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Algorithms and their Affordances: How Crowdworkers Manage Algorithmic Scores in Online Labour Markets

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ABSTRACT On online labour platforms, algorithmic scores are used as indicators of freelancers' work quality and future performance. Recent studies underscore that, to achieve good scores and secure their presence on platforms, freelancers respond to algorithmic control in different ways. However, we argue, to fully understand how freelancers deal with algorithmic scores, we first need to investigate how they interpret scores and, more specifically, what scores can do for them, i.e., perceived algorithmic affordances and constraints. Our interviews and other qualitative data collected with knowledge intensive gig workers on a major platform allow us to explain how the perceived affordances of algorithms (i.e., barrier, individual visibility, self-extension, rule of the game) act as mechanisms that explain different behavioural and emotional responses over time. Our work contributes to the current debate on the positive and negative consequences of algorithmic work by portraying the fundamental role paid by the individual interpretation of algorithmic scores and by integrating the affordance perspective into our understanding of algorithmic work.

Keywords: algorithm, algorithmic management, freelancers, gig work, online labour platforms, technology affordances

INTRODUCTION

Digital platforms are complex algorithmic structures connecting dispersed buyers and sellers of services. On platforms like Uber, for instance, algorithms create optimized rides matching customers' and drivers' destinations. At the end of the ride, algorithms also ask customers and drivers to rate their driving experience, and, starting from these ratings,

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compute an aggregate individual score associated to performance. Similarly, on platforms such as Guru, customers can search for logo designers through algorithms, which provide information about freelancers through aggregated ratings and feedback. In the last decade, such form of work has become widespread so that the online workforce is expected to increase by 20 per cent each year (Kässi and Lehdonvirta, 2018). Forecasts for the post-pandemic world of work predict an even higher number of people working remotely through platforms (Ozimek, 2020), leading scholars to wonder whether platform workers represent the future of work (Kessler, 2018).

The growing number and extensive use of algorithms to manage the workforce are capturing scholarly attention. Whether algorithms are solely constraints to workers' action, or whether there are ways in which workers can still freely operate, even thrive, when managed by 'algorithmic logics', is being increasingly debated in recent literature (Bucher et al., 2021; Cameron and Rahman, 2022; Gandini et al., 2016; Kellogg et al., 2020; Möhlmann et al., 2021; Rahman, 2021; Wood et al., 2019). On the one hand, it is well known that algorithms create power asymmetries (Cameron and Rahman, 2022; Curchod et al., 2020; Graham et al., 2017; Wood et al., 2019) and tensions between platform providers, clients, and workers, who live as 'dependent contractors' (Kuhn and Maleki, 2017; Möhlmann et al., 2021; Veen et al., 2020) subject to algorithmic evaluations. Algorithmic computed scores summarize workers' past performance and clients' reviews – also called ratings – and feedback to previous activities (Dellarocas, 2003; Kokkodis and Ipeirotis, 2016), but the full mechanisms used to compute scores are opaque and invisible to the workforce (e.g., Cheng and Foley, 2019; Rahman, 2021; Veen et al., 2020).

On the other hand, however, recent evidence highlights that workers develop some knowledge about how algorithms work, for example through peer discussions in forums and online communities (e.g., Bucher et al., 2021; Lehdonvirta, 2016) and they deal with opaque algorithmic evaluations by actively experimenting with new ways to improve scores (Rahman, 2021) or by developing practices aimed at complying directly and indirectly with algorithms (e.g., by respectively curtailing client outreach or undervaluing work, Bucher et al., 2021). These findings suggest that, despite algorithmic opaqueness, workers can still exert agency to reduce the asymmetries of an algorithmic-driven environment (Curchod et al., 2020).

