JOURNAL OF DIGITAL SOCIAL RESEARCH

WWW.JDSR.IO ISSN: 2003-1998

VOL. 4, NO. 1, 2022, 49–72

IT'S CROWDED AT THE BOTTOM: TRUST, VISIBILITY, AND SEARCH ALGORITHMS ON CARE.COM

Elizabeth Fetterolf[a]

ABSTRACT

Trust, visibility, and the deepening of existing inequalities are major themes within the platform care work literature. However, no study to date has applied these themes to an analysis of worker profiles. I investigate both how workers communicate trustworthiness through their profiles on Care.com, the world's largest care work platform, and which of these profiles are rendered more and less visible to clients. Through a qualitative content analysis of profiles (*n*=60) sampled from the top and bottom search results in three different US zip codes, I find that visibility is often related to connectivity, response time, and positive reviews, and who is rendered visible mirrors preexisting inequalities. The language of "passion" for the job is common across top and bottom profiles, indicating a contradiction between the deemphasis on professionalization and the high level of connectivity and responsiveness present in top profiles.

Keywords: platform care work; visibility; trustworthiness.

[a] University of Oxford, United Kingdom.

1 INTRODUCTION

In the past several years, the plight of gig economy workers has been increasingly covered in the news (e.g., Bussewitz & Olson, 2020; Conger et al., 2020), academic literature (see Vallas & Schor, 2020 for a review), and within popular culture, as seen by the new documentary *The Gig Is Up* (Walsh, 2021). A clear theme has emerged: the rise of platform-facilitated gig work has, under the guise of increased flexibility, created a precarious, underpaid workforce whose livelihood depends on opaque algorithms and the large technology companies who rely on their labour (Gray & Suri, 2019). But within this large and growing literature, an important kind of platform labour has been overlooked: care work. Before the introduction of platforms, this feminized, racialized workforce performed ununionized and largely unregulated work as nannies, maids, and home healthcare workers; as Ai-Jen Poo, founder of the National Domestic Workers Alliance states, they are "the original gig workers" (Poo, 2017, n.p.).

COVID-19 has highlighted the importance of many kinds of care work, and childcare specifically was put front and centre when school closures across the world left many working parents in need of assistance. The burden has disproportionately fallen on mothers, who experienced an increase in unpaid domestic work and a decrease in well-being (Zhou et al., 2020), a phenomenon that has received significant media attention (e.g., Dickson, 2020; Grose, 2021; Hsu, 2020). However, the pandemic has also taken a massive tole on the "essential and untrusted" childcare workers who are subject to increased levels of surveillance on care work platforms like Care.com and SitterCity (Ticona, 2020). In the low-trust context of the pandemic, opaque algorithms determine which workers are seen and which ones are not.

The present study has two interrelated but distinct aims: I investigate both how workers communicate trustworthiness on Care.com through their profiles, and which of these profiles are rendered more and less visible to clients. Using Noble's (2018) analysis of search algorithms and Ticona and Mateescu's (2018a) work on the key role of worker visibility and trustworthiness on Care.com, I sample profiles from the top and bottom of a general search in three different United States locations and conduct a qualitative content analysis. I find that, despite non-white workers' feelings of hypervisibility on the platform (Ticona & Mateescu, 2018a), they appear largely less visible than their white counterparts. I also find that, in line with existing literature, education, quick response time, and high ratings are used to convey trustworthiness, and yet profile bios often downplay the work of childcare, a phenomenon that provides possibilities for new avenues of research in this emerging literature.

2 LITERATURE REVIEW

2.1 Care Work as Gig Work

Despite the characterization of care and domestic workers as the "original" gig workers (Poo, 2017), care work has been understudied in gig economy research (Kaine et al., 2020; Ticona & Mateescu, 2018a; Ticona et al., 2018). In-home care and domestic work have a long history of being left out of the picture; domestic and childcare workers have been excluded from the labour movement (Burnham & Theodore, 2012; Poo, 2017), nannies provide "hidden" support for white-collar women entering the workforce (Macdonald, 2011), and racialized domestic workers are expected to act "invisible" within white homes (Glenn, 1992). In this section, I will highlight the ways in which platforms mirror past iterations of paid care work. Then, I will draw on the emerging platform care work literature to detail two major changes that platforms have prompted: an emphasis on visibility and a deepening of preexisting inequalities.

First, I will define my use of "gig work" for the purposes of this paper. The definitions of the gig economy and gig work are flexible and have at times been contested (Montgomery & Baglioni, 2021). In their review of the platform labour literature, Schor and Vallas (2020) make a distinction between gig workers who are contracted via a platform but perform the services offline and platform workers who perform short tasks entirely online. In contrast, Bajwa et al. (2018) embrace a broader definition of gig work, using the term to encompass workers who are not employees, are paid by task, and whose work is mediated in some way by a platform. In this review, I use the latter, broader conception of "gig work," while recognizing that the off-platform delivery of the service is a distinctive component of care work.

While some earlier scholars of the gig economy argued that platforms would transform work (Parker et al., 2016) or, in some cases, abolish it (Sundararajan, 2016), platform care work shares much in common with its earlier iterations. A 2018 report on gig work reports low wages, non-employee status, lack of unions, and general precarity among workers (Bajwa et al., 2018). However, these challenges are not new to in-home care workers. In Cooke's (1950/2015) investigative reporting on the "Bronx Slave Market," an area in New York where Black domestic workers would gather to sell their labour by the hour to white housewives, her depictions of the women's uncertainty regarding their next "gig," clients' attempts to renege on pre-agreed payments, lack of unionization opportunities, and strategies for navigating the "informal" yet highly codified marketplace mirror modern studies of gig workers, such as those by Graham and Anwar (2019) and Gray and Suri (2019).

Like modern-day gig work, low wages, and precarious status in the "gray economy" are historic characteristics of in-home care work. A widely cited study by England et al. (2002) demonstrated that relative to other professions, care workers' wages were significantly lower, even when controlling for education and experience.

In-home childcare and domestic workers are rarely full-time employees of the families that hire them, and these arrangements are often precarious, unpredictable, and inconsistent (Burnham & Theodore, 2012). The shape and character of this work has undergone changes that contextualize the introduction of platforms; for example, the former half of the 20th century saw a shift from governesses and servants to nannies and domestic workers (Glenn, 1992) and the rise of neoliberalism came with increased outsourcing of intimate life (Hochschild, 2013).

If invisibility and precarity have historically been characteristics of in-home care work, platforms like Care.com and Sitter City attempt to make it more visible and less "under the table" through increased surveillance of workers (Flanagan, 2019; McDonald et al., 2021; Tandon & Rathi, 2021; Ticona & Mateescu, 2018a). They do so through trust-focused branding, background checks, optional platform-mediated payment mechanisms, and client-facing literature that discourages paying workers in cash (Tandon & Rathi, 2021; Ticona & Mateescu, 2018a; Ticona et al., 2018). Trust was also key in pre-platform care work arrangements, and Flanagan (2019) points out that agencies facilitated trust between families and workers. However, care work platforms differ in their strategy; by making these measures "optional," platforms ensure that risk is transferred from the company to the individual workers and clients (van Doorn, 2017). This abdication of risk is one way that care work platforms protect themselves, while exerting control over their workers (McDonald et al., 2021).

