International Journal of Research in Marketing 39 (2022) 522–540

Contents lists available at ScienceDirect

International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Examining artificial intelligence (AI) technologies in marketing via a global lens: Current trends and future research opportunities

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A R T I C L E I N F O

Article history:
First received on October 2, 2020 and was under review for 6½ months
Available online 15 November 2021

Area Editor: V Kumar

Keywords:
Artificial intelligence
Global marketing
Inequality
Glocalization
Ethics and privacy
Human–machine interaction
Automated analysis of text
Audio
Images
Video

A B S T R A C T

Artificial intelligence (AI) has captured substantial interest from a wide array of marketing scholars in recent years. Our research contributes to this emerging domain by examining AI technologies in marketing via a global lens. Specifically, our lens focuses on three levels of analysis: country, company, and consumer. Our country-level analysis emphasizes the heterogeneity in economic inequality across countries due to the considerable economic resources necessary for AI adoption. Our company-level analysis focuses on glocalization because while the hardware that underlies these technologies may be global in nature, their application necessitates adaptation to local cultures. Our consumer-level analysis examines consumer ethics and privacy concerns, as AI technologies often collect, store and process a cornucopia of personal data across our globe. Through the prism of these three lenses, we focus on two important dimensions of AI technologies in marketing: (1) human–machine interaction and (2) automated analysis of text, audio, images, and video. We then explore the interaction between these two key dimensions of AI across our three-part global lens to develop a set of research questions for future marketing scholarship in this increasingly important domain.

1. Introduction

Academic scholars have been intrigued by the prospects and perils of artificial intelligence for decades. An eight-week Dartmouth Summer Research Project on Artificial Intelligence in 1956 is widely considered the founding event that initiated academic interest in this technology (Haenlein & Kaplan, 2019). Today, artificial intelligence (AI) is one of the world's most promising new technologies and entails programs, algorithms, systems and machines that mimic intelligent human behavior (Huang & Rust, 2018; Shankar, 2018). These technologies typically include machine learning, natural language processing,

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https://doi.org/10.1016/j.ijresmar.2021.11.002
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and neural networks (among others), and allow machines to autonomously sense, comprehend, act, and learn via human–machine interaction (HMI) (Davenport, Guha, Grewal, & Bressgott, 2020).

In recent years, AI has captured substantial interest across a wide array of marketing scholars (see Davenport et al., 2020 for a recent review). Collectively, extant research in this domain has made important contributions in terms of defining AI, identifying its promise and perils, forecasting its future and opining on its implications for marketing thought and practice. Our paper seeks to contribute to this domain by examining AI technologies in marketing via a global lens across three levels (i.e., country, firm and consumer). At a country level, our objective is to examine if and how AI may narrow (or widen) economic inequality across countries. At a firm level, our goal is to study the impact of AI on a firm's broader glocalization efforts. Finally, at a consumer level, we seek to assess how firms and governments can address the issues of ethics and privacy that arise due to AI. This conceptual structure is depicted in Fig. 1.

We believe that viewing AI technologies via this multi-level global lens is important for at least three key reasons. First, the growth of AI technologies, and their corresponding data collection efforts, create a virtuous cycle in which AI technologies provide an ideal vehicle for collecting consumer data, and the data collected enables AI technologies to become more effective. One outcome of this synergistic relationship is the issues of data privacy and ethical concerns. However, the degree of awareness about these concerns, and measures to address them, vary considerably across different cultures (Scherer, 2016). Second, at a firm level, the deployment of AI technologies across a wide array of countries necessitates glocalization, as AI firms seek to manage the tension between global technologies vs. local adaptation (Jobin, Lenca, & Vayena, 2019). Finally, at the country level, there is tremendous economic inequality between developed vs. developing nations, and AI has the potential to either shrink or widen this gap. Our three-part (i.e., country, firm, consumer) global perspective regarding the role of AI technologies in marketing seeks to help marketing scholars and managers preserve the benefits of AI technology while also highlighting a set of potential concerns for both marketing theory and practice.

We propose that the global impact of AI technologies in marketing is strongly shaped by a variety of country, company, and consumer considerations. First of all, AI is an advanced and costly technology and most leading AI companies are located in developed economies (Kozinets & Gretzel, 2021). Thus, the development, adoption, and usage of AI is likely to vary based on a country's economic resources. For example, Singapore (a world leader in the use of AI) has a per capita GDP of over $80,000, while Angola (a laggard in the use of AI) has a per capita GDP of less than $3000.

As a result of these inequalities, AI technologies may act as either a global unifier or divider. To date, this aspect of artificial intelligence has received scant attention from marketing scholars. However, marketing literature focused on reducing inequality issue in underdeveloped countries has begun to emerge (Anderson, Chintagunta, Germann, & Vilcassim, 2021). Due to the economic (and digital) divide, the benefits of AI (e.g., customized and self-paced remote learning) may not reach poor nations. On the other hand, AI technologies may act as a unifier by providing economic opportunities to impoverished countries. For example, AI-based human–machine interaction platforms enable firms and governmental agencies in emerging countries to offer services that minimize disparities among consumers (e.g., enhancing accessibility to health services or farm prices) (International Finance Corporation, 2020; Mathew, 2018). Thus, our country-level lens focuses on the heterogeneous impact of AI technologies in terms of economic *inequality* across countries.

Our second level focuses on the interplay between AI and the *glocalization* efforts of companies. Marketing scholars have proposed that due to vast differences in culture, economics, and technology, companies engaged in global marketing should practice glocalization by adapting their offerings to a local context (e.g., Thompson & Arsel, 2004; Kjeldgaard & Askegaard, 2006). In essence, glocalization is an approach where the forces of globalization are co-shaped with local cultures via strategic adaptation (Thompson & Arsel, 2004). We propose that glocalization is also relevant for AI technologies because while the hardware that underlies these technologies may be global in nature, their application necessitates adaptation across various local cultures. On the surface, AI technologies such as machine learning, neural networks, and natural language processing may seem to be global by nature and applicable across multiple cultures and countries. However, the deployment of these technologies will likely need to be adapted to local conditions and needs. For example, Netflix has designed its machine-learning powered algorithms to develop programming adapted to various local consumer tastes (Smith & Telang, 2018).

Finally, at the consumer level, AI technologies often collect, store and process a cornucopia of personal data (Bradlow, Gangwar, Kopalle, & Voleti, 2017). Indeed, the effectiveness of AI technologies in marketing is often based on their ability to collect conspicuous amounts of individual-level data (Bleier, Goldfarb, & Tucker, 2020; SAS, 2021). For example, Facebook's AI-based ad placement algorithm collects a wealth of personal data in order to enhance segmentation and targeting. Today, AI technologies collect more data than ever and track customer behavior both offline and online through a variety of mobile and connected devices. For example, Amazon's granular data collection efforts provide a rich, 360-degree view of customer shopping behavior both offline and online (via a partnership with physical retailers). While concerns regarding the ethics of these types of AI-enabled practices have intensified in recent years, threats to data privacy have raised more concerns in some countries (e.g., France) than others (e.g., U.S.A.) (Trepte et al., 2017). For example, the contrast between Europe's extensive efforts to ensure data protection (i.e., GDPR) versus the apparent lack of data privacy in China highlight both the issue of ethics and privacy in the use of AI technologies, as well as the degree of heterogeneity among countries in terms of AI regulation. Thus, consumer ethics and privacy represent the third and final facet of our global lens.

