A Systematic Literature Review of Anti-Discrimination Design Strategies in the Digital Sharing Economy

Miroslav Tushev, Fahimeh Ebrahimi, and Anas Mahmoud

Abstract—Applications of the Digital Sharing Economy (DSE), such as Uber, Airbnb, and TaskRabbit, have become a main facilitator of economic growth and shared prosperity in modern-day societies. However, recent research has revealed that the participation of minority groups in DSE activities is often hindered by different forms of bias and discrimination. Evidence of such behavior has been documented across almost all domains of DSE, including ridesharing, lodging, and freelancing. However, little is known about the underlying design decisions of DSE platforms which allow certain demographics of the market to gain unfair advantage over others. To bridge this knowledge gap, in this paper, we systematically synthesize evidence from 58 interdisciplinary studies to identify the pervasive discrimination concerns affecting DSE platforms along with their triggering features and mitigation strategies. Our objective is to consolidate such interdisciplinary evidence from a software design point of view. Our results show that existing evidence is mainly geared towards documenting and mitigating issues of racism and sexism affecting platforms of ridesharing, lodging, and freelancing. Our review further shows that discrimination concerns in the DSE market are commonly enabled by features of user profiles and commonly impact reputation systems.

Index Terms—digital discrimination, sharing economy, systematic review, evidence-based design

1 Introduction

Over the past few years, the Digital Sharing Economy (DSE)—also known as the sharing, shared, or gig economy—has become one of the most ubiquitous manifestations of mobile technology. Unlike conventional business models, applications of DSE provide access to, rather than ownership of, underutilized assets and resources via Peer-to-Peer (P2P) coordination [1]. This on-demand, convenient, and ecologically sustainable form of resource consumption has attracted consumers and investors around the globe. As of today, there are thousands of DSE platforms, enabling consumers to sell, rent, swap, lend, and borrow services and assets at unprecedented scales.

The unique form of direct business exchange that DSE platforms have enabled has been linked to significant levels of economic growth, especially in communities at the lower end of the economic ladder, helping unemployed and partially employed individuals to generate income, increase reciprocity, and access resources that are unattainable otherwise [1], [2], [3], [4], [5]. However, recent research has exposed a serious discrimination problem affecting these platforms [6], [7], [8]. Discrimination, as a general term, refers to incidents where *"members of a minority group (women, Blacks, Muslims, immigrants, etc.) are treated differentially (less favorably) than members of a majority group with otherwise identical characteristics in similar circumstances"* [9]. In the context of DSE, discrimination (also commonly known as *digital* discrimination) refers to a phenomenon where **an online business transaction over a DSE platform is influenced (biased) by race, gender, age, or any other non-business related characteristic of service providers or consumers** [2], [6], [7], [8], [10].

Manuscript received June 1, 2021; revised July 1, 2021.

The problem of digital discrimination in online DSE markets has gained increasing attention in recent years. Numerous large-scale surveys, field studies, and data analysis papers have documented significant evidence on different patterns of discriminatory behavior across almost all domains of DSE, including ridesharing (e.g., Uber), lodging (e.g., Airbnb), and freelancing (e.g., TaskRabbit). Such patterns include discrimination based on ethnic background (racism), gender or sexual orientation (sexism), and physical disability (ableism) [6], [7], [11], [12], [13], [14], [15]. For instance, a recent study of ridesharing services found that Black riders using Uber waited on average 30% longer to be picked up [6]. Another study of P2P lodging services reported that non-Black Airbnb hosts were able to charge 12% more than Black hosts [7]. In the freelancing domain, a study of worker profiles on TaskRabbit revealed that the gender and race of workers were significantly correlated with their ratings [8].

Existing research on digital discrimination often tackles the problem from socio-economic and regulatory points of view [6], [7], [16], [17], [18], [19], [20]. In general, researchers seek to prove and document discriminatory behavior in the DSE market as well as propose legislation to counter such behavior [2], [18], [19], [21], [22]. However, the research on the design aspects of DSE software which enable such a complex socio-technical phenomenon to emerge online remains underdeveloped. This can be partially attributed to the fact that existing evidence on digital discrimination is scattered across a broad range of interdisciplinary venues. Locating, interpreting, and synthesizing such evidence can be a very challenging task, especially in highly agile environments where the main focus is on solution deployment rather than problem research.

To bridge this knowledge gap, in this paper, we conduct a first-of-its-kind effort to systematically consolidate a large body of interdisciplinary research on digital discrimination, a complex socio-technical problem that is currently affecting millions of users in one of the fastest growing software ecosystems in the world. Our objective is to facilitate evidence-based software design strategies [23] by helping DSE developers to **a)** identify the main discrimination concerns in their domain of operation, **b)** understand how the interactions between their functional features and user goals can facilitate bias and differential treatment of DSE users, and ultimately **c)** deliver DSE solutions that can promote equality and mitigate bias by design.

The rest of this paper is organized as follows. Section 2 describes our review protocol and presents a quantitative analysis of existing evidence. Section 3 qualitatively synthesizes available evidence on digital discrimination in the DSE literature. Section 4 discusses our main findings. Section 5 addresses threats to validity. Finally, Section 6 concludes the paper and describes our future work.

2 Method and Quantitative Analysis

The research on digital discrimination in the DSE market aims to provide strong empirical evidence on the different patterns of bias affecting different DSE platforms and suggest feature changes to enhance these platforms' resilience to inequality. To locate such evidence, in this section, we conduct a systematic literature review (SLR) of this body of research. According to Kitchenham et al. [24], SLR as a research methodology consists of three main steps: planning, conducting, and reporting. Under the planning phase, the need for the review is justified, the review protocol is established, and the research questions are defined. During the conducting phase, the review protocol is put into action, including the identification of primary studies and categorizing and synthesizing existing evidence. Finally, under the reporting phase, the results are reported in a way that is tailored for the intended audience. In what follows, we describe our review protocol in greater detail.

2.1 Research Questions

It is essential to identify a set of research questions before taking on a review study. Research questions are necessary to identify the *scope* of studies (papers) to be included in the search process and to outline the objectives of the review. In this study, our research questions are:

- **RQ$_1$**: ***What types of discriminatory behavior do DSE platforms exhibit?*** Discrimination can take many forms; some are more prominent than others. Therefore, under this research question, we seek to determine the specific types of discriminatory behavior, or bias, that are common in the DSE market.
- **RQ$_2$**: ***What domains, or platforms, of DSE are affected the most by discrimination?*** DSE platforms extend over a broad range of application domains, from ridesharing, to lodging, and even dog walking (e.g. Wag!). Therefore, under this question, we seek to identify the application domains of DSE that are commonly affected by discrimination.
- **RQ$_3$**: ***What are the main features and user goals that are related to discrimination in DSE platforms?*** This research question is concerned with synthesizing evidence on the underlying design decisions and feature-goal interactions of DSE platforms that are responsible for enabling discriminatory behavior.
- **RQ$_4$**: ***Are there any suggested feature changes to counter digital discrimination?*** Under this research question, we seek to locate evidence on any design strategies that have been suggested to counter, or mitigate, the different types of discrimination prevalent in the DSE market.

