Achieving the Double Bottom Line with Artificial Intelligence by Addressing Inequity: A Global Comparative Analysis of an Educational Technology Firm

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Completed Research Paper

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Abstract

Can companies use artificial intelligence to attain the Double Bottom Line (simultaneous pursuit of financial performance and social impact) by enhancing equity? Drawing on equity theory, we develop a conceptual model whereby perceived AI quality positively affects firm performance that is mediated by equity in the educational technology sector. Using observational data collected from a global AI-powered learning app, we find support for educational equity as a full mediator between perceived AI quality and firm performance. Moreover, we also find support for conditional indirect effects. The mediating role of educational equity is moderated by political, economic, socio-cultural, and technological factors. Our research contributes to the growing popularity of transforming a business model from a bottom line to a double bottom line approach. We discuss how our study extends the IS literature on the integration between artificial intelligence and equity and the managerial implications for an inclusive information system.

Keywords: (In)equity, artificial intelligence, social impact, educational technology, double bottom line

Introduction

Can firms pursue financial motives (e.g., profit maximization) and social impact simultaneously? Can these two coexist? Although tensions between the two may be unavoidable, increasingly more firms such as Toms (donating shoes), Bombas (donating socks), and Lemonade Insurance (donation to customer's choice of charity) are transforming their business model from the bottom line to the double bottom line (DBL) (e.g., Emerson 2003). One such social impact that has received significant attention around the world regardless of economic development is educational equity (e.g., Kizilcec and Lee 2020). Educational equity or lack thereof has garnered elevated attention from multiple stakeholders that range from media, government, school bodies, to parents and students, especially during the global pandemic of COVID-19 (e.g., Shum and Luckin 2019). During such challenging times, educational inequity has transcended from an educational to a political issue fraught with controversy. The COVID-19 pandemic has resulted in an aggravation of the gap between low- and high-SES students' access to educational resources (Bacher-Hicks et al. 2021). Furthermore, McKinsey reports that students of color will experience disproportionately more loss of learning and expects future earning disparity to widen between different races in the United States (Dorn et al. 2020).

Against the above backdrop, this research draws on equity theory in the IS literature (e.g., Kailash 1989; Trauth and Connolly 2021) to examine whether technology (e.g., artificial intelligence) can play a pivotal role in addressing inequity and thereby contribute to enhanced firm performance. We study this in the Educational Technology (EdTech) sector as our key research question is "Can EdTech firms marry education and technology to deliver greater equity, and hence improve firm performance?" Although the benefits of education and technology integration have taken on the status of a veritable mantra in many global leading EdTech companies in the form of mission statements and business strategies, there is surprisingly little empirical evidence to substantiate these claims, especially from the students' perspective. The goal of this research is to shed light on this conundrum.

On the one hand, managers at EdTech firms underscore that technology can play an instrumental role in democratizing education to those that need it most. For example, Ruangguru—an Indonesian EdTech firm—advances that "Technology is an equalizer. It's a vehicle to equalize access to quality education for everyone." Ruangguru further advances that the role of technology is amplified when accessibility and infrastructure are not evenly available to everyone to the same degree. Other proponents of technology have also echoed the role that Artificial Intelligence (AI) can play in mitigating the learning divide (Luckin, 2017).

On the other hand, despite these promising claims, recent empirical findings suggest otherwise. MOOC (Massive Open Online Courses) is a case in point. Despite MOOC's expanded reachability due to its open online accessibility, findings suggest that MOOC did not contribute to democratizing education (Hansen & Reich, 2015). They conclude that "Nevertheless, our research on MOOCs—along with previous decades' research examining the access and usage patterns of emerging learning technologies—should provoke skepticism of lofty claims regarding democratization, level playing fields, and closing gaps that might accompany new genres of online learning, especially those targeted at younger learners." Further scrutiny finds that many students who take MOOC courses use them to advance their careers and are those who already possess a baseline level of education that is higher than the general population (Emanuel, 2013). Thus, counter to expectations, MOOC seems to be reinforcing "the rich get richer" phenomenon by failing to reach the disadvantaged.

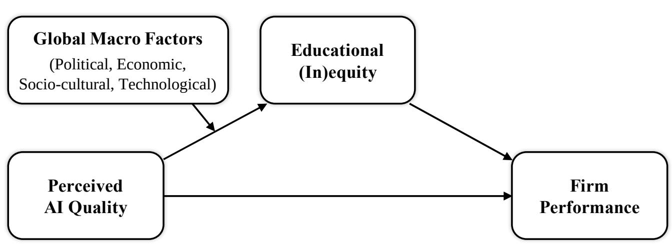

Figure 1. Conceptual Model

Given the above inconsistency between what is believed to be the role of technology in democratizing education and what the results have revealed, how can we reconcile and make sense of this conflict? Is technology not living up to its promise in leveling the playing field in education in terms of accessibility, equity, and affordability? To this end, the goal of this paper is to investigate whether an AI-powered learning app can improve its revenue by increasing educational equity. That is, we conceptualize and empirically test whether educational equity will mediate the relationship between AI and firm performance. Furthermore, we test this from a global perspective by drawing on 35 countries across five continents where the learning app is currently used. Finally, we employ political, economic, social, and technological (i.e., PEST analysis framework) global macro factors as moderators that can shape how AI can differentially influence educational equity (see the conceptual model in Figure 1).

The contribution of this research is threefold. First, while equity theory has been discussed in the IS literature (e.g., Kailash 1989; Trauth and Connolly 2021), only recently has AI been linked to equity (Ravanera and Kaplan 2022; Zhang et al. 2021). However, the intricate linkage between AI, equity, and firm performance has received sparse attention. To this end, this research expands the literature on the interplay between AI, equity, and firm performance.

Second, we show that educational equity is a full mediator between perceived AI quality and firm performance. As perceived AI quality increases, this results in greater educational equity, which in turn leads to higher firm performance. This suggests that social impact in the form of enhanced equity and financial returns can coexist and does not have to be a zero-sum game (Emerson 2003). In fact, our results, at least in the EdTech space, imply that without achieving educational equity, firm performance cannot be realized by improving AI quality alone. From a practical perspective, these results corroborate that achieving DBL as a business strategy is a viable option and that rather than viewing social impact and financial return as parallel paths, firms should work towards the convergence of the two.

Third, we unveil that our mediation effect of educational equity is contingent on the PEST factors. That is, we find support for a conditional indirect (i.e., moderated mediation) effect across the PEST factors. The mediating effect of educational equity was strengthened when the PEST factors were low compared to high. When democracy index (political factor), GDP per capita and government spending on education (economic factor), language and religion (socio-cultural factor)[1], and mobile penetration rate (technology factor) were all low (vs. high), educational equity was a stronger mediator between perceived AI quality and firm performance. These findings suggest that although educational equality is universally important, its role takes on elevated significance and is especially more pronounced under certain global macro factors. For EdTech firms wishing to expand globally, our results suggest priority setting in developing entry strategies for different markets.

The balance of this paper is as follows. We first provide the theoretical background to this research followed by hypotheses development. Subsequently, we explain our main study and the data used to test the hypotheses. We then report our findings and conclude with theoretical and managerial implications.

Literature Review

The relationship between technology innovation and its business impact has been a long-studied topic in the field of IS and other business disciplines (Mithas and Rust 2016). With the prominence of AI in recent years, a rising number of scholarly works has examined how AI affects business efficiency (Lou and Wu 2021), consumer choice (Fügener et al. 2021), employee productivity (Kim et al. 2022), and firm performance (Lui et al. 2021).