In this paper, we employ these three facets of our global prism (i.e., economic inequality at the country level, glocalization at a company level, and ethics and privacy at the consumer level), to examine two key dimensions of AI technologies in marketing: (1) human–machine interaction and (2) automated analysis of text, audio, images, and video. We focus on these two

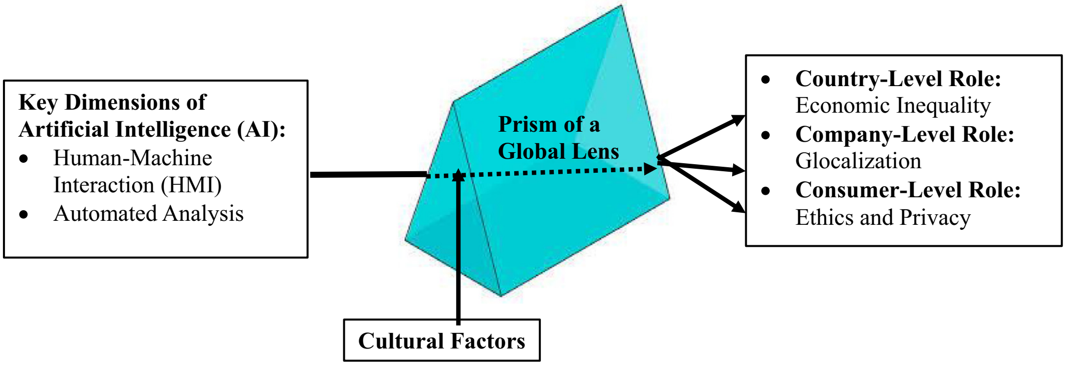

Fig. 1. Conceptual structure.

dimensions because AI is essentially a technology that supplants the role of humans in terms of obtaining data and conducting automated analysis (Huang & Rust, 2018). In essence, AI technologies involve two main players: humans and machines. Machines automate and predict, while humans apply their unique insight and use machine-generated predictions to solve marketing-related problems in a more efficient and/or more profitable manner (Ma & Sun, 2020). For example, Haenlein, Kaplan, Tan, and Zhang (2019) argue that AI and data analytics allow managers to know their customers as well as, or even better than, customers know themselves. Likewise, Syam and Sharma (2018) propose that AI technologies will revolutionize how firms engage in a variety of sales-related tasks, including targeting, demand estimation, lead generation, and closing. We extend and enrich these and other studies in this domain by providing an understanding of the nuances of human–machine interaction in the deployment of AI technologies in marketing via a global perspective.

In addition to altering the role of humans, AI technologies also enable the automated analysis of text, audio, images, and video. This automation has the potential to enhance our understanding and prediction of a wide array of customer behavior. For example, Wang and Kosinski (2018) use a deep neural net algorithm to analyze over 35,000 facial images and correctly distinguish between homosexual versus heterosexual individuals 50% more successfully than human judges. We examine the interplay of these two key dimensions of AI technologies in marketing across three levels of abstraction (i.e., country, company and customer) in order to highlight global commonalities as well as local differences. We posit that the interplay between HMI and automated analysis, and inequality, glocalization, and ethics and privacy are moderated by a variety of cultural factors (Hofstede, 2001).

We hope that this global lens approach will enable marketing scholars and practitioners to study and employ AI technologies in a manner that is not only more effective for firms but also more aware of and responsive to important cultural, economic, and social differences across the globe. Appendix 1 provides a summary of recent research on artificial intelligence (AI) technologies in marketing in terms of whether the studies examine these two dimensions of AI (HMI and automated analysis) as well as the facets of our global prism of inequality, glocalization, and ethics and privacy.[1]

2. Human-Machine interaction (HMI)

Human-machine interaction (HMI) refers to the various ways people and automated systems interact and communicate via touch, gestures, voice, and sensors. HMI-based, AI-powered applications entail both humans assisting machines as well as machines assisting humans (Wilson & Daugherty, 2018). HMI is enabled by cognitive technologies such as computer vision, machine learning, natural language processing, speech recognition, and robotics, and these technologies are increasingly capable of performing tasks traditionally conducted by humans (https://www2.deloitte.com/us/en/insights/deloitte-review/issue-16/cognitive-technologies-business-applications.html). In addition, AI-powered machines can augment human abilities by amplifying their cognitive strengths and extending their physical capabilities. As recently noted by Kaplan and Haenlein (2019a), AI systems and humans can symbiotically coexist: Humans can focus on feeling tasks, while AI can be used as a tool to allow humans to make better decisions. As an example of this symbiotic relationship, Huang, Rust, and Maksimovic (2019) examine how firms should decide whether to assign tasks to humans or machines, and suggest that AI will first replace mechanical tasks, followed by analytical tasks, and eventually, intuitive and empathetic tasks.

Given AI's increasing ability to supplant or even replace humans, a growing number of marketing scholars have begun to express concerns about its possible limitations. For example, both Ma and Sun (2020) and Rai (2020) argue that while machine learning methods are powerful in terms of processing large-scale unstructured data and demonstrate strong predictive performance, these technologies are lacking in terms of transparency and interpretability. Likewise, Proserpio et al. (2020) highlight the importance of human input and insight in AI applications. According to both Cook, Berman, and Dajee

[1] Appendix 1 shows that our choice of HMI and automated analysis as the two key dimensions of AI is indeed appropriate as they have been examined by prior studies, and our novelty is in examining the interplay between AI and our global lens of economic inequality, glocalization, and ethics privacy.

(2019) and Davenport et al. (2020), AI could become more effective by augmenting (instead of replacing) human managers. As an example of this type of augmentation, Chintagunta, Hanssens, and Hauser (2016) discuss how big data and analytics can be used to provide relevant product recommendations to customers, thus highlighting the value of HMI. For instance, North Face and IBM Watson have developed a personalized online experience where an AI-powered online quiz recommends specific "high-match" and "low-match" apparel based on the customer's preferences. As illustrated by this example, the retailing sector has appealing characteristics, such as its large size and good data availability, that are conducive to the development of better HMI applications (Bradlow et al., 2017; Dekimpe, 2020; Wang, Ryoo, Bendle, & Kopalle, 2020).

HMI can also allow firms to offer individual, bidirectional real-time communication with customers through the use of chatbots (Gentsch, 2019). For example, chatbots such as 1–800-Flowers' Facebook Messenger bot have transformed customer service delivery, while conversational chatbots such as eBay's bot designed for Google Assistant expedites the customer search process across multiple product categories. A recent field experiment by Luo, Tong, Fang, and Zhe (2019) shows that AI chatbots are just as effective as experienced employees and four times more effective than inexperienced workers in engendering customer purchases.

Other relevant HMI-related studies focus on a wide variety of applications, including the internet-of-things (IoT) and smart objects (Hoffman & Novak, 2018), collaborative decision-making systems (Metcalf, Askay, & Rosenberg, 2019), virtual and augmented reality (Wedel, Bigne, & Zhang, 2020), personalization (Tong, Luo, & Bo, 2020), virtual reality experiences (Kang, Shin, & Ponto, 2020), and facial recognition (e.g., Amazon's cashierless Go stores). Extant research has also examined how HMI enables complex decision-making in purchasing departments (Allal-Chérif, Simón-Moya, & Ballester, 2021), provides insights to improve digital interactions between buyers and sellers (Bharadwaj & Shipley, 2020), impacts consumer decision-making processes via voice assistants (Dellaert et al., 2020), affects shopping behavior with real-time spending feedback (Van Ittersum, Wansink, Pennings, & Sheehan, 2013), and influences consumer consumption in interactions with humanoid service robots (Mende, Scott, van Doorn, Grewal, & Shanks, 2019). HMI has also been applied to behavioral research design (Hagen et al., 2020), data-based automation of marketing (Wertenbroch, 2019), B2B marketing (Paschen, Kietzmann, & Kietzmann, 2019), and has been shown to improve sales forecasts (Boone, Ganeshan, Jain, & Sanders, 2019). For example, Kaplan and Haenlein (2019a) illustrate the use of HMI in organizations, while Di Vaio, Palladino, Hassan, and Escobar (2020) focus on the impact of HMI on resource management. In this paper, we consider machine-to-machine (M2M) interaction as part of the machine aspect of HMI, and we leave M2M interactions for future research.

As seen from this review, extant research on HMI has made important contributions across a wide variety of marketing applications. However, only a handful of studies have examined HMI from a global perspective. In an early study in this domain, Kaplan (2004) explores how cultural issues affect consumers' views of humans versus robots. More recently, Kumar, Rajan, Venkatesan, and Lecinski (2019) highlight the role of HMI in personalized engagement and provide predictions regarding how AI-enabled branding and customer management practices may differ in developed vs. developing countries. Finally, Nam and Kannan (2020) recently offer a framework to help explain the impact of cross-cultural and socioeconomic factors upon customer journeys in a digital environment. Our research seeks to augment and enhance this prior work by examining the role of HMI at the country, firm, and consumer level (see Appendix 1).

