Bad Client Feedback on Digital Labor Platforms: How Freelancers Navigate the Peril Posed by Negative Reviews on Upwork

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Abstract

Freelancing on digital labor platforms is becoming an increasingly important source of income for workers. As self-employed professionals, freelancers rely on positive reviews to attract new jobs and new clients. Previous positive reviews help to reduce uncertainty about freelancers' ability to deliver their services. However, research to date has primarily examined positive reviews, but not how negative reviews affect freelancers' success nor what strategies freelancers use to navigate negative reviews. This is especially important because we know that negative reviews on other platforms undermine vendor sales. To identify strategies that freelancers use to overcome negative reviews, we conducted a qualitative fuzzy set analysis of 1,712 freelancer profiles. Thus, we show how sets of communication skills, collaboration skills, and sharing complete information influence freelancers' success. In the presence of negative ratings, we identify five pathways and six conditions that predict freelancer success on digital labor platforms.

Keywords: Negative reviews, Digital labor platforms, Online freelancing, Online reviews, Fuzzy-set qualitative comparative analysis (fsQCA).

1. Introduction

The importance of work done via digital labor platforms is increasing and growing rapidly. In 2020, about 36% of the U.S. workforce (59 million people) worked as freelancers (Upwork, 2020). In particular, the Upwork platform is seeing an increase in skilled freelancers, such as those in computer programming and IT (Upwork, 2021). This growing number of projects and tasks on digital workplaces suggests that this trend will not end anytime soon (Jabagi et al., 2019; Kässi & Lehdonvirta, 2018).

When freelancers offer their services on platforms, their success and the acquisition of jobs is highly dependent on the ratings found in the platform's reputation system. Research has already underscored the importance of reviews, especially positive reviews, on digital platforms. Due to the high degree of anonymity and purely digital matching between freelancers and clients, positive reviews are seen as a mechanism that helps reduce uncertainty between actors in labor markets (Bellesia et al., 2019; Bunjak et al., 2021; Idowu & Elbanna, 2022; Tóth et al., 2022; Yoganarasimhan, 2013). Moreover, the success of workers on digital labor platforms depends on their reputation and clients' reviews on the platform (Cram et al., 2020; Idowu & Elbanna, 2022; Möhlmann et al., 2021; Tóth et al., 2022; Yoganarasimhan, 2013). On competitive labor platforms, reviews differentiate freelancers from others (Kanat et al., 2018). Because negative information exerts a more powerful information on decisions than positive information, negative client reviews are likely to have a stronger impact on potential clients' decisions than positive reviews (Chevalier et al., 2018; Yin et al., 2016).

However, the impact negative reviews have on digital labor platforms and how freelancers can navigate them is not well understood. There is research on negative consumer reviews in e-commerce markets such as for hotels (Proserpio & Zervas, 2017). However, unlike e-commerce markets where companies interact with consumers, online freelancers are individuals who only offer their work through the digital platform (Caza et al., 2022). They are therefore responsible for any assurance and their career development and success (Ashford et al., 2018).

Notably, negative reviews in online labor markets may function differently than in the e-commerce space. For example, on Upwork, the focus of reviews is on the performance of the worker and the quality of the service they provide, and not on the physical characteristics of a product as in e-commerce markets (Deng & Joshi, 2016; Mayer et al., 2020). Also, the reviews of jobs and services can be much more heterogeneous and subjective. Reviews on digital labor platforms usually focus on the quality of services provided by freelancers. These reviews can cover aspects such as communication or professionalism. Therefore, self-employed

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freelancers must navigate a more complex environment that rates not only product quality but also their behavior, such that they can compensate in case they receive negative reviews.

Based on this line of reasoning, we examine how negative reviews impact freelancers' opportunities on digital labor platforms. This paper addresses the following research question:

RQ: How can online freelancers navigate negative reviews on digital labor platforms and remain successful?