However, despite the global call for academia to take part in contributing to equity and fairness, only a handful of work in the IS literature looks into how businesses influence social justice via utilizing technologies, including AI. Some previous works find the positive impact of information technology on social justice, such as improving societal well-being (Ganju et al. 2016) and providing assistance to the economically disadvantaged (Burtch and Chan 2019). Yet, previous literature on social justice and AI has found mixed effects: some show the benefit of AI on equity (Hosny and Aerts 2019, Zhang et al. 2021) while some raise concerns about amplifying existing biases (Zhang et al. 2021).

In the field of education, there also exists a lack of consensus on how utilizing technologies influences inequity among students. While some studies found that accessibility of the technology itself may not guarantee equitable access and opportunities, but rather widen the existing educational accessibility gap (Emanuel 2013, Hansen and Reich 2015), others found that sophisticated technologies such as AI has the potential to resolve the issues that arise from the heterogeneity between learners such as language, culture, motivation, and prerequisite knowledge, and contribute to educational equity (Cheddadi and Bouache 2021, Marras et al. 2022). As AI can be applied across multiple EdTech domains and has the potential to make significant social impact (Gambardella et al 2021), further research on AI and its influence on educational equity is warranted.

[1] For the socio-cultural factor of language and religion, non-English and non-Christianity were classified as low and all others as high.

The inconsistency in the previous literature may be due to the different country-level factors as the impact of AI on educational equity differs depending on global macro factors. The level of scarcity in educational resources has an effect on the input students need to access education, and the output they receive from education (Dobson 1998). For example, if pupil-to-teacher ratio decreases from 100 to 10, the quality of education a student receives (i.e., output) is likely to improve as teachers can allocate more time and effort to each student. Also, the time a student needs in order to ask questions to the teacher (i.e., input) is likely to decrease when there are more teachers available. In other words, the level of resource scarcity is likely to influence the value AI can provide because resource scarcity affects the current state of students' input and output. While the volume of educational resources depends on economic factors such as the income of the household or school district funding (Teachman 1987), global macro factors such as socio-cultural factors also influence the accessibility of educational resources directly (i.e., predominance of North American culture related content) and indirectly via its link to economic factors (i.e., income disparity between ethnic groups). In general, minorities are likely to have less educational resources compared to majorities (Abercrombie et al. 2008). Therefore, how the various global macro factors (e.g., PEST factors) shape the relationship between perceived AI quality and educational equity needs to be further explored.

Furthermore, exploring the link between AI and equity is also critical to businesses, as contributing to equity is closely tied to business performance (Sen and Bhattacharya 2001). With the rising expectation on the responsibility businesses share in reaching social justice (Scheyvens et al. 2016), scholarly work on AI, equity, and business performance may provide meaningful implications to managers and policymakers. Hence, we try to fill the gap in the literature by examining the impact of AI on the firm's double bottom line.

Hypotheses Development

Educational Inequity

The definition of equity is closely related to the framework of fairness and justice. We refer to inequity as the existence of unfair and unjust events between social actors (Colquitt et al. 2001). According to Clemmer and Schneider (1996), there are three dimensions of inequity: distributive, procedural, and interactional. Distributive inequity involves the unjust distribution of outcomes; procedural inequity refers to perceived unfairness in processes (Leventhal et al., 1980); and interactional inequity indicates injustice during interactions (Bies and Moag 1986). Clemmer and Schneider's theory has been applied to many different fields ranging from employee-customer relationships (e.g., Smith et al. 1999) to student-teacher relationships (e.g., Chory-Assad and Paulsel 2004). In this research, we focus on distributive inequity because this particular type of inequity is the most common and relevant in the AI context. We posit that procedural and interactional inequity are less prevalent in AI-human interactions. When users receive AI-powered services, interactional and procedural justice are rarely violated as an AI algorithm (unlike a human) does not discriminate by providing preferential treatment (e.g., more friendly and customer-oriented service) to some but not to others based on their characteristics. This is especially true for AI-powered learning, as students' information such as race and gender are not used in the learning and assessment process, and the outcome (i.e., grades) students achieve can be explained based on the rubrics and answer sheets. Hence, in this research, we focus on distributive inequity in the AI context.

According to equity theory, distributive equity is achieved when fairness in the distribution of outputs compared to inputs is achieved (Adams 1965). In the context of education, inequity exists where there is a disparity in the output-to-input ratio among students. That is, inequity can occur in various forms but broadly in the following three ways: (a) output is constant but input increases compared to other students, (b) input is constant but output diminishes compared to other students, and (c) output diminishes and input increases compared to other students. For example, distributive inequity can occur when one student needs to invest more input (i.e., time, effort, money) to gain access to a similar quality of education compared to other students (Fleurbaey et al. 2002). For example, a student living in a rural area may have to drive an hour to attend class while a student living in an urban area only needs to drive ten minutes to get to class. In this case, there exists educational inequity due to geographic barrier, as these students' input to output ratios are different.

Educational inequity occurs when there exists a scarcity of educational resources that are not evenly distributed among students (Dobson 1998). In the previous example, educational inequity occurs as schools are relatively scarce in rural areas compared to urban areas. Thus, building more schools will lead to an equal amount of input across students (i.e., a ten-minute drive to class for both students in urban and rural areas) that can address educational inequity. AI-powered learning levels the playing field and adjusts the imbalance in distributive injustice by allowing both students to study at home (input lowered) and providing higher quality education (output raised).

Perceived AI Quality and Educational Inequity

We apply the 5A framework–the five benefits that AI-powered learning provides (Affordability, Actionability, Accommodability, Assurance, Accessibility)–to examine how AI-powered learning contributes to lowering educational inequity. With an increase in efficiency and productivity, AI-powered learning mitigates educational inequity by reducing the disparities in the costs/efforts (input) as well as improving the quality of education (output) to disadvantaged students.

	Low AI-powered learning	High AI-powered learning
Input	**Low Affordability** (High Cost) **Low Actionability** (Delay in receiving feedback)	**High Affordability** (Cost friendly) **High Actionability** (Instant gratification)
Output	**Low Accommodability** (Inflexible learning path) **Low Assurance** (Less relevant and more variability in content/feedback) **Low Accessibility** (Limited access to quality education)	**High Accommodability** (Adaptive learning path) **High Assurance** (Competent, consistent, and accurate outcome) **High Accessibility** (Enhanced access to quality education)

Table 1. Impact of AI-powered Learning on Students' Input/Output Ratio

Table 1 illustrates how AI-powered learning influences educational equity by mapping the 5As into the input-output ratio of equity theory. Considering AI's negligible marginal cost (Hosny and Aerts 2019), we expect that the affordability of AI-powered learning will increase as AI quality improves. Further, as human inputs are no longer needed, students benefit from the high actionability as they can receive instant gratification at their demand. Furthermore, AI quality positively affects the level of personalization and reliability of the AI-driven solutions. As accommodability and assurance improve student engagement and learning outcomes (Luckin et al. 2016), we expect output (i.e., educational quality) to increase as AI quality improves. Moreover, AI advancement enriches students' access to educational content and assistive technology, leading to a further increase in output.

Although we expect that AI advancement will reduce input and increase output for students, we assert that the impact of AI quality differs between socially disadvantaged and not disadvantaged students due to the prevailing disparities in resource distribution. Due to disparities in educational opportunities and income, the relative cost of education is much higher for socially disadvantaged students. Thus, similar to our previous example of students from rural and urban areas, AI-powered learning will mitigate the disproportionate input/output ratio between students. Hence, we expect that an increase in perceived AI quality will mitigate educational inequity by providing personalized assistance to disadvantaged students.