While scholars acknowledge that freedom and control are two sides of the same coin (Cameron and Rahman, 2022), to date, the literature has prominently emphasized the *negative* algorithmic impact on freelancers' work and limited agency of workers. As a result, existing literature shows that several response practices to algorithmic control and evaluations exist but fails to describe (1) whether workers perceive or interpret algorithms differently and when algorithms are perceived to provide opportunities and positive experiences; (2) the mechanisms that drive different workers' responses (see Rahman, 2021, for an exception). As the online workforce is steadily growing and it is highly heterogeneous, it is paramount to develop a better theoretical and empirical understanding of why online workers behave differently (Cropanzano et al., 2022; Kuhn et al., 2021), or how they can thrive under uncertain working conditions (Ashford et al., 2018).

In this paper, we thus take an agentic perspective on the way online workers deal with algorithmic scores and investigate, first, how algorithmic scores are interpreted by online workers and, second, the consequences in terms of behavioural and emotional responses.

We therefore aim at answering the following research question: *How do freelancers in online labour platforms interpret algorithmic scores and with what emotional and behavioural consequences?* We draw on the theory of Technology Affordances (e.g., Leonardi, 2011; Leonardi and Vaast, 2017; Zammuto et al., 2007) – defined as 'action possibilities and opportunities that emerge from actors engaging with a focal technology' (Faraj and Azad, 2012, p. 241) – to uncover the (different) opportunities for action provided by algorithms to workers from a major platform. Our data come from interviews with those workers and their public online profiles.

This study extends our understanding of digital environments characterized by algorithmic management and contributes to the emerging literature on crowdworkers and gig workers' responses to algorithmic scores. First, we identify a key mechanism explaining the heterogeneous freelancers' behaviours and behavioural responses to algorithmic management – i.e., the different technology affordances, or, in other words, what freelancers believe scores can do for them. Specifically, we show that algorithms provide the affordances of individual visibility and self-extension, or they are perceived as barriers or a 'rule of the game'. Our grounded model further shows that behavioural and emotional responses vary accordingly. Second, our findings reveal that workers change their responses over time. In particular, they adjust their behaviours according to the perceived affordances only after an initial period of compliance to algorithmic rules, that is, the time when they are new to the platform and lack positive reviews. During this initial period, algorithmic scores are perceived as *barriers*, thus, instead of providing opportunities for action, they constrain workers' actions. Third, even if our findings confirm that negative feelings, such as frustration or anxiety, are likely to arise, our affordance perspective allows us to underscore *when* such negative feelings happen, and when, instead, gig workers' experience becomes bearable, even exciting.

THEORETICAL BACKGROUND

Algorithmic Scores and Gig Workers' Responses in Online Platforms

Online labour markets connect customers with a potentially endless supply of workers (Howe, 2006; Lehdonvirta, 2018). However, geographical distance between parties, technology mediated communication, cultural differences, or simply workforce diversity can prevent clients from finding the right match, and freelancers from communicating their capabilities and their willingness to contribute with high quality work. To overcome these obstacles, platforms have created algorithmic scores that are expected to act as indicators of freelancers' work quality and future performance. For instance, on platforms like Freelancer.com or Fiverr, clients can navigate workers' profiles and find scores associated with their past performance on the platform (Kokkodis and Ipeirotis, 2016). Algorithmic scores and how workers attribute different potentials for action to these scores represent the main focus of our study.

As scores are essential for workers' survival and can affect their ability to win new contracts (Cameron and Rahman, 2022; Lin et al., 2018), we are witnessing increased scholarly attention to how workers (1) experience and (2) respond to algorithmic management. A first strand of studies focuses primarily on issues of flexibility and autonomy juxtaposed to critical debates on control and surveillance. On the one hand, working in environments managed by algorithms may increase people's autonomy and flexibility, as well as task complexity, and offer new, unprecedented opportunities for professional growth (Bellesia et al., 2019; Elbanna and Idowu, 2022; Idowu and Elbanna, 2021). On the other hand, the lack of computation transparency is assumed to create unbalanced power structures and to enhance platforms' control over workers (Curchod et al., 2020; Lee et al., 2015; Rosenblat and Stark, 2016), who are consequently forced to 'experiment' and make sense of algorithms to continue their work (Cheng and Foley, 2019). To this regard, Blaising et al. (2018) show that workers in online labour markets lack information about reasons for rejection or failure, other online workers' success, client expectations, and algorithmic scores calculations, leading to experiencing precarious working conditions. Other studies acknowledge workers' feelings of fear and frustration when dealing with algorithms (e.g., Gandini et al., 2016; Veen et al., 2020).