Through a qualitative fuzzy set analysis of 1,712 freelancer profiles from a prominent digital labor platform, we identify configurations of freelancer profiles and reviews that lead to the success or failure of online freelancers. In the face of negative reviews, we analyze combinations of freelancer characteristics to predict their success. The results show that despite negative reviews, online freelancers can succeed when they possess a combination of team support, good English skills and a complete profile. Furthermore, we illustrate two paths to success independent of negative reviews and highlight which combination of freelancer characteristics lead to failure on the platform regarding earnings.

2. Theoretical Background

2.1 Literature Review

Online freelancers can be classified as independent, self-employed contractors who perform and coordinate knowledge-intense jobs online through digital labor platforms. They have a high degree of personal responsibility for all aspects of work and career, as they do not receive support from a permanent employer (Agrawal et al., 2015; Ashford et al., 2018). Digital labor platforms provide the digital infrastructure for freelancers for all mechanisms such as payment, communication, feedback, and ranking systems, and mediate between clients and freelancers (Damarin, 2006; Rai et al., 2019).

Research has highlighted the importance of reviews, especially positive reviews, on digital labor platforms (Hong & Pavlou, 2017; Idowu & Elbanna, 2022; Jarrahi et al., 2020; Lin et al., 2018; Tóth et al., 2022). On digital labor platforms, a certain number of stars are assigned as reviews for each freelancer's job (Ashford et al., 2018; Jarrahi et al., 2020). Freelancers cannot directly influence these reviews from clients but the quality of these reviews is very important for freelancers and a good review must be established, as it acts as a status indicator and influences future job acquisition (Gussek & Wiesche, 2023; Rahman, 2021). The influence of negative reviews on digital labor platforms has been discussed only briefly in previous research. For example, Blaising et al. (2021) report on reviews as "leverage" and the damage to reputation caused by negative reviews. Kinder et al. (2019) note that freelancers share negative client feedback and possible reactions in online communities. Reactions such as adjusting the price, creating a new profile or improving communication skills were mentioned. However, these assumptions were not further empirically tested or explored. Additionally, Sutherland et al. (2020) found that a larger number of reviews from freelancers could mitigate possible future negative reviews. Finally, Moreno & Terwiesch (2014) show that negative shocks to the reputation of sellers on service marketplaces increase the likelihood of a platform exit.

Furthermore, some research examines negative client reviews in e-commerce markets. For example, previous research has examined the helpfulness of negative reviews (Choi, 2022; Yin et al., 2021; Yin et al., 2016). Furthermore, positive reviews are less valued than negative reviews (Z. Chen & Lurie, 2013; Chevalier et al., 2018). Negative reviews in e-commerce have even been found to have a positive effect on sales by increasing product awareness (Berger et al., 2010). In addition, customer reactions to negative reviews have been researched (Allard et al., 2020; Ordabayeva et al., 2022). Finally, the reactions of sellers to negative reviews in e-commerce have been widely researched. Responses may include the change of prices by sellers (Kübler et al., 2018). Especially, research deals with the issue of responding to negative reviews on the platforms, which has different effects for positive and negative reviews (W. Chen et al., 2019; Chevalier et al., 2018; Proserpio & Zervas, 2017; Wang & Chaudhry, 2018). A public response from sellers especially to negative reviews is critical to subsequent customer reviews as they can have a significant positive impact on subsequent opinions. Tailored responses to negative reviews also makes the complaint management strategy of sellers more specific (Wang & Chaudhry, 2018). Furthermore, managers should respond more and in more detail to negative reviews and briefly to positive reviews (W. Chen et al., 2019; Chevalier et al., 2018).

In summary, while negative reviews have been studied in e-commerce, the impact of negative reviews on digital labor platforms and how freelancers can deal with them has not been fully explored in research.

2.2 Conceptual Research Model

In the following, we use the literature to identify the conditions that help freelancers to navigate negative reviews and lead to their success. Figure 1 shows our conceptual research model.