2.2 Identifying Primary Studies

To identify our set of primary studies, we started by formulating our search query. The most common term that is often used to refer to discriminatory behavior in DSE is *digital discrimination*. To account for other variations and synonyms of the word *discrimination*, we referred to Oxford English Dictionary. The following synonyms were included in our search query: *bias*, *prejudice*, *inequity*, and *bigotry*. In addition, we considered specific types of discrimination—in case a primary study referred to a specific type of discrimination and not the word *discrimination* or its synonyms. Table 1 lists the main acts of discrimination as described by the U.S. Equal Employment Opportunity Commission. These acts commonly appear in diversity and social justice literature [25]. Based on this list, we added the terms *racism*, *sexism*, *ableism*, *ageism*, *parental*, *classism*, and *religious*. Given that some of these types are more common than others, we also included other variations for less popular types of discrimination, such as *disability* and *accessibility* for ableism and *LGBT* for sexism. We further enhanced our query with information about the popular domains and platforms of DSE, including ridesharing (Uber and Lyft), lodging (Airbnb, Couchsurfing, and Vrbo), freelancing (TaskRabbit, Fiverr, and Upwork), and food delivery (DoorDash and UberEats). Note that these terms were chained using an (**OR**) command to avoid omitting any other, less popular, domains or platforms. Finally, to make sure we were being specific to the domain of sharing economy, we added the terms *sharing economy*, *gig economy*, and *shared economy*. In summary, our query can be described as follows:

> *((Digital discrimination)* ***OR*** *discrimination* ***OR*** *bigotry* ***OR*** *bias* ***OR*** *prejudice* ***OR*** *inequity* ***OR*** *racism* ***OR*** *sexism* ***OR*** *LGBT* ***OR*** *ableism* ***OR*** *ageism* ***OR*** *parental* ***OR*** *classism* ***OR*** *religious* ***OR*** *disability* ***OR*** *accessibility)* ***AND*** *(ridesharing* ***OR*** *Uber* ***OR*** *Lyft* ***OR*** *Lodging* ***OR*** *Airbnb* ***OR*** *Vrbo* ***OR*** *food delivery* ***OR*** *Doordash* ***OR*** *UberEats* ***OR*** *Postmates* ***OR*** *freelancing* ***OR*** *TaskRabbit* ***OR*** *Fiverr* ***OR*** *Upwork* ***OR*** *(Sharing Economy)* ***OR*** *(Shared Economy)* ***OR*** *(gig economy))*

Our search was conducted over Google Scholar, the ACM Digital Library, IEEE Xplore, and Scopus. The results of the search were iteratively examined to add more terms to the query and explore more research venues. The process stopped when no more new primary studies were found [26]. In total, 84 papers were located using our iterative search process.

TABLE 1: Most common types of discrimination.

Type	Discrimination against:
Racism	Ethnicity, color, or nationality.
Sexism	Gender or sexual orientation.
Ableism	Physical, sensory, or intellectual disability.
Parental	Parents with children or pregnant women.
Ageism	Older or younger people.
Religious	Perceived religion or a set of beliefs.
Classism	Particular social class.

2.3 Inclusion and Exclusion Criteria

In SLRs, the inclusion and exclusion criteria are used as a basis for selecting primary studies. Such criteria should be determined beforehand during the planning phase. Our inclusion criteria in this paper are:

- Books, papers, and technical reports.
- Studies that explicitly investigate design issues of digital discrimination in DSE.
- Studies that are published in English.

We used the following exclusion criteria to exclude any studies that are irrelevant to our survey goals:

- Short papers (less than 4 pages), editorials, summaries of keynote, tutorial papers, and grey literature.
- Duplicate reports of the same study. In case of duplication, the most recent version is selected.

To include and exclude papers, each paper was examined by each of the three authors individually. Specifically, each author read the title, abstract, and if necessary, the body of each of the 84 papers to determine their relevance to our survey. Each judge flagged each paper as `Include`, `Neutral`, or `Exclude`. The paper was then included or excluded based on the protocol shown in Table 2. Cases of conflicts were resolved using majority voting. Applying our inclusion/exclusion criteria to our initial round of search resulted in 40 papers (48%). Our main observation during this process is that a large number of papers were specific to regulatory issues, or legislation to enforce equality in DSE markets, with no discussion of aspects related to platform design. These papers were excluded.

To reduce the risk of omitting relevant studies, we also performed a lightweight backward-forward-snowballing on the included papers [27]. We basically inspected the studies cited by each of our included primary studies and the publications that subsequently cited the study. In total, 18 more papers were identified, raising the number of our studies to 58 papers. We did not enforce a venue criterion on our primary studies, mainly because the problem itself is inherently interdisciplinary, thus, enforcing specific venues might lead to omitting important related work.

2.4 Quantitative Analysis

We start our review by performing basic quantitative analysis on our included studies. This involved each of the authors individually going through each study to determine the types of discrimination the paper tackles, the specific DSE domain or platform being investigated in the paper, and the research methodology used. A discussion session was then held to consolidate our findings. Results are organized in an Excel sheet (http://seel.cse.lsu.edu/data/TSE2021.xlsx).

TABLE 2: The decision making process. IN: Include, EX: Exclude, and NU: Neutral.

Researcher$_1$	Researcher$_2$	Researcher$_3$	Final Decision
IN	IN	IN/EX/NU	Include
EX	EX	IN/EX/NU	Exclude
NU	NU	IN/EX/NU	Consensus Meeting
IN	EX	NU	Consensus Meeting

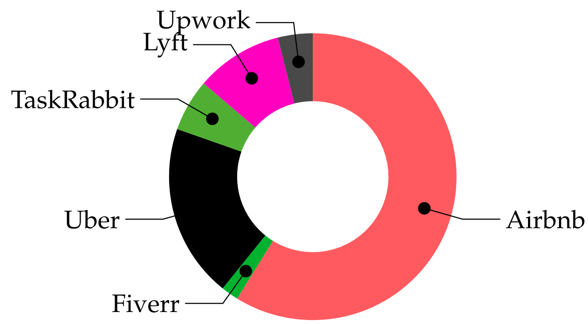


Fig. 1: Distribution of studies over DSE platforms.

With regard to **RQ$_1$** and **RQ$_2$**, our results show that discrimination problems are mainly investigated in the domains of ridesharing, lodging, and freelancing. In terms of platforms, Airbnb and Uber are the most investigated platforms (Fig. 1). This actually was expected given that discrimination concerns are more likely to manifest over such popular platforms as they tend to have significantly larger and more heterogeneous userbases in comparison to less popular platforms. Our results also show that racism and sexism are the most common types of discrimination investigated in the literature. These studies started appearing early in the past decade, before taking off in 2015 (Fig. 2). A specific index of these papers is shown in Table 3. In terms of methodology, our review shows that the majority of primary studies on digital discrimination take the form of field studies [6], [29], [30], [31] and large-scale surveys [11], [32]. Studies that rely on analyzing online platform data (user reviews or service listings) are also common [8], [14], [33], [34], [35].