In a second group of studies, the debate focuses on how people not only experience algorithmic management, but also respond to it. These studies delve into how freelancers actively adapt their behaviours (Bucher et al., 2021; Cameron and Rahman, 2022; Curchod et al., 2020; Karanović et al., 2021; Kellogg et al., 2020; Rahman, 2021). The work of Curchod et al. (2020) provides an initial investigation of how online freelancers work around algorithmic control. In their study of eBay sellers, the authors discovered that freelancers were able to create 'a space within which their own rules applied and thereby made their relationships with buyers less asymmetrical. Instead of accommodating algorithmic procedures, they tried to influence buyers' behaviour in a preferred direction' (Curchod et al., 2020, p. 664). The attempts to influence clients' behaviours have been confirmed also by Rahman (2021), who shows how Upwork workers are willing to reduce their hourly wages or provide free services in order to secure high ratings. Similarly, Bucher et al. (2021) suggest that Upwork workers can use different indirect anticipatory compliance practices (e.g., triggering positive ratings from clients by providing additional services or engaging in emotional labour) coupled with direct practices (e.g., not using language that could cause a suspension) to avoid algorithmic scrutiny and punishment. Cameron and Rahman (2022) further suggest that the tactics deployed by workers may change along the various stages of the gig task lifecycle (before, during and after the task is complete) because the workers' latitude to engage in resistance tactics (like vetting customers) diminishes in each sequential stage. Other studies classify gig workers based on their most typical behaviours. For example, some gig workers prefer to play 'relational games', i.e., they spend efforts in building relationships with clients; others prefer to play 'efficiency' games, i.e., they set boundaries with clients and focus on maximizing how much they can be paid (Cameron, 2022). Some gig workers display typical behaviours of self-employed workers, e.g., resisting platform's instructions and algorithmic control or switching between alternative platforms; others enact organization-like responses, e.g., expressing attachment, gratitude, and loyalty towards the platform (Möhlmann et al., 2021).

To sum up, a growing number of scholars have highlighted that algorithmic scores influence workers' experiences and have therefore started to classify different behaviours in reaction to these experiences. However, we still do not have a detailed understanding of how workers' experiences translate into different responses. In other words, we still do not know the mechanisms driving different behavioural and, in particular, emotional responses to algorithmic scores. We believe this lack of theoretical understanding may be due to the prominent scholarly perspective of algorithms as opaque and controlling entities, which assumes that gig workers perceive algorithms in similar ways. As a consequence, we argue that, to fully understand how gig workers behave in reaction to algorithmic scores, we need to first understand how they relate to the algorithmic score itself. How exactly do workers develop interpretations of the scores and the future possibilities or constraints associated to the scores? How do gig workers act differently according to these different interpretations? To address these questions, we bring the algorithm to the fore and adopt the perspective of technology affordances (Faraj and Azad, 2012) to uncover how individuals perceive algorithmic scores as they work on platforms.

An Affordance Perspective on Algorithmic Scores

Stemming from the affordances perspective of ecological psychologists (Gibson, 1986; Heft, 2003; Hutchby, 2001), technology affordances have been defined as 'action possibilities and opportunities that emerge from actors engaging with a focal technology' (Faraj and Azad, 2012, p. 241). According to the relational perspective on affordances (e.g., Fayard and Weeks, 2014), the features of technology are seen as a necessary, but not sufficient condition for changes in work behaviours (Leonardi and Vaast, 2017; Markus and Silver, 2008; Zammuto et al., 2007). Thus, the same material feature of a technology may offer different opportunities (or constraints) to different actors, based on their interests, motivations, expertise, cognitions, training, etc. To this regard, Leonardi (2011) provides examples of perceived affordances and constraints of the features of a software application used in a R&D unit. In his study, engineers initially appropriated different combinations of the technology's features, depending on how they looked at the new technology, i.e., as a tool to speed up their work or as a constraint. That is to say, they enacted different individualized affordances in their work behaviours.

