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Online Ranking System Effects on Perceived Fairness: Gender, Income and Education

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The gig economy, which is also referred to as the sharing or on-demand economy, involves the use of online platforms to offer and find short-term work, goods, and services on a flexible basis. These platforms, which allow freelancers and independent contractors to connect with clients in need of their services, have gained widespread popularity in recent years. However, the gig economy has been the subject of much controversy, particularly regarding the fairness of platform rating systems and their impact on workers' income and job security. This article presents an analysis of the distribution of fairness and perceived satisfaction with ranking systems in these work markets and discusses the ways in which these systems may lead to unfair outcomes for workers. It also examines the effects of these systems on workers' income and job security and investigates the potential influence of factors such as gender, age, and employment status on the fairness of these rating systems. The article suggests directions for further research on this topic and considers the implications of these findings for policymakers and practitioners.

Keywords: Online Workplace Platforms, Gig Economy, Social Inequalities

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The gig economy, also known as the sharing or on-demand economy, refers to the growing trend of individuals and businesses using online platforms to offer and find work, goods, and services on a flexible, short-term basis. Online work platform marketplaces, in particular, have become increasingly popular in recent years. This is because they offer a convenient and efficient way for freelancers and independent contractors to connect with clients who need their services. However, the gig economy has also been the subject of much debate. This is due to concerns about the fairness of platform ranking systems and the impact of these systems on workers' income and job security.

Ranking systems on online work platform marketplaces are used to evaluate the performance and quality of workers and determine their visibility and access to job opportunities. These ranking systems are often based on subjective evaluations by clients rather than objective measures of performance. There is a growing body of research that suggests that these systems may not be fair. In particular, there are concerns that ranking systems may be biased against certain groups of workers, such as those who are less skilled at self-promotion or those who are from disadvantaged backgrounds.

In this article, we aim to provide a review of the existing literature on online work platform marketplaces and ranking fairness and assess empirically the impact of those rankings on individual's sense of fairness. We will examine the ways in which ranking systems on these platforms may lead to unfair outcomes for workers. We will also examine the impact of these systems on workers' income and job security. We will also consider the potential role of factors such as gender, age, and employment status in the fairness of these ranking systems. Finally, we will discuss the implications of these findings for policymakers and practitioners and suggest directions for future research on this topic.

While a number of studies have investigated the aspect of 'fairness' regarding the *outcomes* of ranking systems, conceptually the notion of fairness implies subjective measurement, both of the giver and the recipient of the measurement. In this study we examine fairness as it is *received* rather than assessed. As such, we propose that the internalization of fairness regarding outcomes is vital to establishing just benchmarks regarding the ranking process for online labor marketplaces.

Accordingly, we examine the following hypotheses:

(H1) An individual's assessment of the fairness of their online gig economy rating varies with the type of platform category, with knowledge-based platforms having a higher impact and transactional platforms having a lower impact;

(H2) Age, gender and education level affect how an individual perceives the fairness of their online marketplace rating.

BACKGROUND

Online work platform marketplaces, such as Upwork, Freelancer, and Fiverr, are websites or apps that facilitate the matching of freelancers or independent contractors with clients or employers who are seeking their services. These platforms have become a significant part of the gig economy, which refers to temporary or project-based work.

However, there are also challenges and concerns related to job security, benefits, and potential inequalities for workers in the gig economy (Codagnone et al., 2016; Schor & Attwood-Charles, 2017).

Ratings on online work platform marketplaces can play a significant role in determining the success or failure of a seller or provider (Elbassuoni et al., 2020). Research has identified several potential biases in rating systems, including self-selection bias, in which individuals with certain characteristics are more likely to rate a product or service, and novelty bias, in which newly introduced products or providers are more likely to receive higher ratings (Elbassuoni et al., 2020; Ess & Sudweeks, 2005).

In addition to the potential for bias in ratings, there are also concerns about the overall fairness of rating systems on online work platform marketplaces (Elbassuoni et al., 2020). For example, a study by Patro et al. (2022) found that the ranking algorithms used by some online marketplaces may favor certain sellers or providers over others, leading to unequal opportunities and outcomes. Another study by Li et al. (2021) found that the use of artificial intelligence (AI) in ranking systems can also result in unintended consequences and discrimination, particularly if the training data used to develop the AI algorithms is biased.

To address these issues, some researchers have proposed the use of fairness metrics and fairness-aware algorithms to evaluate and improve the fairness of ranking systems (Dwork et al., 2012; Elbassuoni et al., 2020b). For example, a study by Hardt et al. (2016) proposed the use of individual fairness metrics, which aim to ensure that similar individuals are treated similarly, and group fairness metrics, which aim to ensure that disadvantaged groups are not disproportionately affected by a ranking system.