First, the freelancing model chosen in terms of working hours (part-time or full-time) and type of work (whether solo or team-based) can affect success. Full concentration on freelancing, and thus coping with negative reviews, is potentially higher in a full-time model. In addition, teamwork is especially relevant to success in this context. Freelance work is typically done alone (Ashford et al., 2018). Freelancers are purely digitally connected to their clients and other freelancers on digital labor platforms. They lack relationships with colleagues with whom they can share ideas or use as sources of support (Ashford et al., 2018; Kunda et al., 2002). This loneliness and lack of role models can be challenging for freelancers, as they have few opportunities to develop and succeed (Grugulis & Stoyanova, 2011). Support for freelancers can come in two forms. First, several freelancers can join together on the platform to form groups or teams. Second, support can come from an agency on the platform to which the freelancer belongs (Barley & Kunda, 2011; Kost et al., 2020). These relationships have a positive impact on the freelancer's success and thus can potentially mitigate negative reviews as a signal of support (Gussek & Wiesche, 2023).

Moreover, a number of personal factors of the freelancers may have an impact on success and can help to navigate negative reviews. Previous platform experience, the ability to communicate, and the sharing of information on the profiles are crucial factors for success on digital labor platforms. First, we assume that platform experience is crucial for freelancer success (Holthaus & Stock, 2018; Lin et al., 2018). Previous jobs on profiles, and thus accumulated experience and knowledge, can provide evidence of effective client relationships. In addition, these jobs may serve as an advertisement or positive advertisement for the freelancer's skills, potentially making negative reviews seem less important (Durward et al., 2016; Gussek & Wiesche, 2023). Second, we consider freelancers' communication skills as significant for success due to frequent interaction with clients. Since English is an international language, a freelancer who is comfortable with this language may receive more jobs because potential clients may view them likely to provide higher quality of work due to better communication and responsiveness (Popiel, 2017; Taylor & Joshi, 2019). Third, the completeness of the information shared on freelancer profiles is important, as it allows freelancers to introduce themselves and reduce new clients' uncertainties about their ability to complete work. The amount of information provided can thus be a proxy for the integrity and trustworthiness of freelancers and shows how committed they are to working on the platform (Holthaus & Stock, 2018; Ludwig et al., 2022; Sison & Lavilles, 2018).

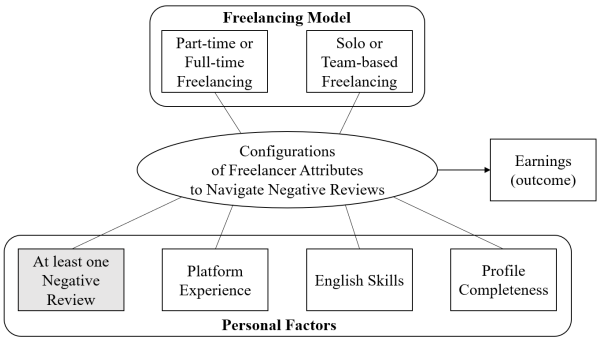

Figure 1. Conceptual research model.

3. Research Methodology

We used fuzzy set qualitative comparative analysis (fsQCA) (Ragin, 2000). FsQCA is an established configurational approach to the study of behavior in the IS discipline (Sun et al., 2021). The analysis draws on set theory to analyze how multiple conditions combine to produce an outcome in the form of configurations.

We conduct an fsQCA analysis because of its many strengths, which are especially useful in our research context to study the diverse profiles and types of freelancers on digital labor platforms. The fsQCA analysis allows us to analyze the effects of combined variables on an outcome, which can be explained by different configurations of variables. In this context, the occurrence of an outcome influenced by a variable does not necessarily have to be caused by its presence, but can also be caused by its absence, which is particularly useful in the context of negative reviews (Greckhamer, 2016). This study conducted fsQCA in six steps, which are described in more detail in the following (Mattke et al., 2022):

1. Collect and validate data
2. Calibrate the data
3. Analyze necessary conditions
4. Analyze sufficient configurations
5. Report the results
6. Validate the results

3.1. Data and Measures

To examine how freelancers navigate negative reviews and how these interventions impact subsequent success, we collected profile data from 1,712 online freelancers from the IT field on the Upwork platform. This digital labor platform was chosen because it is the largest freelancing website in the world (Claussen et al., 2018; Seifried et al., 2020). The data were collected for the first time in February 2021 and for the second time in February 2022.

