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Technological Platforms and Social Change: The Uber Case

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ABSTRACT

Objective: this study examines the perception of social impact on Uber users, testing hypotheses about Uber's association with various types of social change and addressing social issues. **Method:** a quantitative study with 843 Uber users in Belo Horizonte, Brazil, was conducted using six social change indicators to consider the platform's characteristics. Multiple linear regression and correlation analyses were used to test the hypotheses about the frequency of use. **Results** the research shows that peer-to-peer platforms like Uber are linked to social change by addressing social needs and solving issues through interaction. Quality of life and employability are critical for passengers, while drivers prioritize employability and economic concerns. The correlation model indicates a positive relationship across all social change categories, with employability and environment emerging as the main predictors of use. **Conclusion:** the Uber platform affects non-material culture, policy outcomes, traditional organizational models, and the economy. This research addresses gaps in understanding how technological platforms meet social needs and offers a new perspective on measuring social change. The model helps managers improve market and service offerings and supports public policies for socioeconomic development.

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INTRODUCTION

Recent advancements in peer-to-peer technologies have significantly affected the socioeconomic landscape by addressing environmental and social challenges. These technologies are central to the 2030 Agenda (United Nations, 2015). The rise of the internet and digital platforms has driven the global expansion of the digital economy, profoundly influencing society (Ferreira et al., 2021). Digital platforms and collaborative consumption are prominent in various social and economic dimensions, mainly in urban transportation, as exemplified by Uber (Ferreira et al., 2022). The rapid growth of mobility apps has affected organizational environments, individual interactions, and social preferences, a process that remains underexplored (Alrmayh et al., 2021; Barreto et al., 2020; Selmer et al., 2022; Smith et al., 2023).

Digital technology-based platforms are transforming business ventures and extending their impact beyond innovative practices to influence culture, politics, and society. These platforms have restructured social relationships. However, limited research has fully explored the profound relationship between digital platforms and social change (Ahlstrom et al., 2020; Si et al., 2023; Tomizawa et al., 2020). Our limited understanding of the social impact of digital technology stems largely from fragmented knowledge across various disciplines. Researchers in information systems focus on the ontological aspects of digital technology, whereas those in entrepreneurship and innovation concentrate on how digitalization affects commercial changes (Si et al., 2023). However, the existing literature is yet to fully integrate these perspectives to systematically understand the social transformations deployed by peer-to-peer technological platforms (Ametowobla & Kirchner, 2023), especially aspects related to non-material culture (Parente et al., 2018; Stallkamp & Schotter, 2021) and institutional aspects (Ferreira et al., 2023).

Indeed, peer-to-peer platforms, in which access to products and services is accomplished through online services to connect providers and consumers, present an alternative to traditional mobility models and cause significant changes in the entire urban mobility segment by directly linking suppliers and customers (Edvardsson & Trovoll, 2020; Trabucchi & Buganza, 2020). However, the consequences extend beyond this market and affect laws, habits, mental models, and individual perceptions, suggesting institutional disruption (Ferreira et al., 2023). Technological platforms can change people's mindsets and generate social transformation (Avelino, 2021; Wen, 2023), solving social issues (Kolk & Ciulli, 2020), providing new services and employment opportunities (Kirchner et al., 2022; Rosenblat & Stark, 2016), diversity, environmental sustainability (Henao & Marshall, 2019), and socioeconomic development (Beliaeva et al., 2020; Wen, 2023). Some scholars emphasize the need for practical studies on how technological platforms address social problems (McGahan et al. 2021; Mair & Gegenhuber, 2021), including empirical research on meeting social needs (Caridà et al., 2022; Kavanagh et al. 2021) and measuring the rate of social change despite its complexity (Kavanagh et al. 2021). As a result, this article aims to address three critical questions that have received limited attention in the literature:

RQ1. Does using Uber's platform drive social change and address social issues?

RQ2. How has the Uber platform impacted passengers and drivers at various levels?

RQ3. Is there a correlation between the changes induced by the platform and the frequency of its use?

This study investigates the social implications of a peer-to-peer digital platform enabling large networks in which members act as clients and suppliers. The central objective is to examine whether platform adoption is associated with various forms of social change, including solving social issues and identifying the differences in social change levels between drivers and passengers. In pursuit of this goal, the present study is based on the hypothesis that the peer-to-peer technological platform Uber is associated with social change, solving social issues (Kolk and Ciulli, 2020), integrating habits, and other non-material cultural elements (Ogburn, 1922) such as unemployment, lack of services, good access, quality of life, and sustainability (Kavanagh et al. 2021). This study enhances our understanding of the effects of peer-to-peer platforms on social change activities. It views these platforms as drivers of social transformation by identifying the elements that enable actors to collaborate purposefully to achieve positive systemic social change.

We offer a paradigm for integrating social change discourse with peer-to-peer platforms by stressing how the fundamental functionalities of platforms enable the essential aspects of social change and how the platform's architecture supports and empowers these aspects, enabling them to emerge as new types of societal transformation. This study examines the social and practical implications of peer-to-peer platforms such as Uber. It identifies the critical factors of social change influenced by these platforms, such as social well-being and mobility options for low-income individuals. This study highlights the need for adaptive public policies to address issues such as unemployment. By proposing a model with six variables (employability, inequality, quality of life, environmental concerns, economic concerns, and policy management) to measure social change, this study helps researchers and managers understand and enhance these platforms' impact. This demonstrates that Uber significantly affects drivers and passengers differently, improving their quality of life and employability, thus supporting socioeconomic development.

This study offers methodological contributions to social change metrics. Measuring social change is complex because of methodological challenges, as respondents may need clarification on measures and questions (Einola & Alvesson, 2020). Additionally, social life measurement relies on socially organized knowledge, which can change over time, and societies are reflexive, using social science knowledge to alter practices and beliefs (Giddens, 1971). At the micro level, concepts and data collection are susceptible to change (Smith, 2005). This study considers recent arguments from Kavanagh et al. (2021), who suggest viewing change as a subjective phenomenon and focusing on its impact on users' lives, as seen in the Holmes and Rahe stress scale (1967). This contributes to social change measurement, adapting to the technological platform context according to user perspectives.

TECHNOLOGICAL PLATFORMS AND SOCIAL CHANGE

Technological platforms

Different types of technology platforms have emerged globally, making it challenging to develop broad and precise concepts. Milojević and Inayatullah (2015) note that expanding technological consumer platforms have generated 'disintermediation' between producers and final consumers, raising expectations of material progress, social inclusion, and improved quality of life for large demographic groups. However, Gawer (2014) identified shared fundamental characteristics among these platforms: the ability to coordinate agents capable of innovating and competing, the capacity to create value and profit from economies of scope linked to supply and demand, and a modular technical architecture with a core and periphery, all connected in a network. Essentially, these communities are formed by sharing specific resources (items, services, knowledge, etc.).

Technology platforms and the sharing economy can be found within this framework. The emergence of the sharing economy has significantly disrupted incumbent organizations, institutional regimes, and society as a whole (Garud et al., 2022; Hossain et al., 2022; Lehmann et al., 2022). Defined as "a web of markets in which individuals use various forms of compensation to transact the redistribution of and access to resources, mediated by a digital platform operated by an organization" (Mair & Reischauer, 2017, p. 12), the sharing economy has sparked considerable controversy and has been heavily contested among various actor groups, including new entrants, incumbents, politicians, consumers, and local stakeholders (Acquier et al., 2020; Uzunca et al., 2018). Indeed, the sharing economy is often portrayed as a quintessential example of a technology-driven institution-challenging discontinuity (Weber et al., 2019).

Recent studies further emphasize the disruptive impact of the sharing economy on traditional business models and regulatory frameworks. For instance, Ferreira et al. (2023) highlight how platforms like Uber have altered institutional environments by changing social norms and regulatory systems. Similarly, Stocker et al. (2021) discuss the socioeconomic implications of the sharing economy, noting its potential to enhance participation, welfare, and ecological sustainability. Research on the sharing economy has increasingly focused on the institutional change processes. Studies have shown that various actor groups engage in institutional work by intentionally creating, maintaining, and disrupting institutions (Lawrence et al., 2013; Lehmann et al., 2019; Mair & Reischauer, 2017; Vith & Höllerer, 2020; Zvolska et al., 2019). New entrants in the sharing economy use this work to gain legitimacy and strive to establish their actions as desirable and appropriate within socially constructed norms, values, beliefs, and definitions (Suchman, 1995; Suddaby et al., 2017).