Overall, the literature suggests that online work platform marketplaces have the potential to create new opportunities for workers. However, they also raise concerns about job security, benefits, and fairness in ranking systems. Further research is needed to better understand the impacts and implications of these platforms and to address issues related to ranking fairness.

Bias

Bias in online rating systems has been a topic of concern in the literature on online work platform marketplaces. Research has shown that ratings can be influenced by various factors such as the quality of the product or service, the communication skills of the seller or provider, and the buyer's expectations (Elbassuoni et al., 2020). However, there are also potential biases in rating systems that can impact the fairness of the ratings and the overall ranking of sellers or providers on a platform.

One type of bias that has been identified in online rating systems is self-selection bias, which refers to the tendency of individuals with certain characteristics, such as gender or race, to rate products or services more frequently than others (Kleinberg et al., 2002). For example, a study by Ess and Sudweeks (2005) found that males were more likely to rate products on an online marketplace compared to females, leading to a gender bias in the ratings. Another study by Elbassuoni et al. (2020b) found that sellers with higher ratings were more likely to be located in wealthier neighborhoods, suggesting the possibility of a geographical bias in ratings.

Another type of bias that has been identified in online rating systems is novelty bias. This refers to the tendency for new products or providers to receive higher ratings than more established ones (Elbassuoni et al., 2020). This bias can result in a skewed ranking of sellers or providers, with new entrants receiving an unfairly high position in the rankings.

In addition to self-selection and novelty bias, there are also concerns about the impact of fake or manipulated ratings on the fairness of online rating systems (Konstan et al., 2002). For example, a study by Elbassuoni et al. (2020b) found that some sellers on online marketplaces use fake or manipulated ratings to artificially inflate their rankings, leading to an unfair advantage over other sellers.

To address these biases in online rating systems, some researchers have proposed the use of fairness metrics and fairness-aware algorithms (Dwork et al., 2012; Elbassuoni et al., 2020b). These approaches aim to evaluate and improve the fairness of ranking systems by considering factors such as the characteristics of the individuals or groups being rated. In addition, they consider the potential for bias in the ratings.

Overall, the literature suggests that bias in online rating systems can impact the fairness of ranking systems on online work platform marketplaces. Further research is needed to better understand the sources and impacts of these biases and to develop effective strategies for mitigating their effects.

Fairness

In addition to the issue of bias in online rating systems, there has also been research on the overall fairness of ranking systems on online work platform marketplaces. Some studies have found that the ranking algorithms used by these platforms may favor certain sellers or providers over others, leading to unequal opportunities and outcomes (Elbassuoni et al., 2020; Patro et al., 2022).

For example, a study by Patro et al. (2022) examined the effects of seller characteristics, such as the seller's reputation and the price of their products or services, on search rankings in an online marketplace. The authors found that these characteristics had a significant impact on search rankings, with sellers with higher reputations and lower prices receiving higher positions in the rankings. This result suggests that ranking algorithms may be biased towards certain sellers or providers, leading to an unfair advantage for those who are ranked higher.

Another study by Elbassuoni et al. (2020) also examined the impact of seller characteristics on search rankings in an online marketplace. The authors found that sellers with higher ratings and more reviews received higher positions in the search results. This suggests that ranking algorithms may be biased towards sellers who have already achieved a certain level of success on the platform.

In addition to these studies, there has also been research on the use of artificial intelligence (AI) in ranking systems and the potential for AI to result in unintended consequences and discrimination (Hardt et al., 2016; Li et al., 2021). For example, a study by Li et al. (2021) found that the use of AI rating systems can lead to a lack of transparency and accountability, as it is often difficult to understand the exact factors that contribute to a seller's or provider's ranking. Another study by Hardt et al. (2016) identified the potential for AI-based ranking systems to perpetuate existing societal inequalities if the training data used to develop the algorithms is biased.

To address the issue of fairness in online rating systems, some researchers have proposed the use of fairness metrics and fairness-aware algorithms (Dwork et al., 2012; Elbassuoni et al., 2020b). These approaches aim to evaluate and improve the fairness of ranking systems by considering factors such as the characteristics of the individuals or groups being ranked. In addition, they consider the potential for bias in the ratings. For example, a study by Hardt et al. (2016) proposed the use of individual fairness metrics, which aim to ensure that similar individuals are treated similarly, and group fairness metrics, which aim to ensure that disadvantaged groups are not disproportionately affected by a ranking system.