2.1. The country-level role of HMI: economic inequality

At the country level, HMI-based AI technologies have the potential to both exacerbate the digital divide and reduce the economic inequality between developed nations and developing countries (2017). As illustrated by a recent field experiment by Anderson et al. (2021), marketing efforts can help enhance the economic performance of small-scale entrepreneurs in developing nations such as Uganda. Likewise, we propose that AI technologies in marketing have the potential to help alleviate the economic inequality between developed and developing countries. Unfortunately, important contextual differences and nuanced insights about local customs and behaviors appear to be often obscured by HMI-based and algorithmic-driven marketing strategies (Kozinets & Gretzel, 2021; Puntoni, Reczek, Giesler, & Botti, 2021). Thus, country-specific HMI implementation is needed to serve economically disadvantaged customers and, hopefully, reduce inequality. For example, Amazon employs AI-based digital technologies to assist the marketing efforts of small, uneducated retailers in India (Kumar et al., 2019). As a result, retailers who otherwise do not have access to marketing expertise now have access to custom-crafted marketing solutions due to the power of AI-fueled algorithms.

One important divide across countries is access to reliable and high-speed Internet service. Today, billions of humans across our planet must interact on a daily basis with a variety of digital machines such as computers and smartphones in order to conduct a variety or transactions and access to the Internet is often necessary in order to interact with these machines. Unfortunately, Internet access varies widely between developed and developing countries (Bamford, Hutchinson, & Macon-Cooney, 2021). This digital divide limits consumer access to a wide range of offerings and transactions. For example, during the recent COVID-19 pandemic, millions of students, particularly in low-income countries, were unable to engage in online education (where HMI is key) due to a lack of access to high-speed Internet (Wall Street Journal, December 14, 2020). Likewise, in emerging countries such as India, multiple children often try to learn via a single low-end cellphone with weak bandwidth connection and sparse network coverage (Wall Street Journal, November 24, 2020). Even in developed countries such as the U.S., millions of children live in homes without high-speed internet or access to a home computer (Wall Street Journal, December 14, 2020).

In contrast to promoting this digital divide, HMI can also act as a unifier by reducing economic inequality and bringing the world closer together. For example, teachers from lower- to middle-income families from small towns in India are now able to use digital HMI tools to provide remote lessons on topics such as calculus and computer programming to children living in the U.S. (Wall Street Journal, October 30, 2020). Likewise, education startups like Khan Academy and Byju are trying to bring affordable quality education to all. Furthermore, HMI-based telehealth services reduce administrative burdens, address medical staff shortages, ensure the safety of health care employees, empower patients to access at-home care, and limit the transmission of COVID-19 (Graff, 2020). Moreover, HMI-technologies can help scientists identify transmission patterns among infected patients, determine at-risk patients, expedite COVID-19 diagnoses (Mei et al., 2020), and model predictions of how the virus can infect cells (e.g., Microsoft and ImmunityBio). Thus, HMI technologies appear to be enhancing education and healthcare in emerging markets by accounting for their nuances and cultural complexities. For example, by lowering language barriers across countries, eBay's human–machine translation service has been associated with a significant increase in global trade and a reduction in economic inequality across the globe (Meltzer, 2018). Likewise, M-Shwari, an HMI-powered paperless banking service in East Africa reduced economic inequality by helping deliver small loans to millions of Kenyans (https://medium.com/@IFC_org/artificial-intelligence-supports-development-in-emerging-markets-f0047c48f209).

2.2. The company-level role of HMI: glocalization

At present, most HMI platforms typically support only English and few other major languages. While this approach may inadvertently enable globalization via language standardization, we propose that HMI technologies customized to the heterogenous and diverse local conditions often found in emerging markets would result in greater effectiveness. Indeed, the interactions of humans and machines in any AI technology should be strongly influenced by what customers expect, prefer, and do (Puntoni et al., 2021). Conversely, if human–machine interactions are not localized, AI technologies run the risk of market failure (Kozinets & Gretzel, 2021). Hence, it is important to train HMI technologies using data drawn from consumers who live and engage across various local markets. As an illustration, consider the granular insights that influenced the development of India's streaming media platforms (which require human–machine interaction) that have led to the emergence of a growing array of regional online content across the subcontinent. In response to this increasing preference for "regional" content, many streaming platforms are investing in programming in languages beyond Hindi and English to cater to India's linguistically and culturally diverse population (Smith & Telang, 2018).

In addition to enhancing the effectiveness of local operations, glocalization may also enhance global operations via incorporating heterogeneous preferences and local customer experiences that exist within each culture. The HMI-based Netflix platform is a good example. Today, Netflix produces original content across several countries, including India, South Korea, and Israel. This localization effort, in turn, has fueled Netflix's global expansion, as its diverse offerings have attracted considerable global appeal (Smith & Telang, 2018). In sum, the glocalization of HMI appears to be a successful approach across a variety of AI applications.

2.3. The consumer-level role of HMI: ethics and privacy

Here, we examine how concerns about ethics and privacy impact (and may impede) AI applications in terms of human–machine interactions. HMI refers to the manner in which people and automated systems interact and communicate. In particular, the adoption of AI technologies is facing growing concern about its high degree of intelligence and autonomy and the degree to which these features may result in harm or disadvantage (e.g., Davenport et al., 2020; Etzioni & Etzioni, 2017; Kaplan & Haenlein, 2020). For example, as recently noted by Manheim and Kaplan (2019), AI technologies are often capable of identifying anonymized data and may result in algorithmic bias. Moreover, a growing chorus of voices suggest that AI may harbor a less apparent but more pernicious threat to users of this technology in the form of reduced autonomy. For example, Taddeo and Floridi (2018) propose that AI's increasing invisibility and ubiquity may quietly nudge humans to delegate decision-making. They suggest that, over time, this subtle process of nudging and delegating may result in "the erosion of human self-determination" (p. 752). As AI becomes more ubiquitous and embedded in everyday devices such as automobiles and appliances, it is likely to make its own autonomous decisions and nudge human behavior in a manner that is barely perceptible. For example, Dawar (2018) suggests that AI-enabled assistants such as Amazon's Alexa may soon be able to monitor telecommunication patterns and automatically switch consumers to less expensive providers. Although these actions may often result in savings in terms of both time and money, they also raise concerns about consumer privacy.

In addition to challenging human agency, AI may also eventually replace humans and perform tasks that were once done by people (Huang & Rust, 2018). According to a recent report by (2019), AI and automation will dramatically alter many professions over the next decade, including many marketing-related tasks such as customer service, sales and management. Verganti, Vendraminelli, and Iansiti (2020) propose that AI will soon be capable of surpassing humans in terms of innovation and design, and cite a number of early examples where this is already taking shape, including Airbnb, Netflix, and Tesla. For example, Netflix is currently using AI not only to predict what types of content customers prefer but also to design and develop this content (e.g., House of Cards). Verganti et al. (2020) suggest that as AI takes over these types of creative tasks, the role of humans will shift towards "sensemaking, that is, understanding which problems should or could be addressed" (p.

212). This shift from placing less focus on how to create new products and more focus on what problems these products are designed to address raises intriguing questions regarding the types of problems that firms will seek to solve. The movement from human-labor to machine-labor is also likely to vary across the globe, as the cost-benefit ratio of machines vs. humans should be considerably more favorable for high income countries (e.g., Germany) compared to low-income countries (e.g., Senegal) (Frey & Osborne, 2017).

The encroachment of AI upon tasks that were previously conducted by humans is also likely to further exacerbate the suspicion and distrust that many individuals have towards this new technology (Davenport et al., 2020; Longoni, Bonezzi, & Morewedge, 2019). For example, AI's growing autonomy may increase the sense of alienation and lower psychological well-being among consumers who delegate decision-making to a machine. Schmitt (2020) notes that these negative reactions may foster the rise of speciesism, which could eventually be viewed as a form of racism against artificially intelligent agents. According to Schmitt (2020), speciesism "seems to be the result of a fundamental, categorical comparison of human and machine" (p. 4). Thus, as AI advances, a growing number of individuals and organizations are likely to advocate for the ethical treatment of artificial intelligence (MacLennan, 2014).