H1: *As perceived AI quality increases, educational inequity decreases.*

Educational Inequity and Business Performance

Promoting educational equity entails diversifying an EdTech firm's customer base by catering to formerly underserved market segments, such as socially and economically underprivileged students. In light of this, achieving educational equity may not always serve the goal of increasing a firm's revenue because these markets tend to have lower purchasing power. Moreover, attempts to serve multiple market segments may result in a rise in the firm's operational costs as well as negative externalities, since the student learning environment becomes more congested.

Notwithstanding, we anticipate that the performance of AI-powered EdTech firms will increase by mitigating educational inequity. First, owing to the characteristics of AI, serving more underprivileged students will not create congestion and drive out students that were previously served, but will lead to customer expansion. AI enables businesses to service customers at scale and with near-zero operational expenses (Rifkin 2014). For EdTech firms, AI can offer educational services on a broad scale at minimal cost because educational content may be provided with little human intervention (Rifkin 2014). In addition, an increase in customer base will not be subject to negative externalities (Wu and Banker 2010); rather, existing users of the AI-powered learning service may benefit from the increase in customer base, as more data points will be generated and stored, thereby improving the performance and efficacy (e.g., enhanced training) of AI algorithms (Argenton and Prüfer 2012). Also, tailoring to serve the needs of different customer segments in AI-powered services is less costly compared to traditional services. For example, an AI translator allows an EdTech company to serve students in multiple different languages without much increase in their operational cost compared to non-AI approaches.

Second, socially and economically underprivileged students, who are often dissatisfied with the quality of traditional education (Young 1969), are likely to use AI-powered learning more frequently compared to privileged students. As accessibility influences perceived value positively (Swoboda et al. 2013), underprivileged students are likely to be more satisfied with AI-powered learning in developing countries, where there is a limited selection of education services and the market is therefore less competitive (Reutskaja and Hogarth 2009). Since satisfaction is a key determinant of customers' persistent service usage behavior (Chou et al. 2013), we argue that mitigating educational inequity increases firm performance by increasing continued usage of its services.

Furthermore, we expect that EdTech firms will be able to monetize improved educational equity through in-app advertisement revenue. The population in developing countries is about five times greater than the population in developed countries (Haub 2008). With in-app ads, a large market size implies an increase in the quantity of ads that can be shown. Therefore, similar to Walmart's low-price high-volume strategy (Blanchard et al. 2008), AI-powered EdTech firms may generate additional revenues through the expansion of their customer base and their engagement while simultaneously contributing to educational equity.

In conclusion, we anticipate that the performance of AI-powered EdTech firms will increase by mitigating educational inequity because the expansion of the customer base will generate more revenue due to AI-powered service's scalability as well as its near-zero marginal cost of serving additional students.

H2: *As educational inequity decreases, AI-powered learning firms' revenue increases.*

Many AI-powered learning firms are startups whose goal is to improve the efficiency of their AI-based algorithm to generate revenue. However, empirical support between AI quality and firm performance is not clear as many AI-based startups have yet to experience revenue generation. In this research, by integrating the prior two hypotheses (i.e., perceived AI quality's impact on educational equity and educational equity's impact on firm performance) we posit that educational equity is a conduit between perceived AI quality and firm performance. Thus, we expect a positive mediating role of educational equity between AI perceived quality and firm performance.

H3: *Educational equity positively mediates the relationship between perceived AI quality and firm performance.*

Moderating Effect of Global Macro Factors

We posit that the impact of perceived AI quality on mitigating educational inequity is stronger in countries with more scarcity in educational resources compared to countries with relatively abundant educational resources. Therefore, we study the moderated mediation (i.e., conditional indirect) effect by examining how various global macro factors can shape the relationship between perceived AI quality and educational equity and thus influence the indirect path between perceived AI quality and firm performance. Specifically, we employ the PEST (Political, Economic, Socio-cultural, and Technological) analysis framework as a structured approach for categorizing countries based on each of the four dimensions of PEST.

Political: The scarcity of high-quality educational resources is linked to political factors such as political regimes and political institutions (Cooray and Potrafke 2010). Previous literature finds that countries under autocratic regimes do not invest in education as the educated middle class will seek democratic governance with transparency and accountability (Welzman 2010). Furthermore, the political regime is related to the quality of the institution. Under a democratic regime, institutional quality is high as the system monitors government officials and political elites (Acemoglu et al. 2005). As institutional quality positively affects educational quality (Fomba et al. 2022), we expect that students in countries with a non-democratic regime to have limited access to high quality educational resources. As educational scarcity amplifies the positive effect of perceived AI quality on educational equity, we expect that the indirect path from perceived AI quality to firm performance strengthens in countries with democratic systems compared to those with non-democratic regimes.

Economic: Economically developed countries have better educational resources compared to developing countries. The relationship between educational resource quality and economic factors is evident, as educational resources such as teacher quality are directly linked to school funding (Akiba et al. 2007). Further, insufficient government spending on education shifts the cost of education to households, which is another economic barrier to access to education (UNESCO 2019). As the level of economic resources is directly linked to the level of educational resources, we expect that students from economically less developed countries who have fewer educational alternatives (e.g., private tutoring, cram schools) may benefit disproportionately more from an increase in AI quality, thus further reducing inequity. Thus, we expect a moderated mediation effect whereby the indirect relationship between perceived AI quality and firm performance will be strengthened in countries that are less (vs. more) economically developed.

Socio-Cultural: The UN classifies minorities based on people's nationality, ethnicity, religion, and language (United Nations Minorities Declaration of 1992), and these factors are closely related to the socio-cultural aspects of students. Socio-cultural factors are closely tied to the amount and quality of educational resources. For example, English-speaking students have relatively abundant educational resources compared to non-English-speaking students as most research articles and online educational resources such as MOOC are provided primarily in English (Emanuel 2013). Other aspects such as religion and culture based on nationality and/or ethnicity also influence the amount of educational resources available to students (Kizilcec et al. 2017). For example, students often feel more comfortable and are able to relate more when reading passages about their own cultural rituals compared to other cultures that they are less familiar with. In sum, socio-cultural minorities have relatively scarce educational resources compared to socio-cultural majorities. Hence, the impact of perceived AI quality on educational equity will be amplified in countries that are socio-culturally minor and thus the indirect path between AI quality and firm performance will be strengthened in countries that are socio-culturally minor (vs. major).

Technological: Technological barriers such as lack of access to ICT significantly limit the quantity and quality of educational resources (Evans and McIntyre 2014). For example, students who share a computer with their families are likely to have limited access to educational resources compared to students who have their own laptop. Hence, AI's personalization and efficiency will have a stronger impact on the input of students with limited technology access compared to the input of students with ample technology access. Therefore, we expect that the indirect path between AI quality and firm performance is strengthened in countries with technological barriers compared to countries without technological barriers.

In sum, we expect that students from countries with low (vs. high) global macro factors will experience a stronger (vs. weaker) mediation effect of educational equity.