TABLE 3: Included papers by discrimination type.

Type	Papers
Racism	[6], [7], [16], [19], [30], [31], [36], [37], [38], [39], [40], [41], [8], [15], [20], [29], [35], [42], [43], [44], [45], [46], [47], [48], [49]
Sexism	[8], [12], [14], [29], [34], [44], [45], [47], [49], [50], [51], [52], [53]
Ableism	[54], [55], [56], [57]
Classism	[13], [14], [35], [50], [58]

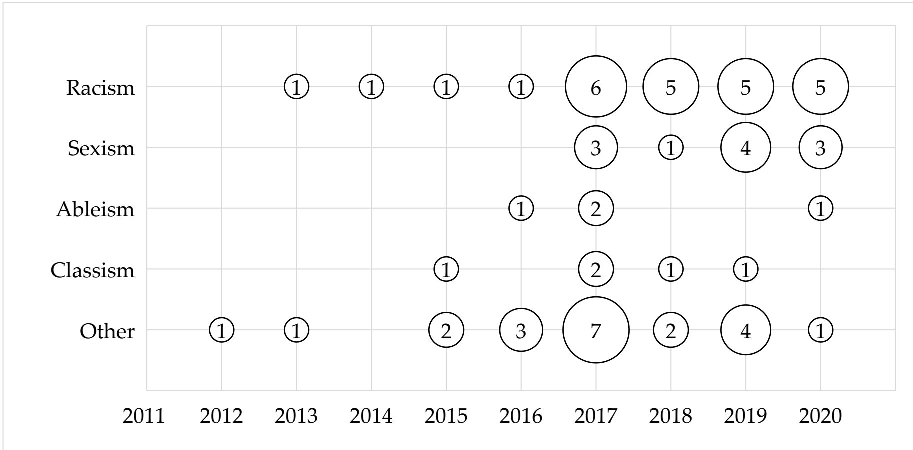


Fig. 2: A bubble chart of the growth of digital discrimination literature in DSE over time.

3 Qualitative Analysis of Evidence

A major goal of our SLR is to synthesize evidence on the features or goals of DSE platforms that have been proven to enable discriminatory behavior in the DSE market (**RQ$_3$**) as well as their mitigation strategies (**RQ$_4$**). A functional feature can be described as any observable behavior of the system that satisfies a specific stakeholder need, and a user goal, or a softgoal, can be defined as any abstract user objective that the system should achieve [59]. Unlike functional features, user (soft) goals do not have a clear-cut criterion for their satisfaction, however, they can be partially met, or *satisficed* through functional features [60], [61], [62]. To extract such evidence, we utilize a grounded theory approach of open coding and memoing [63]. This process can be described as follows:

- Each member of the review team (three authors) examined the title, abstract, and body of the paper. The main goal is to extract evidence on **RQ$_3$** and **RQ$_4$**.
- Categories of evidence were recorded as they emerged in the text. Reviewers used memoing to keep track of the reasoning behind their categorization.
- An axial coding session was then held to consolidate individual reviewers' categorizations into more abstract categories.
- Generated categories were then iteratively revised until no more categories or evidence were found.

By the end of our analysis, two main categories of features (profile information and reputation systems) and four user goals (trust, safety, accessibility, and inclusion) have emerged. These categories are described next.

3.1 Profile Information

DSE platforms use users' personal (profile) information as a means to enable effective search for service providers and receivers as well as to reduce anonymity and facilitate identification offline [33], [35]. However, our review revealed that user profiles were commonly associated with digital discrimination. Basically, service providers or receivers can decline or cancel a transaction based on certain physical traits, such as ethnicity, gender, or age, that can be inferred from profile pictures, user names, or location [29], [43]. In what follows, we review evidence related to patterns of digital discrimination enabled by DSE user profile information as well as the main strategies to counter these patterns.

3.1.1 Evidence

In the literature, profile pictures have been mainly linked to racism and sexism. For instance, based on an empirical analysis of 395 Airbnb's listings, Ert et al. [33] found that more trustworthy-looking Airbnb hosts charged higher prices for similar apartments. In another study of 200 U.S. consumers, Su and Mattila [34] reported that female consumers were more likely to book an Airbnb property listed with female profile pictures. In a study of 1,020 Airbnb listings, Jaeger et al. [35] reported that photo-based impressions of hosts' attractiveness significantly influenced their rental prices. The authors also reported that Black hosts charged lower prices for their apartments compared to White hosts. In a more recent field study of 100,000 Airbnb profiles across 24 cities, 14 countries, and 3 continents, Jaeger and Sleegers [37] found that personal information about sellers, as inferred from their names and pictures, led to widespread discrimination against hosts from racial minorities. In fact, racial profiling based on pictures is not specific to African-Americans; other independent large-scale studies have reported significant photo-induced discrimination against Asian and Hispanic hosts on Airbnb [39], [40]. For instance, in a recent study of hiring biases in freelancing, Leung et al. [29] asked 206 subjects to make hiring decisions for a mathematically intensive task. Significant biases against Black workers and less attractive workers and preferences towards Asian workers and women workers were detected.

Similar to profile pictures, user names were also linked to sexism and racial profiling [44]. For instance, according Foong et al. [50], Upwork workers with a unisex or unidentifiable name had on average a $2.26 higher mean bill rate than female users. Another study by Barzilay and

Ben-David [14] showed that women's average hourly rates on P2P freelancing platforms were about two-thirds of men's rates. In a field experiment of 1,801 Airbnb hosts, Cui et al. [30] found that requests from Airbnb guests with Black–sounding names were 19.2% less likely to be accepted than those with White-sounding names. In another field study of 6,400 Airbnb requests, Edelman et al. [7] reported that guests with Black–sounding names were 16% less likely to be accommodated relative to identical guests with White-sounding names. Ge et al. [6] conducted a field study of 1,500 UberX and Lyft ride requests on controlled routes. The authors observed more frequent cancellations by Uber drivers against passengers with Black-sounding names. These findings seem to persist globally [31], [46], [47]. For instance, in a field experiment of 952 carpooling requests in Germany, Carol [47] observed that women with German names were least likely to experience discrimination, while men with Turkish names were the most likely to face discrimination. Another experiment of 1,599 Airbnb requests in Norway showed that guests would spend less money on an apartment when the host was *"Abdi"* from Somalia rather than *"Martin"* from Norway [31]. Names were also found responsible for discrimination against the LGBT community. For instance Ahuja and Lyons [12] analyzed Airbnb host responses to listings indicative of LGBT relationships (e.g., *"My name is (male/female name) and my (boyfriend/girlfriend) and I are .."*). The results showed that hosts were more likely to not reply at all rather than replying *"no"* to male-male pairs inquiring about room availability.