Various studies have described how new entrants in the sharing economy strategically disrupt existing institutions (Boon et al., 2019; Laurell & Sandström, 2017), construct new institutions (Mair & Reischauer, 2017; Maurer et al., 2020), and narrate their activities within existing institutional frames (Acquier et al., 2020; Grinevich et al., 2019). Incumbent organizations, perceiving challenges from the sharing economy, primarily defend established institutions by questioning the legitimacy of new entrants (Chang & Sokol, 2022; Weber et al., 2019). At the macro level, policymakers, interest groups, and local governments engage in institutional work to integrate new sharing economy entrants into existing frameworks (Smolka & Heugens, 2020; Vith & Höllerer, 2020).

Sharing activities have significantly increased and have branched out from the purely informational realm to include a wide range of goods and resources, including peer-to-peer platforms such as Uber, which link locally based users and globally based providers for urban mobility (Barnes & Mattsson, 2016; Stocker et al., 2021). New techniques to build trust between strangers are made possible through technical feedback mechanisms on urban sharing platforms. Trust is developed through a system of reputation based on openness and validity, as seen in the example of Uber and many other platforms offering services through peer-to-peer networks (Ferreira et al., 2022; Ferreira et al., 2023). Most of these platforms invest in developing evaluation and categorization systems that are nourished by users (providers and consumers). These systems are beneficial for improving platforms and assisting users in making effective decisions (Stocker et al., 2021).

The cultural and cognitive presumptions of inviting strangers into one's house and sharing possessions with them are challenged by technology. Using technological solutions lowers the risks related to new practices and lowers transaction costs. The state's traditional role in policing is another presumption undercut by this kind of innovation; on online platforms, a new peer policing system is used (Zvolska et al., 2019). As platforms become more transparent, they reveal information about product interfaces and launches, thus enabling third parties to create complementary or alternative products and services. This level of openness is uncommon for businesses that do not use platforms for collaborative consumption (Altman, & Tushman, 2017; Stocker et al., 2021). By using an independent supplier model (Schor & Attwood-Charles, 2017), platforms present diverse rewards and assessment methods for employed workers (Curtis et al., 2020; Guyader et al., 2023) and radically change work relations (Graham & Woodcock, 2018; Rauscher, 2021; Suseno & Rowley, 2023). Additionally, some platforms rely on ratings and reputation data, as well as analytics that measure user participation to lower risk and boost trust (Prada & Iglesias, 2020; Ransbotham et al., 2015). By controlling many interactions and impacting the entire value chain (Wegner et al., 2023), social change can be promoted (Lou et al., 2021; Misuraca & Pasi, 2019).

Social change and technological platforms

Social change refers to transforming a society's social structure due to shifts in social institutions, actions, or relations. Sustaining these changes on a broader scale can lead to significant social transformation (Kavanagh et al., 2021). Various systematic approaches have been proposed to understand social change. From a Marxist perspective, it results from fundamental conflicts within the system, acting as a mechanism that allows the system to navigate periodic oscillations, regain equilibrium, and expand further (Giddens, 1971). Eisenstadt (1973) emphasizes the modernization processes, including social mobilization, structural differentiation, the creation of unrestricted resources, and the construction of institutional frameworks capable of continuously absorbing change. As society modernizes, new demands and constituencies emerge, requiring political, economic, social, and other sectors to adapt, while maintaining some degree of continuity.

According to Murdock (1961), social change involves several stages: innovation, social acceptance, selective elimination, and integration. Innovation is the formation of a new habit by an individual that is then accepted by others. Social acceptance occurs when users share innovation. Selective elimination occurs when more rewarding ideas are adopted, whereas less adaptable ideas are abandoned. Integration is the final stage, in which accepted behaviors adapt to other accepted behaviors, forming a cohesive unit. The acquired habit not only changes the social environment or culture but also evolves with it. Ogburn (1922) introduced the concept of cultural lag, which occurs when shifts in non-material culture (knowledge, beliefs, morals, laws, and traditions) lag shifts in material culture (technical inventions). Recent studies have expanded these theories. Kavanagh et al. (2021) discuss how digital platforms and technological advancements accelerate social change by reshaping social interactions and institutional structures. Similarly, Klitkou et al. (2022) highlighted the interconnected dynamics of social practices driving transformative change, emphasizing the need for comprehensive interventions to manage these complex interactions.

According to Kavanagh et al. (2021), it is critical to differentiate between technological and social since we are tempted to presume that a change in one will result in a change in the other. Furthermore, the presumed causation is often from technology to social, yet the technological and social are mutually intertwined because they are challenging to disentangle operationally, and doing so risks introducing some technological determinism. While social and technological are inextricably intertwined, it nevertheless makes it essential to maintain the separation between the two (Kavanagh et al. 2021), particularly when measuring the rate of social change (Bauer, 1966; Lynd & Lynd, 1929; Phillips, 2011; Sheldon & Moore, 1968).

The measurement of social change has been a significant concern for social theorists for several decades. This interest dates back to the 1920s, notably with Ogburn's publication on 'Social Change concerning cultural and original nature' (1922). During the same period, the Lynds conducted a seminal study on the changes in the white population of a typical American city between 1885 and 1925, examining social transformation in six areas: leisure time, home and family, employment, youth and learning, government, religion, and community (Lynd & Lynd, 1929). However, measuring social change remained a peripheral concern in the social sciences until the emergence of the social indicator movement in the late 1960s. This movement was catalyzed by Bauer's edited collection (1966) and Sheldon and Moore's indicators of social change (1968). Sheldon and Moore (1968) categorized their indicators into demographic, economic, social mobility, technological advancements, cultural shifts, political and educational developments.

Caplow et al. (2001) expanded the scope of social indicators to include demographic changes, economic trends, technological innovations, cultural changes, political developments, educational progress, and additional structural categories such as health and well-being, environmental impact, and urbanization. This broadened focus sparked renewed interest in understanding how and why these indicators changed. Initially, studies were mainly confined to quantifiable domains such as economic development, voting, and population.

Kavanagh et al. (2021) classified their findings into seven categories: religion, health, wealth, population, home, education, work, and law. However, these trends only provide a limited perspective on the rate of social change. A more comprehensive inquiry should examine qualitative elements, such as beliefs, mores, and values. Sheldon and Moore (1968) argued that social change represents a significant alteration of social structures, including patterns of action and interaction, as well as the consequences and manifestations of these structures embodied in norms, values, and cultural products or symbols. These elements are closely linked to the institutional context (North, 1996).

Measuring social change is inherently complex because of the various methodological challenges. Respondents may find a researcher's measures, terms, and questions ambiguous, irrelevant, or misleading (Einola & Alvesson, 2020). Additionally, measuring social life relies on socially organized ways of knowing subject to change. What a society chooses to measure and how it funds and executes this measurement are socially determined and can evolve over time. Societies are also reflexive: individuals use social science knowledge to alter and interpret their practices and beliefs (Giddens, 1971). At the micro level, understanding a concept, its empirical operationalization, and data collection, analysis, and dissemination are all susceptible to change (Smith, 2005). For instance, the concept of 'crime rate' depends on an organized effort to conceptualize, detect, and measure crime, complicating any attempt to determine the 'true' or 'real' crime rate (Reiss, 1986).

Kavanagh et al. (2021) argue that addressing methodological issues requires viewing change as a subjective phenomenon, focusing on its impact on our lives. For instance, the Holmes and Rahe stress scale (1967) measures stress from life events in 'life change units.' Significant life events, such as the death of a spouse or divorce, are key to studying social changes. The top eight stressful events on this scale include death of a spouse, divorce, marital separation, imprisonment, death of a close family member, personal injury or illness, marriage, and dismissal from work (Holmes & Rahe, 1967).

This approach has guided our study, considering that Uber is changing the culture (Martin, 2022), triggering different policy outcomes (Wen, 2023), causing a long-term erosion of traditional organizational models (Kirchner & Schüßler, 2020), and culminating in a contagious 'Uberization' of the entire economy (Kirchner et al., 2022). This case requires a more contextualized approach to analyze the social impact of this platform. From the third century onward, the rise in private automobile use has increased traffic jams and urban space occupation, raising concerns about urban mobility, traffic accidents, bottlenecks, pollution, inadequate public transportation, and socioeconomic inequalities (Carvalho & Pereira, 2011). Adaptable, low-cost solutions, such as Uber, can improve the quality of life, health, and economic activity (Taylor et al., 2015). These solutions meet the need for private vehicles, simplifying the value chain through peer-to-peer models that connect users directly through low-cost technology platforms (Hagel et al., 2015).