Recent research on algorithmic control has proposed the affordance perspective to analyse how *employers* can use algorithms to interact with workers (e.g., Kellogg et al., 2020; Leonardi and Vaast, 2017). Kellogg et al. (2020) identify four types of affordances of algorithms, as perceived by employers, i.e., comprehensiveness, instantaneity, interactivity, and opaqueness. In this paper we are the first to take the perspective of *gig workers*, and we argue that they may develop different interpretations of how algorithmic scores pose constraints or offer opportunities for their work experiences on platforms. These different interpretations, we argue, drive different behavioural and emotional responses. Understanding how algorithmic affordances drive different responses is fundamental to explain the tensions between positive and negative experiences of workers in new technology mediated work settings.

METHODS

We addressed our research question through an exploratory qualitative field study. Our data sources encompass 66 semi-structured interviews with freelancers on one of the most popular online labour markets (OLM), which from now on will be fictitiously referred to as 'GigStars'. Concurrently, we collected freelancers' platform profiles (66) and 190 articles from GigStars' blog. More details on the context and data sources are reported in the next paragraphs.

Context

GigStars hosts both requests for short and more complex jobs ('gigs'), like graphic design, virtual assistance, software and mobile development, and translations. Clients (e.g., individuals or organizations) can post job requests that freelancers can easily navigate and apply for. Interactions take place at a distance and are mediated by communication technologies, either provided by GigStars or external to the platform environment.

In this context, freelancers are asked to fill out online profiles with details about their personal background and other relevant information. The same profiles track freelancers' working history (e.g., total number of worked hours and past jobs) and performance details (e.g., algorithmic scores). When contracts end, the job performed is listed on the working history section of freelancers' profiles, and freelancers and clients are asked to access the rating system and rate their working experience within 14 days. Parties can provide both a private and a public rate. The public rate has both a quantitative and a qualitative section. The quantitative evaluation is given in stars (i.e., from one to five stars), while the qualitative one is a written comment on freelancers' work. If given, the job-associated public rate (also referred to with the term 'review') is shown on freelancers' profiles. The private rate, instead, is inaccessible and follows different evaluation criteria – i.e., the platform asks clients whether they would recommend freelancers to other clients via a one-to-ten scale.

Both private and quantitative public ratings contribute to scores calculation. Scores are algorithmically calculated numbers (i.e., percentages) reflecting past performance on the platform; this means that starting from the evaluations left by clients, algorithms compute an aggregate score signalling the percentage of success on the platform. Scores appear right behind freelancers' names on their profiles and within the list of potential 'matches' when clients search for freelancers on GigStars. Newcomers need at least six completed and reviewed jobs to get their score visible. How algorithms calculate the score is not fully clear to freelancers, as only partial information is given by GigStars. For instance, GigStars tells freelancers that multiple, simultaneous, long open contracts negatively affect the score. Similarly, multiple jobs without feedback in the job history decrease the score. However, freelancers do not know and cannot estimate how much these instances can impact their scores. Similarly, they do not have access to private feedback, and thus they lack information about potentially unhappy clients or the magnitude of negative feedback.

Along with the algorithmic score, freelancers can also gain the 'Top Performer' or 'Rising Star' status, which further indicates they are among the best talents on GigStars. Nonetheless, also in this case, they have only partial information on how to obtain these prestigious recognitions.

Sample and Data Collection

Interviews. We focused our attention on knowledge workers and collected interviews as main data sources. As knowledge workers are more likely to apply for complex services and less likely to apply for simple, repetitive jobs, we believe they represent a better focus for our investigation. Those who aim for repetitive and simpler jobs compete through pricing policies and are less sensitive to scores issues (Gandini, 2016a).