Profile information was also found responsible for other, less popular, types of discrimination such as classism, ageism, parental, and ableism. For instance, Moody et al. [11] surveyed 1,100 of UberPOOL and Lyft riders. The results showed that White passengers who lived in predominantly White communities were more likely to discriminate against other passengers they perceived to belong to a lower social class. In another study of classism, Thebault et al. [13] surveyed workers on TaskRabbit from the Chicago metropolitan area. The authors found that requests from customers in the socioeconomically disadvantaged South Side area were less likely to be accepted. As an example of ageism and parental discrimination, a survey of 192 Airbnb hosts by Karlsson et al. [32] found that hosts were more likely to accept older people and women. The survey also found that couples with a child in their profile pictures were disadvantaged. In a study of discrimination against people with disabilities, a randomized field experiment of 3,847 lodging requests by Ameri et al. [57] revealed that hosts were less likely to approve requests from travelers who declared blindness, cerebral palsy, dwarfism, or spinal cord injury in their profiles than to approve travelers without disabilities.

3.1.2 Mitigation Strategies

Our review has uncovered several design strategies that have been proposed and evaluated in the literature to control for discrimination issues stemming from profile information. These strategies can be described as follows:

- **Withholding Information:** A main strategy to counter profile-induced discrimination is to minimize visual or verbal cues of users, allowing transactions to happen in relative anonymity [18]. For example, Uber prevents drivers from learning the identity or destination of their clients until they accept a request. Withholding, or delaying the exposure, to such information was found to have a significant positive effect on minimizing discrimination [64]. For instance, Mohammed [41] evaluated Airbnb's policy of delaying the exposure of guests to hosts' profile photos in four U.S. cities. The results provided a clear evidence on the success of this redesign in narrowing the racial booking gap in Airbnb.
- **Self-disclosure information:** While withholding pictures and names can mitigate discrimination, entirely concealing such information is expected to deteriorate safety [65]. To work around this dilemma, a recent study suggested that Airbnb hosts who discussed self-disclosure topics in their profiles, such as their tastes in music and food, work, or study, were often perceived as more trustworthy, thus were more likely to be chosen as hosts [38], [66]. In other words, *non-deterministic* information helps to alleviate racial profiling by enabling a more humane perception of users as well as challenging stereotypes [39]. In general, converging evidence suggests a redesign of user profiles, where information indicative of ethnicity, religion, or gender are hidden until after the transaction is confirmed, while more self-disclosure information (e.g., socially rich pictures or emotionally dynamic text [67]) are provided to reduce uncertainty and signal trustworthiness [18], [66].
- **Asset-based profile pictures:** In their field study, Hannák et al. [8] reported that workers who did not use a profile picture at all received significantly smaller numbers of reviews. The impact of not using a picture at all was also studied by Tjaden et al. [48] who found that Arab/Turkish/Persian drivers without a profile picture were observed to be much more disadvantaged than drivers from the same ethnic group with a profile picture. However, according to Ert e al. [64], workers who used a picture that was related to their assets (rental place as in Fig. 3) or skills (advertisements for the worker's task) but not a face picture did not experience such decline. These findings suggest that workers can use their profile pictures to emphasize their skills while obfuscating their true demographics but without negatively affecting their reputation [64].
- **Fully automated matching:** Another mitigation strategy of profile-induced discrimination is to fully automate the P2P matching process. For instance, Uber riders do not have the luxury to choose from a list of nearby drivers. In Airbnb, the *Instant Booking* feature enables a guest's request to be automatically accepted without an explicit consent action from the host. Hosts who enroll in this option are rewarded with a better search placement and Superhost status. According to several studies, this design decision helps to minimize the chances of biased assessment as service providers and receivers do not engage in any negotiations beforehand [12], [45].
- **Cashless payments:** In a study of 1,704 Uber, Lyft, and taxi trips in Los Angeles, Brown [42] reported that cashless payments in P2P ridesharing services may counter racial discrimination. In particular, drivers in-

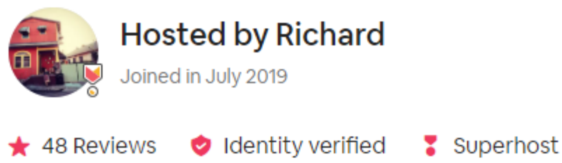


Fig. 3: A host profile on Airbnb

dicated that paying through the app eliminated fears of fare evasion, thus reduced proxy discrimination against Black male riders.

3.2 Reputation Systems

Reputation systems (ratings and reviews) are considered the *de facto* trust-building mechanisms in DSE [36], [53], [68]. However, our review of existing evidence revealed that the current design of these systems can enable discrimination. In particular, the aggregated reputation scores often reinforce prior discrimination beliefs of DSE users [49], [52], [69]. In what follows, we review evidence related to patterns of digital discrimination affecting reputation systems of DSE platforms as well as the main strategies to counter these patterns.

3.2.1 Evidence

Hannák et al. [8] analyzed 13,500 worker profiles on TaskRabbit and Fiverr. They found that Black workers received worse ratings and fewer reviews than similarly qualified White workers. The authors also analyzed linguistic bias in textual reviews. They observed that reviews for workers perceived to be Black women included significantly fewer positive adjectives, while reviews for Black workers contained significantly more negative adjectives. These results were remarkably consistent after controlling for platforms and cities from which the data was collected. In a more recent study, Goel et al. [49] analyzed a dataset of 8,218 listings on Airbnb from New York City, including 5,716 listings from White hosts and 2,502 from non-White hosts. The results confirmed that the ethnicity of the host and the majority ethnicity of the neighborhood had a significant effect on ratings and prices.

Our review also showed that bias in ratings and reviews influenced minorities' participation in DSE. For instance, Teubner et al. [68] analyzed 15,198 Airbnb listings from 86 German cities. They found that reputation, quantified through higher ratings and higher number of reviews, actually translated into significant economic value, either by attracting more demand or by allowing hosts to set higher listing prices. Several explanations were proposed for this phenomenon. For instance, Hannák et al. [8] reported that bad reviews or ratings often led to lower search ranks in freelancing platforms. In their field experiment, Cui et al. [30] reported that positive reviews posted on Airbnb guests' pages significantly reduced discrimination towards guests' with Black-sounding names. In addition, in an experiment with 8,906 Airbnb users, Abrahao et al. [53] reported that having a decent reputation was enough to counteract homophily, or the tendency of people to prefer or seek others who are similar. Another study by Brown et al. [42] reported that rider ratings may reduce proxy discrimination by drivers as they can use star ratings to infer how safe or considerate a rider may be.