Uber has emerged to address urban mobility issues, transforming the urban transport market and impacting various sectors, including the taxi industry, government, public policy, economy, vehicle assemblers, public transport, infrastructure, and society (Ametowobla & Kirchner, 2023; Kirchner et al., 2022; Martin, 2022). Shared mobility platforms such as Uber can drastically change living standards, posing threats to incumbents and distorting established institutions (Christensen, 1997; Ferreira et al., 2023; Laurell & Sandström, 2016). Uber influences social behavior by providing income opportunities, reducing drunk driving, and offering mobility alternatives to low-income individuals (Hall & Krueger, 2018; Hampshire et al., 2017; Rogers, 2015; Ferraz & Torres, 2004). Politically, Uber has faced resistance because of accusations of unfair competition, safety concerns, and debates over driver employment status (Azevedo et al., 2015). The app's entry has significantly affected the social field, changing people's choices, behaviors, and urban mobility decisions.

In this study, we examined aspects of social change related to addressing social issues such as unemployment, access to services and goods, quality of life, and sustainability (Kolk & Ciulli, 2020). Our primary focus is to determine whether the diffusion of material culture, specifically the technological platform Uber, has led to changes in its users' non-material culture (Parente et al., 2018; Si et al., 2023; Stallkamp & Schotter, 2021). This focus is justified by the fact that, from antiquity to the present, technology in means of transport has influenced the growth of urban areas and land use (Falcocchio & Levinson, 2015) and interfered with the population's standard of living (Ferraz & Torres, 2004). Uber reshapes societal norms and pioneers innovative practices in a gig economy.

Unlike traditional employees, Uber drivers are considered independent business owners with flexible schedules. Uber employs psychological strategies and social science techniques to enhance efficiency to influence when, where, and for how long drivers work. This approach balances rider demand with driver supply, thereby reducing costs for both passengers and the company (Martin, 2022). Our approach utilized Uber's characteristics to establish the main analytical categories of social change, which were operationalized to support the social change indicators developed in this research. Considering the Uber platform's characteristics, the first potential impact pertains to quality of life.

Quality of life

Uber affects users' quality of life by facilitating transactions between buyers and sellers without owning the goods or services exchanged (Ametowobla & Kirchner, 2023). It provides convenient and reliable transportation, enhances mobility in urban areas, and allows individuals to travel freely and efficiently (Rayle et al., 2016). This increased accessibility improves the quality of life through comfort and convenience (Kavanagh et al., 2021; Milojević & Inayatullah, 2015; Taylor et al., 2015). In addition, Uber's safety features, such as GPS tracking and driver ratings, contribute to passenger security (Greenwood & Wattal, 2017). These characteristics align with social change indicators, such as leisure time (Lynd & Lynd, 1929), social mobility (Sheldon & Moore, 1968), and health and well-being (Caplow et al., 2001; Kavanagh et al. 2021). Therefore, we hypothesize as follows:

> Hypothesis (H_1): Uber use significantly affects the quality of life of urban residents by providing convenient and reliable transportation options, enhancing mobility, and contributing to a sense of security in commuting.

Employment conditions

Uber has transformed employment conditions in the gig economy by offering flexible work opportunities (Kirchner et al., 2022) and employment (Ametowobla & Kirchner, 2023; Azevedo et al., 2015; Jha et al., 2016). This flexibility allows drivers to balance work with other commitments, potentially improving their overall life satisfaction (Rosenblat & Stark, 2016; Kirchner et al., 2022). However, classifying drivers as independent contractors rather than employees has sparked debates regarding job security and benefits (Si et al., 2023). Wen (2023) found that the interests of riders and platform owners are not aligned, with riders advocating for stricter safety measures and owners resisting them. Employment conditions are a social change measure that was also considered by Lynd and Lynd (1929) and Kavanagh et al. (2021). Based on these points, we propose the following hypotheses:

> Hypothesis (H_1): Uber significantly impacts employment conditions due to the flexibility and opportunities offered by the platform, compared to traditional employment models.

Environmental

The environmental impacts of Uber are multifaceted. This has reduced emissions by optimizing vehicle usage and reducing the need for personal car ownership, thus promoting sustainability (Henao & Marshall, 2019; Curtis & Mont, 2020). However, the overall environmental impact varies depending on the local context and usage pattern (Henao & Marshall, 2019). Uber has also promoted zero-emission vehicles (ZEVs) with significant increases in zero-emission trips and drivers in recent years (Uber, 2024). Caplow et al. (2001) have also considered the environmental aspect in social change measurements. Based on these points, we propose the following hypothesis:

> Hypothesis (H_1): Uber's ride-hailing services significantly impact the environment by reducing emissions through optimized vehicle usage.

Economic concerns

Multisided technical platforms enhance market efficiency by increasing transactions and matching supply with demand. They also foster innovation by providing space for developers and entrepreneurs to create and test new products and services (Wen, 2023). For instance, Uber has had a substantial economic impact by creating new income opportunities for drivers and generating additional business revenue. In 2021, Uber contributed $10 billion in economic value, including driver earnings and incremental revenue for restaurant partners (Cramer & Krueger, 2016). In addition, Uber's dynamic pricing model can reduce transportation costs and make mobility more affordable Hall & Krueger, 2018; Punt et al., 2023). As a peer-to-peer flexible and low-cost solution (Hagel et al., 2015; Kirchner et al., 2022; Taylor et al., 2015), the platform addresses economic concerns (Beliaeva et al., 2020; Jha et al., 2016; Taylor et al., 2015). Economic change is the focus of many studies measuring social change (Caplow et al., 2001; Kavanagh et al. 2021). Based on these points, we propose the following hypothesis:

> Hypothesis (H_1): Uber's platform significantly enhances market efficiency and economic value by

creating new income opportunities for drivers, generating additional revenue for businesses, and reducing transportation costs through dynamic pricing

Policy management system

Recent scholarship has increasingly recognized the inherent conflicts within multi-sided digital platforms, where various actors and stakeholders have competing interests and often resist the rules, standards, and policies governing platform use (Wen, 2023). In response to political backlash, digital platform companies can strategically leverage different groups of actors within these platforms to advocate policy changes and gain support from various government agencies and initiatives (Ametowobla & Kirchner, 2023; Martin, 2022; Wen, 2023).

Uber's operations have notably influenced policy management systems, changed public policy (Le Vine & Polak, 2015), and impacted various sectors of government and society (Azevedo et al., 2015; Wen, 2023; Zvolska et al., 2019), especially regarding the regulation of gig economy workers (Rogers, 2015). The classification of Uber drivers as employees rather than independent contractors in the UK has set a precedent for other gig economy platforms, significantly impacting labor laws and worker rights (Dungca, 2020). This shift has sparked discussions on the need for updated labor regulations to protect gig workers better (Ametowobla & Kirchner, 2023). Many studies have explored policy changes as a measure of social change (Caplow et al., 2001; Kavanagh et al., 2021; Lynd & Lynd, 1929). Considering these points, we propose the following hypothesis.

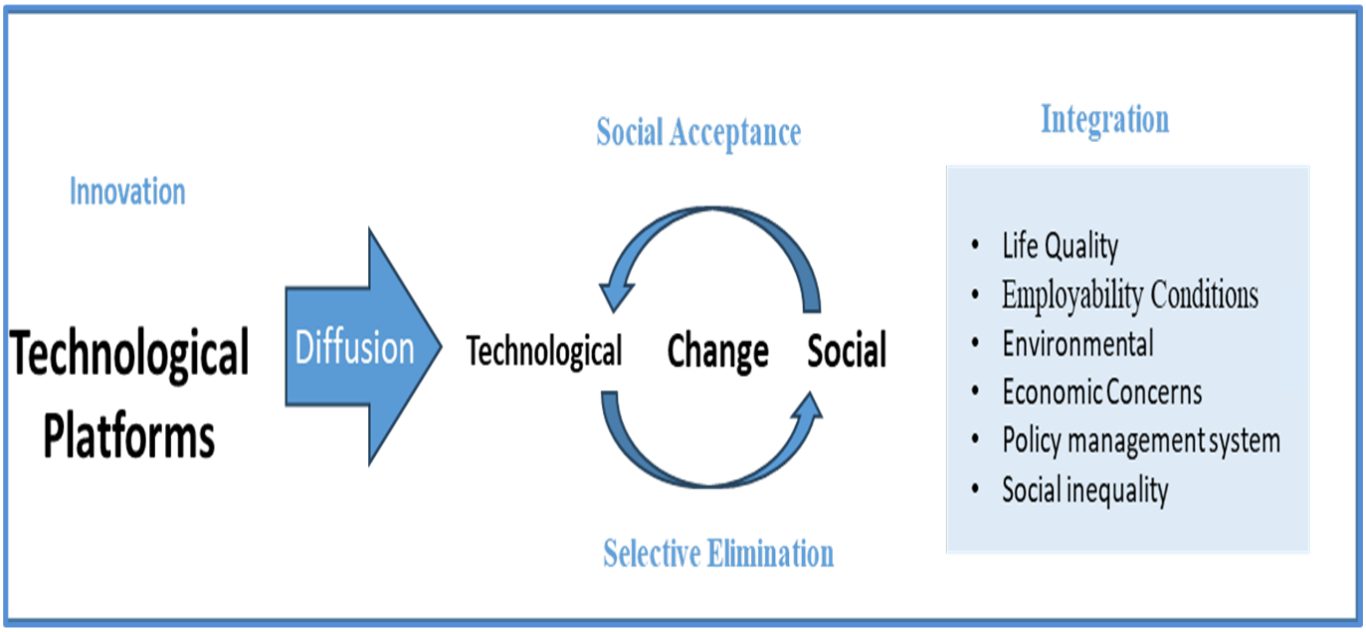
> Hypothesis (H_1): Uber's operations significantly influence policy management systems by changing public policy and impacting labor laws and worker rights, particularly in the gig economy.