While these types of privacy and ethical issues are receiving increased attention, the degree to which these issues raise concerns appears to vary across the globe. Likewise, the proposed remedies also differ from country to country (Davenport et al., 2020; Kaplan & Haenlein, 2020; Manheim & Kaplan, 2019). For example, regulation is often evoked as a possible solution to the impact of HMI upon consumer privacy. However, the global reach of AI makes the development of regulatory frameworks (which are often country-specific) particularly challenging. Although various international regulatory efforts are underway, these efforts have mainly engaged developed nations such as the U.S., U.K., and Japan and contain little input from Africa, Central Asia, or South America (Erdélyi & Goldsmith, 2018). One underlying reason for this variation in regulatory action may be due to cultural differences in the degree of concern about possible AI infringement on human agency. For example, cultures high in power-distance (e.g., Brazil) may be more willing to subjugate decision-making to artificial entities compared to those low in power-distance (e.g., U.S.A.) (Basabe & Ros, 2005).

3. Automated analysis of text, audio, images, and video

The data typically analyzed by marketing scholars and practitioners have traditionally been obtained via primary data collection in the form of observation, surveys, and experiments. While these forms of inquiry have produced impressive insights, they have a number of limitations (Churchill, 1979). For example, surveys are often constrained by an inability to infer causality, while experiments are often limited in their generalizability. Automated analysis presents the promise of overcoming some of the limitations of traditional forms of inquiry for at least three key reasons. First, due to the digital revolution, many firms now have access to primary data that are vast in terms of scale and scope. For example, Amazon and other firms in India have access to millions of reviews from Amazon U.S. consumers and learn from such reviews. Second, AI's data collection processes are typically less obtrusive than other forms of inquiry, which minimizes potential biases such as the observation effect (Spano, 2006). Thus, instead of imposing on customers to respond to a battery of survey questions or putting participants into (artificial) lab settings, researchers and practitioners now have access to voluminous behavioral based data unobtrusively collected in real time (Matz, Kosinski, Nave, & Stillwell, 2017). Third, AI has enabled primary data to be more easily collected from hitherto underutilized sources that can be automatically collected and collated across various digital platforms (Du, Netzer, Schweidel, & Mitra, 2021). For example, AI-based technologies has automated the collections (and often analysis) of customer conversations across multiple social media platforms.

Today, automated technologies such as natural language processing, autonomous web scraping, and computer vision are capable of extracting rich insights from unstructured and non-numerical data such as text, audio, images, or video. Text-based data include both consumer-originated data such as social media postings and customer reviews, as well as firm-originated data such as advertising copy and financial reports (Berger et al., 2020). Audio-based data include spoken words and non-text (voice, music, and sounds). Finally, image-based data include a wide variety of still images and video content (see Klostermann, Plumeyer, Böger, & Decker, 2018; Li, Shi, & Wang, 2019). A good example of automated analysis is Millie, a in-store virtual assistant that detects consumer emotion by analyzing the speech and body language of retail shoppers in order to deliver enhanced customer service (Mejia, 2020).

Looking forward, experts predict "autonomous intelligence" may fully automate the collection, processing, and utilization of these various forms of data and will significantly augment human analytical competencies (Davenport, 2018). Thus, firms may eventually be transformed into automated analysis-based organizations replete with highly nuanced understandings of their global customers and capable of mass customizing offerings that harness and act on data-driven insights with little, if any, human intervention (Briggs, Henry, & Main, 2019).

Although automated analysis may produce a variety of benefits, this technology also raises a number of data-related concerns. For example, automating data collection processes (e.g., robots completing responses to surveys) could lead to data distortion and biased inferences. Likewise, these types of algorithms have also been accused of (automatically) creating misleading content such as social media trolling or fake reviews (Shao et al., 2018). In order to stem this problem, companies such as Amazon are using natural language processing to detect and correct potential data distortion (Kauffmann et al., 2020; Proserpio et al., 2020). Moreover, little is known about the implications of these automated analysis from a global perspective. Thus, we examine the degree to which automated analysis of text, audio, images, and video may play a role in inequality, glocalization, and global ethics and privacy concerns.

3.1. The country-level role of automated analysis: economic inequality

As noted earlier (Anderson et al., 2021; International Finance Corporation, 2020; Mathew, 2018), AI benefits individuals residing in economically disadvantaged countries. For instance, AI's textual, sound, image, and video processing capabilities enable both large and small firms to assess, analyze, and identify behaviors that maximize salesperson performance (Luo, Qin, Fang, & Zhe, 2021). In addition, AI's automated processing capabilities can also help optimize marketing communication efforts across various local (first) languages. For example, firms like Cogito and Chorus are using real-time AI speech analytics to listen to conversations between salespeople and their customers and provide instant feedback on an array of dimensions that may impact their performance such as their voice modulation, speaking tone, and degree of empathy.

Moreover, AI-fueled technologies can help companies offer a broader range of services for underserved populations, which may reduce economic inequality. For example, Google's AI laboratory in Accra, Ghana, has enhanced the ability of its natural language algorithms by incorporating speech and text from over 2000 African languages (Hao, 2019). Likewise, Unilever and Telkomsel are working with the conversational platform Kata.ai in Indonesia to categorize and automate more than 95% of customer interactions with minimal human intervention (TRPC and IIC, 2020).

AI's autonomous abilities may also act as a unifier by reducing differences between rich and poor. For example, many customers in emerging markets such as India cannot afford a personal computer, and thus typically watch videos on their phones. Netflix's Dynamic Optimizer uses an AI-powered algorithm to enhance their viewing experience by analyzing videos scene-by-scene and compressing data without affecting image quality, thus providing a good quality streaming on a poor man's phone (Wong, 2017). Likewise, AI's speech recognition and speech-to-text capabilities can help emerging markets circumvent the challenges posed by low literacy and thereby serve previously underserved populations (e.g., Google translate). Thus, the successful implementation and mass-adoption of locally applied AI-based text, audio, images, and video analytics is likely to enrich the lives of individuals residing in economically disadvantaged countries.

On the other hand, AI's autonomous abilities may also lead to a class-based divide between (1) the masses who work for algorithms (i.e., the low-wage gig worker), (2) a smaller privileged professional class who have the skills and capabilities to design and train algorithmic systems, and (3) an elite set of ultra-wealthy technocrats who own the algorithmic platforms that run the world (Walsh, 2020). As recently noted by Kozinets and Gretzel (2021), creating, maintaining, and upgrading AI algorithms is an extremely complicated and expensive process that requires expertise and is possessed by only a select set of companies which may perpetuate this divide (e.g., Apple, Amazon, Tesla). Similarly, Korinek and Stiglitz (2017) suggest that AI-automation will likely increase the wealth gap since the benefits of AI may only accrue to a small number of firms. In sum, AI's autonomous abilities may exacerbate the class-based divide.

As a related concern, AI-powered automated services are likely to replace a considerable portion of the human workforce in the near future (Hao, 2020). According to Huang and Rust (2018), routine jobs such as call-center agents are at considerable risk of being supplanted by artificial intelligence. These tasks are typically executed by lower-skilled workers and companies often outsource call centers to economically disadvantaged regions, such as the Philippines (Einhorn, Alegado, & Lopez, 2021). Moreover, AI-driven automated solutions may affect different industries in different ways. For example, consumer-facing industries like retailing are more likely to use AI technologies within marketing and sales, whereas industries with a focus on manufacturing are more likely to use technologies within supply chain and logistics (Chui, Manyika, Miremadi, Henke, Chung, Nel, & Malhotra, 2018). As a consequence, inequalities may rise if some countries lack the needed supply of AI technologies that align with the composition of their industry structure.

