Artificial Intelligence and Distributive Inequity: A Global Comparative Study

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This is currently a working paper and in the stage of data analysis finalization.

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ABSTRACT

Can companies reduce inequity through the use of artificial intelligence? This study aims to address this question by developing a conceptual model that examines the mitigating effect of artificial intelligence efficacy on distributive inequity in the educational technology (EdTech) sector. Our research fills a notable yet important gap in the extant literature by integrating three streams of research that have progressed in parallel fashion despite value for cross pollination: AI, social impact, and globalization. To this end, this research does not focus on a single country case but instead presents a global comparative study, drawing on a dataset of 45 million users from 35 countries across 5 continents collected from a global artificial intelligence-powered education app. Our findings provide robust evidence that as AI efficacy improves, distributive inequity is reduced and that this effect is more pronounced in impoverished environmental conditions, including political regimes, economic development, socio-cultural aspects, and technological resources. We discuss how our research extends the literature on the integration of artificial intelligence and equity and the implications of our findings for artificial intelligence firms seeking to expand globally.

***Keyword*:** Distributive (in)equity, Artificial intelligence, Globalization, Social impact, Educational technology

1. Introduction

Artificial Intelligence (AI, hereafter), broadly defined as "a comprehensive collection of computer-assisted systems for task performance, encompassing machine learning, automated reasoning, knowledge repositories, image recognition, and natural language processing" (von Krogh 2018, p. 405), is rapidly becoming ubiquitous across societies worldwide. Its influence is gradually extending into all facets of our lives and finding widespread applications in industries ranging from robotics, automobiles, education, healthcare, and finance, to retailing and government operations across different countries. Digital technology, including AI, transcends national boundaries and enhances connectivity among global partners. Consequently, AI's impact is not only economic but also social, with the potential to positively transform people's lives.

Although AI's global prevalence in practical applications is increasing, the academic community has been sluggish in progressing research that examines AI from a global perspective. In fact, Luo and Zahra (2023, p. 403) in their editorial states, "4IR has been added as one of the two sub-domains (along with global sustainability) to be covered by *JIBS*[1]." They further go on to urge scholars that "The IB field has a major opportunity to address social impacts and consequences of 4IR across countries, particularly the role of technology (p. 412)." In line with this growing demand for research, our study seeks to fill this gap by converging three domains that have seldom been united in a single model: AI, social impact, and globalization. In doing so, our research not only enriches the literature on social innovation and engagement but also offers valuable insights for social enterprises aiming to leverage AI for broader global outreach.

The advantages and shortcomings of AI have ignited an ongoing discourse that commands keen attention from a diverse array of stakeholders, including customers, employees, regulators, and politicians. While it is widely acknowledged that AI enhances efficiency and scalability, broadens accessibility for marginalized communities, reduces costs, and expedites task completion, there is also a shared belief that

[1] JIBS: Journal of International Business Studies

AI contributes to social deprivation (Tang et al. 2023) and perpetuates biases based on race and gender (Zhang et al. 2021).

Given the multitude of perspectives and the emergent state of AI, its societal impact remains complex and rife with contradictory outcomes across different regions. As such, the need for research is apparent to discern when AI is beneficial and when it can be detrimental on an international scale. A comprehensive investigation into the boundary conditions of AI's effectiveness in addressing inequities is lacking, and this is the research question we aim to tackle in this study.

The global Education Technology (EdTech, hereafter) market attained a valuation of USD 123.40 billion in 2022, and it is anticipated to register a compound annual growth rate (CAGR) of 13.6% from 2023 to 2030 (Grand View Research 2023). The usage of EdTech within K-12 schools has experienced a remarkable surge of 99% since 2020, with the COVID-19 pandemic widely acknowledged as the catalyst for this exponential expansion in the EdTech market. This study delves deeply into the influence of AI efficacy, which refers to the extent an AI solution can successfully address a user's query, on distributive inequity in the EdTech realm.

Distributive inequity, deeply explored by Adams (1965) and further by Huseman et al. (1987), is a principle wherein disparities exist in the rewards received (output) relative to the effort or resources invested (input) among users. Expanding on this, in the broader context of global education and EdTech, these disparities become even more pronounced. Some countries, with advanced infrastructures and resources, have more established EdTech landscapes, while others may struggle due to limited accessibility, infrastructure, or funding. This global disparity is further accentuated by the seminal works on distributive justice, such as John Rawls' "A Theory of Justice" (Rawls 1971) and Walzer's "Spheres of Justice" (1983). When applied to EdTech, it implies that students in certain nations or regions might gain significantly more from AI-driven educational tools than others, not just because of individual effort, but also due to systemic advantages or disadvantages. Such discrepancies in outcomes can perpetuate and even exacerbate existing educational and socio-economic divides on a worldwide scale, reinforcing the need for a thorough examination in the age of AI-enhanced education.

We direct our focus on the AI-distributive inequity relationship within the EdTech context for several compelling reasons. First, there is a mounting societal interest and concern surrounding AI. There exists a significant apprehension that AI has the potential to perpetuate discrimination, bias, stereotypes, and various forms of marginalization (Ravanera and Kaplan 2022). The implications of AI on distributive inequity in the EdTech sphere have garnered considerable attention globally, encompassing a range of stakeholders such as EdTech companies, media, governmental bodies, educational institutions, parents, and students (Holstein and Doroudi 2021; Kizilcec and Lee 2021).

Second, we believe that AI can act as a catalyst for positive social transformation and can facilitate access to education that might otherwise be inaccessible. For instance, Ruangguru, an Indonesian EdTech firm, contends that "Technology is an equalizer. It's a vehicle to equalize access to quality education for everyone." Ruangguru emphasizes that technology's role becomes even more pivotal when equitable accessibility and infrastructure are not uniformly available to all, underlining the capacity of technology to democratize education, particularly for those most in need.

Outside the educational sphere, examples further underscore AI's potential for positive social impact. Novo Nordisk, a prominent pharmaceutical company, introduced an AI-powered chatbot named Sophia, which enhances medical assistance accessibility by providing information beyond conventional call center hours (Bulik 2020). Similarly, Forus Health, a health technology enterprise, collaborated with Microsoft to develop an AI-based medical tool that enables more efficient and affordable detection of retinal diseases, widening the reach of medical care to low-income patients (Culler 2019).

Hence, the interplay between AI efficacy and distributive inequity may be more intricate than initially perceived. Viewing this as a straightforward association through a universal lens could be misleading. Instead, acknowledging that the impact of AI efficacy on distributive inequity can be a double-edged phenomenon highlights the value of adopting a contingency lens, which considers specific conditions that can provide illuminating insights. Examining the relationship between AI efficacy and distributive inequity within the framework of certain moderating factors holds significance both theoretically and practically.