When collecting the data, we paid attention to a high variance in the variables in order to include as many different freelancers as possible in the sample. We did not pay specific attention to negative reviews and thus accurately capture the rate of negative reviews in the freelancer population on the platform.

We measure the *dependent variable* of success using earnings, rounded to integers, earned by each freelancer on the digital labor platform over a one-year period between February 2021 and February 2022. Accordingly, we were able to collect 1-year earnings information for each freelancer for the year following the use of the various interventions and profile information.

The *independent variables* (conditions) are derived from the first point of data collection in February 2021, as we want to test the impact of the negative reviews and the navigating behavior of freelancers on one-year earnings.

For the freelancing model, we use two variables. First, we measure through a dummy variable whether the freelancer works full-time (more than 30 hours per week) on Upwork or only part-time. Second, we use a dummy variable that indicates whether the freelancer is part of an agency or a team.

In addition, we consider four variables that describe personal factors of freelancers. First, we measure through a dummy variable whether the freelancer has received at least one negative review (2.5 stars or less) from clients in his work history. Second, we consider the experience on the platform through the number of completed jobs of the freelancer. Third, we include the freelancer's English skills in our analysis. Upwork offers freelancers the possibility to indicate their language skills and the respective level in their profile. Thus, there are the variants "basic", "conversational", "fluent" or "native or bilingual". The English skills variable is therefore ordinally scaled and can take values between 0 (no English skills) and 4 (highest possible English skills). Finally, we measure the information provided by the freelancer through the completeness of the profile as the number of completed fields of the freelancer profile, ranging from 0-9. The following nine filling options provided by Upwork are considered: availability information, response time, skills information, language skills, skill certificates information, education information, information about work experience outside the platform, other experiences, and testimonials from clients.

3.2. Calibration and Descriptive Statistics

The first step of fsQCA involves a calibration process, which converts data about causal conditions and the outcome into fuzzy scores. The fsQCA is based on fuzzy set memberships, where conditions and outcomes must be expressed in values between zero and one. A fuzzy set membership of zero means that a condition holds at a low level. In contrast, a value of one means that the condition holds at a high level.

In line with previous research, we used quantile-based thresholds to calibrate fuzzy sets (Kollmann et al., 2021; Palmer et al., 2019). We chose 5%, 50%, and 95% quantiles to represent non-membership, a crossover threshold, and full membership, respectively (Covin et al., 2016; Fiss, 2011; Woodside, 2013). Table 1 shows the descriptive statistics and calibration thresholds of the variables.

Table 1. Descriptive statistics and calibration thresholds.

	Descriptive Statistics				Calibration thresholds		
Variable	Mean	SD	Min.	Max.	Fully in	Cross-over	Fully out
Outcome							
Earnings	2.586,02	7.068,46	2,50	107.940	12.443,49	400	15
Conditions							
Full Time	0,77	0,42	0	1	1	n/a	0
Team	0,21	0,41	0	1	1	n/a	0
At least one Negative Review	0,11	0,31	0	1	1	n/a	0
Platform Experience (Jobs)	23,79	48,65	1	925	108,45	6	1
English Skills	3,04	0,59	1	4	4	3	2
Profile Completeness	5,83	0,95	3	9	7	6	5

Note. N 1712; Mean arithmetic mean; SD standard deviation; Min. minimum; Max. maximum.

3.3. Analysis using fsQCA

The software program fs/QCA 4.0 supported the data analysis (Ragin & Davey, 2022). To examine the necessary conditions, we analyzed the calibrated constructs to determine whether they were necessary for high or low freelance earnings to occur. Necessary conditions must have a consistency threshold of 0.9 and a coverage threshold of 0.6 (Mattke et al., 2022). Consistency explains the extent to which individuals with the same condition have the same outcome. Coverage explains how much of the sample covers a condition (Ragin, 2006).