H4a: *The indirect path between perceived AI quality and firm performance is stronger in countries with low political factors compared to countries with high political factors.*

H4b: *The indirect path between perceived AI quality and firm performance is stronger in countries with low economic positions compared to countries with high economic positions.*

H4c: *The indirect path between perceived AI quality and firm performance is stronger in countries that are socio-culturally minor compared to countries that are socio-culturally major.*

H4d: *The indirect path between perceived AI quality and firm performance is stronger in countries with low technological resources compared to countries with high technological resources.*

Data

We partnered with a global AI-powered learning platform to collect data. The focal app provides supplementary learning and guidance primarily on math education for K-12 students. Its core service is two-fold: (1) problem search and (2) 1:1 Q&A with a tutor. For problem search, students can take and upload a photo of a math problem they need help with, and the focal app utilizes advanced AI techniques such as deep learning and optical character recognition to intelligently retrieve and provide line-by-line explanations and solutions within a few seconds at no cost. When students are unable to find solutions for the problems asked or need additional help, the focal app can connect students to human tutors so that students can ask questions in real-time at a modest fee (about $1 USD). The company has a strong global presence, solving more than 3.1 billion problems for over 50 million students from 200 different countries in nine different languages.

The data span from January 2019 to December 2021 and contain information on individual-level student app activities such as access, problem search, and asking questions to tutors, along with transactional information including timestamp, IP address, language versions used, and in-app purchases. The quality of solutions students receive from the app is also available in terms of student's perceived helpfulness (i.e., whether the provided solutions were helpful or not) and algorithm-generated similarity score between the question asked by the student and the solutions provided by the app (i.e., a larger similarity score implies a greater relevant match). In this study, we focus on the students' activities from the top-35 countries with the largest number of users, as our variable of interest—educational inequity—exhibits how users' access counts to the focal app are distributed unevenly across provinces within a country. Therefore, it is not suitable to include countries where the focal app has limited geographic coverage and thus we exclude countries with less than 200 users, resulting in observations of around 45 million users from 35 countries. The sample countries come from all five continents (i.e., Africa, North/South America, Asia, Australia, and Europe) including Argentina, Australia, Bangladesh, Brazil, Canada, Chile, China, Colombia, Ecuador, Egypt, Germany, Hong Kong, India, Indonesia, Iran, Iraq, Japan, Laos, Malaysia, Mexico, Nepal, Nigeria, Pakistan, Peru, Philippines, Saudi Arabia, South Africa, South Korea, Spain, Taiwan, Thailand, United Arab Emirates, United Kingdom, United States, and Vietnam.

Variable Operationalization

As our focal variable, educational inequity, is calculated at the country-month level to reduce potential noise in the access data, all other variables in the data are operationalized and aggregated at the country-month level as well. We also note that some of the variables, especially the PEST factors, are measured and reported only on a monthly basis.

Educational inequity: The Gini coefficient is commonly used to measure the unequal distribution of income in economics. In the field of education, the Gini coefficient is often applied at the group level (i.e., country) to measure the disparities of education within a group, such as impartiality in years of schooling and attainment (UNESCO 2019). In this study, we calculate the Gini coefficient with students' app access data to measure the degree of unequal app access at the country-month level. To obtain the Gini coefficient, we use the following procedure:

1. Aggregate the monthly access count per province (or state) within a country and normalize it with the population count.
2. Draw the Lorenz curve (i.e., a plot of the cumulative access counts against the population within a country) by sorting the provinces from the lowest to the highest access counts.
3. Compute the access Gini coefficient at the country-month level by calculating the ratio of the area between the 45-degree line and the Lorenz curve (A/A+B in Figure 3)
4. Transform the access Gini coefficient into an equity measure by calculating the ratio of access Gini coefficient over income Gini coefficient

The access Gini coefficient measures the degree of unequal app access across provinces. Similar to the income Gini coefficient, the access Gini coefficient ranges from 0 (complete equal distribution of access counts across provinces) to 1 (maximum inequality where the access counts come from a single province).

We further develop an (in)equity measure from the access Gini coefficient, by taking the ratio of the access Gini coefficient over the income Gini coefficient collected from the World Bank. Disparities in access to education are affected by income inequality. Hence, we normalize the access Gini coefficient relative to the income Gini coefficient. Using this ratio also enables us to examine the cross-country effect of educational inequity without the impact of different levels of income disparities between countries. Furthermore, controlling for income disparities better reflects the term 'equity', as it concerns the disproportionate nature of circumstances such as income. In this regard, we believe a ratio of the access over income Gini better exhibits educational inequity. Under this operationalization, a ratio larger than 1 implies that the access count is distributed more unevenly than the income, and a ratio smaller than 1 indicates that the access count is distributed more evenly compared to the income.

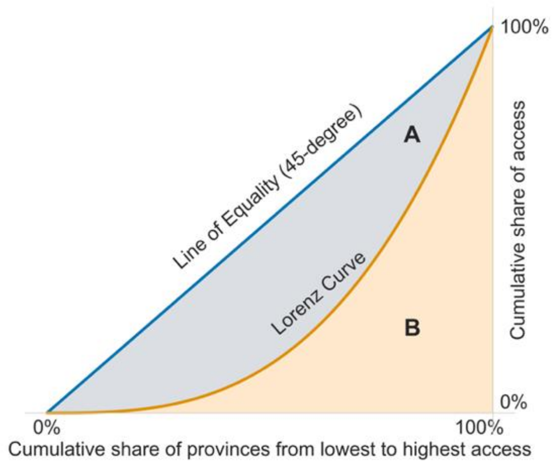

Figure 3. Graphic Illustration of the Gini Coefficient

Perceived AI quality: Due to its intangible nature, it is difficult to objectively measure the quality of AI-powered services (Asubonteng et al. 1996). Because perceived service quality is a function of service performance (Bolton and Drew 1991), we posit that perceived AI quality reflects the performance of AI technology. We operationalize perceived AI quality as students' perception of the helpfulness of the solutions received from their problem search because helpfulness is one of the dimensions that reflect information quality (Wang and Strong 1996). The focal app randomly selects students after their search sessions to ask whether the solutions they have received were helpful or not. We average this rate at the country-month level to represent perceived AI quality.

Firm revenue: As explained previously, the service of the focal firm is two-fold: search at no cost and 1:1 Q&A with a tutor at a fee. When students are using the search service, they are briefly exposed to an ad while a search result is being retrieved. Therefore, firm revenue at the country-month level is operationalized in two different ways: (1) total search count in a given month from a particular country, which serves as a proxy for ad revenue; and (2) total coin spent on Q&A service, which serves as a proxy for in-app sales. We aggregate the variables at the country-month level and take the log in our analysis.

Global macro factors: As mentioned in the above section, we adopt the PEST framework to examine the impact of macro-environmental factors that condition the relationship between AI-powered learning, inequity, and firm revenue. We operationalize PEST with six different measures from four distinct categories: (1) democracy index for the political factor, (2) GDP per capita and (3) government spending on education for the economic factor, (4) language and (5) religion for the socio-cultural factor, and (6) mobile penetration rate for the technological factor.

Specifically, to measure the political factor, we utilize the 2020 Democracy Index assessed yearly by Economist Intelligence Unit. The Democracy Index measures the state of democracy in over 160 countries. The index ranges from 0 to 10, with lower scores suggesting countries similar to authoritarian regime and higher scores suggesting countries resembling a full democracy regime (Economist Intelligence Unit 2020). 2020 GDP per capita (in USD) and the 2019 government spending on the education sector as a percentage of GDP are collected from World Bank and reflect the economic factor of a country. To measure the socio-cultural factor, we utilize the language and religion of the sample countries from Britannica. And lastly, 2020 mobile cellular subscriptions per 100 people from World Bank is used as a proxy for the technological factor. Our sample is representative, as the median of the sample countries is indifferent from the median of the world countries.

After collecting the six measures for the PEST factors, we took a median-split of the sample countries for each measure: 1 for countries with a low level of macro factors and 0 for countries with a high level of macro factors. For socio-cultural factors, we code 0 as non-English speaking, non-Christian countries as English and Christianity are the majority groups.