To reach out to respondents, the first author subscribed as a client and posted different requests for interviews on GigStars. This practice was useful not only to reach out those who were active on GigStars, but also to grasp information on the evaluation form and clients' perspective. We explained to potential informants that ours was a research study and offered a thank-you reward for their time between 8 and 12 US dollars. This compensation was not meant to be a payment for their work but represented a recognition for their time and provided them the support to cover GigStars' fees. Furthermore, consistently with authors who proved that monetary compensation is just a secondary motivation to participate in online studies (Kapelner and Chandler, 2010), our informants mainly participated because of their interest in results, their willingness to contribute to a research project, or the desire to share and voice their experience. In multiple cases, they lowered the reward or refused payment.

Our data collection started in August 2017 and ended in August 2019. We ran eight pilot interviews and started reviewing documents from the platform to gather preliminary information on platforms' rules and freelancers' experience, and pilot the interview protocol. While talking with this first group of freelancers, scores emerged as important for freelancers' image on GigStars.

Then, our sample was built following theoretical logics (Glaser and Strauss, 1967). Specifically, we first contacted IT developers, as previous studies often refer to them as knowledge workers or professionals (Barley and Kunda, 2006; Kunda et al., 2002). We initially started asking questions about freelancers' work experience on GigStars and their motivations to join the platform, trying to grasp information about how GigStars was affecting their work. While collecting this information, freelancers often mentioned algorithmic scores as something constraining their work, but also as essential for their survival on GigStars. Following these first insights, and in line with practices of inductive research (Spradley, 1979), we refined our interview protocol and narrowed the area of inquiry. We then continued to ask additional details about scores and algorithms. Exemplary questions are: How do you catch the attention of clients on GigStars? What do you think about scores on GigStars? What do you do to maintain your score? Furthermore, since we collected additional information from freelancers' online profiles before the interview (see below), we also asked questions about freelancers' current score on the platform. Following a grounded theory approach, our interview protocol changed over time.

As we dug into the interpretation of algorithmic scores and refined our interview protocol, we decided to include also graphic designers among our interviewees, who, given their professional background, may have had less knowledge of how algorithms work and, thus, may have had different thoughts about and experiences with algorithms. This choice was made following Glaser and Strauss' (1967) suggestion to '*choose any groups that will help generate […] as many properties of the categories as possible*' (Glaser and Strauss, 1967). At this stage, indeed, it became clear that, not only did algorithmic scores play a significant role in freelancers' behaviour, but also that freelancers' strategies for dealing with scores changed over time. We thus decided to include designers to collect additional knowledge on the second phase of our grounded model (see further details in the data analysis section).

We ended our data collection once we reached ‘theoretical saturation’ (Charmaz, 2006; Glaser and Strauss, 1967), such that new data were not helpful in either sparking new theoretical insights, nor refining the properties of theoretical categories (Charmaz, 2006).

Overall, we conducted 66 semi-structured interviews of about 75 minutes each, with freelancers actively working on GigStars. All interviews were conducted via Skype. We could record and transcribe 59 interviews, while we used field, jotted notes for the remaining seven. The table in Appendix A contains detailed information for each informant (names are fictitious). This information was collected at the time of the interview either by asking informants or by inspecting their online profiles. Specifically, the table provides information on gender, country, education, years of experience on GigStars, hourly rate and algorithmic scores. For the purpose of brevity, we categorize the various detailed job specialties (e.g., illustrator, graphic designer, software developer, game developer, …) into three macro categories, named IT developer, designer, and translator and virtual assistant. The sample encompasses 32 IT developers, 28 designers, and five virtual assistants and translators.[1] 25 informants are female, 41 are male, and they come from different European or Asian countries, or from the USA. Their age ranges between 19 and 45. On average, they had spent three years on GigStars; 54 had spent more than a year. As far as the algorithmic score is concerned, 31 informants had a 100 per cent score, 19 had more than 90 per cent (i.e., 50 informants were considered successful for GigStars), nine had less than 90 per cent score and seven were building their score, thus had not yet displayed that number (they were still in the ‘Score building’ phase).