We then analyzed sufficient configurations for high and low freelancer earnings. We created a truth table that contained all logically possible configurations of the variables. Since we analyzed six freelancer characteristics, our truth table contained 2^6=64 configurations. We then selected the frequency threshold so that the significant portion (in our case 71% percent) of observations were still included after applying the threshold (Mattke et al., 2022) and therefore removed all configurations with fewer than eight (for high earnings) or 17 (for low earnings) observations. We applied a raw consistency threshold of 0.75 (Ragin, 2006), which sets the minimum level of consistency with which a configuration must explain an outcome. We then removed configurations with a PRI (Proportional Reduction of Inconsistency) value of less

than 0.5 (Mattke et al., 2022), to determine sufficient configurations.

The following analysis of the truth table was performed using the Quine-McCluskey algorithm and the fs/QCA 4.0 software to determine combinations of conditions that consistently lead to the result. In doing so, fsQCA provides configurations that can be marked as present, absent, or "don't care" (Park et al., 2020). The following chapter describes the analysis and related results in detail.

4. Results

In the following, we present the results of the analyses for necessary conditions and sufficient configurations and validate the robustness of our solution.

Regarding necessary conditions, the results all show values below the consistency threshold of 0.9 and the coverage threshold of 0.6, meaning that there was no necessary condition in any of the scenarios (Mattke et al., 2022).

The analysis for sufficient configurations revealed three configurations that lead to high earnings and two configurations that lead to low earnings. We provide a graphical representation of our results in Table 2. Black circles symbolize the presence of a condition, white circles its absence. Empty spaces mean that the condition do not care for the solution.

Table 2. Configurations for high and low earnings.

	Freelancer Success				
	High Earnings			Low Earnings	
Condition	A1	A2	A3	B1	B2
Freelancing Model					
Full Time	●	●	●		●
Team	○	●	●	○	○
Personal Factors					
At least one Negative Review	○	○		○	○
Platform Experience	●	●	●	○	
English Skills		●	●		
Profile Completeness	●		●	○	○
Raw Coverage	.25	.13	.15	.50	.37
Unique Coverage	.25	.03	.04	.18	.04
Consistency	.78	.82	.85	.84	.72
Overall Solution Coverage	.42			.55	
Overall Solution Consistency	.79			.77	

Note:
● = core condition present; ○ = core condition absent; don't care condition = blank spaces.
Consistency threshold = 0.75, PRI = 0.5; threshold unique coverage = 0.01.
Frequency = 8 for high earnings, 17 for low earnings.
Remaining configurations after threshold 71%.

Raw coverage indicates the percentage of membership in the outcome of a configuration, while unique coverage indicates the unique percentage of membership in the outcome of a configuration (Schneider & Wagemann, 2013). The consistency for each configuration indicates the degree to which a configuration consistently leads to the outcome (Park & Mithas, 2020).

In Table 2, it can be seen that the raw coverage of 0.13 to 0.50 indicates that the solutions have high explanatory power. The unique coverage between 0.03 and 0.25. Moreover, the consistency is between 0.72 and 0.85. Following Park and Mithas (2020), the total solution coverage is the total coverage by all configurations combined. The coverage is a measure of how trivial a condition is for an outcome. There is no specific rule for acceptable total solution coverage, but low solution coverage indicates that there are many instances of the outcome that are not explained by the model (Rubinson, 2019). This is not the case here, as the overall solution coverage is 0.42 and 0.55. Finally, the overall solution consistency indicates the extent to which all configurations together consistently result in a high or low outcome. The consistency must be above 0.75 to be acceptable, which in our case is 0.79 and 0.77 (Mattke et al., 2022).

Next, we describe the paths found to success or failure of freelancers on digital labor platforms and assign labels to them. In general, high platform experience and thus more freelancer knowledge, as well as a full-time model, are critical to any path to success. Three factors vary depending on success strategy or freelancer type and to navigate negative reviews: English skills, team membership and providing complete information on the profiles. Furthermore, freelancers can be successful alone or as part of a team, and negative reviews can be successfully navigated.

Paths to Success (High Earnings)

A1 – *Solo image manager* work full time on the platform without a team. They have no negative reviews and need a high platform experience and a complete profile to be successful. Since they work alone, they need to provide clients with a lot of information about themselves in order to appear trustworthy and show their commitment and investment in the platform. Profile completeness is crucial for this path.