Controls: We include country-level fixed effects and month-level fixed effects in our analyses to control for unobserved country-specific and time-varying effects, respectively. As noted previously, the focal app provides services in nine different languages (i.e., locales) and firm-led interventions (e.g., marketing or promotional activities) differ between these locales. Thus, we also add locale-month level fixed effects to control for the firm's input.

In sum, our final data includes 1,245 country-month level observations. Summary statistics of the data are presented in Table 2.

Variables	Mean	Std. Dev.	Min	Max
Precision rate[1]	0.631	0.120	0.296	0.844
Access/Income Gini	1.626	0.598	0.298	2.881
Log(Search)	8.557	3.796	0	18.435
Log(Coin)	9.821	6.195	0	21.667
Democracy[2]	0.488	0.507	0	1
GDP[2]	0.543	0.505	0	1
Ed-spending[2]	0.486	0.507	0	1
Christianity[2]	0.571	0.502	0	1
English-speaking[2]	0.800	0.406	0	1
Mobile penetration[2]	0.514	0.507	0	1

Note: Variables are in country-month level (N=1245). [1] Calculated at a locale-month level to protect data confidentiality (N=252). [2] Country-level binary indicator stating 1 for lower-than-median, non-Christianity, and non-English-speaking countries and 0 otherwise (N=35). Std. Dev., standard deviation.

Table 2. Summary Statistics

Analysis and Results

Our conceptual model hypothesizes the mediating role of educational equity from perceived AI quality to firm revenue and the moderating role of global macro factors that condition the link between perceived AI quality and educational equity. To test our model, we perform mediation and moderated mediation analysis using PROCESS. We estimate the indirect effects of educational inequity by bootstrapping at the 95% confidence level (Hayes 2018).

Mediation Analysis

The mediation analysis examines H1 through H3 and its results are presented in Table 3. As seen in model 1 of Table 3, perceived AI quality is negatively related to educational inequity, in support of H1. Model 2 also shows a relationship between educational inequity and firm revenue for both search counts (free usage) and coin (in-app purchase), supporting H2. In other words, an increase in perceived AI quality mitigates educational inequity, and a decrease in educational inequity leads to positive firm revenue. Furthermore, we also examine the indirect effect of educational inequity through mediation analysis. The last row of Table 3 shows that there exists a positive significant indirect effect from perceived AI quality to firm revenue through educational inequity, in support of H3. One notable finding is that firms gain revenue from searching directly from improved AI, but purchase revenue is earned only through mitigating educational inequity (i.e., full mediation). This suggests that as students are satisfied with the search solutions, they are less likely to consume tutoring services. In sum, our results support H1 through H3, and provide evidence of AI's role in contributing to the double bottom line – it enables firms to realize financial returns with a purpose.

Robustness Checks

We perform some additional analysis to test the robustness of our results. First, we validate our variable operationalization by utilizing alternative measures as proxies for educational inequity and AI quality. For educational inequity, we test our hypothesis with access Gini, access Atkins' ratio, and the ratio of access Gini to income Gini where we calculated the income Gini coefficient with province-level per capita GDP. Also, we employ a similarity score, which is an objective AI quality measure that assesses the similarity between the questions asked and the solutions provided, as an alternative to perceived AI quality. Next, to mitigate endogeneity concerns, we perform additional analysis with lagged perceived AI quality. There can be concerns about the possibility of reverse causality in firms' investment-revenue relationships (Rubera and Kirca 2012), as firms with high revenue have more to reinvest to improve business efficiency and thus increase future revenue. In the case of AI-powered learning, one possible cause of endogeneity may be that firms with high revenue continuously invest in improving their AI technologies, leading to reverse causality concerns. To mitigate this endogeneity concern, we use lagged perceived AI quality following Brynjolfsson and Hitt (1996). Our results in Table 4 are robust to all of these alternative variables.

Model 1: X → M		
M	Ed inequity Acc/Inc Gini	
AI-quality	-0.255*** (0.086)	-0.255*** (0.086)
R^2	0.339	0.339
Model 2: X + M → Y		
Y	Log(search)	Log(coin)
AI-quality	0.953*** (0.215)	0.127 (0.351)
Ed inequity	-0.366*** (0.075)	-0.543*** (0.122)
Controls	Country, Month, Locale-month	Country, Month, Locale-month
R^2	0.288	0.448
N	1200	1200
Test for Mediation		
Indirect Effect	0.093*** (0.037)	0.139*** (0.057)

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust bootstrapping test for mediation, with bootstrapped standard error in parenthesis.

Table 3. Mediation Analysis Results

	Alternative M				**Alternative X**		**Lagged X**	
	Access Gini	Access Atkins	Access Gini	Access Atkins	Similarity score	Similarity score	Lag(prec_ rate)	Lag(prec_ rate)
Model 1: X → M								
AI-quality	-0.071** (0.031)	-0.066* (0.035)	-0.071** (0.031)	-0.066* (0.035)	-0.252* (0.136)	-0.252* (0.136)	-0.257** (0.085)	-0.257** (0.085)
R^2	0.341	0.341	0.341	0.341	0.334	0.334	0.333	0.333
Model 2: X + M → Y								
Y	Log(search)	Log(search)	Log(coin)	Log(coin)	Log(search)	Log(coin)	Log(search)	Log(coin)
AI-quality	0.960*** (0.214)	0.959*** (0.212)	0.128 (0.348)	0.133 (0.346)	1.423*** (0.345)	-0.045 (0.556)	0.740*** (0.202)	0.161 (0.363)
Ed inequity	-1.210*** (0.210)	-1.325*** (0.181)	-1.927*** (0.342)	-2.0142*** (0.295)	-0.414*** (0.075)	-0.559*** (0.121)	-0.362*** (0.078)	-0.630*** (0.140)
R^2	0.299	0.307	0.452	0.459	0.271	0.4461	0.347	0.379
N	1200	1200	1200	1200	1242	1242	1157	1157
Test for Mediation								
Indirect Effect	0.086** (0.037)	0.087* (0.049)	0.137** (0.059)	0.133* (0.077)	0.104* (0.056)	0.141* (0.080)	0.159** (0.051)	0.307*** (0.104)

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust bootstrapping test for mediation, with bootstrapped standard error in parenthesis. Country, month, and local-month fixed effects are included.

Table 4. Robustness Checks

Moderated Mediation Analysis

In addition to the mediation analysis, we perform a moderated mediation analysis to test the effect of global macro factors on the relationship between perceived AI quality and firm revenue. We present the results from six different models utilizing six PEST variables as moderators. Table 5 column (1) shows the positive conditional indirect effect (CIE) of countries with low democracy index countries, in support of H4a. Table 5 columns (2) and (3) present positive conditional indirect effects on countries with low economic factors for both GDP per capita and education spending as moderators, hence supporting H4b. Results in Table 5 columns (4) and (5) show that socio-cultural factors, language, and religion, also have moderating effects, as shown in the positive conditional indirect effects on non-English speaking and non-Christianity countries. Lastly, Table 5 column (6) does not show any significant conditional indirect effect of technological factors, counter to H4d. In sum, in line with our hypotheses, our results show that countries with low macro factors have stronger mediation effects on educational inequity, except for the technological factor.

Post-hoc analysis: As all of our moderated mediation hypotheses except for H4d are supported, we examine the variable mobile penetration to probe for potential explanations. As the median cellular prescription rate exceeds 100 in our sample, which means that some of the countries below the median cellphone penetration rate have more than 100% mobile coverage, we perform a post-hoc analysis using the cut-off point as 100 to better represent the technological barrier. Table 5 column (7) shows the results from the model when countries under 100% of the cellular penetration rate are classified as low technology countries. The results are then in line with H4d, with a positive conditional indirect effect on countries with low mobile penetration rates.