Social inequality

Uber has both mitigated and exacerbated social inequality. On the one hand, it has provided income opportunities for marginalized groups, improving social inequality and accessibility by offering cheaper mobility alternatives and promoting social inclusion for low-income individuals (Carvalho & Pereira, 2011; Ferraz & Torres, 2004; Le Vine & Polak, 2015; Punt et al., 2023; Wen, 2023). However, the gig economy model has been criticized for perpetuating income inequality due to the lack of job security and benefits (Kirchner et al., 2022; Rosenblat & Stark, 2016). Many scholars consider social aspects indicators (Lynd & Lynd, 1929; Sheldon & Moore, 1968), focusing on social inequality (Kolk & Ciulli, 2020; Wen, 2023). Considering these arguments, we propose the following hypotheses:

> Hypothesis (H_1): Uber's operations significantly impact social inequality by providing income opportunities for marginalized groups.

Considering the factors and analyses conducted here, we provide the analytical model used in this study (Figure 1).



Source: Elaborated by the authors.

Figure 1. Analytical model.

In the proposed model, we suggest that the diffusion of innovation, such as a technological platform like Uber, once accepted and adopted by users (Ferreira et al., 2021; Martin, 2022) can promote social change (Ametowobla & Kirchner, 2023; Kavanagh et al. 2021; Kirchner et al., 2022). This integration affects habits and other non-material cultural elements (Ogburn, 1922; Zvolska et al., 2019), including quality of life (Greenwood & Wattal, 2017; Kavanagh et al. 2021), employability conditions (Kirchner et al., 2022; Wen, 2023), environmental conditions (Curtis & Mont, 2020; Henao & Marshall, 2019), economic concerns (Kirchner et al., 2022; Wen, 2023), policy management systems (Ametowobla & Kirchner, 2023; Dungca, 2020; Wen, 2023), and social inequality (Kirchner et al., 2022; Rosenblat & Stark, 2016; Wen, 2023). Thus, this study focuses on indicators of changes related to solving social issues (Kolk & Ciulli, 2020), despite the existence of many other categories in the literature (e.g. Lynd & Lynd, 1929; Bauer, 1966; Kavanagh et al. 2021; Sheldon & Moore, 1968).

METHOD

Demographic profile of respondents

Users of the Uber platform in Belo Horizonte were included in the research universe. Due to the app's confidentiality policy, it was impossible to accurately estimate the number of Uber users at the time of the research. Consequently, the entire population of Belo Horizonte was considered as the research universe. According to the Institute of Geography and Statistics' Demographic Census statistics from 2010, Belo Horizonte has a total population of 2,375,151. According to recent estimates, the population in 2019 was 2,512,070 people, with a population of 1,628,469 adults (18-65 years old). Of these, 46.7% were male, corresponding to 760,080 individuals, and 53.3% were female, totaling 868,388 individuals (Instituto Brasileiro de Geografia e Estatística [IBGE], 2019). According to Malhotra (2019), in stratified probabilistic samples, the universe should first be divided into subgroups called strata. The elements should then be selected based on random criteria. Thus, the research universe was stratified according to gender for consumers, and 32 census sectors in Belo Horizonte were selected. The definition was based on the duration of the interviews, the number of interviews planned, and the project budget limit. Each census sector is randomly defined.

Research strategy and methods

To achieve the study's objectives, a quantitative research strategy was chosen, as it aimed to measure data collected in a structured manner to produce generalized results. Statistical resources were used throughout the data analysis process and hypothesis testing, which are inherent in this investigative approach (Malhotra, 2019). Regarding the number of time points or the temporality in which the data were collected, this research is of a retrospective longitudinal nature, as it captures information from individuals based on past data, comparing the period before and after becoming Uber users. Data were occurred in two phases. The first phase involved a pilot study, followed by a probabilistic sample survey aimed at describing and analyzing the state of one or several variables from May to August 2019. The analysis was performed using the SPSS V.25 software.

Sampling design

Using probabilistic and stratified sampling, field research was conducted on two samples of Uber app users (drivers and passengers) in Belo Horizonte, Brazil. In addition to being a significant metropolitan center, Belo Horizonte was one of the first Brazilian cities to approve the app's operation in September 2014. We used a 95% confidence interval with a 5% margin of error to generate the sample size (n), resulting in 384 clients and 384 drivers (Cochran, 1977). To account for the likelihood of missing data and outliers, the authors expanded the sample to 843 individuals, which included 446 customers and 397 drivers. Subsequently, the authors stratified the sampling by sex and randomly selected city census tracts (Malhotra, 2019). Following the European Social Survey criteria, the sample was reduced to 841 users (444 consumers and 397 drivers) (Sambiase et al., 2014).

We examined both sides of the peer-to-peer process to consider multiple aspects of the platform (Beliaeva et al., 2020; Taylor et al., 2015; Wen, 2023). This configuration accounts for the bilateral relationship facilitated by the platform, promoting direct exchange between producers and consumers (Punt et al., 2023). In this study, we analyzed drivers and passengers to understand the impact of Uber on the social lives of both user groups. Gender stratification is crucial in Uber studies to understand how gender impacts platform use and experience. Cook et al. (2018) found that female Uber drivers earn less than male drivers due to differences in driving patterns and preferences, such as avoiding high-risk areas or late hours. Safety concerns significantly influence the choices of female riders and drivers, with women often opting for Uber because of its safety features (Barrios & Hochberg, 2020). However, these concerns also affect female drivers' decisions and patterns. Angrist, Caldwell, and Hall (2021) noted that men frequently use ride-hailing services, such as Uber, influenced by travel habits and economic considerations. Greenwood and Wattal (2017) observed that female drivers prefer driving during the daytime and in safer neighborhoods, limiting their earnings potential compared to male drivers. Stratifying by gender helps researchers understand these disparities and design interventions to address them, ensuring that both genders are adequately represented and their unique challenges are considered.

Questionnaire design

Content validation entails developing and improving data-gathering instruments (Hoppen et al., 1996). The theoretical propositions and hypotheses derived from the literature review on social change and platforms guided the formulation of the questions. An exploratory factor analysis was used to ensure the scale's internal consistency, and Cronbach's alpha was used to ensure content validation (Churchill, 1979). This type of validation guarantees that the indicators accurately depict the phenomena under consideration. The questionnaire was designed according to the principles established by Perrien et al. (1984). First, we chose several closed question alternatives to cover all possible responses. Only questions directly related to the research issue were used. We also address the implications of the questions in the data tabulation and analysis methods. This study developed a collecting instrument with 25 structured questions derived from the conceptual model. Two blocks of the questionnaire were included. First, the questions were related to the participant characteristics. Second, the questions sought information about the users' perceptions of social changes according to the six integration categories. The questions were designed to have a degree of discordance and concordance, and according to the degrees of the Likert scale, it was possible to understand the impact of each category of social change.

Pretesting

Subsequently, the authors ran a pretest on the data-gathering instrument. The pretest considered the number of questions, word clarity and accuracy, form, order, and introduction (Gil, 2002). Interviews were carried out by telephone with 65 users, and the pretest was operationalized as the number of respondents who met the criteria suggested for the stage (Malhotra, 2019).

Data collection

Malhotra (2019) states that the universe must first be partitioned into groupings called strata in stratified probability sampling. The components must then be chosen randomly using random criteria. The study universe was stratified by gender (for consumer users) and determined by the time and number of interviews predicted. A total of 32 census sectors in Belo Horizonte were selected. Structured interviews were conducted with people who visited schools, malls, and retail complexes in the census sectors between May and August 2019. Respondents signed a free and informed permission form on the virtual platform to operationalize the study.