Transitioning from a universal viewpoint to a contingency-based perspective offers companies and policymakers the opportunity to discern nuanced outcomes. This approach steers clear of oversimplified assertions, avoiding rigid judgments that AI either fosters equal access to opportunities or reinforces societal prejudices and preconceptions. By embracing a contingency approach, we gain the means to address the core research question: when does AI efficacy contribute to distributive inequity? Our rationale is that the appreciation and value assigned to the same AI system may fluctuate depending on the degree of socio-economic challenges prevalent in the users' environment.

Affordance theory (Gibson 1979; Volkoff and Strong 2013) directly addresses the aforementioned concern, prompting us to construct a conceptual model rooted in this theoretical foundation. Affordance, as defined, "denotes what an object offers, provides, or furnishes to someone or something" (Gibson 1979; Volkoff and Strong 2013). While an affordance itself may remain constant, its utilization can vary across different contexts or in response to diverse needs (Faraj and Azad 2012; Majchrzak et al. 2016). To illustrate, a tree can serve as shade, shelter, nourishment, or as a source of energy through combustion—distinct affordances contingent upon the user's requirements (Chemero 2003).

Similarly, a technological artifact (for our purposes, AI) can hold varied potential uses, shaped by the dynamic interplay between the technology and the user (Faik et al. 2020, Salomon 1993). Moreover, within the spectrum of potential uses, users bring about the actualization of affordances by translating the technological artifact into action. This process of affordance actualization is intricately influenced by the users' social and environmental contexts (Gaver1991).

Hence, the manner in which a student engages with AI-powered learning (affordance actualization) is contingent upon the extent of educational resources available to them (environmental setting). Particularly, in situations where alternative supplementary learning opportunities beyond the classroom (such as private tutoring) are constrained, we anticipate that structural and supply-related scarcities will enhance the perceived value of AI-powered learning. Consistent with the principles of affordance theory and the existing technology affordance literature, we propose that global macro-environmental factors exert an influence on the relationship between users and technological artifacts, thereby resulting in variations in the affordances offered by the technological artifact itself (Faraj and Azad 2012).

This contention implies that the impact of AI efficacy in ameliorating distributive inequity may be subject to the influence of social and cultural factors, whereby this effect is more pronounced in countries marked by greater (as opposed to lesser) scarcity of educational resources. Consequently, we incorporate macro-level political indicators (e.g., democracy index), economic indicators (e.g., GDP per capita and government spending on education), social indicators (e.g., religion), and technological indicators (e.g., mobile penetration rate) as moderators—falling within the PEST framework (Political, Economic, Socio-cultural, Technological)—that operate between AI efficacy and distributive inequity (Aguilar 1967; Doherty, Steel, and Parrish 2012).

To assess our conceptual model, we acquire data from a global EdTech application that leverages AI technology. Our investigation centers on AI-powered search engines within the EdTech realm, which function as educational tools, supplying learning materials and answers in response to user queries. The application under scrutiny, integrating both AI and machine learning, facilitates students, in capturing images of math problems, uploading them, and accessing multiple solutions from its database. Our data collection process encompasses comprehensive AI efficacy evaluations and user service access logs, recorded at the individual student level. We draw this data from students, originating from 35 countries across five continents, where our designated AI-driven educational application is actively employed.

Our empirical approach focuses on analyzing country-level macro-environmental factors. These factors encapsulate political frameworks, economic progress, socio-cultural dimensions, and technological resources. By incorporating this array of factors, we aim to test how global macro-environmental factors shape the AI efficacy-distributive inequity relationship in our contingency model.

By doing so, we make significant contributions to the AI-inequity discourse and to the domain of social impact practice. We provide critical insights into a burgeoning research domain that is gaining prominence within both academic and practitioner circles. Despite considerable discussions on the effects of AI on inequities (Ravanera and Kaplan 2022), there is a dearth of systematic research (with Zhang et al.

2021 as a notable exception) that empirically examines the AI efficacy-distributive inequity nexus within a contingency framework, particularly on a global scale. Our investigation reveals that AI efficacy leads to a reduction in distributive inequity, particularly in the context of prevailing global macro-environmental factors. Specifically, we ascertain that distributive inequity diminishes under conditions of heightened AI efficacy amidst impoverished environmental circumstances. This is observed when several indicators, encompassing the democracy index (Political factor), gross domestic product (GDP) per capita and government spending on education (Economic factor), language and religion (Socio-cultural factor), and mobile penetration rate (Technology factor), are all at lower levels.

Furthermore, in response to increasing awareness and interest in ESG (Environmental, Social, and Corporate Governance) and DEI (Diversity, Equity, and Inclusion) in the business community, our study yields a valuable and actionable managerial insight by introducing a concise approach to gauge companies' positive societal impact. We employ the Gini coefficient of access, an adaptation of the traditional Gini coefficient which quantifies inequality in distributions such as income or wealth, now applied to assess disparities in students' access to an AI-powered education app. As a proxy, this metric measures a firm's contribution towards reducing distributive inequity. Such a metric can serve as a yardstick for socially conscious consumers, socially oriented investors, and internal stakeholders. Furthermore, companies can adopt this metric as an internal key social performance indicator, showcasing the extent to which a firm has fulfilled its mission of enhancing society for the less privileged.

In the subsequent sections, we delve into our theoretical background and present our hypotheses. Following this, we proceed to outline the findings of a pilot study, which draws from a survey involving 9,964 app users spanning across 37 countries. Subsequently, we present our primary study, which is underpinned by observations encompassing a user base of 45 million, spanning across 35 countries. Finally, we culminate with a discussion of the theoretical and practical implications, an acknowledgement of the study's limitations, and a delineation of potential avenues for future research.

2. Theoretical Background

2.1. Equity Theory

Inequity pertains to the occurrence of unjust and unfair occurrences among social entities (Colquitt et al. 2001). Clemmer and Schneider (1996) identify three dimensions of inequity: distributive, procedural, and interactional. Distributive inequity encompasses the unfair disbursement of outcomes (Adams 1965); procedural inequity denotes a perceived lack of fairness in decision-making processes and procedures (Leventhal 1980); interactional inequity signifies unjust interpersonal treatment (Bies & Moag 1986).

We assert that procedural and interactional inequities are less prevalent in AI-powered services. This is due to the minimal potential for unfairness in both processes and interactions within AI-human scenarios when compared to human-human interactions. As a result, our research primarily concentrates on distributive inequity.

Distributive inequity arises when there is an absence of fairness in the allocation of outcomes (such as education accessibility) in comparison to inputs (like investments in resources such as time and money) (Adams 1965). Inequity becomes apparent when there is an imbalance in the ratio of outputs to inputs, manifested in the following ways: (a) outputs remain constant while inputs increase, (b) inputs remain steady but outputs decrease, and (c) both outputs and inputs decrease or increase. In the realm of education, distributive inequity frequently manifests in traditional learning modes, where a subset of students has to invest more inputs (such as time, effort, or finances) compared to other groups of students to attain similar-quality education (Fleurbaey et al. 2002). In simple terms, inequity is discerned when the output-to-input ratio seems “unfair” in comparison to the corresponding ratio among other reference points.