One result of this dual focus on visibility and trust is that care work platforms exacerbate existing inequalities between workers, based on race, class, gender, and immigration status (Flanagan, 2019; Ticona, 2020; Ticona & Mateescu, 2018a; Ticona et al., 2018; van Doorn, 2017). Background checks and mechanisms for issuing pay slips protect the company, while creating barriers for undocumented workers (Ticona & Mateescu, 2018a). In a study of domestic work platforms, van Doorn (2017) found that the language of the "sharing" economy gave the illusion of increased worker freedom and meritocracy, while masking the racialized and gendered legacy that the platforms were built upon. In the United States, this legacy involves women of colour, often immigrants, being employed as domestic servants and doing the "dirty work" of the home for white, middle-class housewives (Cooke, 1950/2015; Glenn, 1992).

This history of entwined sexism, racism, and classism continues to play out on care work platforms today. Inequalities between workers share similarities to what Schor (2017) has called the "crowding out" effect on platforms like TaskRabbit and Airbnb, in which highly educated middle-class workers occupy jobs that used to go to low-income workers without college degrees. The childcare sector has been historically dominated by working-class women of colour and defined by a flow of migrants from the Global South to the Global North (Ehrenreich & Hochschild, 2003). White, college-educated nannies have been more prominent in the sector in recent years (Wu, 2016) and class signifiers on care work platforms, such as education, hobbies, and languages spoken, could potentially deepen this divide (Ticona et al., 2018). Ollier-Malaterre et al. (2019) observe that workers' ability to successfully balance connectivity and response time has become its own class signifier, a concept that they call "digital cultural capital." Ticona et al. (2018) identified lack of consistent internet access as a barrier for some low-income users – one of their participants cited this as a reason she stopped using the platform. These barriers may be further exacerbated by care work platforms' focus on "personality matching," a process that can be defined by race and class norms (Ticona & Mateescu, 2018a).

Flanagan's (2019) historical analysis sheds light on the "personality matching" process of 19th and 20th century employment agencies, with an emphasis put on moral "character" and values, rather than references or qualifications. This connects to Ticona and Mateescu's (2018a) interviews, in which workers described curating their profiles for potential clients. Just as domestic servants were advertised by their agencies based on a racialized, classed notion of "character" (Flanagan, 2019), on care work platforms, related kinds of class norms may be playing out in presentation of "personality."

2.2 Algorithms and Visibility

While agencies used to provide a medium for raced and classed "personality matching," on care work platforms algorithms perform this work. Algorithms are often opaque to both the researchers who study them and the workers whose time and income they dictate, and there is a large literature devoted to analysing algorithms' mutually shaping relationship with gig workers (e.g., Chen, 2018; Gray & Suri, 2019; Wood et al., 2019). There is an even larger literature that details how algorithms shape everything from the healthcare individuals receive (e.g., Obermeyer et al., 2019), to the news they consume (e.g., Thurman et al., 2018), to their selection of potential partners (e.g., Sharabi, 2021). Furthermore, scholars like Noble (2018) and Eubanks (2018) demonstrate that while algorithms are often seen as neutral tools, they reflect the racism, sexism, and classism of both their creators and society more broadly. Searches for "Black girls" on Google bring up pornographic images (Noble, 2018) while predictive policing algorithms rely on existing crime data and target neighbourhoods of colour, ignoring the fact the data itself comes from previous over-policing of these communities (Brayne, 2017). Bucher's (2016) conception of "the algorithmic imaginary" illustrates the ways in which algorithms inspire feelings in the individuals whose lives they shape, and in turn those same feelings mould the algorithms; this iterative process is key to understanding how systemic oppression creates unjust algorithms and algorithms create new forms of oppression.

However, as Benjamin (2019) points out, these processes can be hidden a lack of transparency on the part of their creators, creating what she calls an "anti-Black box." This opacity is especially relevant to gig workers, given that they typically have little information about the algorithms that shape their work (Vallas & Schor, 2020). Workers using "on-demand" platforms, like ride-hailing and delivery apps (Ticona et al., 2018), are surveilled and managed by frequently changing algorithms, leading to both stress and exhaustion (Newlands, 2021; Wood et al., 2019) as well as possibilities for resistance and "fissures" in algorithmic power (Chen, 2018; Ferrari & Graham, 2021).

On marketplace platforms, algorithms provide visibility based on where a worker appears in a client's search results (Graham & Anwar, 2019; Ticona et al. 2018; Wood & Lehdonvirta, 2021). Analyses of social media algorithms have identified visibility as a kind of double-edged sword for users (Arriagada & Ibáñez, 2020; Bucher, 2012), both the goal and a risk (Rega & Medrado, 2021). In an analysis of Facebook's EdgeRank algorithm, Bucher (2012) turned Foucault's panopticon on its head; for Facebook users, invisibility presents the true threat. For workers on marketplace platforms, this claim holds. Processes of "algorithmic shortlisting" (Williams et al., 2021) or "algorithmic amplification" (Wood & Lehdonvirta, 2021) are key determinants of success. Interviews with workers indicate that they view getting positive reviews and ratings as key to maintaining visibility within the search (D'Cruz & Noronha, 2016; Graham & Anwar, 2019; Ticona & Mateescu, 2018a).

The current literature I have surveyed focuses primarily on either the experiences of workers (e.g., Graham & Anwar, 2019; Tandon & Rathi, 2021; Ticona & Mateescu, 2018a, 2018b) or an analysis of how the platforms themselves function (e.g., Flanagan, 2019; McDonald et al., 2021; van Doorn, 2017). Though there is discussion of how workers perceive their own visibility to clients, there is little empirical investigation of how visible they appear in practice. And while profiles are the crux of how workers get hired and communicate trustworthiness, there are currently no attempts to analyse the profiles themselves as qualitative data. Finally, though there is a rich literature on algorithmic inequality on all kinds of platforms, the ways in which search algorithms could reinforce existing inequalities among care workers have been underdiscussed. This study attempts to fill these gaps by analysing worker profiles on Care.com.

2.3 Case Study: Care.com

I focus on Care.com over other care work platforms, like UrbanSitter or SitterCity, for two main reasons. First and foremost, Care.com is currently the world's largest and most-used care work platform, hosting 31.7 million members across 20 different countries (Care.com, Inc., 2019). Second, like many care work platforms, much of its branding and public-facing materials centre on trust and trustworthiness (Ticona & Mateescu, 2018a); this is encapsulated by the banner on its homepage, which states "find trusted caregivers for your every need" (Care.com, 2021). Though the site offers eldercare, pet care, tutoring, special needs care, and cleaning services, I look at its largest offering, childcare, and limit my analysis to the United States, where most of its paying members reside (Care.com, Inc., 2019).

While this study does not claim to be internationally generalizable, other scholars have noted that themes of reputation, reviews, trust, and exacerbated inequality are relevant on care work platforms in many countries (Flanagan, 2019; McDonald et al., 2021; Tandon & Rathi, 2021).