Ápice, a junior company at PUC Minas University, supported the operationalization of data collection. Data was collected by a team of experienced professionals, including four researchers, three coordinators-supervisors, and 55 technicians. The team received specific training to carry out data collection and critically analyze the data effectively. The individuals were approached in stratified locations to ensure a random sample. They were asked if they were current Uber users, and if they responded affirmatively, they were invited to participate in the research. Starting from an initial point, the researchers approached individuals on the streets of the sector. For consumer users, people were approached near schools, shopping centers, and commercial areas within the census tract. If individuals refused to participate, the researchers remained in the area until the interview was completed. After each interview, the researchers were instructed to skip five individuals to ensure randomness before starting the next interview.

For drivers, because of the confidentiality of the apps in providing driver registration data, access was obtained by searching queues at airports, bus stations, shopping centers, and through driver referrals, although this involved only five users. A dialog box on the user's data was presented at the beginning of the section to collect the respondents' demographic information. The following procedures were performed to ensure the quality of data collection:

1. Audit of electronic research form transcriptions.
2. Phone calls to interviewees to validate supplied information.
3. Examination of research forms, examining if they were comprehensive and matched the registration in the electronic research system.

Non-response and common method bias

Non-response (Depner, 2007, p. 10) equates to 0.4% of the passengers; non-response was not discovered in the drivers' sample, indicating high research reliability and quality, according to Batinic et al. (1999). According to Longford (2000, p. 73), less than 2% of the non-responses demonstrate high research consistency. Standard method bias occurs frequently when academics employ the same scale with the same number of answer possibilities and when the analysis is transversal, i.e., at a given time (Podsakoff et al., 2003). To check for common method bias, the authors utilized Harman's single-factor test and exploratory factor analysis, which used all the research data to construct a single component.

According to Podsakoff et al. (2003), standard method bias is not a concern when the variation explained by the factor analysis is less than 50%. We used the component extraction approach and unrotated factor solution recommended by Podsakoff et al. (2003) in SPSS V.25. The exploratory factor analysis result showed an explained variance of 34.23% using Harman's single factor test, indicating that there was no substantial evidence of common method bias. Missing data, unusual study response patterns, outliers, and survey straight-lining were also confirmed as acquiescence bias indicators (Hair et al., 2013; Podsakoff et al., 2003). We also used univariate outlier detection to locate outliers. This approach used values of more than four standard deviations as a reference to characterize an out-of-the-ordinary observation.

Measuring instruments

Cronbach's alpha (α) was used to validate the scale's reliability. The goal was to determine the proportion of variance in measurements that were free of random errors (Malhotra, 2019). According to Landis and Koch (1977), values more than 0.61 are acceptable; in this study, Cronbach's alpha was 0.881, demonstrating the internal consistency of the scales used. Furthermore, researchers looked for missing data, unusual response patterns, outliers, and linear response patterns (straight lines), all of which may suggest acquiescence bias (Podsakoff et al., 2003). The univariate analysis accepted values of more than four standard deviations as a reference for describing abnormal observations to check for outliers (Hair et al., 2013). The researchers developed indices to measure the social change rate in terms of employability conditions, social inequality, economic concerns, policy management systems, quality of life, and environmental factors, making it possible to verify whether technological platforms such as Uber have promoted social changes. These indices were operationalized using Likert scale questions. The questions were grouped into six categories (Table 1).

Table 1. Questions according to interest variables.

Categories	Questions
I1. Employability conditions	P1. Uber generates the need to adapt to a new way of earning a living and being paid. P2. The platform increases the feeling of professional independence among service providers. P3. Uber has significantly altered the interaction between corporation, employee, and service provider.
I2. Social inequality	P4. With Uber, I was able to access transportation alternatives that were previously limited to my social status. P5. Uber reduces my sense of social inequality and lack of accessibility.
I3. Economic concerns	Q6. Uber represents an alternative for obtaining income. Q7. I consider the platforms' remuneration logic to be more financially advantageous than conventional salaried employment. Q8. Uber reduces expenses for providing the service compared to individual passenger transport (taxi, bus, or own car). Q9. Uber reduced my overall commuting expenses.
I4. Policy management system	Q10. Uber operates in a totally different way than traditional businesses. Q11. Performance evaluation systems (for example, by reputation) are considerably different from what I was used to in traditional firms. Q12. Uber increases uncertainty about the impacts of a possible change in the regulation of transport via platform.
I5. Life quality	Q13. Uber reduced stress and worries when commuting. Q14. Uber makes commuting in urban centers easy. Q15. Uber positively affects the quality of life of its users.,
I6. Environmental	Q16. Uber allows for better use of the vehicle's physical space compared to individual passenger transport. Q17. Uber reduced the number of vehicles on city streets. Q18. Uber makes a positive contribution to mitigating the impacts of transportation on the environment.

Note. Elaborated by the authors based on the research data.

The same questions were applied to both sides of the platform to understand the social impact from the perspective of both passengers and drivers. Using the same questions, we aimed to analyze the viewpoints of both user groups on the same topic. Considering that drivers can also be passengers and vice versa, understanding their perspectives on the same phenomenon provides a comprehensive understanding of the impact of Uber. To design the questionnaire according to the study's categories, we ensured that all the questions were relevant to the study's objectives (Fowler, 2014). Although the number of questions in each category may vary, we maintained a balance to avoid emphasizing any category over others (Brace, 2004).

The technological social change rate indicator was created and implemented using Likert scale questions applied to platform users to measure the social change rate in each category. The questions were grouped into six key variables: employability conditions, social inequality, economic concerns, policy management system, quality of life, and environment. These were developed based on a theoretical framework. The scale was as follows: 1 = 'completely disagree,' 2 = 'partially disagree,' 3 = 'neutral or indifferent,' 4 = 'partially agree,' and 5 = 'completely agree.' The following formula was used:

$$Ts = \frac{\frac{\sum_k^p (I1)}{n} + \frac{\sum_k^p (I2)}{n} + \frac{\sum_k^p (I3)}{n} + \frac{\sum_k^p (I4)}{n} + \frac{\sum_k^p (I5)}{n} + \frac{\sum_k^p (I6)}{n}}{6} \quad (1)$$

where: *Ts* = technological social change rate; I1, I2, I3, I4, I5, I6 represent Likert scale data; n represents sample size; and k represents the user (k = 1, 2,..., p).

The values were translated into indices ranging from −1 to +1, with −1 corresponding to 1, −0.5, 2, 0 to 3, +0.5 to 4, and +1 to 5 before processing the data in the SPSS software. The indicator considered the average numbers and received statistical treatment using SPSS software. Values less than 0 indicate a negative impact on social change, whereas values greater than 0 indicate a positive effect of Uber on users' social lives according to their perspective.

The lower the index, the less influence platforms have on social change. The stronger the effect of technology platforms on social change, the higher the index. The impact of the social change platform on drivers and passengers can be compared using indicator data. Based on the indicator data, the researchers utilized the t-test for independent samples, combined with Levene's (1960) test, to determine whether the Uber platform impacted passengers and drivers at different levels in Belo Horizonte between 2014 and 2019. SPSS version 25 software was used to conduct the tests. When the standard deviation is unknown, tests related to univariate hypothesis testing are used to compare the means (Malhotra, 2019). The following hypotheses were tested:

> H0 (t-test): The indicator for technological social change is equal to zero ($p > 0,05$).
>
> H0 (Levene's test): The variance of the passengers' technological social change rate is equal to the variance of the drivers' technological social change rate ($p > 0.05$).
>
> H0 (t-test): The average of the passengers' technological social change rate is equal to the average of the drivers' technological social change rate ($p > 0.05$).