A2 – *Communicative team players* work full time on the platform. They need to be able to converse well in English, have a high level of platform experience and do not need a complete profile due to existing support from the team. They do not have negative reviews. As part of the team, they need to be able to communicate well, but profiles do not need to be complete. Consequently, English skills are crucial for this path.

A3 – *Negative review navigators* work full time as part of a team on the platform and can be successful even with negative reviews if there is completeness of their profile, high platform experience and English skills

to compensate for negative client feedback. The team provides additional help and support in this regard. For this path, the English skills and the completeness of the profile are crucial.

Paths to Failure (Low Earnings)

B1 – *Platform beginner* have no experience on the platform. Their profile is incomplete and they work alone without a team. They also have not yet received a negative review on the platform, which is related to the fact that they do not have any platform experience in the form of jobs.

B2 – *Failed solo full-timers* work full time on the platform and are not successful. They have no team support but work alone. They also have an incomplete profile.

In summary, we have found that for freelancers who work alone, the completeness of the profile is crucial. For team players, English skills are crucial. We found that if a freelancer works in a team, has good English skills, and creates a complete profile, negative reviews have no impact on success.

In contrast, we have found that freelancers who do not have negative reviews are less likely to be successful if they lack platform experience and cannot provide a complete profile. If a freelancer works full time and has no negative reviews, they are less successful if they work alone and have an incomplete profile.

Finally, we tested the configurations in a robustness test for their sensitivity to the consistency threshold (Mattke et al., 2022). We increased the threshold from 0.75 up to 0.8. The analysis revealed the same results. In summary, our results are robust.

5. Discussion

5.1. Theoretical Implications

Our work provides insights into the different paths taken by successful freelancers on digital labor platforms who prefer to work alone or in teams. Rather than negative reviews driving away clients, we show that team membership, high platform experience, communication skills, and complete platform profile information seem to attract clients to freelancers even when they have negative reviews.

First, we contribute to the research on the relevance of reputation on digital labor platforms, which has so far mainly focused on positive reviews (Hong & Pavlou, 2017; Idowu & Elbanna, 2022; Jarrahi et al., 2020; Lin et al., 2018; Tóth et al., 2022). We show that negative reviews are not necessarily detrimental to freelancers' success and how they can handle negative reviews (Blaising et al., 2021; Moreno & Terwiesch, 2014). We also identify six factors that contribute to freelancers' success and illustrate different strategic choices or configurations for high and low freelancer earnings. Thus, we extend research on possible responses to negative reviews by showing which combination of responses can be used by freelancers(Kinder et al., 2019; Sutherland et al., 2020). Our results also extend research on seller responses to negative reviews in e-commerce by illustrating that negative reviews on digital platforms can be circumvented by combining responses (W. Chen et al., 2019; Chevalier et al., 2018; Proserpio & Zervas, 2017; Wang & Chaudhry, 2018).

Second, our results show that there is no necessary condition for success on digital labor platforms. No factor is essential for success, confirming the high levels of autonomy and freedom already identified in research on career design in online labor markets (Bellesia et al., 2019; Deng et al., 2016; Wood et al., 2019). Consequently, freelancers can take different paths and potentially compensate for missing factors in their profiles with other alternative factors. Hence, for success on digital labor platforms, there is not one perfect path to success, but alternative career structures and patterns depending on the type and characteristics of freelancers.

Third, we challenge two characteristics of freelancing identified in previous literature. While some research highlights the loneliness and lack of support of freelancers, who consequently mostly work alone and independently advance their careers as lone fighters (Ashford et al., 2018; Kunda et al., 2002), we illustrate that team support is important in two of the three paths to success on digital labor platforms. On the one hand, teams help mitigate negative reviews, and on the other hand, they can compensate for information on freelancers' profiles. In addition, we examine the impact of the chosen freelancing model in terms of working hours (part-time or full-time) and show that a full-time model leads to freelancers' success in all three paths. However, previous research has mostly emphasized the short-term nature of freelancing, which is reinforced by the time constraints of platform work, as no freelancer has a "permanent job" (Ashford et al., 2018; Kalleberg, 2000, 2009).