3.2.2 Mitigation Strategies

Similar to profile information, several design strategies have been proposed in the literature to control for bias affecting reputation systems. These strategies (functional measures) can be described as follows:

- **Mutual reviews:** To prevent biased reviews, Airbnb rolled out a design change to ensure that hosts and guests can see the reviews only after both parties have submitted their reviews. According to Airbnb, *"Both hosts and guests may worry that if they leave an honest review that includes praise and criticism, they might receive an unfairly critical review in response. To address this concern, reviews will be revealed to hosts and guests simultaneously."* This change was evaluated by Ert et al. [64] through an independent field study. The results showed that hiding reviews until the other party submitted their reviews significantly reduced discriminatory charged text in reviews.
- **Structured reputation systems:** A suggested design strategy to mitigate bias in reviews is to eliminate free-text reviews altogether. Instead, feedback should be structured in a set of predefined fields where input categories, along with acceptable inputs for each category, are provided [58]. While this change does not entirely eliminate bias, it can at least limit subjective reviews. For example, in a field experiment of 952 entry-level workers from Upwork, Pallais [70] observed that providing more structured (objective) evaluations substantially limited sentiment in reviews and improved workers' subsequent employment outcomes. This can be very critical for service providers as a study of 47,651 Airbnb listings and 1,014,134 reviews found that guests, especially female travelers, were likely to be influenced by the sentiment of reviews [51].
- **Explicit trust cues:** The controlled experiments conducted by Nødtvedt et al. [31] showed that racial discrimination in the DSE market disappeared in the presence of an explicit trust cue (e.g., a visible 5/5 rating from a customer), giving an indication that reputation-based information can counteract the tendency to discriminate against out-group members. Along the same lines, Tjaden et al. [48] conducted a field study of 16,624 real carpooling rides from Germany. The results showed that objective reputation cues about drivers, such as measured experience or higher ratings, can decrease the magnitude of ethnic discrimination in drivers' ratings. In general, trust cues can reduce discrimination over DSE platforms by explicitly signaling trust for service consumers and providers, acting as a source of information about the perceived value of the provided service. Such cues can take the form of a reputation badge appearing next to the user's name (e.g., a Superhost badge in Fig. 3) to reduce the weight placed on the name itself.
- **Hiding older reviews:** emerging evidence suggests that DSE platforms could consider showing only the most

recent reviews for each user, while hiding the rest along with the total number of reviews per user. According to Hannák et al. [8], this design decision can *level the playing field* for workers, while still providing timely and testimonial feedback. These results were confirmed by Qiu et al. [71] who found that hiding the number of reviews on a platform such as Airbnb helps to avoid systematically disadvantaging newer users and ensure that biases displayed by users are kept in check.

- **Bias-free rating elicitation:** Goel et al. [49] implemented an incentive mechanism to elicit fair ratings from users. The method utilizes a peer-consistency mechanism known as the Peer Truth Serum for crowdsourcing [72]. The authors provided significant proof that such reward mechanisms can encourage users to try the service of individuals belonging to disadvantaged social classes and at the same time elicit truthful ratings about the quality of received service.
- **Bias correction:** This feature involves adjusting individual worker's ratings to compensate for measurable sources of bias. In particular, since biases do exist, and can be effectively quantified, their effect can be reversed by adjusting rating scores for minority individuals [8]. In their work on reputation systems biases, Goel et al. [49] used the covariance between the aggregated reputation scores and the ethnicity as a proxy to measure bias. Applying the proposed transformation on a dataset of Airbnb reviews showed that adjusting for sensitive attributes such as ethnicity removed their impact, while the impact of other relevant attributes remained significant.

3.3 User Goals

User goals in DSE can range from economic growth and ecological sustainability to building up social capital [2]. Our qualitative analysis of existing literature has exposed four types of user goals that are explicitly related to digital discrimination. The distribution of these goals over our primary studies is shown in Table. 4. These goals are:

- **Inclusion:** Inclusion (participation or equality) can be considered as the antidote of discrimination. All included studies are geared towards addressing this goal. Ultimately, users want to be able to engage in DSE activities as service receivers or providers without being treated differently for reasons unrelated to the nature of their transactions.
- **Trust:** Trust refers to the willingness of a party to be vulnerable to the actions of another party [73]. Our review has revealed that trust is a key user goal in DSE [34], [51], [64], [74], [75]. The concept itself stems from the fact that conducting business transactions with uncertified strangers involves inherent risk, therefore, providers and receivers at both ends of the P2P connection need to establish a certain level of mutual trust before a transaction can take place [33], [76]. In fact, almost all DSE platforms provide a trust statement on their websites, listing all the measures taken to establish trust in the platform and its users, such as reviews and ratings.

TABLE 4: The distribution of goals over primary studies.

User goal	Papers
Trust	[2], [33], [43], [53], [64], [65], [66], [67], [68], [71], [75], [76], [78]
Safety	[21], [38], [77]
Accessibility	[54], [55], [56], [57]
Inclusion	all primary studies

- **Safety:** As mentioned earlier, DSE is inherently risky. Therefore, safety is another major goal of DSE users. For example, riders need to feel safe before they get into a stranger's car and hosts need to trust that guests would not harm their families or destroy their property. In the digital discrimination literature, safety is often referenced indirectly [21], [38], [77]. For instance, while profile information is used to enforce user safety (establishing trust and enabling identification offline), such information can be a main enabler of discrimination. Overall, the relation between safety as a user goal and discrimination as a user concern and the nature of interaction between them is still unclear.
- **Accessibility:** Accessibility is another major user goal for people with disabilities as well as parents. Accessibility in our context refers to the accessibility of the service itself. Primary studies tackling ableism emphasize accessibility as a main user goal [54], [55], [56], [57].

3.4 Summary of Evidence

Our review shows that existing evidence on digital discrimination in the DSE market is mainly geared towards documenting and addressing issues of racism and sexism as well as suggesting mitigation strategies for these issues (**RQ_1**). The majority of these studies are published after 2015. Less evidence is available on other types of discrimination, such as classism or ableism, which are often investigated from a regulatory point of view [54], [55]. Our review also shows that most studies analyze discrimination in the domains of ridesharing, lodging, and freelancing (**RQ_2**). This calls for more research to investigate discrimination in other domains of DSE such as food delivery or asset sharing [56], [79]. In terms of features and goals, our analysis revealed that discrimination concerns are commonly enabled by information available on user profiles and often find their way to reputation systems (**RQ_3**). A list of mitigation strategies are proposed to control for discriminatory behavior that might manifest through these features (**RQ_4**). These strategies range from preventive (e.g., withholding information, structured reviews, and trust cues) to corrective (e.g., bias correction and hiding older reviews) and even reactive (e.g., penalty for bias-based cancellations). A summary of these measures is listed in Table 5. Finally, we observe that inclusion, trust, safety, and accessibility are the main user goals often impacted by discrimination concerns.

4 Discussion and Impact

The research on digital discrimination has gained a significant momentum over the past four years. This can be attributed to the unprecedented widespread of DSE systems

TABLE 5: A summary of suggested design changes in the literature to mitigate discrimination

Design change	Papers
Withholding information	[6], [7], [18], [40], [58], [64]
Self-disclosure information	[18], [20], [38], [66]
Asset-based profile pictures	[35], [64]
Fully-automated matching	[45], [78]
Cashless payments	[42]
Mutual reviews	[30], [64]
Structured reputation systems	[70]
Explicit trust cues	[31], [48]
Hiding older reviews	[8], [71]
Bias correction	[8], [49], [80]
Bias-free rating elicitation	[49]

and the general shift in society towards more equality and prosperity. As more research is conducted, it becomes harder for software engineers to keep up with this growing body of research. To address this limitation, our review in this paper is intended to systematically synthesize existing evidence on digital discrimination from a software design point of view. In general, our review shows that digital discrimination is far from being a simple problem. Such complex socio-technical phenomenon emerges from equally complex interactions between system features and their operational environment. Therefore, it is safe to say that there is no silver bullet for solving discrimination in the DSE market. However, *satisficing* solutions could be developed to mitigate the problem. These solutions can be inferred from existing interdisciplinary evidence which detects and documents discriminatory behavior in DSE platforms through large scale field studies and controlled experiments.