Variations in output may emerge among students due to disparities in school funding and teacher quality, thereby influencing the caliber of education received. Additionally, distributive inequity among students can arise if educational resources are unevenly distributed, primarily due to economic, socio-cultural, political, and technological barriers.

Among the numerous touted advantages of AI in education, accessibility and affordability are widely recognized as primary. Enhanced AI efficacy leads to improved accessibility and affordability, consequently alleviating distributive inequity by lessening disparities in costs (input) and augmenting the quality of education (output) for disadvantaged students. Given AI's minimal marginal cost (Hosny and Aerts 2019), it is anticipated that the affordability of AI-driven learning will expand with increasing AI efficacy. Furthermore, since students' reliance on human involvement and physical space is reduced, they gain from the extensive accessibility that operates around the clock. Thus, advancements in AI efficacy are poised to ameliorate distributive inequity among students with limited educational resources. This improvement will be achieved by balancing (and even favoring) the output-to-input ratio (via reduced input and heightened output), especially when compared to students enjoying abundant educational resources.

Consider the following scenario. A student residing in a rural locality who might need to travel an hour to attend a class, while a student in an urban area may only need a ten-minute drive. Beyond travel times, disparities in school funding and teacher quality can also lead to differences in educational outcomes for these two students. Distributive inequity emerges when a shortage of educational resources leads to an uneven distribution among students (Dobson 1998). This inequity becomes more pronounced when high-quality schools and educators are less accessible in rural regions compared to urban locales. In this context, distributive inequity is accentuated by geographical barriers, causing the output-to-input ratios for the two students to diverge. AI-powered learning has the potential to level the playing field by enabling both students to study from home (thereby reducing the input) and still receive a high-quality education (maintaining or increasing the output).

2.2. Hypotheses

Building upon the foundations of affordance theory and the technology affordance literature, we contend that the interaction between global macro-environmental factors and the user-technology artifact relationship will engender disparities in the affordances of the technological artifact (Faraj & Azad 2012). Affordance theory elucidates that a technological artifact (an entity uniform for all such as AI) can harbor myriad potential uses, shaped by the dynamic interplay between technology and the user (Faik et al. 2020; Salomon 1993). For instance, users can harness an AI-powered search service in diverse manners—be it for class preparation, homework aid, exam readiness, or as a primary learning source, each representing an affordance. Consequently, we posit that the actual utilization of AI-powered search (affordance actualization) hinges on the extent of educational resources accessible to users (environmental setting).

This line of reasoning implies that the effect of AI efficacy on distributive inequity is influenced by the abundance of educational resources within a given country. As such, we adopt the PEST (Political, Economic, Socio-cultural, and Technological) framework as a structured tool to categorize countries based on each dimension of PEST (Doherty, Steel, and Parish 2012).

Political: The availability of high-quality educational resources is intricately linked to political underpinnings, specifically the nature of political regimes and the robustness of institutions (Cooray & Potrafke 2011). Numerous studies attest to the observation that autocratic regimes often underinvest in education, largely due to fears surrounding the educated middle class's inclination towards democratic governance, which emphasizes transparency and accountability (Welzman 2010, Glaeser et al. 2004). Conversely, democracies generally boast higher institutional quality, given that inherent checks and balances that monitor the activities of government officials and political elites (Acemoglu et al. 2005, Dahl 1998). A pivotal link has been established between institutional quality and the elevation of educational standards (Fomba et al. 2022, Hanushek and Woessmann 2012). Consequently, it is reasonable to anticipate limited access to elite educational resources for users in countries under non-democratic regimes. This scarcity can intensify the challenges in harnessing the full potential of AI for education. Thus, in countries where educational resources are scant due to political systems, the role of AI in addressing distributive inequity becomes even more critical. We hypothesize that the effect of AI efficacy on distributive inequity will be more pronounced in non-democratic countries compared to democratic ones.

H1: *AI efficacy leads to a greater reduction in distributive inequity in less (vs. more) democratic countries.*

Economic: The disparity in educational resources between economically developed countries and developing countries is stark and well-documented (Hanushek 2006, Psacharopoulos and Patrinos 2004). The relationship between the quality of educational resources and economic underpinnings is profound, notably manifesting in areas such as teacher quality and school funding (Akiba et al. 2007, Woessmann 2001). Furthermore, when government expenditure on education is insufficient, the financial responsibility frequently shifts to households, exacerbating the economic barriers to accessing quality education (UNESCO 2019, Birdsall and Orivel 1996). Given this established connection between economic status and educational resources, it is plausible to anticipate that individuals from economically disadvantaged nations—with fewer alternative educational avenues like private tutoring or cram schools—stand to benefit disproportionately more from heightened AI efficacy. This enhanced AI potential can dramatically alter the landscape of educational access, bridging gaps, and thereby mitigating distributive inequities. Based on these considerations, we put forth the following:

H2: *AI efficacy leads to a greater reduction in distributive inequity in less (vs. more) economically developed countries.*

Socio-cultural: The United Nations characterizes minorities based on distinct parameters such as nationality, ethnicity, religion, and language (United Nations n.d.), and these classifications bear significant relevance to the socio-cultural nuances of users. It is evident that socio-cultural dimensions significantly dictate both the quantity and quality of educational resources to which users can access. Case in point, English-speaking users typically enjoy an expansive array of educational materials since a significant portion of academic articles and digital educational platforms, including massive open online courses (MOOCs), are predominantly published in English (Emanuel 2013, Parr 2013). Beyond the language, intertwined facets like religion, culture, nationality and ethnicity also influence the diversity and caliber of educational resources a user can access. It is noteworthy that many educational resources are tailored by and for socio-cultural majorities, inadvertently leading to inadequacies when catering to the diverse needs of socio-cultural minorities (Kizilcec et al. 2017). Such dynamics result in a relative resource scarcity for these minorities. This dearth profoundly influences the manner in which users navigate AI-powered educational platforms and tools. Taking all these considerations into account, we formulate the following:

H3: *AI efficacy leads to a greater reduction in distributive inequity in socio-culturally minor (vs. major) countries.*

Technological: Technological disparities, specifically the lack of access to information and communications technology (ICT), wield a decisive influence on both the availability and caliber of educational resources (Alcorn et al. 2015, Warschauer and Matuchniak 2010). Consider users who, out of necessity, must share a computer with multiple family members; they are invariably at a disadvantage in accessing online educational content compared to those with individual devices. This dynamic resonates with the scarcity effect articulated by Jung and Kellaris (2004)—the notion that items in short supply are inherently perceived as more valuable. Given this, AI stands to offer a pronounced benefit to users with limited technological access. Such users, constrained by technological deficits, are likely to derive greater value from AI-powered educational solutions, recognizing their potential to bridge significant gaps. Therefore, we present the following:

H4: *AI efficacy leads to a greater reduction in distributive inequity in low (vs. high) technological resources countries.*

