.3 | Combinative as a characteristic of AI: Empirical foundation (*N* = 31)

4.3.1 | Managing combinative in IB: Empirical insights

Combinative allows reconfiguration of resources

Managers can utilize AI combined with the core functionality of existing products to enable new functionalities in the global marketplace. For example, managers employ AI as a module for physical products, like heavy trucks, to enable service provision, leading to productivity and profitability for customers (Haftor et al., 2021). Such AI is combined with other technological artifacts like the internet of things (e.g., connected sensors in engines and gearboxes) that produce considerable amounts of real-time data with low-latency monitoring (Gooderham et al., 2022). This combinative capability automatically generates insights based on vehicles' technical configurations, actual usage, and the error code combinations that facilitate efficiency. Such efficiency reduces fuel consumption and enables the predictive maintenance of vehicles.

The combinative approach enables managers to develop solutions to self-analyze, proactively report problems, and take real-time corrective action (Gooderham et al., 2022). Recent empirical evidence shows that configuring autonomous vehicles requires many AI solutions, and not all resources are owned by focal firms (Ji et al., 2020). Therefore, managers must combine their existing AI resources with external ones to produce and sell autonomous vehicles in international markets. This recombination of external resources can be achieved through application programmable interfaces to create new functionalities. Such reconfigurations of resources drive business model innovation.

Business model innovation powered by combinative AI that learns and automatically acts is an established phenomenon. For example, Netflix and Spotify's streaming services continuously collect and learn from data to detect usage patterns and predict users' needs and wants. This learning about user consumption patterns allows managers to deploy an AI-based recommendation engine as a separate module. Such combinative AI automatically personalizes offerings in real-time to gain efficiency. Similarly, early research on AI-driven business model innovation demonstrates how managers create value for focal firms and their customers (Haftor et al., 2021). Through AI solutions that combine learning and autonomy, managers upgrade technical configurations to improve offerings. This combinative AI improves over time with more learning, creating a virtuous circle of generating value for customers. Such an approach automatically produces more data and generates predictions based on usage data, leading to new functionalities (Brynjolfsson et al., 2019; Sjodin et al., 2021). Besides new functionalities, managers can also recombine AI to develop dynamic capabilities.

Combinative develops dynamic capabilities

Managers can configure dynamic capabilities in international operations which combine existing organizing capabilities with new AI-driven capabilities. For example, combining cooperative management capability with AI-driven supply chain analytics enhances operational and financial performance during global supply disruption (Dubey et al., 2020). Together with other advanced technological artifacts like the internet of things, AI can be used to improve export manufacturing firms' strategy formulation process concerning supply chain resilience (Ahmed et al., 2023). The process includes selecting optimal routes, reducing energy consumption, inventory policy, and waste reduction.

Configuring an AI-integrated customer relationship capability and combining it with global customer support, automation, and knowledge management improves firm performance in international marketing (Chatterjee et al., 2023). As an example of knowledge management, managers can use AI in a two-layered inductive learning procedure where two different modules assess international financial risk in internationalization (Tessmer et al., 1993). Such AI with combinative learning capabilities identifies foreign companies' risk structures considering various economic environments. This AI learns from national commonalities and differences while integrating an evaluation scheme independent of national attributes. Managers can have a richer yet relevant and concise decision structure to assess international risk that helps with internationalization decision-making and new investment opportunities.

Combinative aids expanding solutions internationally

The managerial approach is to embrace combinative AI with modular architecture facilitates expansion across different markets. Managers expand digital solutions into markets via diverse combinations of AI to target different customer segments and locations in home and host countries (Sjodin et al., 2021; Tatarinov et al., 2023). The ability to create such combinations leads to openness in the solutions (Ozalp et al., 2022). Consequently, it reduces complexity in deployment, yet managers can add new and novel functionalities based on emerging needs in operating markets (Sjodin et al., 2021). Additionally, the core functions of AI-driven solutions can be replicated across borders with minimal customization (Oliva et al., 2022). Furthermore, each part or module can be modified and recombined with internal resources during internationalization (Tatarinov et al., 2023). In this way, managers can add supplementary peripheral functions to solutions with any adaptations required to match host countries' institutions, such as culture, norms, regulations, and language. The following empirical evidence on language will provide further clarification.