Online profiles. Before or right after the interview, we saved a copy of freelancers’ online profile (66 profiles). These were useful, first, to store information on pay rates and score numbers at the time of the interview, as well as freelancers’ working history and status on the platform. Second, we analysed online profiles to grasp additional information about freelancers’ identity and about how they present themselves online (i.e., their personal description). We also addressed specific questions on a given profile’s information during interviews. By doing so, we could understand how respondents strategically used their profiles in the online environment and gather specific information about current algorithmic score and reviews.

Archival data. As we started conducting pilot interviews, we also collected selected articles and reports from GigStars’ blog to develop and enrich our understanding of the context. Specifically, we reviewed a total of 190 articles during January 2016–June 2018. The documents provide information about GigStars and general tips for freelancers. For instance, we reviewed articles suggesting how freelancers might organize their remote work, how to be freelancers online, and how to stay productive. We also read articles on how to write job proposals, how to become top freelancers on GigStars, or how to set the right rate. These addressed freelancers’ issues concerning how to exploit GigStars’ full potential. Finally, we reviewed articles on tips for clients, like how to write a job call and how to run successful collaborations.

Data Analysis

We built an integrated database with interviews, profiles, and documents. Data analysis followed the grounded theory approach (Locke, 2001; Strauss and Corbin, 1998) and the three-step coding process inspired by the 'Gioia methodology' (Gioia et al., 2013). Thus, data analysis went hand in hand with data collection and with comparing emerging interpretation of the data with similar concepts existing in the literature (Locke, 2001; Strauss and Corbin, 1998). The final outputs of data analysis are the data structure of Figure 1 and the grounded model in Figure 2.

We began by reading interviews' transcriptions individually and identifying recurrent statements and themes. When we met to discuss these themes, we agreed that, when asked about their experience on GigStars, freelancers often mentioned the importance of client trust and, therefore, the need to get good reviews to be considered by prospective clients. Thus, the need to manage algorithmic scores emerged as important from the words of

Figure 1. Data structure

informants as soon as we started to open code (Gioia et al., 2013; Locke, 2001). We then started to systematically look for statements related to scores and grouped them into first order concepts. In this phase, we wanted to stay close to our informants' language and use 'in-vivo' codes as much as possible (Locke, 2001). Moreover, we also started to meet periodically to discuss similar statements and resolve coding discrepancies. For instance, we noticed that several interviewees described algorithmic scores as something 'making your life easy on the platform', but also observed the need to 'be reliable with clients' and 'catch reviews'. Such in-vivo codes suggested that scores were making an impact on the way freelancers behaved on GigStars. In addition, these statements systematically referred to the *beginning* of freelancers' career. As far as reviews and the score are concerned, in fact, we soon understood that freelancers usually referred to two different kinds of experiences: the experience on the platform right after subscription, i.e., *before* obtaining good reviews and achieving a publicly visible score, and the experience *after* receiving a bucket of reviews and having a good score visible to prospective clients.

We thus decided to include a temporal dimension to our coding. In doing so, we used the *process as narrative* approach, meaning that our temporality of interest lies within the interpretations and meanings reconstructed by our informants (Fachin and Langley, 2017), and we employed a temporal bracketing strategy to turn 'a shapeless mass of process data into a series of more discrete but connected blocks' (Langley, 1999, p. 703). We then broke down the data into 'periods' or 'phases'. The first relevant phase refers to the period right after subscription, named *Score building*, when freelancers do not yet have reviews on their profiles. The second one, named *Score management*, refers to a second period when freelancers have obtained reviews and achieved a good algorithmic score. At this time, they start getting invitations and decide to raise their pay rates. In this second phase, freelancers still perceive the need to maintain a high score to survive on the platform; thus, they still have a relation with scores and need to build strategies to deal with it.