5.2. Practical Implications

In addition to the theoretical contributions of our research, implications for practice become clear on the side of freelancers, clients, platform owners and policymakers.

First, we identify three different paths to freelancer success, these could help other workers on digital labor platforms to shape their skills and work experiences to align their career and platform development towards a specific path. Furthermore, it is evident that freelancers should focus on two mandatory profile attributes to be

successful. All three identified paths to success were based on full-time work as a freelancer and high platform experience through completed jobs. However, part-time work and even a lack of platform experience do not always lead to failure, as evident in the two paths to low earnings. As mentioned earlier, this supports the benefits of autonomy and freedom of freelancing in terms of career design.

Secondly, clients on digital labor platforms can also benefit from our results. They can use the information about freelancer types to better select suitable freelancers for their various jobs. Moreover, the identified paths to success potentially reinforce clients not to reject a freelancer just because of a negative review, which increases fairness and equality of opportunity on digital labor platforms.

Third, our results also provide platform owners with an insight into the different freelancer types. Platforms can respond to these different success paths with appropriate policies and incentives to better support freelancers, promote them individually, and keep them on their platform. In this way, more value can be generated on the platform.

Fourth, policymakers can develop appropriate rules and regulations for digital labor platforms to make them fairer. For example, unfounded negative reviews by clients could be prohibited to protect freelancers from the negative consequences of unjustified reputational damage.

6.3. Limitations and Future Research

The results of our study need to be considered in light of their limitations, from which opportunities for future research arise.

First, future research should also verify our results on other digital labor platforms, such as Fiverr or freelancer.com and in other fields outside the IT domain to increase generalizability. Thus, potential bias in data collection can be prevented. Second, through the fsQCA analysis, we can only present an insight into the different paths to success or failure and cannot describe content details of the interaction of factors. Future research should therefore complement the pathways we identified with qualitative data such as freelancer interviews to understand and describe the pathways in more detail. Third, our use of the fsQCA analytical method implies that choices made with regard to the research measures' calibration may affect the study's results (Glaesser & Cooper, 2014). Fourth, regarding the negative reviews, we only considered the star rating and not the specific content of the reviews. Therefore, we believe it is necessary for future work to also examine the actual content of negative reviews and include it in the analysis, for example, whether they are written constructively or not, or whether the length of the review and the type of criticism have an impact on freelancers' navigation strategies. Fifth, we examined the effects of negative reviews and the navigating strategies over one year. A longer-term analysis of developments after negative reviews could provide additional insights at this point. Finally, we refer to our conceptual model, which includes key constructs that affect the success of freelancers, derived on the basis of a thorough literature review. However, we cannot guarantee that all possible causal influences on the success of freelancers are covered. For example, freelancers' education, language skills other than English, or field of activity may also contribute to the causal effects that influence success on digital labor platforms and navigating strategies, which should be considered in future work.

7. Conclusion

In summary, we investigated the impact of negative reviews on freelancer success and appropriate strategies for dealing with negative reviews on digital labor platforms, as previous research has primarily examined positive reviews on digital platforms. Through a qualitative fuzzy set analysis of 1,712 freelancer profiles on the platform Upwork, we investigated six configurations that lead to high or low earnings and thus success or failure on platforms. We contribute to previous research by identifying three paths to freelancer success and two paths to freelancer failure. Thus, we illustrate how combinations of the freelancing model and negative reviews, platform experience, communication skills, and the availability of information on freelancers' profiles interact and how negative reviews can be navigated. We show that negative reviews can be successfully overcome with team membership, extensive platform experience, high communication skills, and complete information on the platform profile, and thus do not completely undercut a freelancers' chances of success. In addition, we illustrate different types of freelancers and three different paths to success, and contrast two paths that freelancers should avoid as they lead to failure. Finally, we presented implications for research and practice, as well as limitations and future research avenues.

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