Managers can utilize automatic AI-based translation as a module to combine with the core functionality of an existing solution during internationalization (Karkaletsis et al., 1998). Such a module is language-independent regarding host countries and can be used in a multilingual setting to produce a user-tailored product interface in digital environments (Brynjolfsson et al., 2019). Furthermore, a multilingual review system can be combined with existing infrastructure to automatically read all user-generated reviews and learn about customer sentiments (Liu et al., 2021). Hence, a managerial approach to combine AI with extant organizational resources may reduce language barriers in international expansion.

Combinative fosters the international expansion of firms

Managers can combine AI to manage their international expansion activities that address institutional barriers. A digital platform-based firm like eBay is an excellent example, where managers deploy AI-based machine translation modules to existing platforms. By adding machine translation, managers increase exports and reduce translation-related search costs and language barriers (Brynjolfsson et al., 2019). The deployment of such AI can significantly increase international growth (e.g., eBay increased exports by 17.5% in Latin American markets, ibid). The application also demonstrates how AI can reduce informal institutional barriers like language. Additionally, the growth effect illustrates how managers can combine AI with other resources in international expansion activities to increase economic efficiency (Denicolai et al., 2021). However, managers can also embed AI capabilities into digital solutions to facilitate firm internationalization that aligns with formal institutional barriers like environmental regulations.

Sticker regulations exist in many countries to protect the environment from fossil-based energy pipelines. Leaks in such pipelines (e.g., oil and gas) imply a loss of material, damage to the environment, and harm to living beings, including underwater. To illustrate, British Petroleum's crude oil spill in the Gulf of Mexico in 2010 remains the worst environmental event worldwide (Meiners, 2020) and many countries subsequently imposed stricter laws to avoid such catastrophes. Therefore, an AI solution can be developed with satellite-based technologies that match host countries' sticker laws on environmental protection concerning detecting leaks in oil and gas pipelines in real time (Oliva et al., 2022). It opens opportunities for managers to deploy AI solutions that facilitate firm internationalization.

4.3.2 | Toward a research agenda: Managing combinative in IB to achieve sustainable production and consumption

Monopolistic competitive advantage in international expansion

We previously argued that managers utilize AI in combination with other digital artifacts or organizational capabilities such as the internet of things, machine translation modules, and satellite technologies. There is no doubt about the economic benefits that managers bring by using such AI. However, while we appreciate AI's combinative capability, we also observe that this characteristic leads to monopolistic behavior in firm internationalization (Ozalp et al., 2022; Rikap, 2022b). Similarly, IB literature cautiously associates such a managerial approach with monopolistic competitive advantages (Ghauri et al., 2021), which are formed through learning about end-user behavior and automatic actions.

Managers of successful companies like Amazon and Uber are front-runners in such an approach (Banalieva & Dhanaraj, 2019; Rikap, 2022a). For example, AI-led dynamic pricing modules in digital platforms automatically learn usage behavior and offer customized prices to end users, thereby maximizing efficiency and profit (Moghaddam et al., 2020). Consequently, Amazon has been accused of illegally exploiting monopolistic competitive advantages through predatory behavior (Clayton & Espiner, 2023). Our observation is reinforced by empirical evidence on how managers innovate new data-driven combinative AI, including search engine capabilities, dynamic pricing, order fulfillment robots, and personalized recommendation modules (Rikap, 2022a). Similarly, managers of the State Grid Corporation of China reconfigure the energy industry toward clean energy and the smart grid with combinative AI in which monopolistic competitive advantages facilitate firm internationalization (Rikap, 2022b). Therefore, we recognize the importance of further investigating managing AI's combinative characteristics at the intersection of gaining monopolistic competitive advantages.

> **Future Research Theme 6.** *Incorporating AI's combinative characteristics to focus on monopolistic competitive advantages during firm internationalization in IB research could offer critical insights on managing AI to achieve global sustainable development*.

Bundling firm-specific assets for social good

Reflecting resource reconfiguration, the combinative characteristics of AI present opportunities for IB research to focus on constructing AI-driven firm-specific assets that balance between economic and social goals (Tatarinov et al., 2023; Verbeke & Hutzschenreuter, 2021). Firm-specific assets are central to firm internationalization and refer to knowledge bundles, including intangible assets, learning capabilities, technological [digital] capabilities, and privilege relationships (Rugman & Verbeke, 2001; Verbeke & Hutzschenreuter, 2021).