3.2. The company-level role of automated analysis: glocalization

As noted earlier, AI technologies in general and automated analysis in particular, are inherently global and universal in nature. However, due to differences in terms of language, culture, or location, text, audio, image, and video analytics applications are often local in nature. For example, over 80% of all retail purchases still occur in physical establishments (eMarketer, 2021). Thus, the automated analysis of shopping behavior is more likely to be local than global (Lu, Xiao, & Ding, 2016). A good example is the AI assistant Duplex (offered by Google), which can make local restaurant reservations for customers based on their residence (Newcomb, 2019). Thus, AI-based text, audio, image, and video analytics are likely to be more successful if locally applied. Another domain where localized automated applications may be particularly valuable is integrated marketing communications (IMC). Prior research suggests that IMC is more likely to be successful if communication activities incorporate differences in culture, language, and socio-demographics (de Villiers, Tipgomut, & Franklin, 2020). Thus, it is not surprising that AI-based automated applications such as call agents, self-service terminals, chatbot applications, and voice-based interactions an largely local in nature and exist across all major languages (Dawar, 2018).

Automated analysis of audio, digital voice-based personal assistants (e.g., Alexa and Siri) and virtual chatbots often apply voice analytics and natural language processing to interact with both current and prospective customers. These interactions encompass a broad range of marketing activities. For example, YouTube employs a NLP speech recognition software that autonomously produces translation (in the form of video captions) into dozens of different languages (Gupta, 2019). Likewise, Spotify recently launched a new campaign called "Only You" that automatically analyzes a user's music streaming behavior to remotely generate user-specific playlists (Antonelli, 2021). In general, automated techniques such as text mining, sentiment analysis, emotion detection, and speech recognition are becoming increasingly language-specific, and hence, signify a shift towards glocalization[2]. In general, regional differences in terms of both consumer culture and corporate culture suggests that automated analysis should be deftly adapted to fit unique conditions (Toukalas, Boye, & Laughlin, 2018).

A good example of this type of glocalization is D-Labs, a new AI-fueled offering that is capable of extracting brand logos from images posted on Instagram (Majewski, 2020). Considering the ubiquity of these types of postings in social media, this type of automated image analysis can help marketers better adapt to local brand preferences across different regions (Sivakumar, Gordo, & Paluri, 2018). As noted by Jack, Garrod, Yu, Caldara, and Schyns (2012), facial expressions and body gestures differ considerably across cultures and countries and these differences are often reflected in images and video. Hence, AI algorithms should be specifically trained to develop a nuanced understanding of differences in body language and nonverbal cues specific to different cultures, and thus necessitate a glocalization approach (Hasler, Oren, Peleg, Amir, & Friedman, 2017).

AI-based video analytics are also increasingly being deployed via both virtual reality (VR) and augmented reality (AR). While these technologies are still in the early stages of development, they are capable of providing realistic imagery visualization (Schmitt, 2020). For example, AR tools such as digital mirrors can enable customers to try on different types of eyewear or clothing online (Hoyer, Kroschke, Schmitt, Kraume, & Shankar, 2020). The efficacy of these types of AI-supported automated interactions may be moderated by cultural factors such as the degree to which an interaction involves individualism vs. collectivism or long-term orientation (Castelo, 2019; Hofstede, 2001). For example, in individualistic cultures the self-focused nature of these technologies might find greater acceptance than in collectivistic cultures. Moreover, customers in certain cultures may appear to be uncomfortable with automated interactions, such as encounters with robots (Schmitt, 2020). Here, newer mixed-reality-based technological advances, such as Microsoft's HoloLens, may provide an avenue to foster greater acceptance and confidence in these technologies among technology resistant consumers across the globe.[3]

3.3. The consumer-level role of automated analysis: ethics and privacy

We now examine how concerns about ethics and privacy may be relevant for AI-based automation of text, audio, images, and video. Automated analysis raises a number of concerns about ethics and privacy, but the degree of these concerns may vary across countries and cultures (Davenport et al., 2020; Kaplan & Haenlein, 2020; Manheim & Kaplan, 2019). First, automated analysis is dependent upon access to large amounts of customer data, which can lead to harmful privacy breaches (Kaplan and Haenlein 2019a, 2020). Prior research suggests that privacy breaches are costly to both firms and consumers (Martin, Borah, & Palmatier, 2017). For example, in 2017, Equifax, one of the largest credit bureaus in the U.S., discovered a data breach that exposed the personal information (including Social Security numbers, birth dates, addresses, and in some cases, driver license numbers) of nearly 150 million consumers. Although automated analysis may not always be the cause, its need for massive data to fuel its machine learning algorithms increases the risk (and costs) of data breaches and makes such breaches more likely.

To mitigate such risks, while at the same time still harvesting the power of automated analysis, firms are becoming increasingly reluctant to store and process individual-level data, and instead, have shifted their focus to meta-data generated through statistical analysis (Wieringa et al., 2021). In this approach, firms collect customer data but only store its statistical properties rather than the raw data itself. For example, consider a firm that uses AI to obtain individual-level data to predict customer churn. Once a churn model has been developed and validated, the individual-level data could be discarded, and only the relevant parameters (e.g., coefficient estimates and standard errors) would be stored. As recently shown by Holtrop, Wieringa, Gijsenberg, and Verhoef (2017), the use of techniques such as a generalized mixture of recursively updated Kalman filters can reach levels of churn prediction performance comparable to models that use individual-level data.

Alternatively, data privacy could be safeguarded by having the analysis take place on the user side. For example, a company could calibrate an artificial neural network via highly granular individual-level data contained on a user's phone. Unfortunately, models that employ data from this type of localized approach are less likely to be robust since the data available will be of limited size and from a single individual. However, this individual-level data could be aggregated into a broader meta-model that compensates for these disadvantages. Moreover, instead of having raw data transmitted to and calibrated by a firm, model calibration could be locally distributed across various user interfaces. Under this approach only model parameters (vs. customer-level data) would be transferred back to the firm, which would then aggregate this information into a broader data archive. This approach, known as federated machine learning, was first proposed by Google in 2016 and has received considerable interest among a wide array of AI researchers (e.g., Konečný, McMahan, Ramage, & Richtárik, 2016; Yang, Liu, Chen, & Tong, 2019).

The growth of automated analysis has attracted increased concerns regarding its potential for algorithmic bias (Manheim & Kaplan, 2019). This bias can result in systematic and repeatable errors that may lead to unfair outcomes, such as privileging one group of users over others (e.g., Friedman & Nissenbaum, 1996). For example, automated facial recognition systems

[2] https://ai.googleblog.com/2019/09/large-scale-multilingual-speech.html

[3] https://www.youtube.com/watch?v=eCseYtBd5_4

appear to perform better for males than females (West, Whittaker, & Crawford, 2019). These types of biases appear to be more pronounced in more homogenous countries (Ukanwa & Rust, 2021).

In addition to being harmful to some individuals, these pernicious biases can also produce damaging societal consequences. Although there appear to be multiple drivers of algorithmic bias, one notable cause is AI's inherent tendency to use past data to provide recommendations for future actions (Kaplan & Haenlein, 2019b). Therefore, if biases are present in input data, they are likely to be reflected in the rules that automated algorithms learn from this data. These rules may then become formalized in decision-making guidelines. Thus, algorithmic bias can result in bias even if designers explicitly seek to reduce or avoid such bias (Lambrecht & Tucker, 2019). One way to combat this type of bias is to employ hybrid sequential decision-making structures in which automated analysis merely suggests decisions to humans who can then either follow or reject those suggestions (Shrestha, Ben-Menahem, & von Krogh, 2019). In sum, concerns about the need to ensure data privacy and reduce algorithmic bias are by-products of the rise of automated analysis and the degree of these concerns is likely to vary across countries.

4. Future research opportunities

Due to their recent rise and rapid adoption, AI technologies present several interesting opportunities for future research by marketing scholars. In this section, we propose a set of future research questions for each of the three levels of our global prism.

4.1. The country-level role of HMI: inequality

As noted earlier, HMI applications have the potential to reduce economic inequality across various countries. For example, back-end HMI applications can help optimize processes, monitor resource utilization, and integrate systems, while front-end HMI applications can offer intuitive, smart, engaging, and culturally relevant interfaces. In recent years, global firms have increased their presence and degree of collaboration with local firms and universities across several emerging markets in order to enhance HMI applications in marketing (e.g., Akinpelu, 2018). These types of applications also provide synergy between the vast resources and technical knowledge of global firms with the local expertise and rich cultural knowledge of local startups and universities. The growing interest in emerging markets is also fueled by the rapid rise of a global young, tech-savvy workforce that is increasingly knowledgeable about artificial intelligence (e.g., Sibio, 2021).