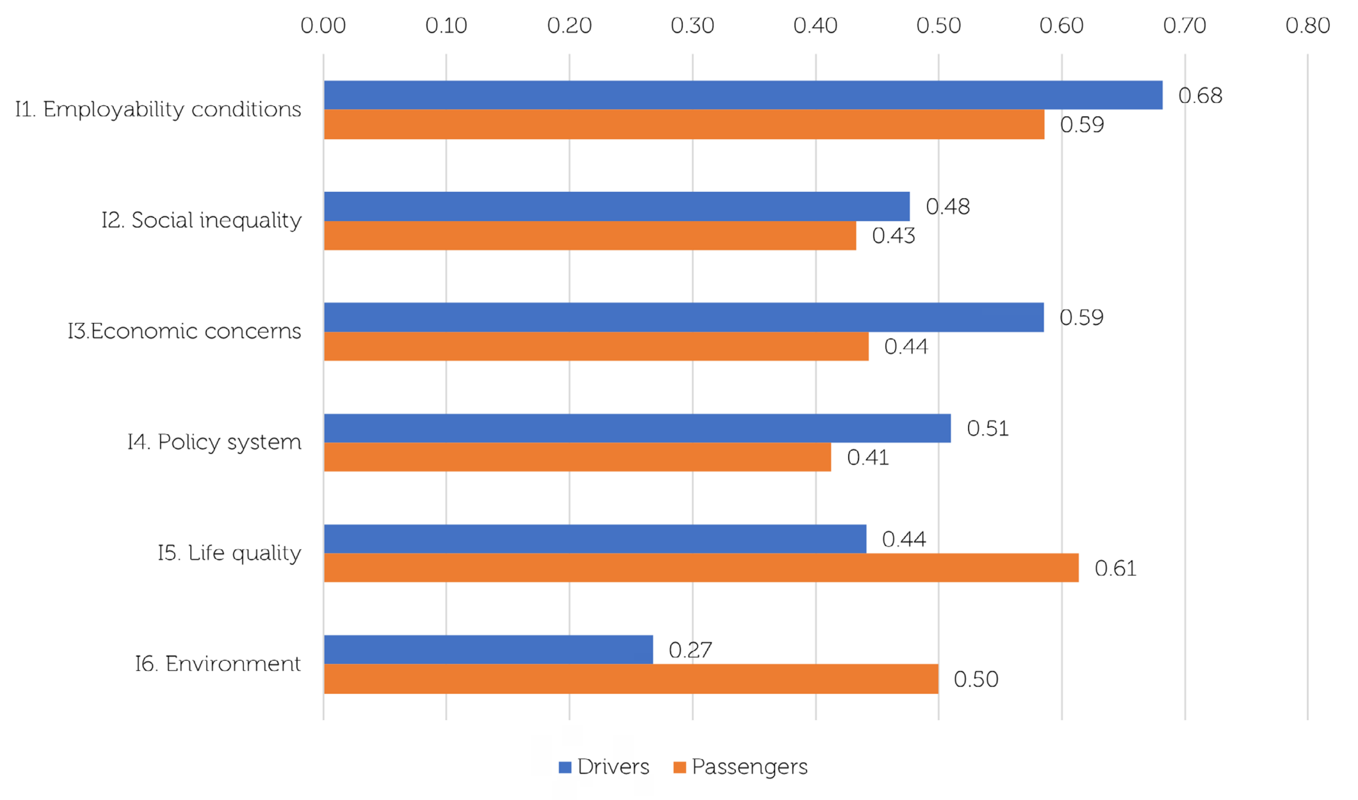
The researchers validated statistical significance by performing normality tests. The data was subjected to the Shapiro-Wilk test for sample normality, yielding a p-value of 0.05.

Data analysis

Hair et al. (2013) used data for a multidimensional analysis. The results from the questionnaire were categorized according to analytical categories and questions using a Likert scale. To summarize the results or conduct a more thorough investigation, researchers concurrently investigated more than two factors. Analytical categories were developed based on the literature, which facilitated the coding and understanding of the data. The data gathered from the surveys were classified into analytical categories. The indicator was generated using structured Likert-scale questions. A t-test, which corresponds to univariate hypothesis testing (Malhotra, 2019), was performed based on the data supplied by the indicator (Malhotra, 2019).

RESULTS

Figure 2 depicts the findings of the indicator technological social change rate elements that compose the perceived disparities in employability conditions, social inequality, economic concerns, policy management system, life quality, and environment between Uber users in Belo Horizonte.



Source: Elaborated by the authors based on the research data.

Figure 2. Technological social change rate.

The data point to the indicator for technological social change, where the variables life quality (0.61), employability conditions (0.59), and environment (0.50) are emphasized for the passenger sample, and for the driver sample, the highest score was for employability conditions (0.68), economic concerns (0.59), and policy management system (0.51). The higher the value, the greater the social change associated with the platform's use. While the most socially changing factor for drivers was employee conditions, for passengers, it was the improvement in life quality provided by the Uber platform. The changes in employee conditions are also recognized as the second most socially impactful factor from the passenger's perspective. Through the equation of the indicator for technological social change rate, the following values were obtained: 0.49 for the sample of just drivers and 0.50 for the sample of only passengers, indicating that the Uber platform plays a major and significant role in social change (Kavanagh et al. 2021). To determine the significance of the data, hypothesis testing was performed (Table 2) to see whether the Uber platform is associated with social change.

Table 2. T-test technological social change rate.

One-sample test						
	Test value = 0					
	t	df	Sig. (2-tailed)	Mean difference	95% Confidence interval of the difference	
					Lower	Upper
Employability Conditions	62.990	840	.000	.6310912	.611426	.650756
Social inequality	32.059	840	.000	.4536	.426	.481
Economic concerns	47.524	840	.000	.5102061	.489134	.531278
Policy management system	34.332	840	.000	.4582894	.432089	.484490
Life quality	42.311	840	.000	.5322001	.507511	.556889
Environmental	24.225	840	.000	.3901034	.358497	.421710

Note. T-test considered $p < 0.05$ for average different than 0.

The p-value is less than 0.05 in all variables linked to social change, implying that the null hypothesis is rejected. As a result, it is reasonable to believe that Uber plays an essential role in changing the non-material culture of its users, such as employability conditions, social inequality, economic concerns, the policy management system, life quality, and the environment. When likening the sample of drivers to the sample of passengers, it is observed (Table 3) that the social changes on economic concerns are 32% greater than those of passengers, followed by policy management systems (24% higher), employability conditions (16% higher), social inequality (10% higher), life quality (28% shorter), and the environment (46% shorter).

Table 3. Comparative individual social capital rate.

Category	Passengers	Drivers	Delta %
I1. Employability conditions	0.59	0.68	16%
I2. Social inequality	0.43	0.48	10%
I3. Economic concerns	0.44	0.59	32%
I4. Policy management system	0.41	0.51	24%
I5. Life quality	0.61	0.44	-28%
I6. Environment	0.50	0.27	-46%

Note. Elaborated by the authors based on the research data.

Regarding the percentage of Uber users, 92% of passengers and 100% of drivers agreed that Uber changes employability conditions; 76% of passengers and 83% of drivers agreed that Uber changes social inequality; 87% of passengers and 93% of drivers agreed that Uber changes economic aspects, solving economic concerns; 71% of passengers and 84% of drivers agreed with changes in the policy management system with different roles and metrics, 88% of passengers and 88% of drivers agreed that Uber improves the quality of life; and 69.8% of passengers and 58.9% of drivers affirm that Uber reduces environmental issues. The independent samples test was used to determine if the indicator scores for passengers and drivers are statistically different (Table 4). Levenes' test and t-test show that all the scores are significantly different between the two samples, except social inequality.

Table 4. Independent Samples Test.

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	95% Confidence interval of the difference	
									Lower	Upper
Employability conditions	Equal variances not assumed	82.754	.000	-4.934	756.658	.000	-.09520	.019295	-.13308	-.05732
Social inequality	Equal variances not assumed	81.868	.000	-1.577	778.602	.115	-.0437	.0277	-.0981	.0107
Economic concerns	Equal variances assumed	.007	.932	-6.794	839	.000	-.14256	.020983	-.18375	-.10138
Policy management system	Equal variances not assumed	62.973	.000	-3.699	820.336	.000	-.09689	.026192	-.14830	-.04547
Life quality	Equal variances not assumed	33.847	.000	7.129	808.431	.000	.17153	.024062	.12429	.21876
Environmental	Equal variances not assumed	90.387	.000	7.556	810.606	.000	.23242	.030758	.17205	.29280

Note. Levene's test considers $p < 0,05$ when equal variances are not assumed, and $p > 0,05$ for equal variances assumed; t-test considers $p < 0.05$.

Thus, with a significance level of 5%, the examination of the t-test and Levene's test findings compared to the indicator data indicates that the Uber platform has affected passengers and drivers at different levels in all categories, except for social inequality, but the positive rate of the indicator suggests that the platform has promoted positive changes, reducing social issues. The data was subjected to the Shapiro-Wilk test for sample normality, yielding a p-value of 0.05. Based on the sample size, Pearson correlation was utilized to produce the results shown in Table 5.

Table 5. Pearson correlation for the variables of interest.

		Uber Frequency	Employability conditions	Social inequality	Economic concerns	Policy system	Life quality	Environmental
Uber Frequency	Pearson correlation	1	.820**	.437**	.446**	.504**	.397**	.503**
	sig. (2-tailed)		.000	.000	.000	.000	.000	.000
	N	841	841	841	841	841	841	841

Note.** The correlation is significant at the 0.01 level (2-tailed). Source: Research data.