Suppose that managers from a fast-moving consumer goods company use AI together with a fusion of satellite imagery and environmental data like climate, soil, and topographical information in their sourcing activities (Shendryk et al., 2021). With this firm-specific bundling capability, they optimize business processes and management decisions with higher certainty that will minimize search and operational costs while achieving sustainable production. Additionally, managers can assess damaging environmental impact hotspots within their value chain networks to reduce their carbon footprint and intervene as required. For example, AI combined with satellite-based Earth observation (monitoring changes of land, marine, and atmosphere) and subnational production data can assist managers in making responsible sourcing decisions (Moran et al., 2020). Managers will also be able to detect illegal and unsustainable uses of resources in fishing or farming. As an example, managers can face a decision to source soy from Brazil's northern production regions, often linked to deforestation, versus southern regions linked to existing agricultural zones. Similarly, managers of a global fashion chain like H&M can identify environmentally polluted hotspots caused by sourcing partners in Bangladesh and make managerial decisions accordingly (Chaturvedi, 2019). Therefore, managerial knowledge of the exact location of sustainability risk hotspots in a particular supply chain within the value chain networks is paramount. However, contemporary IB literature on the global value chain intersecting digitalization has yet to recognize such firm-specific assets (Kano et al., 2020; Strange & Zucchella, 2017). Early research in IB revealed recombinant firm-specific assets that combine AI and Earth observation capabilities and allow managers to create replicable solutions across locations (Tatarinov et al., 2023). This combinative approach opens opportunities to augment global value chains to ensure environmental and social well-being.

> **Future Research Theme 7.** *Incorporating AI's combinative characteristics to construct firm-specific assets that balance economic and social goals in firm internationalization in IB research could offer critical insights on managing AI-driven firm-specific assets to achieve sustainable production and consumption.*

5 | DISCUSSION AND CONCLUSION

Based on a critical realism view and direct content analysis of 85 empirical research papers published on AI in multiple disciplines, this study contributes to our understanding of AI in the context of IB in several ways. First, this study contributes to IB literature by revealing three characteristics of AI, namely autonomy, learning, and combinative. We elaborate on how managers can utilize these characteristics for international expansion and how these characteristics facilitate IB management for sustainable development. We found that AI can enable responsible consumption and production worldwide and help achieve SDGs, but only if we have effective management strategies, policies, and institutions to support their use. Otherwise, they can have opposite, deleterious effects, hindering SDGs. Second, we show how managers can utilize AI characteristics to achieve economic goals in international expansion activities. This provides a working framework for firms to manage AI in international markets. However, we found that current empirical research tends to focus on economic goals, which is problematic when it comes to SDGs. Third, we contribute to the multidisciplinary research on AI and elaborate on how it can be applied to deal with global sustainable development (Jobin et al., 2019; Rahwan et al., 2019; Vinuesa et al., 2020). In international contexts, very limited knowledge exists at the intersection of AI and the sustainability agenda. Therefore, we demonstrate that IB as a research discipline can play a central role in AI research to work toward global sustainable development. To achieve this, managing AI in IB operations to balance economic, technical, and societal goals is paramount. Fourth, we propose future research directions and highlight research questions and themes that, grounded in current knowledge, are important for achieving a more profound understanding of AI in IB and its usage for sustainable production and consumption (SDG #12) internationally.

5.1 | Managerial implications

The insights from our research have significant and timely practical implications for managers. Our study also has important implications for managing AI to automate business processes, learn about markets, and combine resources in international expansion activities. For automation, managers may not want to rely too much on AI in their decision-making to avoid control problems. Instead, intelligence automation can be used to construct systemic capabilities that complement human limitations. Since AI can process voluminous information, it can augment human employees' cognitive limitations on data collection and interpretation (Murray et al., 2021). Additionally, managers must remember humans are very adept at employing their experiential learning, heuristics, and imagination to solve problems. On the other hand, AI may lack empathy, cultural intelligence, and contextual understanding. Therefore, we encourage managers to utilize AI strategically in IB operations to empower and augment employees rather than replace them.

As it relates to learning, the insights of our study point to the imperative of data-driven managerial capabilities through prediction and algorithmic inscrutability in internationalization decision-making. There are growing tensions around complex AI that can be used to learn about end users and manipulate human behavior for profit (Berente et al., 2021; Rahwan et al., 2019). Such AI applications may violate the fundamental right of humans to decide on their free will (European Commission, 2019). Respecting human autonomy, managers must guide responsible AI initiatives (translating ethics into practice) to process data, construct algorithms, train models, and utilize AI to be inclusive, accessible, and transparent (Rakova et al., 2021). Being responsible managers, they must act to comply with human rights and privacy protection by default. Such responsible AI initiatives in international markets would allow managers to safeguard their organizations against reputational, legal, and regulatory risks (Bartneck et al., 2021; Luo, 2022). In this way, managers can more effectively develop learning capabilities in their internationalization decision-making while protecting human rights.