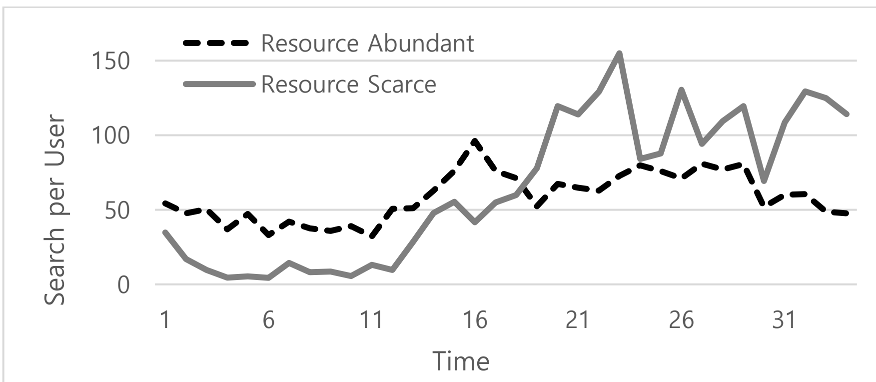
3. Model-Free Evidence

Prior to our empirical analysis, we provide model-free evidence that shows the relationship between users' level of educational resources and their use of AI-powered search. As shown in Figure 3(a), we find that users who live in regions with limited resources (defined as countries with GDP per capita lower than the median GDP per capita) tend to use the search service more compared to users who live in regions with abundant resources (defined as countries with GDP per capita higher than the median GDP per capita), conditional on AI efficacy. Our focal app started in regions with relatively abundant resources (i.e., Korea and Japan) and expanded globally to other regions with relatively limited resources. In Figure 3(b), we can see that AI efficacy differs across geographic areas and evolves over time. In particular, the gap in average

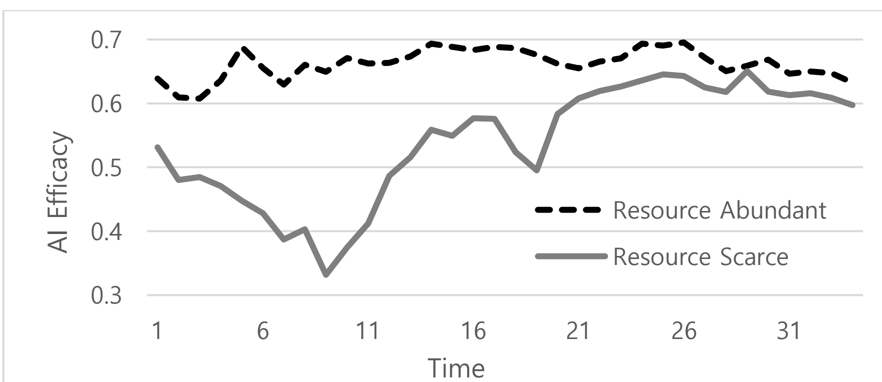
AI efficacy between regions with limited vs. abundant resources is large at first, but gradually converges with time. As AI efficacy between the two regions converges (after month 20), we see that the search per user count in regions with limited resources overtakes the search per user count in regions with abundant resources. Given that economic resources are closely linked to educational resources (Hanushek, 2006), this model-free evidence supports our theoretical model that the utility of an AI-powered search depends on alternative educational resources available to users, while controlling for AI efficacy.

Figure 3. AI-powered Search per User and AI Efficacy over Time based on Resource Abundance

(a) AI-powered search per user



(b) AI Efficacy



Overall, the model-free evidence suggests that users with limited (vs. abundant) resources search more frequently.

4. A PILOT STUDY

This section presents a pilot study conducted in partnership with a global AI-powered learning app, QANDA.[2] The insights from this initial investigation guided the design and execution of a subsequent large-scale empirical data study.

4.1. Setting

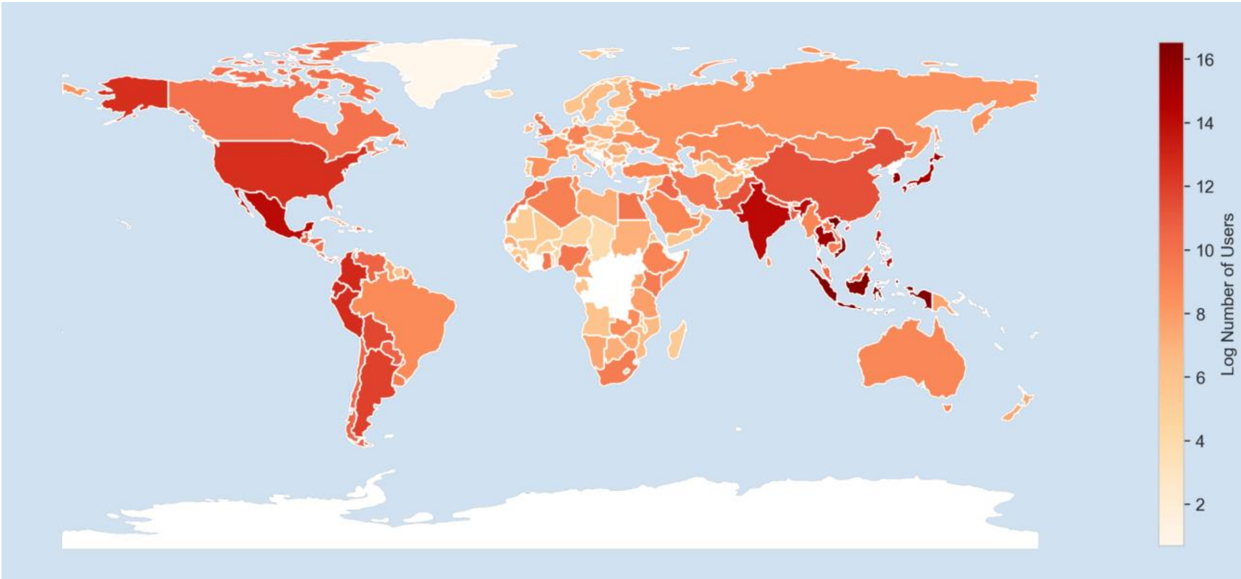
QANDA, a name coined from "Questions and Answers", provides supplementary learning and guidance, predominantly in the realm of math education for K-12 students. Since its establishment in 2016, the app has cultivated a robust global presence, addressing over 4.5 billion problems for more than 70 million students across 200 different countries, all while supporting nine different languages.[3] The expansive global coverage of the app is shown in Figure 2.

The focal app's core service is centered on its problem search feature. This function permits students to capture and upload images of mathematical queries they encounter. Once an image is uploaded, the app employs a combination of AI methods. It incorporates deep learning algorithms, which are structured based on neural networks, to analyze the mathematical context. Additionally, the app uses optical character recognition technology to convert the text and numerical data from the image into digital format. Through this integrated approach, the platform can provide detailed, step-by-step solutions in a limited timeframe. This service is available to users without financial charge.