Sociological Implications

One of the key sociological implications of online ranking systems is their potential to shape social norms and behaviors. A number of studies have shown that rankings can influence how people perceive and interact with one another, leading to a phenomenon known as 'social comparison.' For example, research has found that people are more likely to cooperate with those who have high rankings and to avoid those with low rankings (Cooper, 2003). Additionally, rankings can create a sense of competition and drive people to strive for higher scores, leading to increased effort and achievement (Hsee, 1996).

Another sociological aspect of online ranking systems is their role in shaping online communities. Research has shown that rankings can have a strong influence on how people perceive and participate in online communities, with higher-ranked individuals often gaining more attention and influence (Shen, 2012). At the same time, rankings can also lead to social stratification and exclusion, with those who are ranked lower often experiencing less social support and participation (Zhang & Yu, 2012).

One potential downside of online ranking systems is their potential to perpetuate existing biases and inequalities. For example, research has shown that rankings can be influenced by factors such as gender, race, and class, leading to the amplification of existing inequalities (Zukin et al., 2017). Additionally, ranking systems can create a 'winner takes all' mentality, with a small number of highly ranked individuals receiving the majority of rewards and benefits, while those who are ranked lower are left with few opportunities (Chase, 2015).

Despite these potential drawbacks, online ranking systems also have the potential to provide benefits and opportunities. For example, rankings can serve as a way for individuals to showcase their skills and accomplishments and can provide a means of recognition and validation (Hilbert & López, 2011). Additionally, rankings can provide a way for individuals to learn and improve, as they can see how they compare to others and identify areas for improvement (Schmitt et al., 2007).

Overall, the literature suggests that fairness in online rating systems is a complex and multifaceted issue, with the potential for ranking algorithms to favor certain sellers or providers and for AI-based systems to perpetuate existing inequalities. Further research is needed to better understand the sources and impacts of these issues and to develop effective strategies for ensuring fairness in online ranking systems.

METHODS

The study sample included 1000 participants who were recruited through Amazon Mechanical Turk (MTurk), an online platform that enables businesses and individuals to outsource tasks to a global, on-demand workforce. In order to be eligible for the study, participants had to be at least 18 years old, possess a US-based MTurk account, and have an active Facebook account. MTurk has become a widely used tool for researchers in the social sciences due to its ability to efficiently and cost-effectively gather data from a diverse and extensive sample of individuals.

MTurk is a valuable resource for social science research due to its capacity to access a varied and geographically dispersed sample of participants. Researchers have the capability to focus on specific demographics or countries and can quickly reach a large number of participants through MTurk (Buhrmester et al., 2011). Additionally, MTurk enables researchers to specify the qualifications and payment for each task, enabling them to ensure that only participants with the required skills and motivation complete the tasks (Paolacci et al., 2010). This is a major advantage of MTurk for social science research.

However, using MTurk for social science research also presents several challenges and limitations. One concern is the potential for participant attrition, as MTurk workers may not be as invested in the research as traditional participants (Goodman et al., 2013). Additionally, there is the risk of participant fraud or misbehaviour, as MTurk workers may not always be truthful about their qualifications or may not complete tasks to the required standard (Paolacci et al., 2010). To address these issues, researchers have recommended using multiple methods of data collection. In addition, they recommend carefully selecting and training participants, and taking steps to ensure the validity and reliability of the data collected (Goodman et al., 2013).

Despite these challenges, MTurk has been employed in numerous social science research studies, including studies on decision-making, social influence, and personality. For instance, researchers have used MTurk to examine how individuals make decisions under uncertainty (Busemeyer, 1985), how social influence impacts consumer behaviour (Dellarocas, 2003), and how personality traits relate to decision-making and risk-taking (Kim & Hodgins, 2017).

This survey was administered via MTurk with several considerations in mind. Firstly, filters were implemented to screen out invalid responses. Secondly, demographic questions were included to ensure diversity in the sample of responses. Finally, a screening question was included to confirm that all respondents were active social media users.

Procedure

The survey questionnaire was created in HTML and administered online. Before starting the survey, participants were informed about the purpose of the study and asked to provide informed consent. The questionnaire took approximately 2 minutes to complete, and respondents were compensated for their participation. Data were collected over the course of 24 hours and then analyzed using R statistical software. Descriptive statistics, including means, standard deviations, and frequencies, were calculated for all variables.

T-tests and an ANOVA were conducted to examine the relationships between perceived ranking fairness and how these relationships varied by demographic factors. The raw data from this study is available on Zenodo at the following url: https://zenodo.org/record/8139506.

Measures

The survey questionnaire included a range of measures to assess respondent perceptions of platform rankings. Demographic questions included age, gender, education level, and the urbanity of the participants' location.