Regarding the combinative approach, our research suggests that managers can reconfigure resources to gain competitive advantages through hybrid human–machine collaboration. In this case, managerial falsifiability is deemed necessary to empirically test the decision output in intended use cases if harmless to humans and safe to do so (Floridi et al., 2020). We argue that falsifiability is essential to ensure the legitimacy of the AI-aided decision-making process and AI deployment in the global value chains that embody ethical principles (Bartneck et al., 2021; European Commission, 2019). Once an AI system is ready for deployment, constant falsifiability and taking incremental steps is crucial. This would allow managers to critically reflect on operating context or institutions (e.g., norms, value judgment, culture) and detect unintended negative consequences at early stages (Hasan et al., 2021; Rahwan et al., 2019). Consequently, managers would be able to make changes to AI systems to ensure local responsiveness while reconfiguring resources. In summary, we advocate for repeated falsifiability and incremental deployment of AI in international expansion activities.

5.2 | Limitations of the study and additional directions for future research

We acknowledge certain limitations in this study that are important to consider. First, the literature concerning the intersection of AI and IB is still in a nascent stage, necessitating further empirical studies to comprehensively cover the phenomenon. Specifically, the papers examined in this research were sourced from various scientific fields with only a few concentrating on AI's utilization in a firm's international activities or internationalization. Consequently, this knowledge gap provides development opportunities. Further fine-grained empirical analysis can be done to combine dimensions of a firm's international activities, which we argued in our study. For example, IB scholars can focus on aspects like managing AI-driven dynamic capabilities and bundling firm-specific assets for social goods, benefitting from economics of scale while reducing carbon emissions and air pollution (Ercan et al., 2022). Other opportunities lie in AI-driven learning about consumption patterns in distance markets that protect consumers' privacy, which reduces the liability of foreignness or complements a managerial lack of experiential learning (Johanson & Vahlne, 2009; Zaheer, 1995).

Second, by recognizing the limitation concerning the absence of direct knowledge, IB scholars could also employ a similar methodological approach (qualitative directed content analysis) in other contexts to derive novel insights into IB. For example, researchers could examine AI's autonomy at the intersection of managing sustainable global value chains (Dimitropoulos et al., 2023), and human–machine complementarity versus the fear of replacement in international management (Man Tang et al., 2022). Similarly, future research can explore AI's learning perspective regarding data-driven strategic resources in global expansion (Hartmann & Henkel, 2020) and international sports sponsorship management (Koronios et al., 2021). Furthermore, IB scholars could also extend AI's combinative aspects on the human augmentation versus augmenting automation debate (Raisch & Krakowski, 2021; Tschang & Almirall, 2021), human–machine collaboration that conjointly learns (Lyytinen et al., 2021; Murray et al., 2021), and modular products architect to facilitate firm internationalization (Habib et al., 2020; Ojala et al., 2018).

Third, due to the extensive scope of the articles reviewed, there is always a possibility that significant works could have been overlooked. As the field matures and more direct knowledge becomes available on this phenomenon, employing a systematic literature review could reinforce and further develop the findings of this study.

Fourth, the empirical insights naturally limited us to covering embedded AI[1] and production-related issues. Consequently, we could not bring widespread insights to other types of AI (e.g., robotic AI) that are generally utilized in consumer-centric activities in different cultures (Hermann, 2022; Lim et al., 2021). Therefore, we suggest extending our research to focus on the perspective of responsible consumption in IB. For instance, future research can focus on AI's autonomy to examine deception and manipulation during consumption through cross-country analysis (Kaminski et al., 2017; Sharkey & Sharkey, 2021). Similarly, IB scholars can extend the autonomy perspective to examine how consumers anthropomorphize AI differently (relating machine to human ability) and develop control problems across national cultures (Duffy, 2003; Lim et al., 2021).

Fifth, reflecting on our sociotechnical view of AI to balance between economic and social goals, we could not bring a wide perspective of environmental goals. Therefore, IB researchers can take another view of managing AI to achieve SDG #12. We see value in further developing our findings by taking the dynamic capabilities or extended value chains perspective to balance economic and environmental goals. Researchers can employ the dynamic capabilities view to focus on AI-enabled circular business model innovation (Sjödin et al., 2023) or the extended value chains perspective to focus on AI-driven circular economy in IB operations (Chabowski et al., 2023).