One way in which HMI is reducing economic disparities is via applications of cognitive technologies (e.g., machine learning) that make work-from-home more secure and convenient for many individuals across the world. For instance, Google Meet uses machine learning to detect and reduce background noise during virtual meetings (Aten, 2020). These types of cognitive technologies also play an important role in democratizing online education by helping create smart content, identify students who need extra help, and aid the evaluation of student submissions (Kim, Kim, Kwak, & Lee, 2021). Moreover, HMI-based tools such as language translation can enable greater diversity and inclusivity in virtual classrooms, enhance consumer well-being, and reduce economic inequality, particularly in developing countries (International Finance Corporation, 2020). Thus, future research that can assess the ability of HMI tools to level the economic playing field may offer an important contribution. We recommend that scholars interested in investigating this issue examine the field experimental approach recently employed by Anderson et al. (2021) to examine the impact of business support intervention in Uganda. Field experimental research may effectively demonstrate the impact of HMI tools on achieving firm-level outcomes (e.g., growth, sales, revenue) and customer-level outcomes (e.g., customer experience, customer satisfaction) in emerging markets and developed markets. Text analytics and other machine learning techniques can also be applied to study the impact of language-related HMI tools (e.g., language translation, online education) on reducing economic inequality between emerging markets and developed markets.

RQ1: *To what extent can HMI technologies help reduce the economic disparity between emerging markets and developed markets?*

A related question centers around the implementation of HMI across different cultures and economies. Implementing HMI requires a number of critical decisions such as identifying and developing the specific cognitive technologies to implement, finding the talent to manage this implementation, and adapting this technology to local contexts (Wilson & Daugherty, 2018). Another implementation challenge is trying to market these technologies to consumers in cultures that may resist adoption due to low levels of technology acceptance or lack of trust in cognitive technologies. One way to overcome these implementation challenges, particularly in emerging economies, is for firms to collaborate by pooling their financial, technological, human, and data resources (University of Pretoria, 2018). This collaborative approach could also reduce competitive threats and enable collective solutions. In other words, collaborations between firms and local institutions such as universities and governmental agencies can be helpful in directing HMI efforts towards collective goods such as sustainability, healthcare and education, and helping firms find innovative solutions to problems faced by emerging and less developed markets. In sum, future research is needed to understand the role of collaboration in implementing HMI to enhance economic welfare across the globe. In this regard, case studies about collaborations between firms and local institutions, empirical data from such collaborations, and field experiments could be useful to determine the role of collaborations in applying HMI technologies toward achieving collective economic welfare goals in emerging markets and developed markets.

RQ2: *What types of HMI technology related collaborative efforts are most effective in terms of reducing economic inequality between emerging and developed markets?*

4.2. The company-level role of HMI: glocalization

In the future, HMI applications will likely shift from personalization at the individual level to personalization at different moments across an individual's customer journey (Kumar, 2018). This extreme personalization approach will enable firms to adapt their offerings to the micro-level needs, preferences, and expectations of local consumers across the world. Such personalization is likely to be empowered by advances in quantum computing, which offers the benefits of speed, scalability, accuracy, and security (Nielsen & Chuang, 2010). Although quantum computing technology is still at the developmental stage, a growing number of firms have begun to explore its potential applications (Wall Street Journal, January 6, 2020). For instance, Volkswagen is currently experimenting with quantum computing as a tool for simulating the chemical structure of electric batteries (Briggs et al., 2019). As illustrated by this example, quantum computing has the potential to simulate designs and pre-test products which should reduce costs and enhance performance. Likewise, it is our thesis that quantum computing's comprehensive modeling capabilities could possibly be applied to help develop more efficient, resource-saving, and eco-friendly materials.

These simulation and modeling capabilities, may in turn, lead to advancements in data recognition and classification, which can have important implications for developing products that can be easily adapted across different markets, especially emerging markets. Thus, as quantum computing advances and integrates with cognitive technologies, the degree to which this new technology can be employed towards glocalization efforts is an intriguing research question. Researchers may partner with companies like IBM that have been investing in quantum computing technologies and examine the use of such technologies in developing new products, particularly in the emerging markets.

RQ3: *Can quantum computing algorithms help firms develop global products and services that can be easily adapted to local needs, particularly across emerging markets?*

Another intriguing future application of HMI-based technologies is in the area of retail pricing. A typical U.S. grocery store carries about 50,000 stock-keeping units (SKUs). We posit that a scalable HMI technology (with inputs from humans) could help determine optimal prices for these 50,000 SKUs in a manner that is likely to be more profitable and considerably faster than conventional pricing approaches. Although the potential of such an approach is intriguing, the degree to which this type of HMI application can incorporate the varied consumer tastes in emerging markets is an open question. In other words, the degree to which HMI technology can help retailers incorporate and adapt local consumers' preferences (in both emerging and developing markets) to achieve price optimization, is an interesting question for future research.

RQ4: *Can HMI technologies enable retailers to set retail prices aligned with the needs and purchasing powers of different consumer groups in small retail stores in emerging markets versus large retail stores in developed markets?*

4.3. The consumer-level role of HMI: ethics and privacy

Although engaging with AI poses severe threats to data privacy, a substantial number of consumers appear to be willing to trade privacy in exchange for comfort and convenience (Dawar, 2018). For example, anyone who conducts a Google search trades a certain degree of privacy as a form of payment for quickly obtaining needed (and seemingly free) information. While some consumers may care little about privacy, a recent survey suggests that nearly a third of consumers worldwide "care about privacy, are willing to act, and have done so by switching companies or providers over data or data-sharing policies" (Redman & Waitman, 2020). Thus, it appears likely that a substantial number of consumers may defect from companies that violate their expectations of data usage and privacy. In addition to this risk of defection, firms that employ HMI to harvest consumer data face a growing chorus of voices proposing that they provide consumers with some degree of compensation in exchange for their data (Whitaker, 2019). This rise in consumer awareness and agency around HMI-induced threats to data privacy bears a resemblance to the notion of persuasion knowledge, which "shapes how they respond as persuasion targets" (Friestad & Wright, 1994, p. 1).

Concern regarding data privacy and how users should be compensated for their data is not equally held across all countries. Countries vary in terms of privacy standards, and those standards are shaped by customary firm practices in specific region and how those practices are reported (Bellman, Johnson, Kobrin, & Lohse, 2004). In countries where privacy breaches are widely publicized (e.g., U.S., U.K.), consumer concerns is likely to be substantially higher compared to countries in which breaches are largely hidden (e.g., China, Russia). Moreover, the use and visibility of HMI-driven products and services differs by region. For example, while over 20% of U.S. households with internet access have smart speakers, only around 5% of internet-equipped households in Brazil have adopted this technology (https://www.statista.com/statistics/1147348/brazil-digital-readiness-index/). As a result, concerns about the privacy implications of interacting with these devices should be more pronounced in the U.S. than in Brazil. Thus, understanding country and cultural differences in perceptions of AI-related data collection concerns (and their subsequent expectations and behaviors) is an important topic for future research. Researchers interested in these issues could conduct a multi-method inquiry by collecting survey data to assess customer perceptions and then pair this data to archival records of AI-related incidents such as privacy breaches.

RQ5: *To what degree do country and cultural differences about consumer perceptions of privacy affect their perceptions of acceptable AI-related data collection/usage practices, the propensity to defect, and expectations of compensation?*

In addition to concerns about data privacy, the growth of HMI has also led to concerns about human agency. At present, the degree to which HMI can replicate human intelligence is a topic of considerable debate. The predominant belief is that, over time, this technology will increasingly become more human-like in nature (Davenport et al., 2020; Longoni et al., 2019; Schmitt, 2020). Currently, HMI-enabled chatbots can closely mimic human conversation and may soon be viewed as friends and companions. As HMI becomes more human-like, consumers will likely transfer expectations they have towards the behavior of other humans to artificially intelligent actors such as robots (Duffy, 2003; MacLennan, 2014). However, unlike humans, HMI-empowered machines do not have an innate set of moral concerns and human sentiments. As a result, machines that are smart and autonomous "are potentially more likely to be able to choose to cause harm, and therefore require ethical guidance" (Etzioni & Etzioni, 2017, p. 409). This ethical guidance is likely to be influenced by various individuals, including HMI developers, designers, and users (Taddeo & Floridi, 2018).