Care.com, founded in 2006, has been called "Amazon for caregivers" (Farrell, 2014), a comparison that invokes the platform's marketplace nature, in which workers can be viewed as products. Indeed, many of Care.com's affordances are similar to Amazon's (along with other gig work platforms), such as the importance of ratings and reviews, and the "Book Now" feature which promises a quick, frictionless experience for the client. However, Care.com is structured less like Amazon and more like freelancer platforms such as Upwork and Fiverr, where employers can post jobs and search for workers based on a series of criteria such as distance, pay range, and availability. Workers create profiles that detail demographic information (like gender and education, but notably not race), availability, a personal bio, past reviews, and a series of platform-determined icons and badges (for example profile, see Figure 1).

A marketplace platform, Care.com manages the hiring process by "sorting, ranking, and rendering visible large pools of workers" (Ticona et al., 2018, p. 2). However, Care.com's "Book Now" feature, which allows clients to book workers instantaneously based on their listed availability (Care.com, 2021), shares similarities with on-demand platforms on which workers have less control over the client matching process (Shapiro, 2017; van Doorn, 2017).

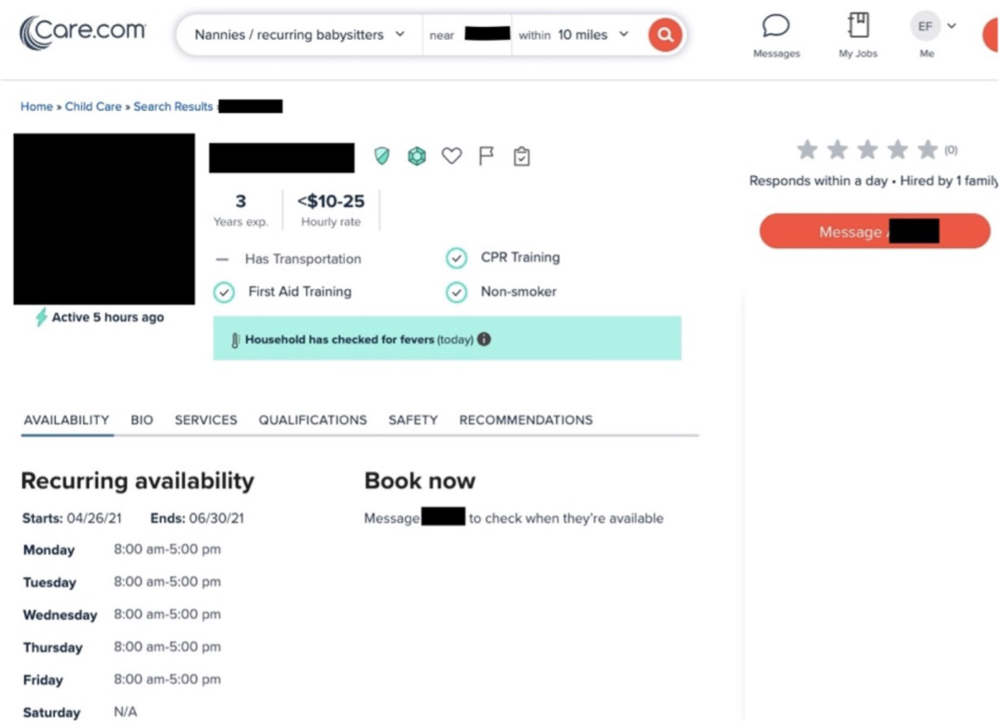

Figure 1. Care.com example profile (Care.com, 2021)

Reputation, reviews, and trust are key to Care.com's functionality. Facilitating "trust between strangers" (Ticona & Mateescu, 2018a, p. 4388) is crucial due to the personal, home-based nature of childcare. Care workers are required to prove their trustworthiness via signifiers, both controlled by the platform and communicated through their bios (Ticona & Mateescu, 2018a). They undergo platform-mediated background checks called "CareChecks," but families are also encouraged to pay for additional background and department of motor vehicles record checks (Gerson, 2019). Workers can also convey trustworthiness by verifying personal information like their cell phone number, email address, and social media accounts, curating their profile (which includes their bio, education, and qualifications), staying active on the platform, and maintaining a quick response time (Ticona & Mateescu, 2018a). As on other marketplace platforms, positive reviews, a five-star rating, and appearing high up in the search are crucial to getting clients (D'Cruz & Noronha, 2016; Graham & Anwar, 2019; Wood & Lehdonvirta, 2021; Wood et al., 2019).

Care.com recently created a "Household Fever Check" status, an optional badge indicating when workers had last checked for fevers at home; no such verification currently exists for clients (Ticona, 2020). Ticona and Mateescu (2018a) observe this lack of reciprocity in nearly all platform-facilitated trustworthiness signifiers. Graham and Anwar (2019) noted a similar asymmetry of information in their interviews with Upwork workers, which limited bargaining power. In the case of care work platforms, it could also compromise worker safety (Ticona & Mateescu, 2018b), given that employer abuse is common (Burnham & Theodore, 2012). Given the features outlined, and the existing literature, trustworthiness and visibility emerge as two crucial, interrelated themes to explore.

3 THEORETICAL FRAMEWORK

To examine this relationship, I apply Noble's (2018) work on how Google search algorithms have shaped trust and knowledge as a theoretical framework. In her work on Google searches, Noble (2018) argues that individuals perceive items that appear at the top of a search as inherently more trustworthy than those that do not. However, she notes that search algorithms are not neutral assessors of the "best" option, but deeply influenced by power, financial resources, and oppression. Research on Google searches have shown that around 70% of search traffic comes from the first page of results, with around 60% of clicks focusing on the top five items (Petrescu, 2014).

Algorithms on marketplace gig work platforms are distinct from search engines in that the client is searching for workers, not simply information. However, I argue that Noble's general theory, that the most visible search results are rendered trustworthy by the algorithm's "objectivity" which is necessarily opaque to the user, is applicable to Care.com. And on this platform, the immediate stakes of this trust are often higher than a Google search for information.

On Care.com, trustworthiness and visibility are intertwined but not mutually exclusive; visibility represents one way in which workers are rendered trustworthy by the platform, but there are other steps they must take to communicate this quality. Here, I use Noble's argument that visibility within a search algorithm engenders implicit trust that the top results will represent what is true. Noble (2018) argues that Google's "enclosure of the public domain" (p. 50) has changed how individuals view information. Most people see Google as an objective receptacle for knowledge and therefore, what appears at the top of the search is trustworthy. I argue that on Care.com, workers appearing at the top of the search renders them more trustworthy; therefore, visibility and trustworthiness are intertwined on the platform, a key finding from Ticona and Mateescu's (2018a) study of workers. Applying Noble's (2018) theory, as well as past work on marketplace platforms and Google searches (Graham & Anwar, 2019; Petrescu, 2014; Wood & Lehdonvirta, 2021), I assume that potential clients trust what they're being shown, and likely will not scroll past the first several pages.[1] I seek to analyse who is rendered implicitly trustworthy by the algorithm, and who is not. Since visibility on the platform represents only one measure of trustworthiness, I also want to examine the signifiers that workers themselves control, such as their qualifications, vaccination status, and the text of their bios.