Moderated Mediation							
	Political	Economical		Socio-Cultural		Technological	
Moderator	Democracy	GDP	Ed-spending	Christianity	English-speaking	Mobile penetration	Mobile[1] (<100)
AI-quality	0.059 (0.115)	0.322*** (0.104)	0.231** (0.115)	0.198 (0.117)	0.691*** (0.199)	-0.234 (0.130)	0.003 (0.103)
Moderator	0.464*** (0.027)	0.357*** (0.033)	0.294*** (0.031)	0.485*** (0.037)	0.688*** (0.034)	0.102 *** (0.033)	0.051 (0.034)
Interaction	-0.288** (0.145)	-0.874*** (0.168)	-0.790*** (0.155)	-0.687*** (0.158)	-1.002*** (0.212)	-0.059 (0.167)	-0.792*** (0.180)
R^2	0.483	0.388	0.402	0.438	0.526	0.351	0.353
Test for Moderated Mediation (DV: Search)							
CIE at High	-0.022 (0.047)	-0.118*** (0.049)	-0.085** (0.045)	-0.073** (0.046)	-0.253*** (0.081)	0.086 (0.053)	-0.001 (0.038)
CIE at Low	0.084*** (0.034)	0.202*** (0.066)	0.205*** (0.057)	0.179*** (0.051)	0.114*** (0.035)	0.107** (0.043)	0.289*** (0.081)
Moderated Mediation Index	0.105** (0.058)	0.320*** (0.097)	0.289*** (0.084)	0.251*** (0.078)	0.367*** (0.102)	0.022 (0.060)	0.290*** (0.091)
Test for Moderated Mediation (DV: Coin)							
CIE at High	-0.032 (0.071)	-0.175** (0.074)	-0.126** (0.069)	-0.108** (0.070)	-0.376*** (0.128)	0.127 (0.080)	-0.002 (0.057)
CIE at Low	0.124** (0.053)	0.300*** (0.102)	0.304*** (0.092)	0.265*** (0.081)	0.169*** (0.056)	0.159** (0.067)	0.429*** (0.129)
Moderated Mediation Index	0.156** (0.091)	0.475*** (0.151)	0.429*** (0.136)	0.373*** (0.124)	0.545*** (0.165)	0.032 (0.091)	0.431*** (0.143)

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust bootstrapping test for mediation, with bootstrapped standard error in parenthesis. Country, month, and local-month fixed effects are included. CIE, conditional indirect effect.

Table 5. Moderated Mediation Effect of PEST

General Discussion

The purpose of this paper was to examine the mediating role of educational equity between perceived AI quality and firm performance in the EdTech context. We examined this through a global study based on 35 countries across five continents. Our findings strongly support an indirect effect between perceived AI quality and firm performance such that financial returns from perceived AI quality can be achieved by promoting educational equity and that such an indirect effect is moderated by PEST global macro factors.

We now discuss the theoretical and practical implications of our results to the IS literature followed by limitations and directions for future research.

Theoretical Contribution

We contribute to theory advancement in IS research by examining the intersection between AI and equity that 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. Equity/fairness research has received limited attention in IS, let alone how equity relates to AI (Kailash 1989; Trauth and 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 and Kaplan 2022; Zhang et al. 2021). Our results reveal that perceived AI quality can significantly improve educational inequity (or mitigate educational inequity) by expanding accessibility to underrepresented and marginalized students. Although there have been much anecdotal evidence and abundance of voice raised from educators, policymakers, and parents on the need to better utilize technology to enhance equity to students from marginalized backgrounds especially in challenging times such as during the global COVID pandemic, there have been a paucity of empirical evidence to support such claims. Our research provides first hand results based on data that span over 35 countries in five continents to corroborate the power of AI in the EdTech context to increase educational equity.

Second, the present study elevates equity research from individual level to 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 and Lee 2020), 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. Although most equity research at the individual level has relied on surveys, our measure of educational inequity was a derived metric at the country level by taking the ratio of access Gini coefficient over income Gini coefficient using observed data. While equity through a survey lens can be susceptible to bias and subjectivity, our operationalization of equity provides a more objective metric that is less vulnerable to idiosyncratic individual differences. Furthermore, our study takes initial steps to advance equity research in education from the current dominant within country analysis approach to a nascent between country analysis approach.

Third, our findings contribute to the social return on investment (SROI) literature (e.g., Rauscher et al. 2012) by providing empirical evidence that social impact and financial return can coexist and does not have to be a zero-sum game in the EdTech sector. As Emerson (2003, p. 37) states, "In truth, the core nature of investment and return is not a tradeoff between social and financial interest but rather the pursuit of an embedded value proposition composed of both." Although profit maximization from a pure capitalistic perspective may be an appealing value proposition, many established big enterprises let alone entrepreneurial startups are pursuing ambidexterity by focusing on not only financial returns but also social impact. Thus, an "and" rather than an "either or" strategy, is gaining traction as evidenced by firms that are transforming their business model from a bottom line (BL) to a double bottom line (DBL) strategy. Our findings are in line with this movement in that educational equity was a full mediator that channeled the effect of perceived AI quality on firm performance. Educational equity as a full mediator is significant from a theoretical perspective because this suggests that perceived AI quality alone cannot positively influence firm performance but must be mediated by educational equity. The presence of educational equity as a mediator in the AI context is a novel finding as this extends current research on the role of AI in contributing to mitigating inequity. Although early writing has taken a piecemeal approach by maintaining that AI can improve equity and that AI can be the next frontier in improving firm performance, scant empirical support from a holistic perspective can be found on (a) how AI, equity, and performance are linked together and (b) what the underlying mechanism is that ties AI to firm performance. Our research provides insights into these two areas of scholarly inquiry.

Last but not least, we find strong support for a conditional indirect effect. That is, the strength of the mediating role of educational equity depends on macro global factors that can be summarized into the PEST framework. We show that educational equity is stronger when democracy index (political factor), GDP per capita and government spending on education (economic factor), language and religion (socio-cultural factor), and mobile penetration rate (technology factor) are all low (vs. high). Such results add another layer of richness and nuance to the mediation effect by disclosing that when global macro factors are low (vs. high), the effect of perceived AI quality on educational equity is more pronounced, resulting in a stronger mediating role of educational equity (i.e., moderated mediation effect).

Affordance theory in the IS literature may provide a potential explanation as to why students from countries that are low (vs. high) on PEST experience greater equity from advancement in AI. According to affordance theory, affordance refers to "what is offered, provided, or furnished to someone or something by an object" (Volkoff and Strong 2013). One of the core tenets of this theory underscores how the "same" affordance (i.e., the AI-powered learning app in this research) is used to different degrees in different contexts or by those with different needs (Majchrzak, Markus, and Wareham 2016). For example, a tree can provide shade, shelter, food, or energy when used for combustion. Although the affordance itself is the same and invariant, the value provided can differ depending on the need of the user. We posit that students from countries that are low on PEST will perceive more value (e.g., economic, social, and educational) from an AI powered learning app compared to students from countries that are high on PEST. We reason this to be the case because students from countries that are low (vs. high) on PEST will find the affordance to be more appreciative and valuable, consistent with the scarcity effect. Furthermore, since other alternative competing supplementary learning opportunities outside of the classroom (e.g., private tutoring) will be more limited in countries that are low (vs. high) in PEST, we also expect structural and supply scarcity to contribute to greater perceived value to students. Therefore, AI has a greater impact on improving equity in countries that are low (vs. high) on PEST, resulting in the supported conditional indirect effect.