Ethics

This study was conducted in accordance with ethical guidelines established by the American Sociological Association. All participants provided informed consent and were informed about the purpose of the study before completing the survey. The confidentiality of participant responses was maintained, and no identifying information was collected.

RESULTS

Figure 1 shows the variation in perceived rating impact across gig economy platform marketplace categories. The highest level of impact appears in 'Knowledge Work', 'Food', and 'Education'. Given the nature of those categories and the requisite level of expertise and judgment, it should come as no surprise that workers feel that the ratings impact them more in these categories. In categories that focus more on transactional work than creative work, the nature of the task and work make it less necessary to rely on the rating system for quality assurance.

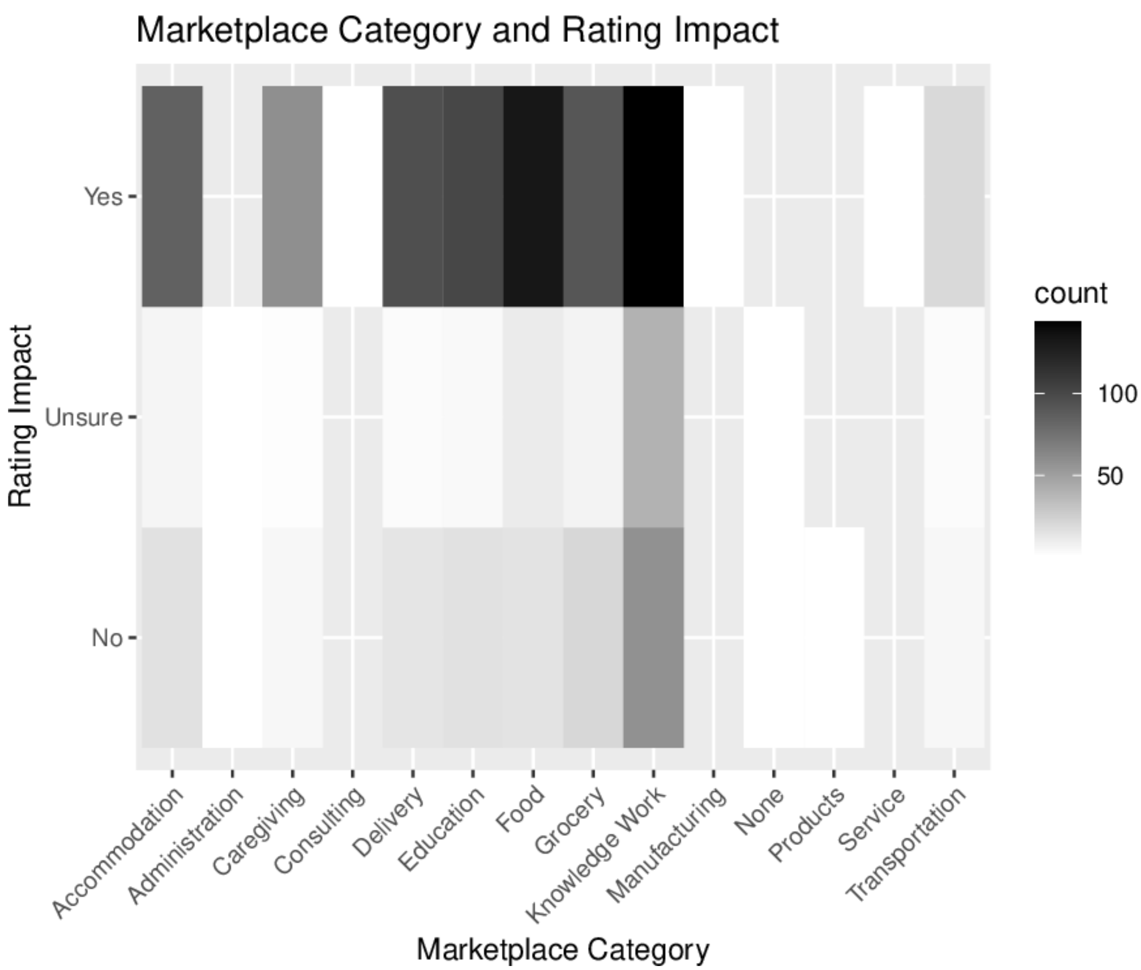

Figure 1. Marketplace Category and Rating Impact

Figure 2 demonstrates that rating satisfaction does not vary significantly by age group. The exceptions are those over 65 years old and individuals who prefer not to specify. From this we can infer that rating impacts are felt relatively similarly across this vector of demographics. This could be due to the lack of visibility of the individual performing the work. Similarly, it could be that the quality of the work is not subject to age-based judgment.