The main objective of our SLR is to help software engineers to comprehend, communicate, and eventually integrate existing evidence on digital discrimination into their working systems. For instance, through our SLR, system designers can get insights into the complex interaction of features that could trigger or mitigate discrimination in their operational environment. Such information can be particularly important in agile environments where there is typically no time to research complex domain phenomena between product cycles. In the long run, the impact of such work will extend to the entire population of DSE users, targeting the deep racial and regional disparities in one of the fastest growing software ecosystems in the world.

The work presented in this paper builds upon on our previous work in this domain [10]. In our recent work, we analyzed a dataset of 667,806 tweets collected from the twitter feeds of six different DSE platforms. Our results showed that various forms of bias frequently appear in user feedback. We further conducted an *ad-hoc* literature review of 17 primary studies on digital discrimination. The results from our user feedback analysis as well as brief review were integrated into a partial model to capture the problem from a requirements engineering perspective. Our work in this paper extends that perspective by conducting a more systematic literature review of existing literature on the problem.

5 Limitations and Threats to Validity

The study conducted in this paper takes the form of a systematic literature review (SLR) [23], [81]. This method is commonly used for advancing the *state-of-the-art* in research and practice based on rigorous research, especially when the problem being investigated is inherently interdisciplinary. However, like most review-based studies, subjectivity threats can be raised about the quality of the quantitative and qualitative analysis performed by the reviewers as well as threats of missing related work. To mitigate these threats, we applied a set of well-known protocols for conducting evidence-based reviews [23]. Specifically, we searched multiple digital libraries for primary studies using a structured query and snowballing. Related studies were then identified using exclusion and inclusion criteria and synthesized using a systematic coding of evidence. To control for the validity of extracted evidence, the majority of primary studies considered in our review included some sort of a large scale field study or a controlled experiment that was conducted using a large number of observations. In addition, we used a grounded theory approach of open coding and memoing to categorize extracted information. We believe that these actions helped to mitigate several potential threats affecting our study.

6 Conclusion

In this paper, we systematically synthesized evidence from 58 interdisciplinary primary studies to extract information on the different types of discrimination concerns impacting DSE platforms along with their mitigation strategies. The results showed that existing evidence is often related to issues of racism and sexism affecting the domains of ridesharing, lodging, and freelancing. The results also showed that discrimination concerns are commonly associated with the features of user profiles and reputation systems. These concerns are partially mitigated by a variety of design strategies that are introduced to prevent offline forms of systematic bias from transitioning online. Our review also showed that inclusion, trust, safety, and accessibility are the main user goals commonly intertwined with concerns of digital discrimination.

Our work in this paper is intended to facilitate tasks of evidence-based software engineering in DSE app development. In the future, we will seek to advance this line of work by integrating our synthesized evidence into actual working DSE prototypes. This will enable us to investigate the impact of implementing some of the identified mitigation strategies in practical settings and objectively measure their success, or failure, in countering digital discrimination.

Acknowledgment

This work was supported by the U.S. National Science Foundation (Award CNS 1951411).

References

[1] C. Martin, "The sharing economy: A pathway to sustainability or a nightmarish form of neoliberal capitalism?" *Ecological Economics*, vol. 121, pp. 149–159, 2016.

[2] T. Dillahunt and A. Malone, "The promise of the sharing economy among disadvantaged communities," in *Annual ACM Conference on Human Factors in Computing Systems*, 2015, pp. 2285–2294.

[3] J. Hamari, M. Sjöklint, and A. Ukkonen, "The sharing economy: Why people participate in collaborative consumption," *Journal of the Association for Information Science and Technology*, vol. 67, no. 9, pp. 50–63, 2016.

[4] G. Zhu, K. So, and S. Hudson, "Inside the sharing economy: Understanding consumer motivations behind the adoption of mobile applications," *International Journal of Contemporary Hospitality Management*, vol. 29, no. 9, pp. 2218–2239, 2017.

[5] S. Shaheen, N. Chan, A. Bansal, and A. Cohen, "Mobility and sharing economy: Impacts synopsis," 2015.

[6] Y. Ge, C. Knittel, D. MacKenzie, and S. Zoepf, "Racial and gender discrimination in transportation network companies," no. NBER Working Paper No. 22776, 2017.

[7] B. Edelman, M. Luca, and D. Svirsky, "Racial discrimination in the sharing economy: Evidence from a field experiment," *American Economic Journal: Applied Economics*, vol. 9, no. 2, pp. 1–22, 2017.

[8] A. Hannák, C. Wagner, D. Garcia, A. Mislove, M. Strohmaier, and C. Wilson, "Bias in online freelance marketplaces: Evidence from TaskRabbit and Fiverr," in *ACM Conference on Computer Supported Cooperative Work and Social Computing*, 2017, pp. 1914–1933.

[9] M. Bertrand and E. Duflo, *Handbook of Field Experiments*. Elsevier, 2016, ch. Field Experiments on Discrimination, p. 310.

[10] M. Tushev, F. Ebrahimi, and A. Mahmoud, "Digital discrimination in sharing economy a requirements engineering perspective," in *IEEE International Requirements Engineering Conference*, 2020, pp. 204–214.

[11] J. Moody, S. Middleton, and J. Zhao, "Rider-to-rider discriminatory attitudes and ridesharing behavior," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 62, pp. 258–273, 2019.

[12] R. Ahuja and R. Lyons, "The silent treatment: LGBT discrimination in the sharing economy," Trinity College Dublin, Department of Economics, Dublin, Tech. Rep., 2017.

[13] J. Thebault-Spieker, L. Terveen, and B. Hecht, "Avoiding the south side and the suburbs: The geography of mobile crowdsourcing markets," in *ACM Conference on Computer Supported Cooperative Work & Social Computing*, 2015, pp. 265–275.

[14] A. Barzilay and A. Ben-David, "Platform inequality: Gender in the gig-economy," *Seton Hall Law Review*, vol. 47, no. 2, pp. 393–431, 2017.

[15] M. Todisco, "Share and share alike? Considering racial discrimination in the nascent room-sharing economy," 2015.

[16] M. Chenga and C. Foley, "The sharing economy and digital discrimination: The case of Airbnb," *International Journal of Hospitality Management*, vol. 70, pp. 95–98, 2018.

[17] G. Quattrone, D. Proserpio, D. Quercia, L. Capra, and M. Musolesi, "Who benefits from the "sharing" economy of Airbnb?" in *International Conference on World Wide Web*, 2016, pp. 1385–1394.

[18] K. Levy and S. Barocas, "Designing against discrimination in online markets," *Berkeley Technology Law Journal*, vol. 32, no. 3, pp. 1183–1238, 2017.

[19] N. Leong and A. Belzer, "The new public accommodations: Race discrimination in the platform economy," *Georgetown Law Journal*, vol. 105, no. 5, pp. 1271–1322, 2017.