[2] https://qanda.ai/

[3] These include English, Indonesian, Japanese, Korean, Portuguese, Spanish, Thai, Turkish, and Vietnamese.

Figure 4. Global presence of focal app.



Note: The map is colored based on the log number of users for each country.

4.2. Survey Design

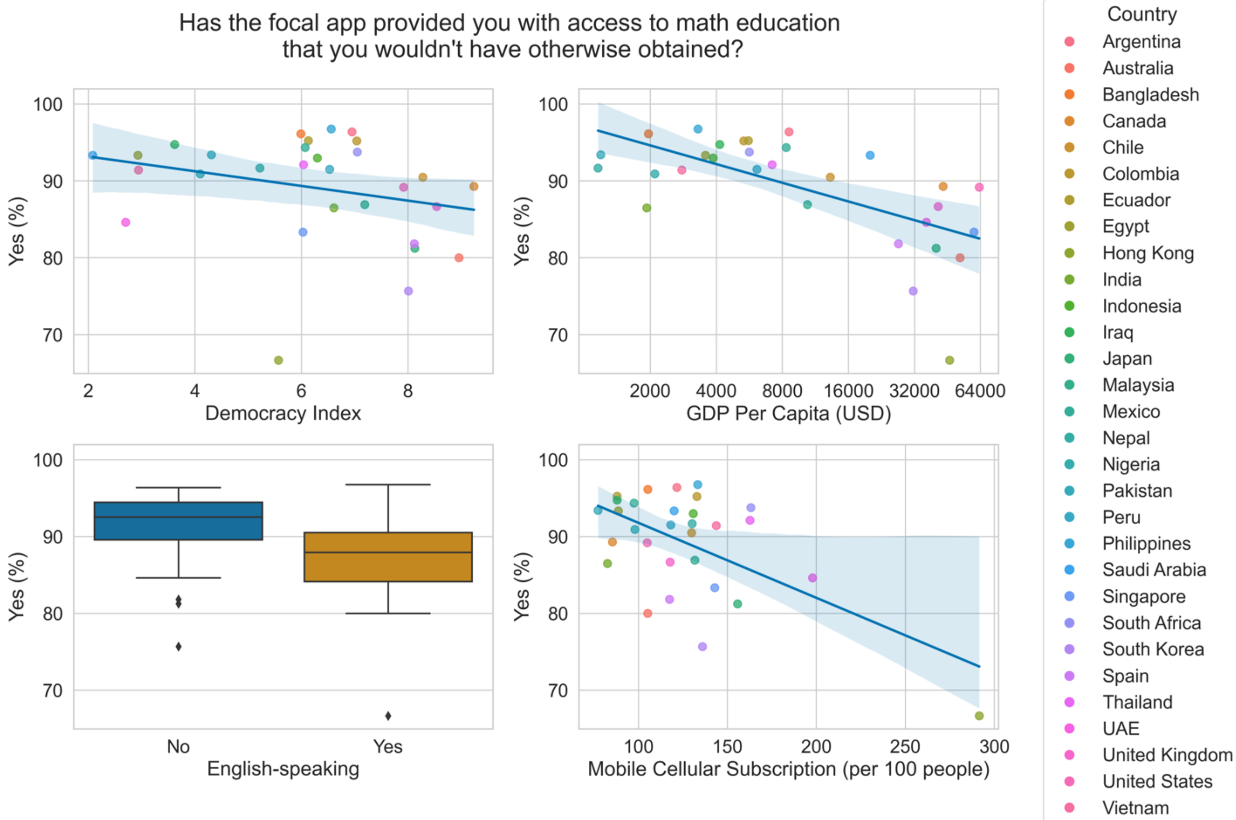
The pilot study involved a worldwide survey conducted over a four-week period from November 2 to November 30, 2020. We distributed the survey through all available language versions of the QANDA app. Responses were collected from a total of 9,964 app users from 37 selected countries. The primary aim of the pilot study was to gauge the potential role of the focal app in enhancing distributive equity in the EdTech landscape. Despite the singular focus of the survey question, it served to underline the principal aspect of accessibility that is at the core of the educational equity debate in line with UNESCO's goal of "inclusive and equitable quality education for all" (UNESCO, 2015). Given the constraints and resource limitations of the partnered company we were working with, the single-question survey was crafted to encapsulate the essence of the distributive equity concern. The question aimed to understand if technology could serve as a bridge to mend educational disparities by providing access to mathematical education across various geographical regions across the globe. In light of this, we asked students the question "Has the focal app provided you with access to math education that you wouldn't have otherwise obtained?"

4.3. Survey Results

Our survey sheds light on the tremendous advantages of AI-powered learning. Specifically, 85.2% of students confirmed that the app provided them with access to math education previously beyond their reach. We further investigated whether survey response differences exist across various countries, considering differing macro-level factors by leveraging the PEST framework. Interestingly, our survey results reveal model-free evidence that the benefits of AI-powered learning are asymmetric across all PEST macro factors. As depicted in Figure 3, a negative correlation exists between the perceived accessibility of AI-powered learning by students and the democracy index, GDP per capita, and mobile cellular subscription rate of the student's home country. This trend is also confirmed when comparing English-speaking against non-English-speaking countries. That is, students from countries that are *less democratic*, *still developing*, *primarily non-English-speaking*, and *have lower mobile cellular subscription rates* are reaping greater advantages than their counterparts in *more democratic*, *developed*, *English-speaking nations with higher mobile cellular subscription rates*. This outcome provides initial evidence supporting the notion that AI-powered learning could help narrow the learning achievement gap by serving as a valuable tool in democratizing access to education, especially in underserved areas.

To assess the stability of our survey results, we contrasted early and late responses, following the method outlined by Armstrong and Overton (1977). After dividing the respondents into two equal groups based on the timing of their response to the survey, we found no statistically significant difference in their answers (p-value = 0.392). Thus, the timing of the responses did not influence the outcomes, affirming the consistency of the survey results.

Figure 5. Survey responses vs. PEST global macro factors.



Note: Sources of each PEST factors are: (1) 2020 Democracy Index (Political) from Economic Intelligence Unit, (2) 2020 GDP per capita in USD (Economic) from World Bank, (3) English-speaking countries (Socio-cultural) from Encyclopedia Britannica, and (4) 2020 Mobile cellular subscriptions per 100 people (Technological) World Bank.

4.4. Justification for the observational study

The pilot study, while offering valuable insights, encountered two distinct challenges. The first was its limited sample size, which restricted the breadth of our findings and potentially reduced the generalizability of the results. The second concern, inherent its design was the potential for response bias, particularly the social desirability bias (Fisher 1993). Given its self-reported nature, there is a possibility that participants adjusted their answers to portray themselves in a more favorable light. To mitigate this bias, we implemented measures like ensuring the anonymity and confidentiality of all responses. Furthermore, to bolster the integrity of our findings, we sourced log data directly from the company's database.