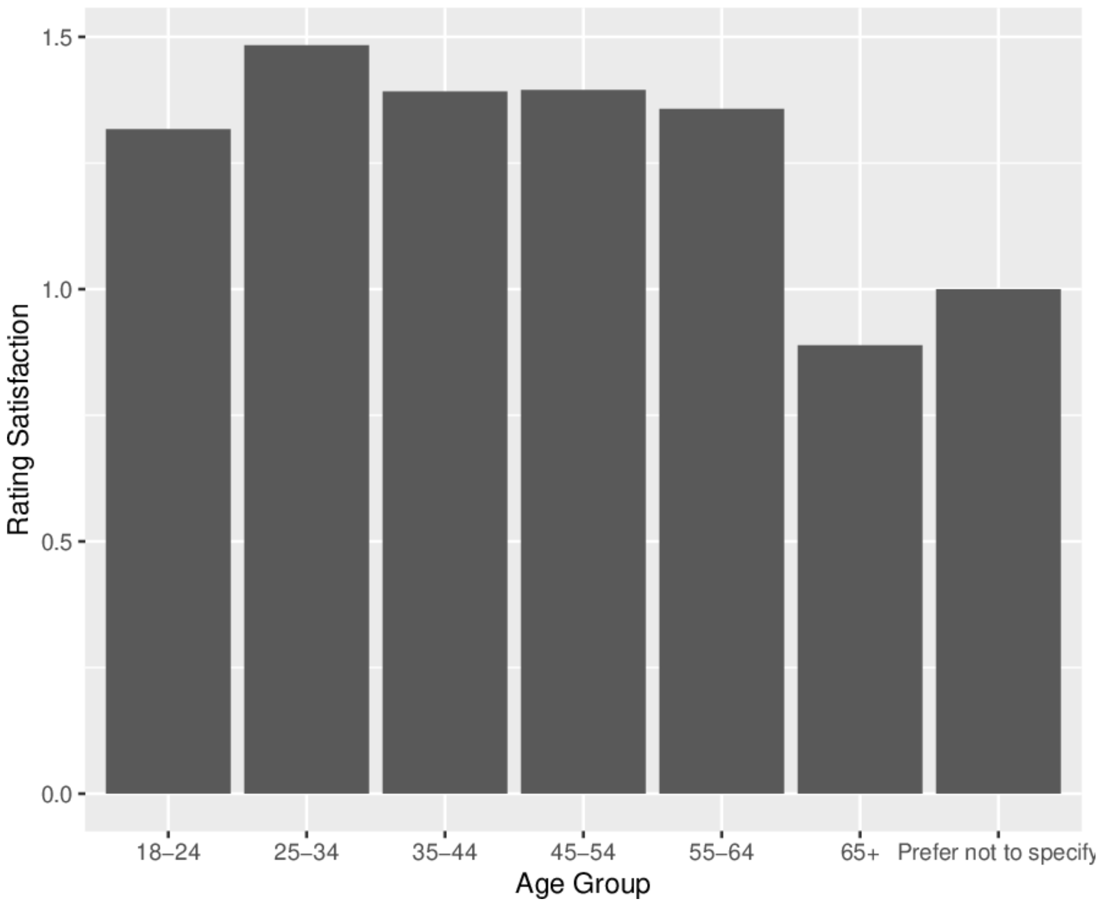

Figure 2. Rating Satisfaction by Age Group

Figure 3 demonstrates that rating satisfaction does not vary significantly by gender, except for those who did not select male or female. From this we can infer that rating impacts are felt relatively similarly across Men and Women. Both "Other" and "Prefer not to specify" had only a single response, so those groups should not be considered representative.