In sum, this study attempts to understand how workers render themselves trustworthy, while simultaneously being rendered as trustworthy or less-so by an opaque, commercial algorithm. I undertook a qualitative content analysis of Care.com worker profiles, guided by three research questions: *What are the characteristics of profiles at the top of the search? What are the characteristics of the profiles at the bottom? How do profiles at both the top and the bottom communicate trustworthiness to potential clients?*

4 METHODS[2]

I conducted a qualitative content analysis of 60 Care.com worker profiles from three different locations in the US. I sampled the top 10 profiles along with a random sample of 10 profiles from the bottom 20% in each area, in order to investigate which profiles are made most visible and which are unlikely to be seen. The random sample from the bottom was obtained by selecting the last profile on each page in the bottom 20% of total pages. Given that the profiles at the very end of each search might be blank, long inactive, or very new, I chose instead to sample from a section of the search results that few prospective clients were likely to see, given that each zip code had at least several hundred profiles. Search algorithms change frequently based on time, date, and location, so my samples represent exploratory "snapshots"

[1] This assumption, on which my theoretical framework heavily relies, should be tested by future research—to my knowledge, an empirical study of clients has not been conducted yet.

[2] This project was reviewed and approved by the Oxford Internet Institute's Departmental Research Ethics Committee.

(Noble, 2018); longitudinal and more extensive sampling are required to draw generalizable conclusions.

4.1 Data

I chose search locations based on zip code, with the awareness that most search results would be from the surrounding areas. Due to algorithmic opacity (Wood & Lehdonvirta, 2021) it is unclear exactly how search results are sorted on Care.com, but I wanted to simulate the experience of a client from that particular neighbourhood searching for a caregiver. I chose to focus on neighbourhoods in Brooklyn, New York, and Atlanta, Georgia, partly because these were two of the locations used in Ticona and Mateescu's (2018a) interview study. Fremont, California, was selected primarily because it is an affluent suburb with a majority non-white population. Locations were chosen with the goal of variation in terms of race, class, geographic location, and urbanity (see Table 1 for a breakdown).

Table 1. Demographic and Geographic Breakdown of Search Locations[3]

	Brooklyn, NY (Park Slope)	**Atlanta, GA (Northwest)**	**Fremont, CA (Fremont)**
Racial demographics	72.1% White, 7.2% Black, 6% Asian, and 4.9% Hispanic (nonwhite)	88.6% Black, 8.5% White, 2.5% Hispanic (nonwhite), 1.4% Multiracial, 0.5% Asian, and 0.4% Other	58.2% Asian, 24.1% White, 7.8% Hispanic (nonwhite), and 3.4% Multiracial
Median household income	$122,002	$28,017	$127,374
Home ownership	38.2% (majority renters)	47% (majority renters)	61.6% (majority homeowners)
Urban or suburban?	Urban	Urban	Suburban
United States region	Northeast	South	West Coast
City included in Ticona and Mateescu (2018a)?	Yes	Yes	No

4.2 Sampling

I created a free client account, used an incognito window to prevent cookies from affecting the results, and conducted general caregiver searches. To create an account, I provided only a name and email address. I used three filters: I set the pay

[3] Data are from Data USA (2018a, 2018b) and City-Data (2019).

range as wide as possible ($10–50/hour) so that rate would not affect my results, I chose “recurring” versus “one time,” and I set the search radius to five miles in New York and Atlanta and 10 miles in Fremont, given the smaller number of profiles.[4] The searches in each city were conducted on different days during the last week of March 2021.

4.3 Analysis

I analysed the text and image descriptions of the 60 profiles in NVivo, using a qualitative content analysis as outlined by Schreier (2014). I coded for platform-mediated trustworthiness signifiers identified by Ticona and Mateescu (2018a), such as five-star ratings, positive reviews, CareChecks, response time, platform activity, qualifications, and education (for an example profile, see Figure 1). Care.com states that Premium accounts increase visibility (Care.com, 2017), so I also coded for whether profiles had a Premium badge, as well as demographic data listed in the profile (age, gender, and languages spoken).[5] I first developed a codebook with two main hierarchical levels: worker demographics and trustworthiness signifiers. Then, I refined the codebook in a trial round, developing thematic codes for the bios and focusing on formal ones, such as ratings and response time, for profile features. Finally, I conducted two rounds of coding, with an interval of one week between each (Schreier, 2014).

5 RESULTS

5.1 Tracking visibility: Characteristics of top and bottom profiles

5.1.1 Response Time and Connectivity

Response time, availability, and activity on the platform proved to be key differences between top and bottom profiles across locations. Workers’ response times are listed only if they respond within a few days. Every top profile either had either a quick response time listed, had been active on the platform within hours or days, listed recurring availability, or had all three characteristics. Having both a listed response time and recent activity on the platform was one of the most consistent features of top profiles (see Table 2). In contrast, bottom profiles typically listed no response time. There was one notable exception, which will be discussed below. Client interaction is required to generate response time, so this could be because profiles at the bottom did not have chances for interactions due to lack of visibility. However, some bottom profiles did indicate that they’d been hired by at least one

[4] Care.com requires the client to choose either “one time” or “recurring” before searching.
[5] Given that workers do not typically disclose race but do post a picture, clients’ assumptions could affect perception. Therefore, I deemed it necessary to include “perceived race” in my analysis, dependent on the fact that (like many clients) I am a white person making assumptions.

family. Regardless, the relationship between response time and visibility highlights a potentially vicious cycle: more visible profiles list response times, but profiles can only improve their response time through client interaction, which requires increased visibility.

Book Now, a more "on-demand" feature, did not prove common, with profiles that listed it making up only 11% of the total sample. However, all but one of the profiles that did include the feature were in the top 10, which could indicate some algorithmic amplification of profiles using this feature. Further research on this point is required.

A common feature among bottom profiles was the status "Active Over 1 Month Ago," which appeared in 8/10 bottom profiles in Atlanta, 7/10 in Fremont, and 2/10 in Park Slope, with the latter number likely due to Brooklyn's much larger volume of profiles. This could indicate that users who don't engage regularly with the platform are made less visible. Nearly every top 10 profile had been active in at least the past few days, enforcing the idea that regular use of the platform and quick response time are key to visibility.

Table 2. Breakdown of Response Time among Top and Bottom Profiles

	Responds within minutes	**Responds within hours**	**Responds within a day**	**Responds within a few days**	**No response time listed**
Atlanta (Top 10)	0	3	4	3	0
Brooklyn (Top 10)	0	3	2	4	1
Fremont (Top 10)	0	3	3	4	0
Atlanta (Bottom 10)	0	0	0	0	10
Brooklyn (Bottom 10)	1	0	0	0	9
Fremont (Bottom 10)	0	0	0	0	10

5.1.2 Reputation

Interview studies with marketplace gig workers have found ratings crucial to visibility (Graham & Anwar, 2019; Ticona et al. 2018; Wood & Lehdonvirta, 2021), and the majority of profiles at the top of each location had reviews and five-star ratings. Similarly, most of the profiles at the bottom had no rating or reviews, or, in rare cases, a negative review (see Table 3). The combination of no ratings, no reviews, and no response time was a common characteristic among bottom profiles across locations. Only one profile had a negative review (one star), and it appeared at the bottom. These results supported Ticona and Mateescu's (2018a) findings regarding worker perceptions that reputation was essential to visibility.