There is a positive correlation between the frequency of Uber use and all categories, but with varying degrees. The highest correlation is with employability conditions. Policy management system and environmental factors show a moderate correlation, while social inequality, economic concerns, and life quality have a small correlation. For the correlation analysis, Cohen's (1988) categorization was used: values less than 0.30 are small, 0.30 to 0.70 are moderate, and more than 0.70 are large. Multiple linear regression was employed to test whether categorical factors predict the frequency of Uber use, generating a mathematical model of this connection. The dependent variable was the frequency of platform use, and the independent variables were employability conditions, social inequality, economic concerns, policy management system, life quality, and environment. Table 6 presents the forward method, where each variable was added in turn. The model with all variables had an adjusted R^2 of 0.674 and an R of 0.822, indicating its ability to explain 82% of the variations in platform use. The closer the R is to 1, the better the model's performance.

When the model is subjected to the ANOVA test (Table 7), a p-value of 0.05 is obtained, suggesting a different model fit in the absence of a predictor. This finding indicates that the addition of analytical categories improves the model.

Table 6. Model summary.

R	R square	Adjusted R square	Std. error of the estimate	Change statistics					Durbin-Watson
				R square change	F change	df1	df2	Sig. F change	
.822[a]	.676	.674	144.372	.676	290.258	6	834	.000	1.080

Note. a. Predictors: (constant), environmental, social inequality, economic concerns, life quality, employability conditions, policy system. Source: Research data.

Table 7. Anova[a].

	Sum of squares	df	Mean square	F	Sig.
Regression	36299420	6	6049903	290.258	.000[b]
Residual	17383211	834	20843.18		
Total	53682631	840			

Note. a. Anova based on multiple linear regression of the model described in the Table 6. b. Significance level. Source: Research data.

The analysis resulted in a statistically significant model [$F(6) = 290.258$; $p < 0.001$; $R^2 = 0.674$]. However, when the t-test was conducted for each variable (Table 8), the results differed by category. Some categories had p-values greater than 0.05, indicating that the null hypothesis — that the components were created randomly — was not rejected.

In this regard, a new model was created that excluded variables with p-values greater than 0.05 (Table 9), retaining only those related to employment conditions and environment.

Table 8. Coefficients general performance.

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.	Collinearity statistics	
	B	Std. error	Beta			Tolerance	VIF
(Constant)	85.368	13.293		6.422	.000		
Employability conditions	705.699	24.382	.797	28.943	.000	.512	1.952
Social inequality	3.224	14.828	.005	.217	.828	.628	1.592
Economic concerns	-22.937	20.473	-.029	-1.120	.263	.582	1.719
Policy system	15.891	18.202	.025	.873	.383	.487	2.055
Life quality	-27.022	18.826	-.039	-1.435	.152	.538	1.859
Environmental	38.730	15.603	.072	2.482	.013	.464	2.155

Note. a. Dependent variable: frequency of platform use. Source: Research data.

Table 9. Model summary[b].

R	R square	Adjusted R square	Std. error of the estimate	Change statistics					Durbin-Watson
				R square change	F change	df1	df2	Sig. F change	
.821[a]	.675	.674	144.369	.675	868.815	2	838	.000	1.075

Note. a. Predictors: (constant), environmental, employability conditions. Dependent variable: frequency of the platform use. b. New regression model Source. Research data.

When the model is subjected to the ANOVA test, a p-value of 0.05 indicates predictor validity (Table 10).

Table 11 shows the authors' verification of collinearity statistics for general performance. We aimed to ensure that the tolerance values for each category were greater than 0.1 and the VIF values were less than 9, indicating the absence of multicollinearity. Regarding the residuals, we identified the existence of outliers.

Table 10. Anova[a].

	Sum of squares	df	Mean square	F	Sig.
Regression	36216594.456	2	18108297.2278889	868.815	.000[b]
Residual	17466036.331	838	20842.525		
Total	53682630.787	840			

Note. a. Anova based on multiple linear regression of the model described in the Table 9. b. Significance level. Source: Research data.

Table 11. Coefficients general performance[a].

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.	Collinearity statistics	
	B	Std. error	Beta			Tolerance	VIF
(Constant)	75.864	12.326		6.155	.000		
Employability conditions	698.816	21.199	.789	32.965	.000	.678	1.476
Environmental	29.477	12.913	.055	2.283	.023	.678	1.476

Note. a. Dependent variable: frequency of platform use. Source: Research data.

The categories employability conditions ($\beta = 0.789$; $t = 32.965$; $p < 0.05$) and environment ($\beta = 0.055$; $t = 2.283$; $p < 0.05$) are predictors of Uber frequency of use. The model equation is given by: y = 75.864 + 698.816 (employability conditions) + 29.477 (environment). Thus, despite the positive correlation between the social change categories and the frequency of use (Table 3), at a statistical significance level of 0.05, only employability conditions and environmental factors are predictors of Uber use frequency.

DISCUSSION

The research findings support the proposition that the peer-to-peer technological platform Uber is associated with social change (Kavanagh et al. 2021). By facilitating user interaction (Wen, 2023), the platform can meet social needs (Caridà et al., 2022; Kavanagh et al. 2021) and address social issues (Kolk and Ciulli, 2020). The results indicate that Uber is transforming a non-material culture (Martin, 2022; Parente et al., 2018; Si et al., 2023; Stallkamp & Schotter, 2021), influencing policy systems (Wen, 2023), and eroding traditional organizational models (Kirchner & Schüßler, 2020). The technological social change indicator positively impacts social change in both samples, with the platform affecting passengers (0.50) slightly more than the drivers (0.49). This result aligns with studies indicating a balance between riders and drivers, affecting both sides of the platform (Beliaeva et al., 2020; Cramer & Krueger, 2016; Jha et al., 2016; Kavanagh et al. 2021; Martin, 2022; Taylor et al., 2015; Wen, 2023).

The first hypothesis regarding the quality of life shows that Uber significantly impacts the quality of life of passengers and drivers but at different levels. The quality-of-life social change rate was higher for passengers (0.61) than drivers (0.44). Users agree that Uber has reduced stress and worries (Greenwood & Wattal, 2017; Kavanagh et al. 2021) by providing convenient and reliable transportation options, enhancing mobility (Rayle et al., 2016), and improving quality of life with comfort and convenience (Kavanagh et al. 2021; Milojević & Inayatullah, 2015; Taylor et al., 2015). We noted a slight positive correlation coefficient when verifying the correlation between platform usage frequency and life quality improvement improvement ($r = 0.397$; $p < 0.01$). However, t-tests in the regression model showed that life quality was not a predictor of Uber utilization frequency ($p > 0.05$). Thus, despite both user groups agreeing that Uber positively impacted their quality of life, there is no significant evidence that this impact predicts Uber utilization frequency.

The second hypothesis regarding employability conditions shows that Uber has significantly impacted employment conditions due to its flexibility and opportunities compared to traditional employment models (Kirchner et al., 2022; Rosenblat & Stark, 2016). The employability condition indicator confirms that Uber has changed the employability conditions of drivers (0.68) and passengers (0.59) (Ametowobla & Kirchner, 2023; Rosenblat & Stark, 2016; Wen, 2023). The platform provides employment opportunities (Azevedo et al., 2015; Kirchner et al., 2022; Jha et al., 2016; Rosenblat & Stark, 2016), allowing drivers to balance work with other commitments and potentially improving their overall life satisfaction (Kirchner et al., 2022; Rosenblat & Stark, 2016). The correlation between employability and Uber use frequency showed a high positive correlation ($r = 0.820$; $p < 0.01$). T-tests in the regression model indicated that employability predicted Uber frequency ($\beta = 0.789$; $t = 32.965$; $p < 0.05$). These results suggest that the platform impacts employability conditions, which, in turn, affects usage frequency. The higher the employability condition, the greater the platform use, making it a significant predictor in the regression model.

The hypothesis regarding the environmental impact shows that Uber's ride-hailing services significantly reduce emissions through optimized vehicle usage (Henao & Marshall, 2019). Environmental rates (0.50 for passengers and 0.27 for drivers) indicate that the platform positively contributes to mitigating transportation impacts, promoting sustainability (Jha et al., 2016), and reducing city space requirements and vehicle numbers. The higher rate for passengers suggests a more significant impact on them than drivers, possibly due to the drivers' continued high dependence on vehicles. The correlation between environmental factors and Uber use frequency was moderately positive ($r = 0.503$; $p < 0.01$). T-tests in the regression model indicated that environmental factors predicted the Uber frequency ($\beta = 0.055$; $t = 2.283$; $p < 0.05$). These results suggest that the platform impacts the environment and usage frequency, making it a significant predictor in the regression model.