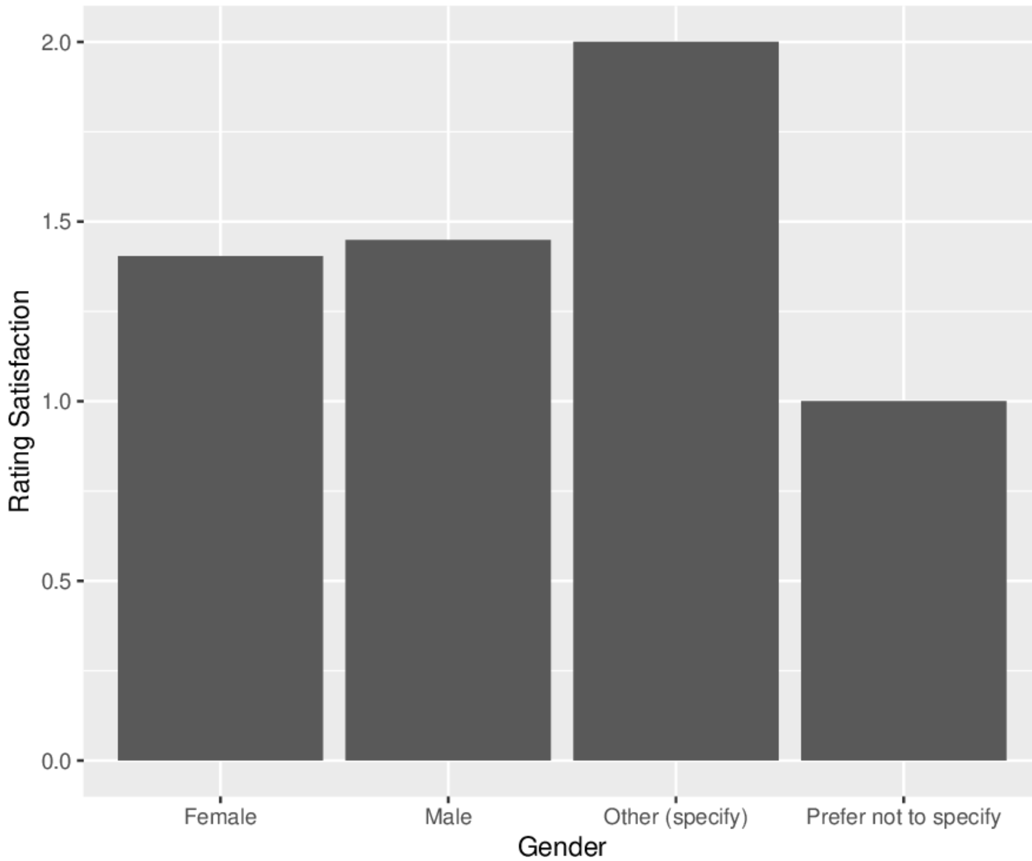

Figure 3. Rating Satisfaction by Gender

In Figure 4, it is evident that rating satisfaction does vary by education level, with the increase in education level resulting in an increase in rating satisfaction, with the exception of those with only a high school education. This demonstrates that the variability of rating satisfaction is significantly affected by education. The perceived fairness of the rating is not felt evenly across individuals with different levels of education.

Figure 5 demonstrates that rating satisfaction does vary significantly by employment status. Those individuals who classify themselves outside of the Full Time or Part Time categories typically have lower rating satisfaction than others. This demonstrates that the variability of rating satisfaction is significantly affected by employment status. The perceived fairness of the rating is not felt evenly across individuals with different classifications of employment.

According to the ANOVA output in Table 1, there is a significant effect of age, education, and employment status on the rating satisfaction scale. Specifically, there is a statistically significant difference in rating satisfaction scores between different age