However, a departure from their findings emerged, especially among the top profiles in various locations. There were exceptions at the top and the bottom, with several profiles without five-star ratings listed at the top in all three cities, and at least one five-star profile at the bottom in Brooklyn and Fremont. For example, despite worker sentiment that lack of a five-star rating would preclude them from being boosted by the search algorithm (Ticona & Mateescu, 2018a), only half of the top profiles in Atlanta had one. Patterns among these exceptions provide an interesting window into how visibility might be related to inequalities among workers, as outlined below.

Table 3. Breakdown of Profile Ratings in Top and Bottom 10

	Profiles with five-star rating	Profiles with less than five-star rating	Profiles with no rating
Atlanta (Top 10)	5	1	4
Brooklyn (Top 10)	8	0	2
Fremont (Top 10)	8	0	2
Atlanta (Bottom 10)	0	1	9
Brooklyn (Bottom 10)	2	0	8
Fremont (Bottom 10)	2	0	8

5.1.3 Notable Exceptions Defined by Race

The exceptions to typical characteristics of top and bottom profiles (like response time, activity, and ratings) were often defined by perceived race. There were several instances of white-presenting workers missing key trustworthiness signifiers (such as response time or five-star ratings) in the top 10, as well as Black- and non-white-presenting workers with said trustworthiness signifiers appearing at the bottom. For example, Inez[6] a Black-presenting woman in Brooklyn, had the fastest response time of the entire sample ("within minutes") but appeared in the bottom. Kayleen,

[6] All names are pseudonyms and identifying details have been changed.

a white-presenting woman in Atlanta, had no reviews or rating, but still appeared number two in Atlanta, a majority Black city. She was listed above other more experienced caregivers with five-star ratings, faster response times, and many reviews. In Fremont, Lela and Katie, both young Asian-presenting women, were recently active on the platform, had five-star ratings and at least one positive review, but appeared in the bottom 10. However, Anne, a White-presenting woman of a similar age, had no reviews, rating, and no safety trainings, yet appeared near the top.

5.1.4 Black-presenting Workers Less Visible

These exceptions tie into another finding: Black-presenting workers consistently showed up in the bottom 10. In Brooklyn there were three Black women in the sample, all listed at the bottom. In Fremont there was one Black woman and one Black man, both at the bottom. In Atlanta, where the population of both the neighborhood and the city is majority Black (see Table 1), there were only three Black women in the top 10, out of the eight Black women in the sample. Even in a city with a majority Black population, Black-presenting women specifically were still less visible than their white-presenting peers. Furthermore, some of the Black-presenting women who ended up at the bottom had profiles that possessed many other trustworthiness signifiers, such as five-star reviews and quick response time. For example, Marta, who was listed in the bottom 10 in Brooklyn, had three five-star reviews, a 100% "Would Rehire" rate, and ample recurring availability listed. These findings indicate that despite workers' attempts to communicate trustworthiness (discussed further below), Black-presenting workers could be rendered less visible, and therefore less trustworthy by the algorithm.

This provides a counterpart to Ticona and Mateescu's (2018a) finding that their Black informants engaged in high levels of "visibility management" on the platform, curating their profiles and qualifications for a presumably white clientele. Ironically, while they may bear the personal burden of managing their perceived visibility, within my sample, Black women were rendered less visible by the algorithm.

5.1.5 Premium Accounts

A little over a quarter of the total profiles displayed "Premium" membership, which is available for purchase but not required. However, there seemed to be a relatively equal distribution of Premium profiles across the top and the bottom, with the exception of Atlanta, where 4/5 premium profiles appeared in the top 10. This finding casts some doubt on Care.com's statement that premium members will be "ranked higher in the search results" (Care.com, 2017, n.p.).

5.2 Communicating Trustworthiness

5.2.1 Ubiquity of Higher Education

The vast majority of profiles (53/60) had at least some college experience. On Care.com, education level is another "optional" piece of information that workers must choose whether or not to disclose. However, if they chose not to list their education, that portion of the profile will read as "not listed." Of the seven profiles that had no higher education listed, only two were in the top 10, and both profiles had multiple positive reviews, five-star ratings, and quick response times.

Furthermore, explicit mention of degrees, student status, or educational experience was one of the most common themes in the bios. Many bios made mention of current graduate school studies, college majors, and plans for further education. They often restated the name of their school, despite the fact that this information was already listed on their profile. Mention of education (or having a college degree) was consistent across top and bottom profiles.

5.2.2 COVID Safety

COVID safety was not as prevalent as expected, but profiles that utilized household fever checks or stated vaccine status were highly visible. I analysed three sub-categories within the code "COVID Safety:" household fever check, mention of COVID safety practices (including vaccination status), and statements of COVID boundaries (for example, only wanting to work with families that work remotely). Only five profiles of the 60 actually utilized the Household Fever Check, a finding that was surprising. However, all five of these profiles appeared in the top 10, providing support for the idea that workers who opt into this extra layer of surveillance could be rendered more visible by the platform. Five profiles total listed that they were fully vaccinated, and all appeared in the top 10. The small number of profiles that displayed vaccine status could be due to the sampling dates—at the end of March 2021 many individuals in these three states were not yet eligible. Several profiles mentioned COVID-safe practices, like social distancing or regular testing, but these were scattered among the top and the bottom. Only one profile in Brooklyn stated any kind of COVID boundaries—an experienced, older white-presenting woman in the top 10, who had multiple five-star reviews.

5.2.3 Passion for the Job

The majority of profiles communicated trust by framing childcare as more than just a job. The most common code that came out of analysis of the worker bios was an asserted "passion" for the job, which often was justified by a naturalized love of childcare. The majority of profiles in all three locations used phrases like, "I have a passion for childcare," "I really enjoy helping others," or "it is my passion to take care of people." Profiles used adjectives like "fun-loving," "compassionate," and "nurturing" and the word "love" appears 43 times within the total sample. Many profiles made reference to childcare being a "fun" job and workers frequently referred to their own families in framing their work experience. One worker cited their history of customer service jobs and remarked, "I'm excited to switch to something I actually like." Here the worker contrasts childcare, framed as a "passion," with a different kind of people-facing job, framed as work.

Within the category of "passion for the job," I identified a sub-code, in which profiles alluded to a naturalized love of childcare, mentioning "innate skills," or asserting that they have "always been pulled towards caregiving." Phrases such as "natural rapport," "natural inclination," or "calling" framed childcare as a profession chosen for the worker, not by them. A worker from Atlanta referred to the fact that she had "always wanted" a big family and "always" nurtured a love of children; both were framed as unquestionable, naturalized facts and followed by a pitch for why this caregiver was right for the job. Clients also employed this language in their reviews. A five-star one stated, "she works with children because she has a genuine, deep-rooted love for what she does." The quote both emphasizes the importance of this worker's "authenticity" as success (and therefore, trustworthiness) and subtly implies that money isn't her primary motivation, love is.