[20] M. Laouenan and R. Rathelot, "Ethnic discrimination on an online marketplace of vacation rental," p. 2017.

[21] B. Rogers, "The social costs of Uber," vol. 82, no. 6, 2015.

[22] L. Ratti and N. Countouris, "The sharing economy and eu anti-discrimination law," *The Cambridge Handbook of the Law of the Sharing Economy*, pp. 486–498, 2018.

[23] B. A. Kitchenham, T. Dyba, and M. Jorgensen, "Evidence-based software engineering," in *International Conference on Software Engineering*, 2004, pp. 273–281.

[24] B. Kitchenham, P. Brereton, D. Budgen, M. Turner, J. Bailey, and S. Linkman, "Systematic literature reviews in software engineering–A tertiary study," *Information and Software Technology*, vol. 51, no. 1, pp. 7–15, 2009.

[25] M. Adams, W. Blumenfeld, C. R. C. neda, and H. Hackman, *Readings for diversity and social justice*. Routledge, 2013.

[26] R. Rosario and G. Widmeyer, "An exploratory review of design principles in constructivist gaming learning environments," *Journal of Information Systems Education*, vol. 20, no. 3, pp. 289–300, 2016.

[27] C. Wohlin, "Guidelines for snowballing in systematic literature studies and a replication in software engineering," in *Inter. Conf. on evaluation and assessment in software engineering*, 2014, p. 38.

[28] S. Mcilroy, W. Shang, N. Ali, and A. Hassan, "User reviews of top mobile apps in apple and google app stores," *Communications of the ACM*, vol. 60, no. 11, pp. 62–67, 2017.

[29] W. Leung, Z. Zhang, D. Jibuti, J. Zhao, M. Klein, C. Pierce, L. Robert, and H. Zhu, "Race, gender and beauty: The effect of information provision on online hiring biases," in *CHI Conference on Human Factors in Computing Systems*, 2020, pp. 1–11.

[30] R. Cui, J. Li, and D. Zhang, "Reducing discrimination with reviews in the sharing economy: Evidence from field experiments on Airbnb," *Management Science*, vol. 66, no. 3, pp. 1071–1094, 2020.

[31] K. Berg Nødtvedt, H. Sjastad, S. Skard, H. Thorbjornsen, and J. Van Bavel, "Racial bias in the sharing economy and the role of trust and self-congruence," *Social Science Research Network*, 2020.

[32] L. Karlsson, A. Kemperman, and S. Dolnicar, "May i sleep in your bed? Getting permission to book," *Annals of Tourism Research*, vol. 62, pp. 1–12, 2017.

[33] E. Ert, A. Fleischer, and N. Magen, "Trust and reputation in the sharing economy: The role of personal photos in Airbnb," *Tourism Management*, vol. 55, pp. 62–73, 2016.

[34] N. Su and A. Mattila, "Does gender bias exist? The impact of gender congruity on consumer's Airbnb booking intention and the mediating role of trust," *International Journal of Hospitality Management*, vol. 89, pp. 102–405, 2020.

[35] B. Jaeger, W. Sleegers, A. Evans, M. Stel, and I. van Beest, "The effects of facial attractiveness and trustworthiness in online peer-to-peer markets," *Journal of Economic Psychology*, vol. 75, pp. 102–125, 2019.

[36] T. Ye, R. Alahmad, C. Pierce, and L. Robert Jr, "Race and rating on sharing economy platforms: The effect of race similarity and reputation on trust and booking intention in Airbnb," in *International Conference on Information Systems*, 2017.

[37] B. Jaeger and W. Sleegers, "Racial discrimination in the sharing economy: Evidence from Airbnb markets across the world," *Journal of Economic Psychology*, 2020.

[38] E. Picard, "Racial discrimination in the sharing economy evidence from online experiments," Louvain School of Management, Universitè catholique de Louvain, Tech. Rep., 2018.

[39] V. Kakar, J. Voelz, J. Wu, and J. Franco, "The visible host: Does race guide Airbnb rental rates in San Francisco?" *Journal of Housing Economics*, vol. 40, pp. 25–40, 2018.

[40] D. Wang, S. Xi, and J. Gilheany, "The model minority? not on Airbnb.com: A hedonic pricing model to quantify racial bias against asian americans," *Technology Science*, 2015.

[41] A. Mohammed, "Designing for racial impartiality: The impact of relocating host photos on the Airbnb website," *Job Market Paper*, 2017.

[42] A. Brown, "Prevalence and mechanisms of discrimination: Evidence from the ride hail and taxi industries," *Journal of Planning Education and Research*, 2019.

[43] J. Doleac and L. Stein, "The visible hand: Race and online market outcomes," *The Economic Journal*, vol. 123, no. 572, pp. F469–F492, 2013.

[44] O. Abramova, "What's in a name: Examining discrimination on sharing platforms and its possible remedies," in *European Conference on Information Systems*, 2020.

[45] V. Koh, W. Li, G. Livan, and L. Capra, "Offline biases in online platforms: a study of diversity and homophily in Airbnb," *EPJ Data Science*, vol. 8, no. 11, 2019.

[46] B. Simonovits, I. Shvets, and H. Taylor, "Discrimination in the sharing economy: evidence from a hungarian field experiment," *Corvinus Journal of Sociology and Social Policy*, vol. 9, no. 1, pp. 55–79, 2018.

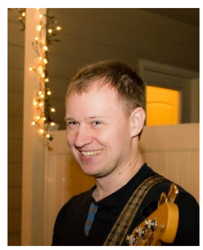
[47] S. Carol, D. Eich, M. Keller, F. Steiner, and K. Storz, "Who can ride along? Discrimination in a german carpooling market," *Population, Space and Place*, vol. 25, no. 8, p. e2249, 2019.

[48] J. Tjaden, C. Schwemmer, and M. Khadjavi, "Ride with me. Ethnic discrimination, social markets, and the sharing economy," *European Sociological Review*, vol. 34, no. 4, pp. 418–432, 2018.

[49] N. Goel, M. Rutagarama, and B. Faltings, "Tackling peer-to-peer discrimination in the sharing economy," in *ACM Conference on Web Science*, 2020, pp. 355–361.