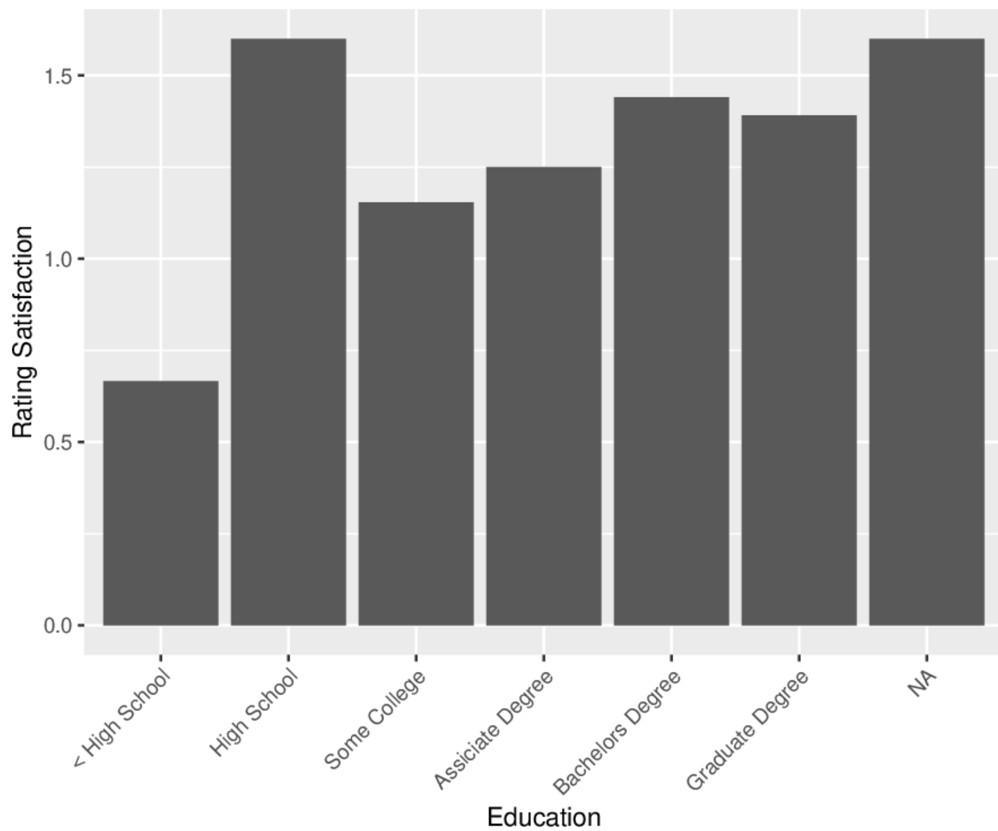

Figure 4. Rating Satisfaction by Education Level

groups (F(6,942) = 3.111, p = 0.005), education groups (F(6,942) = 3.747, p = 0.001), and employment status groups (F(6,942) = 2.829, p = 0.009). There is no significant effect of gender on rating satisfaction scores (F(3,942) = 1.415, p = 0.237).

It is worth noting that the p-values reported in the output represent the probability of obtaining the observed results if the null hypothesis is true. In this case, the null hypothesis is that there is no significant difference between the groups being compared.

Therefore, p-values that are less than 0.05 (indicated by the "*" in the output) indicate that the null hypothesis can be rejected and that there is a significant difference between the groups being compared.

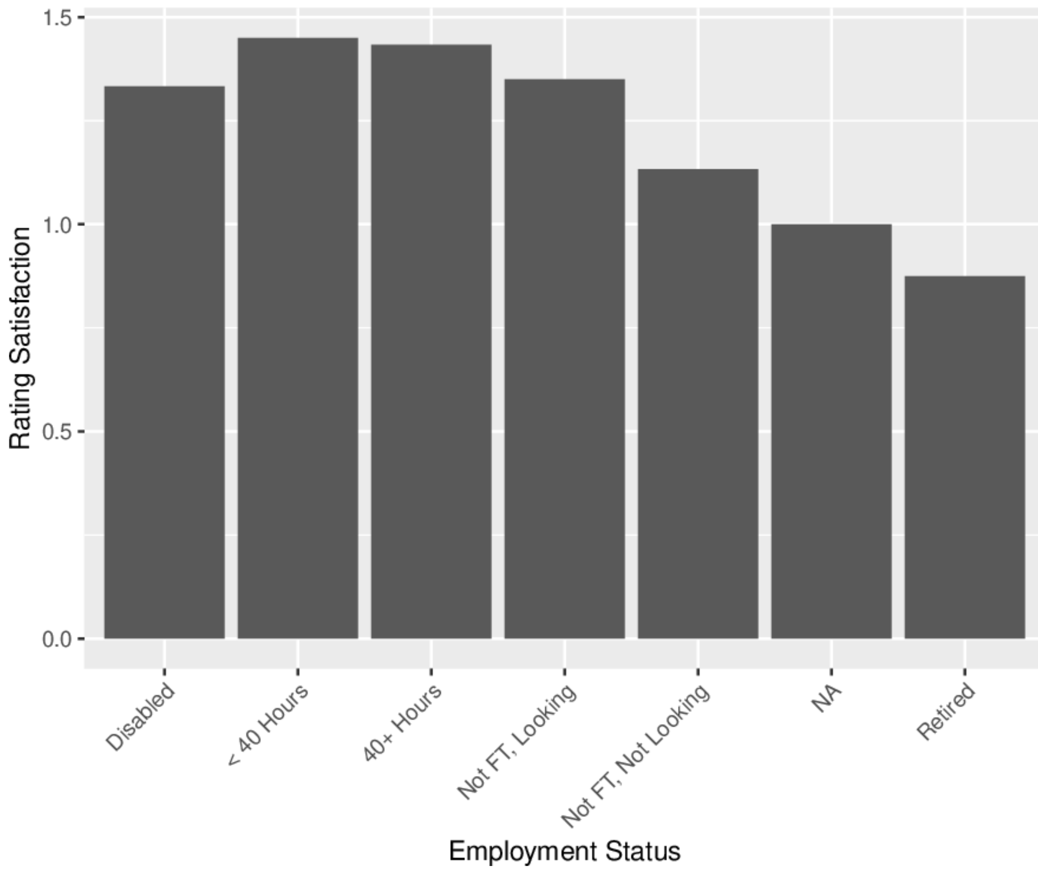

Figure 5. Rating Satisfaction by Employment Status

It is also critical to consider effect sizes for significant results. The effect size can be calculated using the mean squares from the ANOVA output and can provide a sense of the magnitude of the difference between groups. However, it is imperative to consider both statistical significance and effect size when interpreting the results of an ANOVA.