Recognizing these challenges, we were motivated to adopt a more comprehensive and less intrusive approach to capture user behaviors. This led us to embark on a large-scale observational data analysis, detailed in the subsequent chapter. Specifically tailored to address the limitations of the pilot study, this observational approach facilitated a broader and unobtrusive examination of user behaviors, enriching and complementing our initial insights from the pilot study.

5. EMPIRICAL CONTEXT

The data for the large-scale observation study span from January 2019 to December 2021, covering 36 months, and contain information on individual-level student activities of QANDA. These activities include access and problem search, along with transactional information such as timestamp, IP address, and language versions used. The quality of solutions users receive from the app is also available in terms of student's evaluation of AI efficacy (i.e., whether the solutions were relevant to their questions) and algorithm-generated similarity scores between the problem asked and the corresponding solutions (i.e., a larger similarity score implies a greater relevant match).

We began our investigation by excluding countries with fewer than 200 users, as the sparse usage data from these locations could compromise the integrity of our findings. This led us to focus on approximately 45 million users spread across the top 35 countries with the most substantial user bases.[4] Our primary variable of interest is distributive inequity. This metric reveals the disparities in users' access to the focal app across different states or provinces within a country. Specifically, it helps shed light on areas where access might be uneven or limited, providing insights into potential geographical biases or challenges within a given country.

Next, we delve into the specifics of our study by detailing the operationalization of the key variables used in our analysis, aggregating the data at the country-month level.

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[4] The samples come from five continents (i.e., Africa, North America, South America, Asia, Australia, and Europe), including the following countries and territories: Argentina, Australia, Bangladesh, Brazil, Canada, Chile, China, Colombia, Ecuador, Egypt, Germany, Hong Kong SAR, India, Indonesia, Iran, Iraq, Japan, Laos, Malaysia, Mexico, Nepal, Nigeria, Pakistan, Peru, Philippines, Saudi Arabia, South Africa, South Korea, Spain, Chinese Taipei, Thailand, United Arab Emirates, United Kingdom, United States, and Vietnam.

AI efficacy

We employ AI efficacy as a representative measure for the performance of AI-powered search services. The evaluation of AI efficacy can be bifurcated: from the viewpoint of service providers (via algorithm-calculated performance metrics) and users (through their quality perceptions). We posit that changes in distributive inequity align more directly with user-perceived AI efficacy. Prior work has often adopted the precision rate—the percentage of solutions retrieved that are relevant to a search query—as an efficacy benchmark for search. Notably, it is typically the users who ascertain this relevance (Gordon and Pathak, 1999; Voorhees and Harman, 2005).

Within the framework of the focal app, the metric derived from the algorithm, such as the similarity score between the problem presented by the use and solution retrieved, remains consistent for countries grouped under the same language division, termed as a 'locale'. To illustrate, the United States, Canada, and the United Kingdom all fall under the English locale, while countries like Spain, Mexico, and Argentina are categorized under the Spanish locale. The company deploys an algorithm and database specifically tailored for each language group. Consequently, while the AI quality—quantified by metrics such as the similarity score—remains consistent within a locale, individual users' perception of AI efficacy can vary therein.

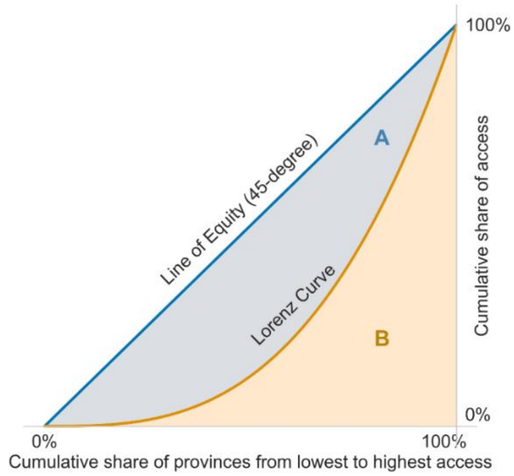
Given these considerations, we posit user-evaluated AI efficacy better mirrors the advancement and capabilities of AI-powered search engines. The observed variations in user assessments within these locales substantiate our choice of user-evaluated AI efficacy as our primary metric, facilitating a more detailed comparison of AI's influence across a variety of countries.

Distributive inequity

Our objective is to assess how AI technologies might influence distributive inequity, which we do by measuring the spread of the AI-powered app access across various regions, such as states or provinces, within a country. For this purpose, we employ the Gini coefficient, a standard metric used to quantify the extent of uneven distribution of resources like wealth or educations access. In our context, we introduce the 'access Gini coefficient', which evaluates the disparities in app accessibility on a country-month basis.

To compute the access Gini coefficient, we use the Lorenz curve—a graphical depiction of access distribution within a country's regions. As shown in Figure 4, it plots cumulative access counts against a country's population, arranging regions from the least to the most accessed. Formally, the coefficient is determined as the area between the Lorenz curve and a 45-degree line (represented as A/(A+B) in Figure 4), with values ranging from 0 for perfectly even distribution to 1 for a scenario where one region monopolizes access.

Figure 6. Graphical illustration of the Gini coefficient.



To contextualize the access Gini coefficient, it is crucial to factor in a country's economic backdrop. For this reason, we normalize the access Gini coefficient against the income Gini coefficient. This normalization achieves two key aims:: First, it strips away broader economic variations, allowing us to pinpoint the app's specific contribution to distributive inequity. Second, by referencing the income Gini coefficient, the measure becomes universally comprehensible and valid, facilitating comparisons across countries with distinct economic landscapes. With this normalization, a ratio surpassing one suggests the app access is less evenly distributed than income, while a value below one signals a more even app access distribution relative income.

In operational terms, our measure of distributive inequity undergoes the following process:

1) We start by consolidating the monthly app access for each region within a country and adjust these figures according to their respective population sizes.
2) A Lorenz curve is then plotted, with the cumulative app access counts on the y-axis and the cumulative population percentages on the x-axis. This plot orders the regions based on ascending app access counts.
3) Using this curve, the access Gini coefficient is computed at the country-month level by determining the area between the 45-degree line and the Lorenz curve.
4) Lastly, we convert this coefficient into a more holistic (in)equity metric by normalizing it against the income Gini coefficient.