Verification of the hypothesis regarding economics showed that Uber's platform significantly enhances market efficiency and economic value (Wen, 2023) by creating new income opportunities for drivers (Cramer & Krueger, 2016; Kirchner et al., 2022), generating additional revenue for businesses, and reducing transportation costs through dynamic pricing (Hall & Krueger, 2018). This finding supports the solution of economic concerns (Beliaeva et al., 2020). As an alternative for obtaining income and reducing transportation expenses compared to traditional means of transport (taxi, bus, or car), the driver's rate was higher (0.59) compared to passengers (0,41). The correlation between economic concerns and Uber use frequency was significantly positive but presented a lower degree ($r = 0.446$; $p < 0.01$). T-tests in the regression model showed that economic concerns did not predict the Uber frequency ($p > 0.05$). These results indicate that despite both user groups agreeing that Uber has positively impacted the economic dimension of their lives, there is no significant evidence that this impact predicts Uber utilization frequency.

The following hypothesis regarding the policy management system shows that Uber's operations significantly influence policy management by changing public policy and impacting labor laws and worker rights, particularly in the gig economy. Uber's operation also changed the policy management system (0.51 for drivers and 0.41 for passengers). Users agree that Uber's operational logic differs significantly from that of traditional companies, with performance evaluations based on user reputation and sensitivity to changes in government and law regulations (Dungca, 2020; Wen, 2023). The positive rate confirms the hypothesis that Uber has changed public policy (Le Vine & Polak, 2015; Martin, 2022) and impacted various sectors of government and society (Azevedo et al., 2015; Dungca, 2020; Rogers, 2015; Wen, 2023; Zvolska et al., 2019).

The correlation between the policy management system and Uber usage frequency was moderately positive ($r = 0.504$; $p < 0.01$). T-tests in the regression model showed that this category was not a predictor of the Uber frequency ($p > 0.05$). These results indicate that, despite both user groups agreeing that Uber has impacted the policy management system, there is no significant evidence that this impact predicts Uber utilization frequency.

The last hypothesis regarding social inequality shows that Uber's operations significantly impact social inequality by providing income opportunities for marginalized groups (Kirchner et al., 2022; Rosenblat & Stark, 2016; Wen, 2023). The indicator shows a higher score for drivers (0.48) than for passengers (0.43); however, there is no significant difference between them. Nonetheless, a positive rate indicates that Uber has been reducing social inequality and improving accessibility (Carvalho & Pereira, 2011; Le Vine & Polak, 2015) by offering cheaper mobility alternatives and promoting social inclusion for low-income individuals (Ferraz & Torres, 2004 ; Wen, 2023). Although Uber is part of the gig economy, the analysis suggests that contrary to the proposition that Uber perpetuates income inequality due to the lack of job security and benefits (Kirchner et al., 2022; Rosenblat & Stark, 2016), users' perspectives indicate an opposite opinion.

The correlation between social inequality and the frequency of Uber use was also significantly positive but presented a lower degree ($r = 0.437$, $p < 0.01$). The t-tests in the regression model showed that this category was not a predictor of the Uber frequency ($p > 0.05$). These results also indicate that despite users agreeing that Uber has positively impacted social inequality, there is no significant evidence that this impact predicts the frequency of Uber utilization. Thus, from a broad perspective, the technological social change rate demonstrates that all changes associated with Uber adoption significantly impact the statistical tests and occur at different levels (except for social inequality) for drivers and passengers.

However, they positively impacted both samples, assisting in resolving social issues (Kolk & Ciulli, 2020) and promoting socioeconomic development (Beliaeva et al., 2020). Regarding the categories that are predictors of Uber utilization, only employability conditions ($\beta = 0.789$, $t = 32.965$, $p < 0.05$) and environment ($\beta = 0.055$, $t = 2.283$, $p < 0.05$) were statistically significant for inclusion in the model equation: $y = 75.864+698.816$ (employability conditions) + 29.477 (environment). Thus, all categories are correlated with Uber frequency, but not all are predictors of frequency of use.

CONCLUSION

Theoretical and methodological implications

This study makes an essential contribution to the existing literature. By associating technological platforms and social change approaches to measure and analyze the technological, social change of Uber platform users with a set of original indicators, this study fills gaps related to the current lack of studies that address the technological platform approach to solving social problems and needs (Beliaeva et al., 2020; Caridà et al., 2022; Kolk & Ciulli, 2020; Misuraca & Pasi, 2019).

Indeed, this article also has a significant contribution to measuring the social change rate (Kavanagh et al., 2021), in a different perspective of many scholars (Bauer, 1966; Caplow et al., 2001; Kavanagh et al. 2021; Lynd & Lynd, 1929; Sheldon & Moore, 1968), the approach presented focuses on the non-material culture aspects to solve social issues (Kolk & Ciulli, 2020). It analyzes multiple sides of the Uber platform, capturing the impact from the users' point of view. This approach provides notable outputs, confirming that Uber is changing the culture (Martin, 2022), triggering different policy outcomes (Wen, 2023), impacting traditional organizational models (Kirchner & Schüßler, 2020), and affecting the entire economy (Kirchner et al., 2022). However, this also shows that not all categories of social change influence the frequency of use.

Regarding the frequency of use, the correlation model shows a significant positive relationship in all categories of social change, but the regression model demonstrates that only employability conditions (Kirchner et al., 2022; Rosenblat & Stark, 2016; Wen, 2023) and the environment (Henao & Marshall, 2019) are predictors of frequency of use. This study provides a more integrated understanding of the social changes associated with a technological platform. This shows that, with the technological social change indicator, life quality and employability conditions were the most influential factors for passengers, and employability and economic concerns were the significant factors impacted from the driver's perspective.

Practical implications

Initially, this article emphasizes the importance of a better understanding of the social changes associated with a peer-to-peer technological platform. The proposal of a model that integrates six variables to measure social change, as proposed here, can help researchers measure the impact of platforms on solving social issues. Indeed, knowledge of these variables can help managers formulate strategies to enhance markets and services oriented toward platform users. In addition, by demonstrating that the platform has significantly impacted drivers and passengers in different ways, life quality for passengers, and employability conditions for drivers, this study sheds light on the relevance of the different social impacts of the peer-to-peer technological platform on different users, which are still little known and explored. Finally, the regression model developed in this study can be helpful for managers to fine-tune their marketing efforts, focusing on elements that drive higher demand and consequent income for the platform.

Implications at the level of public policies

Social issues are a concern in many societies, and peer-to-peer platform diffusion has increased over the last few years. This study shows the main factors of social change impacted by technological platforms. This impact also affects the institutions that could benefit from policies to reduce drunk driving, increase social well-being (Greenwood & Wattal, 2017), and provide a mobility alternative to low-income people (Ferraz & Torres, 2004; Wen, 2023), but in the same way that they have to adapt public policies to solve social issues such as unemployment. Therefore, these findings also support public policies that drive social changes in socioeconomic development.

Limitations

This study has some limitations. The first is related to the cross-sectional analysis of the social impacts of the Uber platform. This study addresses the immediate perception of changes associated with technological platforms. However, social changes can have a long-term effect, and the results can be better observed over a longer time horizon than that understood in this work. Another limitation is that although the technological social change indicator provides a way to quantify the impact of a technological platform on social change, adding more elements could enable the indication to be adapted to other and more specific contexts, such as health and the real state. Finally, the absence of a qualitative research method would allow for a more in-depth analysis of how peer-to-peer platforms affect the social context.

Suggestions for future research

New research could, for example, investigate the impacts of peer-to-peer platforms over a long period and check if the social benefits are sustainable. Additionally, other studies can expand platform horizons. There are peer-to-peer platforms in different sectors, and with many intermediate purposes, the social impact of these platforms and the real social benefits are an unexplored field, representing research opportunities.

Concluding remarks

This article addresses some of the many scholars' requests for practical studies that address technological platforms' approach to solving social problems, meeting social needs, and measuring the social change rate. Field evidence leads us to conclude: (a) the peer-to-peer platform has a significant positive impact on changing the non-material culture, such as employability conditions, social inequality, economic concerns, the policy management system, life quality, and the environment; (b) platform interaction enables users to meet their social needs and solve issues; life quality and employability are the most important factors for passengers, while employability and economic concerns are from the driver's perspective; (c) despite a positive correlation between the categories and frequency of use, only employment conditions and environment are predictors of frequency.

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