This theme represents one way that profiles communicate trustworthiness to potential clients: asserting that childcare is not "just" a job, but rather tied to "inherent" qualities of one's personality, such as nurturance, compassion, curiosity, and fun. This theme was common in both profiles at the top and the bottom—stating a passion for the job did not appear related to visibility.

6 DISCUSSION

Overall, class norms, disparities in visibility based on race, connectivity, and the ubiquity of declarations of "passion for the job" were some of the most salient findings. In this section, I will discuss these further and tie them to the theoretical work of Noble (2018), along with Schor (2017), Ollier-Malaterre et al. (2019), and others. Schor's (2017) theory of "crowding out" on gig economy platforms could have some traction on Care.com. The ubiquity of some form of higher education on the platform was one of the most consistent features across profiles, with little variation by location. However, instead of workers with higher education being rendered more visible by the platform, workers with higher education made up the vast majority of profiles. This result could indicate that on Care.com a college education might not just be an advantage, but an unofficial requirement. It also supports the idea that "personality matching" that occurs during selection is often rooted in "class norms" (Ticona et al., 2018). A divide between primarily white, college-educated nannies and working-class women of color has already been identified (Wu, 2016), but these findings indicate that Care.com could exacerbate it. More representative data and interviews specifically with workers without college degrees on Care.com could help support this finding.

Listed response time and recent platform activity as key features distinguishing top from bottom profiles indicates that connectivity could be a potential mechanism through which inequality is exacerbated. This lines up with interviews with other types of platform workers, who speak of the need to be constantly present on the platform in order to get jobs (D'Cruz & Noronha, 2016; Wood et al., 2019). Given that lower-income workers might not have quick and easy internet access, (Ticona et al., 2018) visibility's potential ties to constant connectivity could be another way in which the platform strengthens existing inequalities. Personal caregiving duties, familial responsibilities, age, technology literacy, and commitments to other jobs could be additional barriers to connectivity. Beyond literacy, digital confidence, and ability to successfully "crack the code" of the platform itself could be an overarching factor. This quality is similar to Ollier-Malaterre and colleagues' (2019) concept of "digital cultural capital;" managing one's connectivity and presence on multiple platforms is a skill that not only has immense potential monetary value but is frequently defined by class status. Therefore, low-income workers may be at a disadvantage on the platform when it comes to seamlessly managing their online presence in the face of other obstacles.

Black-presenting women's overall lack of visibility parallels Noble's (2018) findings regarding Google searches—Black women are often hurt by search algorithms due to the ways in which racism and gendered oppression are built into their design. Ticona et al. (2018) noted that Black workers feel "hyper-visible" on the platform, but ironically this may not be translating to visibility via the search. Search algorithms are not neutral but shaped by racism and sexism (Noble, 2018). Care.com's algorithm is not publicly available, but here I provide a potential theory of how these divisions might be playing out. Since race is not measured as a demographic variable among workers, it is unlikely (but not impossible) the algorithm itself is directly suppressing the profiles of Black workers. However, as Noble (2018) notes with her analysis of PageRank, Google's algorithm was racist in part because it relied on what was most popular in a deeply racist society, therefore enforcing stereotypes about Black women. A similar process could be occurring on Care.com: profiles that have more engagement (views, messages, favorites) become more visible to clients. But in engaging with workers, clients (especially white ones) might favor white-presenting workers over non-white ones.[7] Hence, without explicitly filtering based on race, the algorithm could render non-white workers less visible, and therefore less trustworthy, to potential clients.

"Passion for the job" as a major theme among top and bottom profiles framed childcare as a passion first, and a job second. This parallels care work platforms' emphasis on "personality matching" (Flanagan, 2019; McDonald et al., 2021; Ticona & Mateescu, 2018a), and indicates that workers may feel the need to frame childcare as a "passion," rather than a "gig" to appear both trustworthy and

[7] Racism among white clients seeking childcare and domestic work is documented by scholars like Ehrenreich and Hochschild (2003) and Glenn (1992).

appealing to clients. This provides support for the argument that "uberization" models don't fit neatly onto Care.com (Ticona et al., 2018); workers on many other gig platforms are not expected to convey their genuine love for the work to clients.

The "naturalized" way in which this passion for the job is presented also highlights the gendered nature of care work, another feature that makes it distinct from other, more commonly studied gig economy platforms. Much has been written on how care work has been historically gendered and naturalized, partly to maintain a low-paid mostly female workforce in the public sphere and an unpaid one in the private sphere (for an overview, see Bhattacharya, 2017). The overwhelming focus on a naturalized love of childcare highlights the gendered nature of the platform—my total sample was 96% female, which is in line with Care.com's 94% female workforce (Care.com, Inc., 2019).[8] Framing care work as a passion rather than a gig may speak to its gendered nature, and it also may speak to the rhetoric of the so-called "sharing economy," (Sundararajan, 2016) an image that has been used to erase the work of gig work, framing a precarious sector as one of free, mutual exchange. Framing care work as a "labor of love," and gig work as "sharing" both serve an extractive purpose, and the combination of these two narratives converge on Care.com

However, this narrative of childcare as passion presents a contradiction, given that the most visible profiles displayed high levels of connectivity and established reputation through ratings and reviews. Workers must be passionate about the work, but they must also be timely, curated, and ready to trade privacy for platform-mediated trustworthiness signifiers. Therefore, this "personal branding" on the platform could also take the form of downplaying the job's "gig-like" nature while still being held to the same exacting standards as workers on other marketplace platforms (Graham & Anwar, 2019; Wood et al., 2019; Wood & Lehdonvirta, 2021). In this sense, the worker must support the gig system by obscuring the labor that goes into it. To be successful (and perceived as trustworthy) they must frame care work as genuine love or passion, rather than a means of making a living. Ironically, work that is framed as passion may be especially vulnerable to exploitation, as Jaffe (2021) argues in her critique of neoliberalism's "do what you love" ethos. Further qualitative research could explore the potential contrast between how workers present their "passion" for the job on the platform and their day-to-day experience of the work.

Finally, the relative lack of emphasis on COVID safety was a surprising finding. However, given that profiles disclosing vaccine status were listed exclusively at the top during a time in which many individuals were not yet eligible, I would expect this trend to continue. Given that there is not currently a way for workers on Care.com to find out information about clients' COVID-safe practices

[8] Care.com displays gender on each worker's profile. There were only two men in my total sample. Interestingly, one of them (a young, white-presenting man) was ranked number one in Brooklyn. The other (a Black-presenting young man) was in the bottom 10 in Fremont.

or vaccine status, the practice of listing health information could continue to become a one-sided worker-surveillance tool.

As Noble (2018) notes, search results are characterized by constant change. Hence one limitation of this study is that my samples represent snapshots, rather than the full picture. Similarly, my samples are small and not meant to be representative. For the top search results, the selectivity is crucial to understanding who appears most visible. However larger samples from the bottom 20% of the search could be useful in future studies. Further research could collect longitudinal data: running the same search at various periods in time, collecting data, and attempting to replicate these findings.

Another limitation is a reliance on my own, biased assumptions regarding perceived race. However, given that workers do not actually list their race on the platform, perceived race plays a large role in how they are evaluated by clients (Ticona & Mateescu, 2018a). Lack of information about Care.com clients is an additional limitation. This study assumes that clients will be inclined to view top search results as more trustworthy and appealing. To my knowledge, no existing study asks clients directly how they evaluate and choose workers on care work platforms. Further research could explore how they establish trustworthiness on the platform.