DISCUSSION

This research finds support of H1 and H2 an individual's assessment of the fairness of their online gig economy rating varies with the type of platform category, with knowledge-based platforms having a higher impact and transactional platforms having a lower impact. Additionally, age, gender and education level affect how an individual perceives the fairness of their online marketplace rating.

Table 1
Fixed-Effects ANOVA Results Using Rating Satisfaction as the Criterion

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Gender	3	1.17	0.39	1.42	0.2368
Age	6	5.16	0.86	3.11	0.005**
Education	6	6.22	1.04	3.75	0.001***
Employment Status	6	4.70	0.78	2.83	0.009**
Residuals	942	260.66	0.28		

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

The ANOVA results show that age, education, and employment status all have a significant effect on rating satisfaction. This means that individuals with different ages, education levels, and employment statuses are likely to have different levels of satisfaction with their ratings on online work platform marketplaces. These findings are consistent with the literature on bias in rating systems, which has identified self-selection bias as a potential factor that can impact the fairness of ratings.

Self-selection bias refers to the tendency of individuals with certain characteristics to rate products or services more frequently than others. For example, Ess and Sudweeks (2005) found that males were more likely to rate products on an online marketplace compared to females, leading to a gender bias in the ratings. Similarly, the ANOVA results suggest that individuals with different ages, education levels, and employment statuses may be more likely to rate products or services on online work platforms. This may lead to potential biases in the ratings.

The ANOVA results also suggest that gender does not have a significant effect on rating satisfaction. This is in contrast to the literature on bias in rating systems, which has identified self-selection bias as a potential factor that can impact the fairness of ratings. It is possible that the sample size in the current study was not large enough to detect a significant effect of gender on rating satisfaction, or that other factors, such as the quality of the product or service, the communication skills of the seller or provider, or the buyer's expectations, had a stronger influence on rating satisfaction.

Overall, the ANOVA results highlight the potential for biases in rating systems on online work platform marketplaces. They also highlight the importance of understanding and addressing these biases in order to ensure fairness in the ranking of sellers or providers. Further research is needed to identify the specific mechanisms by which these variables influence rating satisfaction and to develop strategies for mitigating any biases that may exist.

Limitations

There are several limitations to the study's methods and findings. One limitation is that the sample was recruited through Amazon Mechanical Turk (MTurk), which may not be representative of the general population. MTurk workers may differ from traditional research participants in terms of motivation, demographics, and other characteristics, which could affect the generalizability of the study's findings. Another limitation is that the study used self-report measures, which may be subject to biases such as social desire and memory biases. Additionally, the study employed a cross-sectional design, which limits the ability to make causal inferences about the relationships between variables. Finally, there is also a risk of participant attrition and fraud in MTurk studies. This is because MTurk workers may not be as invested in the research as traditional participants or may not always be truthful about their qualifications or task completion. This could impact the validity and reliability of the study's findings.

Despite these limitations, the study's results offer insight into the ways in which online platform rankings can be understood. By implementing a large sample size, the study attempted to mitigate some of these biases and limitations by drawing on a larger population to generate more generalizable results. While it is critical to consider these limitations when interpreting the results, the findings offer unique perspectives on understanding potential generalizations of behavior as a result of online platform use.

CONCLUSION

The gig economy, also known as the sharing or on-demand economy, is a growing trend in which individuals and businesses use online platforms to offer and find work, goods, and services on a flexible, short-term basis. Online work platform marketplaces, which allow freelancers and independent contractors to connect with clients who need their services, have become increasingly popular in recent years. However, the gig economy has long been the subject of much debate. This is because there are concerns about the fairness of platform rating systems and their impact on workers' income and job security. An analysis of the distribution of fairness and perceived satisfaction with ranking systems in those work markets is presented in this article. The article discusses the ways in which ranking systems on these platforms may lead to unfair outcomes for workers. It further examines the impact of these systems on workers' income and job security. It also discusses the potential role of factors such as gender, age, and employment status in the fairness of these rating systems. The article also suggests directions for future research on this topic and explores the implications of these findings for policymakers and practitioners.

Given the findings about the variation of rating assessment and satisfaction, there is evidence to suggest that mechanisms which lead to rating systems may attempt to create a system of fairness. However, for the majority participants in the online gig economy the perception of rating impact is not evenly distributed as fair across the entire marketplace. Some demographic and work-category specific factors have an effect on what individuals view as 'fair'.

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Online Connections

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