This multiplicity of influences is further complicated by an array of culturally dependent ethical standards and norms that may differ markedly across various regions. However, since HMI development predominantly occurs in only a few regions (notably the U.S. and China), its ethical standards are unlikely to reflect local standards and practices (Kaplan & Haenlein, 2020). As a result, users living in regions in which HMI is imported (rather than homegrown) may experience a divergence between HMI actors' ethical rules and their human counterpart's ethical expectations. Furthermore, placing blame for an HMI actor's ethical violations is considerably more complicated compared to human actors. In response to this dilemma, Etzioni and Etzioni (2017) suggest that "smart machines should draw on a new AI program that will "read" the owner's moral preferences and then instruct these machines to heed them" (p. 413). In essence, HMI may extend the scope of moral concern and ethical responsibility from individuals (and organizations) to their corresponding HMI agents. This type of ethical extension raises a host of thorny issues (i.e., to what degree should human actors be responsible for an HMI agent's actions) that are likely to vary across countries and cultures. These issues could be investigated via experimental inquiries that present consumers with different types of HMI ethical principles (e.g., global vs. local) and then assessing consumer reaction.

RQ6: *Who should be responsible for developing HMI's ethical principles and its subsequent actions and to what degree should these principles be localized versus standardized across countries and cultures?*

4.4. The country-level role of automated analysis: inequality

From a societal perspective, it is imperative to understand the role of AI automation in reducing (or enhancing) economic inequality within and across countries (Prettner & Strulik, 2020). On the one hand, AI-enabled automated analysis may be used to further economic growth in developing countries. For example, AI platforms like iCow in Kenya (icow.co.ke) employ automated technology to help disadvantaged farmers take better care of their crops and livestock (Nsehe, 2011). These farmers can send specific questions (or images) via SMS to the iCow platform and get free (and customized) advice across a variety of topics, ranging from increasing crop yields to reducing livestock mortality. Moreover, governmental organizations, NGOs and firms can access farmers' interactions on this platform to create a virtuous growth cycle by developing new products and sharing best practices (Emeana, Trenchard, & Dehnen-Schmutz, 2020). As documented by Anderson et al. (2021) multiyear experiment in sub-Saharan Africa, access to these types of insights can have a significant and positive impact on micro-entrepreneurs' assets, profits and growth. Hence, AI-based automated analysis tools such as iCow can contribute towards reducing economic inequality. On the other hand, AI-enabled automated analysis may also result in the substitution of low skilled workers (Prettner & Strulik, 2020). Moreover, AI technology is expensive to develop, and the world's top AI firms are largely concentrated in prosperous western nations (Apple, Google, Microsoft, Amazon, IBM, etc.). Thus, the wealth created from automated analysis is likely to be disproportionately shared. To understand the heterogeneous impact of AI technologies on inequality, we can do a longitudinal cross-country study, look at the AI index (e.g., https://aiindex.stanford.edu/), and assess its impact on the Gini coefficient that measures inequality. Further, insights into these issues may also likely come from natural experiments (say, across similar regions) which have the added benefit of gaining causal insight.

RQ7: *What are the positive and negative impacts of AI-enabled automated analysis on the economic status of small entrepreneurs across the globe?*

RQ8: *What is the impact of AI-enabled automated solutions on global wealth distribution and economic inequality in general?*

4.5. The firm-level role of automated analysis: glocalization

Since the advent of the digital revolution, interactions with online interfaces have been largely in the form of words and letters entered via a keyboard (or similar) device. However, in recent years, voice-based interaction (e.g., Amazon Alexa) have gained popularity, and image-based search (i.e., "reverse image search") is progressing rapidly (Brill, Munoz, & Miller, 2019). These new modes of search have the potential to be applied across a wide array of products that are not easy to specify via words, such as apparel, home decor, etc. What remains uncertain at this stage is how, and under what conditions, consumers will employ voice and image-based search and how these new forms of search will impact their purchase and consumption. Image-based search seems to be highly applicable for consumers in emerging markets where the penetration of smartphones (which easily enable image capture and transfer) far exceeds the penetration of personal computers (Statcounter, 2021). The ubiquity of smartphones should also greatly expand search and purchase opportunities for millions of illiterate (and low literate) consumers across many emerging economies (Pejovic & Skarlatidou, 2020). The implications of the switch from text-based to voice-based and image-based search on how firms promote and distribute products and services across the globe could be an issue for future research.

RQ9: *How does the switch from word-based search to voice-based and image-based search affect how products and services are promoted and distributed across the globe?*

English is clearly the language of global commerce and proficiency in English offers considerable economic advantages. However, English skill across many emerging countries is often limited to a small portion of the population (i.e., those who are highly educated). For instance, in 2016, close to 60% of the 409 million internet users in India were Indic language users (with limited knowledge of English) (KPMG, 2017). Moreover, the number of local-language users appears to be growing exponentially (Rotaru, 2011). Hence, there is likely to be an increase in demand for AI-based automated analyses and applications in localized language environments. The growth of automated translations across an array of local languages can provide new opportunities for information exchange between local producers, buyers, intermediaries, and platforms. The impact of this increased localization upon the analysis and interpretation of language-based content provides a direction for future research. To answer this issue, data on economic developments across regions are required along with measures of localized AI usage.

RQ10: *How does the growth of local language-based content impact AI-related automated analysis and interpretation?*

4.6. The consumer-level role of automated analysis: ethics and privacy

As noted earlier, consumers are increasingly valuing their data as the risks associated with AI-based data breaches become more apparent. As data protection laws gain increased traction (e.g., the GDPR rule in Europe and similar regulations in California), privacy concerns should become even more salient (Goldberg, Johnson, & Shriver, 2019). These privacy concerns will likely increase consumer reluctance to share data with firms (Stourm et al., 2020). This reluctance will likely hamper the development and functioning of automated analyses, which need data to learn and operate (Goldfarb & Tucker, 2011). Thus, ensuring that users are willing to share their data should be a key priority for marketers seeking to employ AI-related automated technologies.

One possible solution to this challenge is to shift the focus of machine learning from firms to users, which should limit the need to transfer consumer data (Konečný et al., 2016). However, this approach requires automated algorithms that can learn from limited data or capable of employing complex frameworks in which the raw data provided by a single user can be integrated with meta-data provided by many other users. This approach may also require firms to compensate users for providing their data, which would likely increase the costs of automated analysis. The efficacy of this approach is also likely to heavily depend on the status of a user's local Internet infrastructure. While technological differences are likely to be minor within the same region, they can become substantial across different countries depending on their degree of economic development.

Firms can also seek to solve this data challenge by employing the services of trusted third parties, which can enable users to control how their data can be used and limit the number of firms that have access to their data. For example, the HAT (Hub of All Things) project at the University of Warwick (in the U.K.) seeks to provide individual users with microservers to store their data and limit access by companies (Ng, 2018). However, these types of approaches are still in their infancy, and it is unclear whether companies that currently possess large amounts of user data (e.g., Alphabet, Amazon, Apple, Facebook, Netflix) would be willing to give up their proprietary data. Moreover, given the costs and complications of establishing a trusted third party, this option is likely unavailable to consumers living in developing regions. Thus, understanding how to reduce consumer reluctance to share data across different countries and cultures is a research question. As a starting point, researchers may wish to conduct surveys to assess the degree of this reluctance and assess the potential drivers of this reluctance (e.g., mistrust, skepticism, fear).