Overall, my findings support arguments that care work platforms may exacerbate inequalities (Ticona & Mateescu 2018a; van Doorn, 2017), specifically here with visibility. I found that to appear visible and hence trustworthy, Care.com workers, like those on other marketplace platforms, must maintain stellar reputations and quick response times. However, unlike freelancer platforms, delivery services, or ride-hailing apps, workers on Care.com cite passion as a primary job qualification, a phenomenon that speaks to the gendered nature of care work, the illusion of the "sharing" economy, and the specific challenges facing workers on care work platforms. These challenges could and should be explored in future research within this emerging literature.

FUNDING STATEMENT AND ACKNOWLEDGMENTS

Many thanks to Dr. Mark Graham at the Oxford Internet Institute, who oversaw this research, Collin Knopp-Schwyn, who provided crucial feedback and copyediting support, and the two anonymous reviewers, whose thoughtful comments greatly improved this paper's arguments.

REFERENCES

Arriagada, A., & Ibáñez, F. (2020). "You need at least one picture daily, if not, you're dead": Content creators and platform evolution in the social media ecology. *Social Media + Society*, *6*(3). https://doi.org/10.1177/2056305120944624

Bajwa, U., Gastaldo, D., Di Ruggiero, E., & Knorr, L. (2018). The health of workers in the global gig economy. *Globalization and Health*, *14*, Article 124. https://doi.org/10.1186/s12992-018-0444-8

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new Jim Code*. Polity.

Bhattacharya, T. (Ed.). (2017). *Social reproduction theory: Remapping class, recentering oppression*. Pluto Press. https://doi.org/10.2307/j.ctt1vz494j

Brayne, S. (2017). Big data surveillance: The case of policing. *American Sociological Review*, *82*(5), 977–1008. https://doi.org/10.1177/0003122417725865

Bucher, T. (2012). Want to be on the top? Algorithmic power and the threat of invisibility on Facebook. *New Media & Society*, *14*(7), 1164–1180. https://doi.org/10.1177/1461444812440159

Bucher, T. (2016). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. *Information, Communication & Society*, *20*(1), 30–44. https://doi.org/10.1080/1369118X.2016.1154086

Burnham, L., & Theodore, N. (2012). *Home economics: The invisible and unregulated world of domestic work.* National Domestic Workers Alliance. https://www.domesticworkers.org/wp-content/uploads/2021/06/HomeEconomicsReport.pdf

Bussewitz, C., & Olson, A. (2020, July 5). Gig workers face shifting roles, competition in pandemic. *Washington Post*. https://www.washingtonpost.com/business/gig-workers-face-shifting-roles-competition-in-pandemic/2020/07/05/3589759e-bec8-11ea-8908-68a2b9eae9e0_story.html

Care.com. (2017, June 14). *What is the premium membership on Care.com?*. Retrieved April 21, 2021, from https://www.care.com/c/questions/29145/what-is-the-premium-membership-on-carecom/

Care.com. (2021). [Homepage]. Retrieved April 24, 2021, from https://www.care.com/ppr.do

Care.com, Inc. (2019). *2018 annual report and form 10K*. United States Securities and Exchange Commission. Retrieved May 9, 2021, from https://www.annualreports.com/HostedData/AnnualReports/PDF/NYSE_CRCM_2018.pdf

Chen, J. Y. (2018). Thrown under the bus and outrunning it! The logic of Didi and taxi drivers' labour and activism in the on-demand economy. *New Media & Society*, *20*(8), 2691–2711. https://doi.org/10.1177/1461444817729149

City-Data. (2019). *30032 zip code (Candler-McAfee, Georgia) profile - Homes, apartments, schools, population, income, averages, housing, demographics, location, statistics, sex offenders, residents and real estate info*. Retrieved April 18, 2021, from https://www.city-data.com/zips/30032.html

Conger, K., Satariano, A., & Isaac, M. (2020, March 18). Pandemic erodes gig economy work. *The New York Times*. https://www.nytimes.com/2020/03/18/technology/gig-economy-pandemic.html

Cooke, M. (2015, October 31). The Bronx slave market. *Viewpoint Magazine*. https://viewpointmag.com/2015/10/31/the-bronx-slave-market-1950/ (Original work published 1950)

Data USA. (2018a). *Fremont, CA*. Retrieved April 18, 2021, from https://datausa.io/profile/geo/fremont-ca

Data USA. (2018b). *Park Slope, Carroll Gardens & Red Hook PUMA, NY*. Retrieved April 18, 2021, from https://datausa.io/profile/geo/park-slope-carroll-gardens-red-hook-puma-ny

D'Cruz, P., & Noronha E. (2016). Positives outweighing negatives: The experiences of Indian crowdsourced workers. *Work Organisation, Labour & Globalisation*, *10*(1), 44–63. https://doi.org/10.13169/workorgalaboglob.10.1.0044

Dickson, E. (2020, July 3). Coronavirus is killing the working mother. *Rolling Stone*. https://www.rollingstone.com/culture/culture-features/working-motherhood-covid-19-coronavirus-1023609/

Ehrenreich, B., & Hochschild, A. R. (2003). Introduction. In B. Ehrenreich & A. R. Hochschild (Eds.), *Global woman: Nannies, maids, and sex workers in the new economy* (pp. 1–14). Metropolitan Books.

England, P., Budig, M., & Folbre, N. (2002). Wages of virtue: The relative pay of care work. *Social Problems*, *49*(4), 455–473. https://doi.org/10.1525/sp.2002.49.4.455

Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.

Farrell, M. B. (2014, August 14). Care.com, the big business of babysitting. *Globe Magazine*. https://www.bostonglobe.com/magazine/2014/08/14/care-com-big-business-babysitting/4Fjpf5q3YUSw3rMn9GraOM/story.html

Ferrari, F., & Graham, M. (2021). Fissures in algorithmic power: Platforms, code, and contestation. *Cultural Studies*, *35*(4–5), 814–832. https://doi.org/10.1080/09502386.2021.1895250

Flanagan, F. (2019). Theorising the gig economy and home-based service work. *Journal of Industrial Relations*, *61*(1), 57–78. https://doi.org/10.1177/0022185618800518

Gerson, E. S. (2019, July 8). *Background checks: What every family needs to know before hiring a caregiver*. Care.com. Retrieved April 22, 2021, from https://www.care.com/c/stories/3147/nanny-background-checks/

Glenn, E. N. (1992). From servitude to service work: Historical continuities in the racial division of paid reproductive labor. *Signs*, *18*(1), 1–43. https://doi.org/10.1086/494777

Graham, M., & Anwar, M. A. (2019). The global gig economy: Towards a planetary labour market? *First Monday*, *24*(4). https://doi.org/10.5210/fm.v24i4.9913

Gray, M. L., & Suri, S. (2019). *Ghost work: How to stop Silicon Valley from building a new global underclass*. Houghton Mifflin Harcourt.