Managerial Implications

Millennials and Generation Z customers may find firms that pursue a double bottom line strategy to be more appealing. Younger and more educated customers may resist firms that are purely interested in profit motives and yearn for firms that are socially active. Given the many social active movements (e.g., Black Lives Matter and #MeToo) in today's society, the pursuit of equity can send a clear and potent signal to customers about the mission and value of the company. Such a signal can be effective not only for attracting customers but also for hiring purposes as well. Firms that push the needle on equity in the marketplace can attract and retain talented employees that share the company's mission, contributing to building a cohesive corporate culture.

Our results can also 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 increasing equity from AI advancement. Another strategy that is conceivable is whom to target for ad placements on the AI platform. Based on our findings, we suggest showing ads of brands with a well-known public image of supporting DEI (diversity, equity and inclusion) initiatives in the local market.

Furthermore, managers need to be cognizant of the potential risk of increasing equity that can have on brand image. Firms should consider the conceivable trade-off between providing greater accessibility and the negative impact equity can exert on brand image. What was once a premium brand can be perceived in the market as a mass brand due to the greater usage from marginalized customers who were once noncustomers. Therefore, managers should judiciously weigh the pros and cons of improving equity before embarking on such an endeavor.

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 MIS system and consider a Social Management Information System (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, as was alluded previously, AI is not a panacea. 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. Governance structures and auditing systems are still in its infancy and there is no widely accepted standard in the industry. This is however changing in the US with the recent Algorithmic Accountability Act introduced in 2019 that mandates big corporations to evaluate their algorithms for bias and discrimination. Building on the momentum from the EU's General Data Protection Regulation (GDPR) established in 2018, similar efforts in AI are underway in the EU as well to create an Artificial Intelligence Act, the first legal framework on AI by a major regulator. We encourage managers to be well informed on not only what AI can do but also on what unintended consequences it can evoke in order to effectively navigate the challenging contours of the Fourth Industrial Revolution.

Limitations and Future Research Directions

This study is encumbered with a few limitations that can be addressed in future research. First, though our study includes representative countries from all continents, its coverage was defined by the global penetration rate of the focal app. Expanding the list of countries would help solidify the generalizability of our findings and uncover any potential edge cases. Second, given that many AI-based companies including those in EdTech are startups, their valuation by external stakeholders or investors are crucial for future growth. This begs the question of whether such startups should target social equity investors or private equity investors or two both to maximize funding opportunities. With the increasing trend and call for social enterprise and socially responsible investing, future research could study how perceived AI quality and inequity affects a firm's valuation. Third, our unit of analysis is at the country-month level across multiple countries. Delving into a more focused region- or country-specific context would help unravel in-depth case studies that awaits further research.

Conclusion

This research contributes to the IS literature by synthesizing AI and equity in the EdTech sector. Our results support educational equity as a full mediator between perceived AI quality and firm performance and that this indirect effect is moderated by global macro factors based on the PEST framework. This research corroborates the increasing voice in academia and practice about the importance and feasibility of pursing the double bottom line. Our study shows that this is indeed a viable strategy by leveraging the power of AI to mitigate inequity, thereby leading to increased firm performance. We hope that our work motivates future studies to further examine how and when AI can result in diminishing inequity in other industries beyond EdTech.

References

Abercrombie, L. C., Sallis, J. F., Conway, T. L., Frank, L. D., Saelens, B. E., and Chapman, J. E. 2008. "Income and racial disparities in access to public parks and private recreation facilities," *American Journal of Preventive Medicine* (34:1), pp.9-15.

Acemoglu, D., Johnson, S., and Robinson, J. A. 2005. "Institutions as a fundamental cause of long-run growth," *Handbook of Economic Growth* (1), pp. 385-472.

Adams, J. S. 1965. "Inequity in social exchange," *Advances in Experimental Social Psychology* (2), pp. 267-299. Academic Press.

Akiba, M., LeTendre, G. K., & Scribner, J. P. 2007. "Teacher quality, opportunity gap, and national achievement in 46 countries," *Educational Researcher*, (36:7), pp.369-387.

Argenton, C., and Prüfer, J. 2012. "Search engine competition with network externalities," Journal of Competition Law & Economics (8:1), pp. 73-105.

Asubonteng, P., McCleary, K. J., and Swan, J. E. 1996. "SERVQUAL revisited: a critical review of service quality," *Journal of Services Marketing*.

Bacher-Hicks, A., Goodman, J., and Mulhern, C. 2021. "Inequality in household adaptation to schooling shocks: Covid-induced online learning engagement in real time," *Journal of Public Economics* (193), 104345.

Bies, R.J. and Moag, J.F. 1986. "Interactional Justice: Communication Criteria of Fairness," *in Research on Negotiations in Organizations* (1) Lewicki, R.J., Sheppard, B.H. and Bazerman, M.H., (eds.), JAI Press, Greenwich, pp.43-55.

Blanchard, C., Comm, C. L., and Mathaisel, D. F. 2008. "Adding value to service providers: benchmarking Wal-Mart," *Benchmarking: An International Journal* (15), pp. 166-177.

Bolton, R. N., and Drew, J. H. 1991. "A multistage model of customers' assessments of service quality and value," *Journal of Consumer Research*, (17:4), pp.375–384.

Brynjolfsson, E., and Hitt, L. 1996. “Paradox lost? Firm-level evidence on the returns to information systems spending,” *Management science* (42:4), pp.541-558.

Burtch, G., and Chan, J. 2019. “Investigating the relationship between medical crowdfunding and personal bankruptcy in the United States: Evidence of a digital divide,” *MIS Quarterly* (43:1), pp. 237-262.

Cheddadi, S., and Bouache, M. 2021. “Improving Equity and Access to Higher Education Using Artificial Intelligence,” in *Proceedings of the 16th International Conference on Computer Science & Education (ICCSE),* IEEE, pp. 241-246.

Chory-Assad, R. M., and Paulsel, M. L. 2004. “Antisocial classroom communication: Instructor influence and interactional justice as predictors of student aggression,” *Communication Quarterly* (52), pp.98-114.

Chou, C. H., Chiu, C. H., Ho, C. Y., & Lee, J. C. (2013, June). *Understanding mobile apps continuance usage behavior and habit: An expectance-confirmation theory*. In PACIS (p. 132).

Clemmer, E. C., and Schneider, B. 1996. “Fair Service,” in T. A. Swartz, D. E. Bowen, and S. W. Brown (eds.), *Advances in services marketing and management* (5), Greenwich, Connecticut: JAI Press Inc, pp. 109-126.

Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O., and Ng, K. Y. 2001. “Justice at the millennium: A meta-analytic review of 25 years of organizational justice research,” *Journal of Applied Psychology* (86:3), pp. 425-445.

Cooray, A., and Potrafke, N. 2011. “Gender inequality in education: Political institutions or culture and religion?” *European Journal of Political Economy* (27:2), pp.268-280.

Dobson, A. 1998. *Justice and the Environment: Conceptions of Environmental Sustainability and Theories of Distributive Justice*. United Kingdom: Oxford University Press, USA.

Dorn, E., Hancock, B., Sarakatsannis, J., and Viruleg, E. 2020. *Covid-19 and student learning in the United States: The hurt could last a lifetime*, McKinsey & Company (June).

Economist Intelligence Unit. 2020. *Democracy Index 2020*.