RQ11: *How can firms reduce consumer reluctance to share data, and what type of adaptations are needed across different countries and cultures?*

Today, many firms collect and use data from consumer purchase behavior or social media activity as inputs for training AI algorithms. However, new data sources will likely allow firms to obtain an even more granular depictions of consumer activity in the near future. In particular, the growth of IoT and connected objects will, in principle, allow for the collection of highly detailed data about nearly all aspects of a consumer's life. For instance, IoT connected robot vacuums equipped with video cameras can collect information about the size and layout of their owners' homes (Astor, 2017). Likewise, data collected by surveillance technologies, such as cameras installed within buildings or public spaces, can easily capture a wealth of data regarding how consumers behave in naturalistic settings. The availability of these types of data sources may differ vastly from one country to another. Firms operating in regions where video surveillance is more culturally accepted (e.g., China) are more likely to have access to this type of data than those operating in regions (e.g., the U.S.) where video surveillance is less culturally accepted. Hence, future research should be directed towards understanding which data sources can and should be used across various countries and cultures. Since video surveillance systems are often installed and operated by firms and institutions in positions of authority, it seems likely that factors such as obedience, conformity and deference to authority may affect consumer acceptance of these systems and these individual differences may also be moderated by a variety of cultural factors such as power distance and individualism/collectivism.

RQ12: *Which data sources can and should be used for algorithmic learning, and to what degree does their acceptable use depend upon cultural norms and local standards?*

5. Conclusion

Advancements in AI-technologies are enhancing the capability of a growing number of firms to collect, store, analyze and utilize a vast variety of customer information (Rust, 2020). We examine the global implications of this technological advancement by exploring the role of two key dimensions of AI, human–machine interaction, and automated analysis of text, audio, images, and video, across three different levels of our analysis (country, firm, consumer) (see Appendix 2 for a summary). At the country level, AI technologies have the potential to both increase as well as decrease economic inequality. At the firm level, AI technologies have begun to transform various aspects of marketing by glocalizing its applications. At the consumer level, AI technologies are raising increased concerns about ethics and privacy, which are leading to an increased need for regulation, education and training. Collectively, these global concerns will likely affect the ability of firms to employ AI to engage in automated analysis and will also alter the nature of human–machine interactions. For instance, artificial intelligence will likely lead to enhanced design and delivery of locally customized global offerings by enabling a greater understanding of customer behavior across a wide array of local cultures. Looking forward, we expect that a growing number of firms will advance toward "autonomous intelligence" in a glocalized fashion. Once intelligence is automated, machines, robots, and other forms of AI-based machine learning will be able to integrate with existing information management systems to augment human analytical competencies (Davenport, 2018). When this state of autonomy is reached, many firms will be transformed into AI-fueled organizations that employ systems of human–machine collaboration designed to harness and act on data-driven insights at a local level. We hope that our global prism sheds new light on the country, firm, and consumer level implications of AI technologies and that our forward-looking research agenda helps motivate and direct future research in this important domain. Thus, while work remains to be done, examining the role of AI technologies in marketing from a global standpoint seems well worthy of the effort required to provide deeper insights.

6. Author note

The authors thank the Editor, AE, and three anonymous IJRM reviewers for their thoughtful comments on earlier drafts of this manuscript. The authors also thank the "Global Marketing Strategy" conference participants hosted by the Indian School of Business.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1. Recent research on artificial intelligence (AI) technologies in marketing

Authors	HMI	Automated Analysis	Economic Inequality	Glocalization	Ethics and Privacy
Allal-Chérif et al. (2021)	Yes	Yes	No	No	No
Anderson et al. (2021)	No	Yes	Yes	No	No
Bharadwaj and Shipley (2020)	Yes	Yes	No	No	No
Boone et al. (2019)	Yes	Yes	No	No	Yes
Bradlow et al. (2017)	No	Yes	No	No	Yes
Davenport et al. (2020)	Yes	Yes	No	No	Yes
Dawar (2018)	Yes	Yes	No	No	Yes
Dekimpe (2020)	No	Yes	No	No	Yes
Dellaert et al. (2020)	Yes	No	No	No	Yes
Di Vaio et al., 2020	Yes	Yes	No	No	Yes
Haenlein and Kaplan (2019)	Yes	No	No	No	Yes
Hagen et al. (2020)	No	Yes	No	No	No
Hoffman and Novak (2018)	Yes	No	No	No	No
Hoyer et al. (2020)	Yes	Yes	No	No	Yes
Huang and Rust (2018)	Yes	Yes	No	No	No
Huang et al. (2019)	Yes	No	No	No	No
Kaplan (2004)	Yes	No	Yes	No	No
Kaplan and Haenlein (2020)	Yes	No	Yes	No	Yes
Kang et al. (2020)	Yes	No	No	No	No
Kauffmann et al. (2020)	No	Yes	No	No	No
Kelley, Fontanetta, Heintzman, and Pereira (2018)	Yes	Yes	No	No	Yes
Klostermann et al. (2018)	No	Yes	No	No	No
Kozinets and Gretzel (2021)	Yes	Yes	No	No	No
Kumar et al. (2019)	Yes	Yes	No	No	Yes
Li et al. (2019)	No	Yes	No	No	No
Longoni et al. (2019)	Yes	No	No	No	No
Luo et al. (2019)	Yes	No	No	No	No
Luo et al. (2021)	Yes	Yes	No	Yes	No
Ma and Sun (2020)	No	Yes	No	No	No
Martínez-López and Casillas (2013)	No	Yes	No	No	No
Mende et al. (2019)	Yes	No	No	No	No
Metcalf et al., 2019	Yes	Yes	No	No	No
Nam and Kannan (2020)	Yes	No	No	No	Yes
Paschen et al. (2019)	Yes	Yes	No	No	No
Proserpio et al. (2020)	Yes	Yes	Yes	No	Yes
Puntoni et al. (2021)	Yes	Yes	Yes	No	Yes
Rai (2020)	No	Yes	No	No	Yes
Rust (2020)	Yes	No	Yes	No	Yes
Schmitt (2020)	Yes	Yes	No	No	Yes
Shankar (2018)	Yes	Yes	No	No	No
Shao et al. (2018)	Yes	Yes	No	No	No
Syam and Sharma (2018)	Yes	Yes	No	No	No
Thorun and Diels (2020)	Yes	No	No	No	Yes
Tong et al. (2020)	Yes	Yes	No	No	Yes
Xiao and Ding (2014)	No	Yes	No	No	No
Wang et al. (2020)	Yes	Yes	No	No	Yes
Van Ittersum et al., 2013	Yes	No	No	No	No
Verganti et al. (2020)	Yes	Yes	No	No	No
Wedel et al., 2020	Yes	Yes	No	No	No
Wertenbroch (2019)	Yes	No	Yes	No	Yes
Wieringa et al. (2021)	Yes	Yes	No	No	Yes
Our Paper	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Appendix 2. Takeaways

	Human-Machine Interaction			Automated Analysis of Text, Audio, Images, and Video		
	Economic Inequality	**Glocalization**	**Ethics and Privacy**	**Economic Inequality**	**Glocalization**	**Ethics and Privacy**
Level of Analysis	Country	Company	Consumer	Country	Company	Consumer
Key Issues	Will HMI increase or decrease EI between developed vs. developing nations?	Tensions in terms of standardizing vs. localizing HMI technology.	Reduction in human agency, job loss, increased alienation.	Will AI-based automated analysis increase or decrease economic inequality between nations?	Using AI-based automated analysis to offer powerful new localized insights.	Safeguarding data privacy, reducing algorithmic bias.
Example	HMI-based telehealth services and remote learning environments.	Streaming media platforms creating regional content.	AI-enabled assistants making purchase decisions for consumers.	Offering custom-crafted marketing solutions to entrepreneurs in underserved populations.	Employing AI to produce video captions that are autonomously translated into many different languages.	Storing consumer data as statistical properties rather than data itself.
Context	Consumer welfare, healthcare, environment, pricing and promotion, targeted advertising, services marketing.	Personalized engagement marketing, customer acquisition, retention, sales training, sales force management, e-commerce, social media, service delivery, virtual assistants.	Consumer policy and protection, personalization, omnichannel marketing, retailing, price discrimination, customer experience, luxury and bottom-of-the-pyramid marketing, autonomous vehicles.	Entrepreneurship, organizational design and learning, product testing, experience design, micro-targeted advertising, pricing and promotion.	Personalized engagement marketing, digital marketing, sales force management, brand value and trust, advertising, service delivery.	Retailing, customer experience, marketing mix decisions, personalization, online reviews, promotional targeting, recommendations, customer service.

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