Grose, J. (2021, February 4). America's mothers are in crisis. *The New York Times*. https://www.nytimes.com/2021/02/04/parenting/working-moms-mental-health-coronavirus.html

Hochschild, A. R. (2013). *The outsourced self: What happens when we pay others to live our lives for us*. Picador.

Hsu, A. (2020, September 29). *'This is too much': Working moms are reaching the breaking point during the pandemic*. NPR. https://www.npr.org/2020/09/29/918127776/this-is-too-much-working-moms-are-reaching-the-breaking-point-during-the-pandemi

Jaffe, S. (2021). *Work won't love you back: How devotion to our jobs keeps us exploited, exhausted, and alone*. Bold Type Books.

Kaine, S., Flanagan, F., & Ravenswood, K. (2020). Future of work (FoW) and gender. In A. Wilkinson & M. Barry (Eds.), *The future of work and employment* (pp. 119–138). Edward Elgar Publishing. https://doi.org/10.4337/9781786438256.00016

Macdonald, C. L. (2011). *Shadow mothers: Nannies, au pairs, and the micropolitics of mothering*. University of California Press. https://doi.org/10.1525/9780520947818

McDonald, P., Williams, P., & Mayes, R. (2021). Means of control in the organization of digitally intermediated care work. *Work, Employment and Society*, *35*(5), 872–890. https://doi.org/10.1177/0950017020969107

Montgomery, T., & Baglioni, S. (2021). Defining the gig economy: Platform capitalism and the reinvention of precarious work. *International Journal of Sociology and Social Policy*, *41*(9–10), 1012–1025. https://doi.org/10.1108/IJSSP-08-2020-0400

Newlands, G. (2021). Algorithmic surveillance in the gig economy: The organization of work through Lefebvrian conceived space. *Organization Studies*, *42*(5), 719–737. https://doi.org/10.1177/0170840620937900

Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. New York University Press. https://doi.org/10.2307/j.ctt1pwt9w5

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447–453. https://doi.org/10.1126/science.aax2342

Ollier-Malaterre, A., Jacobs, J. A., & Rothbard, N. P. (2019). Technology, work, and family: Digital cultural capital and boundary management. *Annual Review of Sociology*, *45*(1), 425–447. https://doi.org/10.1146/annurev-soc-073018-022433

Parker, G. G., Alstyne, M. W. V., & Choudary, S. P. (2016). *Platform revolution: How networked markets are transforming the economy—and how to make them work for you*. W. W. Norton & Company.

Petrescu, P. (2014, October 1). *Google organic click-through rates in 2014*. Moz. https://moz.com/blog/google-organic-click-through-rates-in-2014

Poo, A.-J. (2017, June 16). *Out from the shadows: Domestic workers speak in the United States*. OpenDemocracy. https://www.opendemocracy.net/en/beyond-trafficking-and-slavery/out-from-shadows-domestic-workers-speak-in-united-states/

Rega, I., & Medrado, A. (2021). The stepping into visibility model: Reflecting on consequences of social media visibility – a Global South perspective. *Information, Communication & Society*. Advance online publication. https://doi.org/10.1080/1369118X.2021.1954228

Schor, J. B. (2017). Does the sharing economy increase inequality within the eighty percent?: Findings from a qualitative study of platform providers. *Cambridge Journal of Regions, Economy and Society*, *10*(2), 263–279. https://doi.org/10.1093/cjres/rsw047

Schreier, M. (2014). Qualitative content analysis. In U. Flick (Ed.), *The SAGE handbook of qualitative data analysis* (pp. 170–183). SAGE. https://doi.org/10.4135/9781446282243.n12

Shapiro, A. (2018). Between autonomy and control: Strategies of arbitrage in the "on-demand" economy. *New Media & Society*, *20*(8), 2954–2971. https://doi.org/10.1177/1461444817738236

Sharabi, L. L. (2021). Exploring how beliefs about algorithms shape (offline) success in online dating: A two-wave longitudinal investigation. *Communication Research*, *48*(7), 931–952. https://doi.org/10.1177/0093650219896936

Sundararajan, A. (2016). *The sharing economy: The end of employment and the rise of crowd-based capitalism*. MIT Press.

Tandon, A., & Rathi A. (2021). Care in the platform economy: Interrogating the digital organization of domestic work in India. In B. Dolber, M. Rodino-Colocino, C. Kumanyika, & T. Wolfson (Eds.), *The gig economy: Workers and media in the age of convergence* (pp. 47–57). Routledge. https://doi.org/10.4324/9781003140054-6

Thurman, N., Moeller, J., Helberger, N., & Trilling, D. (2019). My friends, editors, algorithms, and I: Examining audience attitudes to news selection. *Digital Journalism*, *7*(4), 447–469. https://doi.org/10.1080/21670811.2018.1493936

Ticona, J. (2020) Essential and untrusted. *Dissent*, *67*(4), 12–18. https://doi.org/10.1353/dss.2020.0080

Ticona, J., & Mateescu, A. (2018a). Trusted strangers: Carework platforms' cultural entrepreneurship in the on-demand economy. *New Media & Society*, *20*(11), 4384–4404. https://doi.org/10.1177/1461444818773727

Ticona, J., & Mateescu, A. (2018b, March 29). How domestic workers wager safety in the platform economy. *Fast Company*. https://www.fastcompany.com/40541050/how-domestic-workers-wager-safety-in-the-platform-economy

Ticona, J., Mateescu, A., & Rosenblat, A. (2018) *Beyond disruption: How tech shapes labor across domestic work & ridehailing*. Data & Society.

https://datasociety.net/wp-content/uploads/2018/06/Data_Society_Beyond_Disruption_FINAL.pdf

Vallas, S., & Schor, J. B. (2020). What do platforms do? Understanding the gig economy. *Annual Review of Sociology*, *46*(1), 273–294. https://doi.org/10.1146/annurev-soc-121919-054857

van Doorn, N. (2017). Platform labor: On the gendered and racialized exploitation of low-income service work in the 'on-demand' economy. *Information, Communication & Society*, *20*(6), 898–914. https://doi.org/10.1080/1369118X.2017.1294194

Walsh, S. (Director). (2021). *The gig is up* [Film]. Dogwoof Pictures.

Williams, P., McDonald, P., & Mayes, R. (2021). Recruitment in the gig economy: Attraction and selection on digital platforms. *The International Journal of Human Resource Management*, *32*(19), 4136–4162. https://doi.org/10.1080/09585192.2020.1867613

Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad big: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society*, *33*(1), 56–75. https://doi.org/10.1177/0950017018785616

Wood, A. J., & Lehdonvirta, V. (2021). *Platform precarity: Surviving algorithmic insecurity in the gig economy*. SSRN. https://doi.org/10.2139/ssrn.3795375

Wu, T. (2016). More than a paycheck: Nannies, work, and identity. *Citizenship Studies*, *20*(3–4), 295–310. https://doi.org/10.1080/13621025.2016.1158358

Zhou, M., Hertog, E., Kolpashnikova, K., & Kan, M.-Y. (2020). *Gender inequalities: Changes in income, time use and well-being before and during the UK COVID-19 lockdown*. SocArXiv. https://doi.org/10.31235/osf.io/u8ytc