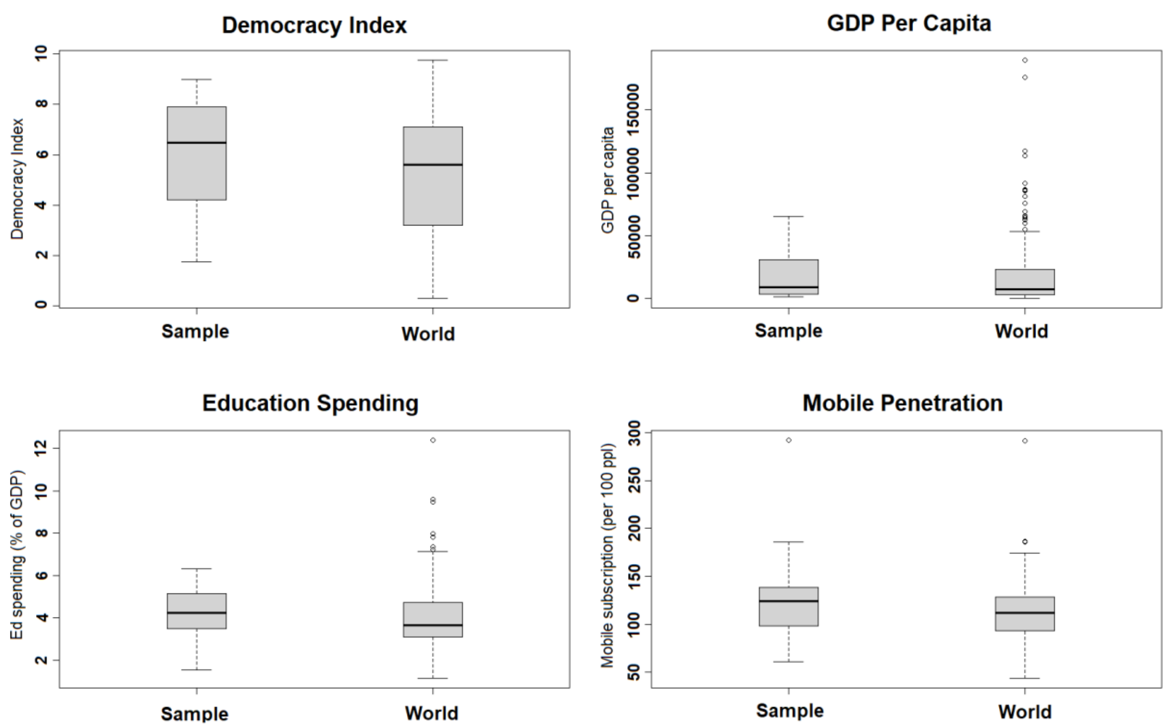
Global macro factors

To delve into the impact of macro-environmental factors that may moderate the relationship between AI efficacy and changes in distributive inequity, we adopt the PEST framework (Aguilar, 1967; Aldehayyat and Anchor, 2008). This framework is operationalized via six unique measures distributed over four categories.

The *Political Factor* is represented by the democracy index. We utilize the 2020 Democracy Index, an annual assessment by the Economist Intelligence Unit that evaluates the state of democracy in over 160 countries. The index scores countries on a scale ranging from 0 to 10, with a lower score suggesting a tilt toward authoritarianism, while a higher score indicates a country's inclination towards a democratic regime. For the *Economic Factor*, we reference data from the World Bank, specifically the 2020 GDP per capita (in USD) and the 2019 percentage of governmental spending on education relative to the GDP. The *Socio-cultural Factor* is captured by considering the dominant language and religion of the countries in our sample. We have relied on data from the Encyclopedia Britannica for this purpose. Lastly, the *Technological Factor* is represented by the mobile penetration rate. We employ the 2020 statistics on mobile cellular subscriptions per 100 people from the World Bank as our chosen proxy for technological advancement and accessibility.

Figure 5 visually juxtaposes our sample countries with the global landscape regarding these PEST factors. Notably, the figure demonstrates that our sample aptly represents the global population, as the plots for our sample countries appear strikingly comparable to those of the world at large, reinforcing the generalizability of our findings.

Figure 7. PEST Factors: Our Sample vs. Global Overview



Note: (a) 2020 Democracy Index for 167 countries, Economic Intelligence Unit; (b) 2020 GDP per capita (in USD) for 206 countries, World Bank; (c) 2019 Governmental spending on education (% of GDP) for 137 countries, World Bank; and (d) 2020 Mobile cellular subscriptions (per 100 people) for 187 countries, World Bank.

To streamline our analysis, we applied a median split to each of the PEST measures among our sample countries. This method resulted in a binary coding system: a code of 1 was assigned to countries that registered low on the macro factors, and 0 was assigned to those scoring high. Within the realm of socio-cultural determinants, countries that are majority English-speaking and Christian were assigned a 1, while all other countries received a 0. The intricacies of our coding system are laid out in Table A.1 of Appendix A.

Controls

In our analyses, we strive to account for unobserved variations specific to different countries and distinct time frames. To achieve this, we incorporate both country- and month-fixed effects as controls. It is worth highlighting again that the focal app operates across nine different locales, each corresponding to a specific language. Given that the company's interventions, such as marketing or promotional campaigns, vary across these locales, it is crucial to address potential biases. Thus, we control for locale-month effects, using them as a surrogate for the firm's varied inputs. We employ the mean difference method to capture and adjust for these variations.

In summary, our final dataset comprises a total of 1,245 country-month level observations. This excludes 15 country-month instances, which lacked user activity, particularly during the months immediately succeeding the app's launch in those respective countries. The summary statistics of the data are presented in Table 2.

Table 2. Summary statistics.

Variables	Mean	Std. Dev.	Min	Max
AI efficacy #	0.632	0.120	0.296	0.844
Distributive inequity	1.626	0.598	0.298	2.881
Log(Search)	8.557	3.796	0	18.435
Democracy†	0.486	0.507	0	1
GDP†	0.543	0.505	0	1
Ed-spending†	0.486	0.507	0	1
Christianity†	0.571	0.502	0	1
English-speaking†	0.800	0.406	0	1
Mobile penetration†	0.514	0.507	0	1

Note: Variables are in country-month level (N=1,245). # Calculated at a locale-month level to protect data confidentiality (N=252). † Country-level binary indicator stating 1 for lower-than-median, non-Christianity, and non-English-speaking countries and 0 otherwise (N=35).

6. General Discussion

The purpose of this paper was to examine the relationship between AI efficacy and distributive inequity and the moderating role of PEST factors in the EdTech context. We examined this through comparative global analyses based on 35 countries across five continents. Our findings from the pilot study provide initial support but due to the inherent limitation associated with the pilot study, a large scale observational study will be undertaken.

6.1. Theoretical Contribution

We contribute to theory advancement in IS research by examining the intersection between AI and equity, which can be summarized in the following four ways. First, in today's society, AI is ubiquitous and is embedded in everyday life, ranging from healthcare, mortgage lending, and hiring to education. Although equity and fairness research in IS has received more attention lately, much is unknown about how equity is related to AI (Hess & Hightower 2002; Kailash 1989; Trauth & Connolly 2021). Our research contributes to the IS literature by expanding the scope of AI research to include equity. Recent research in IS suggests that AI can be a double-edged sword in that it can provide many benefits, but at the same time can perpetuate deeply rooted bias, stereotypes, and inequity thereby reinforcing discrimination towards marginalized groups in society (Ravanera & Kaplan 2022; Zhang et al. 2021). As widely noted by researchers, policymakers, and practitioners in the industry alike, the efficacy of AI is only as good as the input data to train AI (Ravanera & Kaplan 2022; Shum & Luckin 2019). That is, if the data used to train AI are biased and do not effectively and accurately represent the population to which AI is intended to be applied, biased algorithms are inevitable, exacerbating rather than solving the issue at hand. Our results reveal that AI efficacy can allow firms to significantly mitigate distributive inequity by expanding accessibility to underrepresented and marginalized users. Although there has been much anecdotal evidence and an abundance of voices raised from educators, policymakers, and parents on the need to better utilize technology to mitigate inequity for users from marginalized backgrounds, especially in challenging times, such as during the global COVID pandemic, there has been a paucity of empirical evidence to support such claims. Rather, previous literature on online learning has found the negative impact of technology, that online learning, such as MOOC, seems to be reinforcing "the rich get richer" phenomenon by failing to reach the disadvantaged (Emanuel 2013; Hansen & Reich 2015; Kizilcec et al. 2017). Our research provides first-hand results based on data that span over 35 countries on five continents to corroborate the power of how firms can use AI in the EdTech context to mitigate distributive inequity.