Finally, the limited capacity of humans to process a large amount of information makes it possible for us to overlook hidden patterns when analyzing textual data. Our combinative argumentation suggests that IB scholars can reinforce these findings by complementing them with an AI system. For instance, future research could use the Microsoft AI-powered Copilot embedded into Bing chat to analyze textual content. Researchers can extract only text related to empirical insights and conduct intra-content comparisons with careful prompt engineering. They can then systematically combine their insights with the patterns identified by AI to construct emerging characteristics of AI and dimensions of IB management. Such a combinative approach will provide a methodological contribution concerning directed content analysis in IB research and further develop the findings of our study.

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DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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ENDNOTES

[1] We used the term "AI" interchangeably to argue for both AI as a research discipline and AI as computation systems (Glikson & Woolley, 2020; Rahwan et al., 2019). Regarding the latter, we used "AI"

throughout the paper to refer to both complex and simple computational systems used to make decisions and reflect on their embodied representations. Such representations include robotic AI (e.g., industrial or humanoid robots), virtual AI (e.g., chatbots), and embedded AI (e.g., autonomous vehicles).

[2] Of particular note is that, unlike a systematic literature review, our detailed explanation of data collection to construct the dataset is for transparency and authenticity rather than arguing for replicability and reproducibility.

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APPENDIX A: Search protocol

(i) Search strings/sets of keywords	
#1: List of search words related to artificial intelligence	**#2: List of search words related to international expansion and cross-border perspective**
("artificial intelligence" OR "AI" OR "artificial intelligence systems" OR "AI system*" OR "AI agent*" OR "Generative AI" OR "autonomous and intelligent system*" OR "autonomous system*" OR robot* OR chatbot OR "conversational AI" OR "voice assistant" OR "virtual assistant" OR "digital assistant" OR "autonomous product*" OR "autonomous vehicle*" OR "machine learning" OR "deep learning" OR "neural network" OR "natural language processing" OR "large language model" OR "AI-based model" OR "computer vision" OR "responsible AI" OR "AI ethics" OR "AI for social good" OR AI4SG)	("international expansion" OR "global business expansion" OR internationalization OR "internationalization decision*" OR "global expansion" OR globali?ation OR "overseas expansion" OR "international strateg*" OR "global strateg*" OR "firm-specific advantage*" OR "firm-specific asset*" OR "international business" OR "international entrepreneurship" OR "international market*" OR "global market*" OR "cross-cultural market*" OR "international management" OR "cross-cultural management" OR "multinational enterprise*" OR "multinational corporations" OR "multination business enterprise*" OR "internationalized small and medium-sized" OR "internationalization of small and medium-sized" OR "internationalization of SMEs" OR "international SMEs" OR "SME internationalization" OR "international joint venture*" OR "born-global firm*" OR "born-digital firm*" OR "born global and digital" OR "international venture" OR "born global" OR "international business networks" OR "international new venture*" OR "location choice" OR "entry mode*" OR "international partner" OR "international firm*" OR "global firm*" OR "international company*" OR "global company*"OR "global value chain*" OR "international supply chain" OR "global supply chains" OR "international operation*" OR "global operation*")

(ii) Advanced searches in databases

We used each search string separately in the databases and saved searches as #1 and #2, respectively, with such functionality. We then combine both with the 'AND' Boolean operator (#1 AND #2). Otherwise, we used both sets of keywords with the 'AND' Boolean operator in one go. More details can be found below

Web of Science (Web of Science Core Collection):	Scopus:	ProQuest (ABI/INFORM Collection):
1) TS = ("artificial intelligence" OR [...]): Search output saved as #1 2) TS = ("international expansion" OR [...]) Search output saved as #2 3) Combined search: #1 AND #2 Note: The search extracted records $N = 631$	1) TITLE-ABS-KEY ("artificial intelligence" OR [...]): Search output saved as #2 2) TITLE-ABS-KEY ("international expansion" OR [...]): Search output saved as #2 3) Combined search: #1 AND #2 Note: The search extracted records $N = 844$	Combined search: ("artificial intelligence" OR [...]) [All abstract & summery text] AND ("international expansion" OR [...]) [All abstract & summery text] Note: The search extracted records $N = 218$