Emanuel, E. J. 2013. “MOOCs taken by educated few,” *Nature*, 503, 342.

Emerson, J. 2003. “The blended value proposition: Integrating social and financial returns,” *California Management Review* (45:4), pp. 35-51.

Evans, S., and McIntyre, K. 2014. “MOOCs in the humanities: can they reach underprivileged students?” *Convergence: The International Journal of Research into New Media Technologies*.

Fleurbaey, M., Gary-Bobo, R. J., and Maguain, D. 2002. “Education, distributive justice, and adverse selection,” *Journal of Public Economics* (84:1), pp.113-150.

Fomba, B.K., Talla, D.F. and Ningaye, P. 2022. “Institutional Quality and Education Quality in Developing Countries: Effects and Transmission Channels,” *J Knowl Econ*.

Fügener, Grahl, J., Gupta, A., and Ketter, W. 2021. “Will Humans-in-the-Loop Become Borgs? Merits and Pitfalls of Working with AI,” *MIS Quarterly* (45:3), pp.1527–1556.

Gambardella, A., Heaton, S., Novelli, E., and Teece, D. J. 2021. “Profiting from enabling technologies?” *Strategy Science* (6:1), pp.75-90.

Ganju, Pavlou, P. A., and Banker, R. D. 2016. “Does Information and Communication Technology Lead to the Well-Being of Nations? A Country-level Empirical Investigation,” *MIS Quarterly* (40:2), pp.417–430.

Hansen, J. D., and Reich, J. 2015. “Democratizing education? Examining access and usage patterns in massive open online courses,” *Science* (350:6265), pp. 1245-1248.

Haub, C. (2008). *2008 World Population Data Sheet*. 2008 Population Reference Bureau.

Hayes, A.F. 2018. *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd Edition). New York: Guilford Press.

Hosny, H. J., and Aerts, W. L. 2019. “Artificial intelligence for global health,” *Science* (366:6468), pp.955–956.

Kailash, J. 1989. “The measurement of fairness or equity perceptions of management information systems users,” *MIS Quarterly* (13:3), pp. 343-358.

Kim, K. M., Kwak, D. W., and Lee, S. 2022. “Home-Tutoring Services Assisted with Technology: Investigating the Role of Artificial Intelligence Using a Randomized Field Experiment,” *Journal of Marketing Research* (59:1), pp.79–96.

Kizilcec, R. F., and Lee, H. 2020. “Algorithmic fairness in education,” arXiv preprint, arXiv:2007.05443 [cs.CY].

Kizilcec, R. F., Saltarelli, A. J., Reich, J., and Cohen, G. L. 2017. “Closing global achievement gaps in MOOCs,” *Science*, (355:6322), pp.251-252.

Leventhal, G. S. 1980. "What should be done with equity theory?" in *Social exchange*, Springer, Boston, MA, pp. 27-55.

Lou, B., and Wu, L. 2021. "AI on drugs: Can artificial intelligence accelerate drug development? Evidence from a large-scale examination of bio-pharma firms," *MIS Quarterly* (45:3), pp. 1451-1482.

Luckin, R. 2017. "Towards artificial intelligence-based assessment systems," *Nature Human Behaviour*, 1, 0028.

Luckin, R., Holmes, W., Griffiths, M., and Forcier, L. B. 2016. *Intelligence unleashed: An argument for AI in education*.

Lui, A. K. H., Lee, M. C. M., and Ngai, E. W. T. 2022. "Impact of Artificial Intelligence investment on firmValue," *Annals of Operations Research* (308), pp.373–388.

Majchrzak, A., Markus, M.L., and Wareham, J. 2016. "Designing for digital transformation: Lessons for information systems research from the study of ICT and societal challenges," *MIS Quarterly* (40:2), pp. 267-278.

Marras, M., Boratto, L., Ramos, and G. Fenu. 2022. "Equality of Learning Opportunity via Individual Fairness in Personalized Recommendations," *Int J Artif Intell Educ* (32), pp. 636–684.

Mithas, S., and Rust, R, T. 2016. "How Information Technology Strategy and Investments Influence Firm Performance: Conjecture and Empirical Evidence," *MIS Quarterly* (40: 1), pp.223-245.

Ravanera, C., and Kaplan, S. 2022. *An equity Lens on Artificial Intelligence,* Rotman Management Magazine.

Rauscher, O., Schober, C., and Millner, R. 2012. "Social impact measurement und social return on investment (SROI)-analysis," *New Methods of Economic Evaluation*.

Reutskaja, E., and Hogarth, R. M. 2009. "Satisfaction in choice as a function of the number of alternatives: When "goods satiate"," *Psychology & Marketing* (26:3), pp. 197-203.

Rifkin, J. 2014. *The zero marginal cost society: The internet of things, the collaborative commons, and the eclipse of capitalism*. St. Martin's Press.

Rubera G., and Kirca A.H. 2012. "Firm Innovativeness and Its Performance Outcomes: A Meta-Analytic Review and Theoretical Integration," *Journal of Marketing* (76:3), pp.130-147.

Scheyvens, R., Banks, G., and Hughes, E. 2016. "The private sector and the SDGs: The need to move beyond 'business as usual'," *Sustainable Development* (24:6), pp.371-382.

Sen S., and Bhattacharya C.B. 2001. "Does Doing Good Always Lead to Doing Better? Consumer Reactions to Corporate Social Responsibility," *Journal of Marketing Research* (38:2), pp.225-243.

Shum, S. J. B., and Luckin, R. 2019. "Learning analytics and AI: Politics, pedagogy and practices," *British Journal of Educational Technology* (50:6), pp. 2785-2793.

Smith, A. K., Bolton, R. N., and Wagner, J. 1999. "A Model of Customer Satisfaction with Service Encounters Involving Failure and Recovery," *Journal of Marketing Research* (36:3), pp.356–372.

Swoboda, B., Berg, B., Schramm-Klein, H., and Foscht, T. 2013. "The importance of retail brand equity and store accessibility for store loyalty in local competition," *Journal of Retailing and Consumer Services* (20:3), pp. 251-262.

Teachman, J.D. 1987. "Family Background, Educational Resources, and Educational Attainment," *American Sociological Review* (52), pp.548-557.

Trauth, E., and Connolly, R. 2021. "Investigating the nature of change in factors affecting gender equity in the IT sector: A longitudinal study of women in Ireland," *MIS Quarterly* (45:4), pp. 2055-2100.

United Nations Educational, Scientific, and Cultural Organization. 2019. *Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development*.

Volkoff, O. and Strong, D. M. 2013. "Critical realism and affordances: Theorizing IT-associated organizational change processes," *MIS Quarterly* (37:3), pp. 819-834.

Wang, R. Y., & Strong, D. M. 1996. Beyond accuracy: What data quality means to data consumers. Journal of management information systems (12:4), pp. 5-33.

Welzman, Y., 2010. *Development failure and the failure of democracy*. Chapter 4 in: The Persistence of Ineffective Aid. PhD thesis, Bar-Ilan University.

Wu, S. Y., and Banker, R. 2010. "Best pricing strategy for information services," *Journal of the Association for Information Systems* (11:6), 1.

Young, M., Magassa, L., and Friedman, B. 2019. "Toward inclusive tech policy design: a method for underrepresented voices to strengthen tech policy documents," *Ethics and Information Technology* (21:2), pp. 89-103.

Zhang, S., Srinivasan, K., Vir Singh, P., and Mehta, N. September 17, 2021. "AI Can Help Address Inequity – If Companies Earn Users' Trust," *Harvard Business Review*.