Second, the present study elevates equity research from the individual level to the country level. While most research in education, management, and marketing have focused on equity at the individual level (e.g., Colquitt et al. 2001; Kizilcec & Lee 2020; Klein et al. 2021; Sridhar & Singh 2003), sparse research has been conducted that examines equity at the country level. Few studies exist that provide comparative equity analysis among countries at a scale such as ours. Our study takes initial steps to advance equity research in education from the prevalent *within* country analysis approach to a nascent *between* country analysis approach.

Lastly, based on affordance theory and the technology affordance literature in IS, we show that reduction in distributive inequity is stronger when the democracy index (political factor), GDP per capita and government spending on education (economic factor), language and religion (socio-cultural factor), and the mobile penetration rate (technology factor) are all low (vs. high) or minor (vs. major). Such results add another layer of richness and nuance by disclosing that when global macro factors are low (vs. high), the effect of AI efficacy on reducing distributive inequity is more pronounced.

6.2. Managerial Implications

Millennials and Generation Z customers may find firms that pursue a DBL strategy more appealing. Younger and more educated customers may resist firms that are solely interested in profit motives and yearn for firms that are socially active. Given the many active social movements (e.g., Black Lives Matter and #MeToo), the pursuit of equity can send a clear and potent signal to customers about the mission and value of a company. Such a signal can be effective not only for attracting customers but also for attracting employees and investors. Firms that move the needle on equity in the marketplace can attract and retain talented employees who share the company's mission, contributing to building a cohesive corporate culture. Also, providing social impact measures will attract social investors who care about their investment's financial returns as well as social impact. Take the case of Patagonia who in 2018 chose "going purpose" over "going public." A board member of the firm stated, "Companies that create the next model of capitalism through deep commitment to purpose will attract more investment, better employees, and deeper customer loyalty" (Chiu 2022).

Further, previous research on AI-to-equity examines how AI affects equity at the individual level or the change in inequity after an AI adoption. However, since AI continues to evolve, it is necessary to look at the dynamic (not static) impact of AI efficacy over time rather than a before-adoption vs. after-adoption comparison. Hence, there needs to be a more precise and comprehensive metric for measuring a firm's contribution to mitigating inequity as AI efficacy improves over time. ESG (i.e., Environmental, Social, and Governance) metrics reported by companies can be used by a variety of stakeholders to evaluate investment opportunities and make purchasing decisions. Additionally, the significance of impact investors, who want to improve the world through their investments, is rapidly rising. The size of the impact investing market has reached 1.164 trillion U.S. Dollars (USD) worldwide in 2022, making ESG measures more crucial for businesses to attract more investments (Hand et al. 2022). Our research sheds light on how EdTech firms can measure social impact, which can be used as a benchmark for consumers, investors, and internal employees.

Our results can guide and direct managers who are considering global expansion in terms of priority setting when deciding on the sequence of market entry. We suggest that priorities should be given to markets that are low on the PEST-related global macro factors as such markets will deliver the highest dividends in decreasing inequity from AI advancement. Another strategy that is conceivable is whom to target for ad placements on the AI platform. Our findings suggest showing ads for brands with a well-known public image of supporting diversity, equity, and inclusion (DEI) initiatives in the local market.

Given the support of the blended value proposition (financial and social interest) from a growing body of firms, managers may need to revisit their traditional accounting management information system (MIS) and consider a *social* MIS infrastructure and information dissemination system (Emerson, 2003). The value of transforming from an economically driven MIS system to a social MIS system can help align financial incentives with social rewards and prevent the two from competing with one another.

Finally, AI's true value will depend on how it is used and how it is accepted by customers. This implies that reaping the benefits while limiting the perils of AI will require appropriate governance structures and transparent auditing procedures. This calls for policy and oversight design that can control AI implementation in an equitable manner (Young et al. 2019). The recent Algorithmic Accountability Act introduced in 2019 in the US mandates big corporations to evaluate their algorithms for bias and discrimination. Building on the momentum from the EU's General Data Protection Regulation established in 2018, similar efforts in AI are underway in the EU to create an Artificial Intelligence Act, the first legal framework on AI of its kind by a major regulator.

6.3. Limitations and Future Research Directions

This study is encumbered with a few limitations that can be addressed in future research. First, it is important to perform studies to include data from multiple firms to increase generalizability as our empirical results are based on a single global company. Second, our distributive inequity measure captured the social impact an EdTech firm has in its contribution to mitigating distributive inequity. Although this is a good firm-level indicator to understand the accessibility of education, as accessibility to AI-powered search increases, so do ethical concerns such as cheating that can inevitably occur (Wood and Kelly 2023). Therefore, it would be worthy of examining other indicators that capture educational opportunities and outcomes, such as learning (e.g., test scores), completion (e.g., survival rate), and resources (e.g., the size of the database and tutors). Moreover, AI-powered search can be used in fields other than education as evidenced by ChatGPT, which is being used by virtual therapists, immigration assistants, social media marketers, and many more. Hence, examining the social influence of AI-powered search in industries other than education would add value to the literature. Furthermore, although our study focused on mitigating distributive inequity, future studies may also broaden the impact of AI on inequity by examining procedural and interactional inequity.

Lastly, given that many AI-based companies including those in EdTech are startups, their valuation by external stakeholders or investors is crucial for future growth. This begs the question of whether such startups should target social equity investors or private equity investors or both to maximize funding opportunities. With the increasing trend and call for social enterprise and socially responsible investing, future research could study how AI efficacy and equity affect a firm's valuation.

7. Conclusion

This research contributes to the IS literature by synthesizing AI and equity in the EdTech sector. Through a global empirical investigation, our results support that firms can leverage the power of AI to mitigate distributive inequity and that effect is stronger under adverse by global macro conditions. This research corroborates the increasing voice in academia and practice about the importance and feasibility of firms contribution to social change and impact. Our study shows that this is indeed a viable strategy by leveraging the power of AI to reduce inequity. We hope that our work motivates future studies to further examine how and when AI can result in decreasing inequity in other industries beyond EdTech.

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