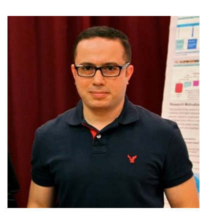
[50] E. Foong, N. Vincent, B. Hecht, and E. Gerber, "Women (still) ask for less: Gender differences in hourly rate in an online labor mar-

ketplace," *Proceedings of the ACM on Human-Computer Interaction*, vol. 2, no. CSCW, pp. 53:1–53:21, 2018.
[51] E. Choi and E. Horvát, "Airbnb's reputation system and gender differences among guests: Evidence from large-scale data analysis and a controlled experiment," *Social Informatics*, pp. 3–17, 2019.
[52] B. Greenwood, I. Adjerid, and C. Angst, "How unbecoming of you: Gender biases in perceptions of ridesharing performance," *Academy of Management Proceedings*, vol. 2018, no. 1, p. 12196, 2018.
[53] B. Abrahao, P. Parigi, A. Gupta, and K. Cook, "Reputation offsets trust judgments based on social biases among airbnb users," *The National Academy of Sciences*, vol. 114, no. 37, pp. 9848–9853, 2017.
[54] R. Reed, "Disability rights in the age of Uber: Applying the Americans with disabilities act of 1990 to transportation network companies," *Georgia State University Law Review*, vol. 33, no. 2, pp. 517–v, 2017.
[55] E. Mapelli, "Inadequate accessibility: Why Uber should be a public accommodation under the Americans with disabilities act," *American University Law Review*, vol. 67, no. 6, pp. 1947–1988, 2018.
[56] M. Ruvolo, *Access Denied? Perceptions of New Mobility Services among Disabled People in San Francisco*. University of California Institute of Transportation Studies, 2020.
[57] M. Ameri, S. Rogers, L. Schur, and D. Kruse, "No room at the inn? Disability access in the new sharing economy," *Academy of Management Discoveries*, vol. 6, no. 2, pp. 176–205, 2020.
[58] H. Galperin and C. Greppi, *Digital Economies at Global Margins*. Cambridge: MIT Press., 2019, ch. Geographical Discrimination in the Gig Economy, pp. 295–318.
[59] A. van Lamsweerde, "Goal-oriented requirements engineering: A guided tour," in *IEEE International Symposium on Requirements Engineering*, 2001, pp. 249–262.
[60] J. Mylopoulos, L. Chung, and E. Yu, "From object-oriented to goal-oriented requirements analysis," *Communications of the ACM*, vol. 1, no. 42, pp. 31–37, 1999.
[61] N. Jha and A. Mahmoud, "Mining non-functional requirements from app store reviews," *Empirical Software Engineering*, vol. 24, no. 6, pp. 3659–3695, 2019.
[62] A. Mahmoud and G. Williams, "Detecting, classifying, and tracing non-functional software requirements," *Requirements Engineering*, vol. 21, no. 3, pp. 357–381, 2016.
[63] C. Wohlin, P. Runeson, M. Höst, M. Ohlsson, B. Regnell, and A. Wesslèn, *Experimentation in Software Engineering*. Springer, 2012.
[64] E. Ert and A. Fleischer, "The evolution of trust in Airbnb: A case of home rental," *Annals of Tourism Research*, vol. 75, pp. 279–287, 2019.
[65] G. Mesch, "Is online trust and trust in social institutions associated with online disclosure of identifiable information online?" *Computers in Human Behavior*, vol. 28, no. 4, pp. 1471–1477, 2012.
[66] X. Ma, J. Hancock, K. Lim Mingjie, and M. Naaman, "Self-disclosure and perceived trustworthiness of Airbnb host profiles," in *ACM Conference on Computer Supported Cooperative Work and Social Computing*, 2017, pp. 2397–2409.
[67] Z. Mao, M. Jones, M. Li, W. Wei, and J. Lyu, "Sleeping in a stranger's home: A trust formation model for airbnb," *Journal of Hospitality and Tourism Management*, vol. 42, pp. 67–76, 2020.
[68] T. Teubner, F. Hawlitschek, and D. Dann, "Price determinants on Airbnb: How reputation pays off in the sharing economy," *Journal of Self-Governance and Management Economics*, vol. 5, no. 4, pp. 53–80, 2017.
[69] F. Monachou and I. Ashlagi, "Discrimination in online markets: Effects of social bias on learning from reviews and policy design," in *NeurIPS*, 2019, pp. 2142–2152.
[70] A. Pallais, "Inefficient hiring in entry-level labor markets," *American Economic Review*, vol. 104, no. 11, pp. 3565–3599, 2014.
[71] W. Qiu, P. Parigi, and B. Abrahao, "More stars or more reviews?" in *Conference on Human Factors in Computing Systems*, 2018, pp. 1–11.
[72] G. Radanovic, B. Faltings, and R. Jurca, "Incentives for effort in crowdsourcing using the peer truth serum," *ACM Transactions on Intelligent Systems and Technology*, vol. 7, no. 4, p. 48, 2016.
[73] R. Mayer, J. Davis, and F. Schoorman, "An integrative model of organizational trust," *The Academy of Management Review*, vol. 20, no. 3, pp. 709–734, 1995.
[74] F. Hawlitschek, B. Notheisen, and T. Teubner, "The limits of trust-free systems: A literature review on blockchain technology and trust in the sharing economy," *Electronic Commerce Research and Applications*, vol. 29, pp. 50–63, 2018.
[75] M. ter Huurne, A. Ronteltap, R. Corten, and V. Buskens, "Antecedents of trust in the sharing economy: A systematic review," *Journal of Consumer Behaviour*, vol. 16, no. 6, pp. 485–498, 2017.
[76] C. van der Cruijsen, M. Doll, and F. van Hoenselaar, "Trust in other people and the usage of peer platform markets," *Journal of Economic Behavior & Organization*, vol. 166, pp. 751–766, 2019.
[77] B. Malin and C. Chandler, "Free to work anxiously: Splintering precarity among drivers for Uber and Lyft," *Communication, Culture & Critique*, vol. 10, no. 2, pp. 382–400, 2017.
[78] M. Luca, "Designing online marketplaces: Trust and reputation mechanisms," *Innovation Policy and the Economy*, no. 17, pp. 77–93, 2017.
[79] G. Williams, M. Tushev, F. Ebrahimi, and A. Mahmoud, "Modeling user concerns in sharing economy: the case of food delivery apps," *Automated Software Engineering*, vol. 27, pp. 229–263, 2020.
[80] B. Hanrahan, N. Ma, and C. Wen Yuan, "The roots of bias on uber," in *European Conference on Computer-Supported Cooperative Work*, 2017.
[81] A. Nowak and H. Schünemann, "Toward evidence-based software engineering: Lessons learned in healthcare application development," *IEEE Software*, vol. 34, no. 5, pp. 67–71, 2017.
[82] V. Garousi, M. Felderer, and M. Mantyla, "Guidelines for including grey literature and conducting multivocal literature reviews in software engineering," *Information and Software Technology*, vol. 106, pp. 101–121, 2019.



Miroslav Tushev received the Bsc. in management and organization in 2013 from the Russian Academy of National Economy and Public Administration. He is currently a PhD candidate of Computer Science and Engineering at Louisiana State University. His main research interests include digital discrimination, Open Source Systems, and natural language analysis of software.

Fahimeh Ebrahimi received the B.S. and M.S. degrees in Information Technology Engineering in 2013 and 2015 from Amirkabir University of Technology (Tehran Polytechnic). She is currently a PhD student of Computer Science and Engineering at Louisiana State University. Her main research interests include mobile app privacy, app store analysis, natural language processing, and requirement engineering.



Anas Mahmoud received the MS and PhD degrees in Computer Science and Engineering in 2009 and 2014 from Mississippi State University. He is currently an associate professor of Computer Science and Engineering at Louisiana State University. His main research interests include requirements engineering, app store analytics, program comprehension, code navigation, and natural language analysis of software.