We then started to perform axial coding (Gioia et al., 2013; Locke, 2001) and grouped together similar attitudes towards algorithmic scores, underscoring similar affordances' perceptions. Concurrently, we tried to associate behaviours to perceived affordances, and pay attention to fit each perception into the right stage. We also gradually moved from in-vivo codes to more abstract categories. For instance, we built the 'Compliance' category by grouping together strategies to work around the constraints of algorithmic scores in the Score building phase. Thus, here we find open codes related to 'under-billing' or 'choosing smaller projects'. Concurrently, we compared the abstract categories that we were building to concepts we found in the literature, and in some cases, we decided to adopt similar labels. This is the case, for instance, of 'under-billing', which we found in the work of Bucher et al. (2021). During the first round of axial coding, we also drafted a preliminary version of the grounded theory.

While performing some of these analyses, we collected additional interviews. We used the new data to refine existing categories, build aggregated dimensions (Gioia et al., 2013), and find support for relationships between them (Strauss and Corbin, 1998). However, before performing this last step, we did another round of open and axial coding and found evidence for emotions related to each perceived affordance and subsequent behaviours. We thus integrated emotional responses into our theory, and ultimately

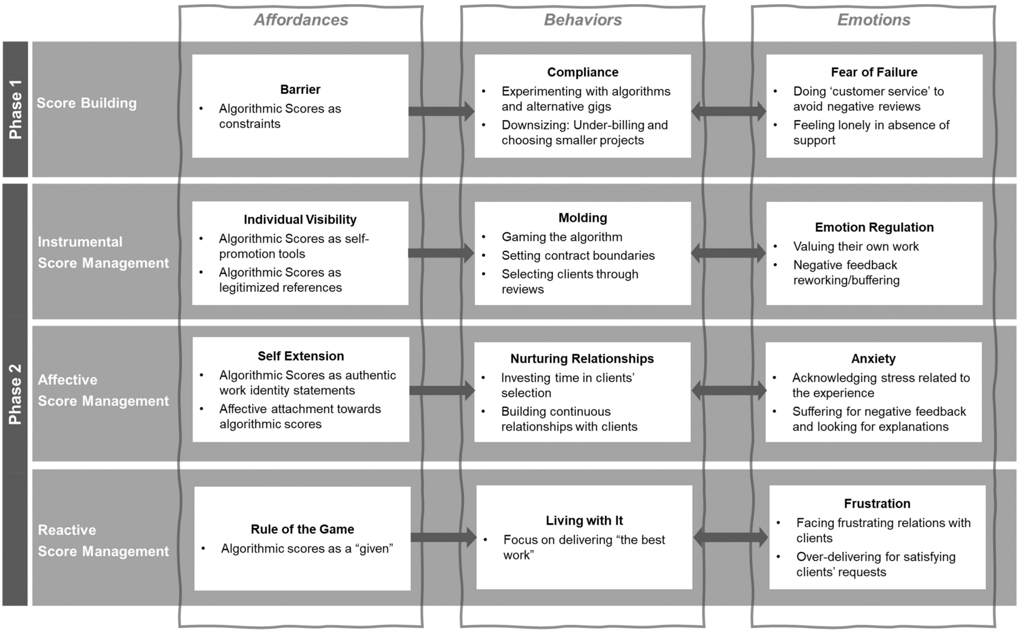

Figure 2. Grounded model

grouped categories into aggregated theoretical dimensions (e.g., 'Behaviours'). The data structure of Figure 1 summarizes our first order concepts, second order themes, and aggregate theoretical dimensions.

Finally, we looked for relationships between the categories. More specifically, we further examined data to understand relations between technology affordances, behavioural strategies, and emotional consequences. As it was difficult to grasp relationships across categories from initial interviews, we later discussed with key informants about some relationships in the emergent grounded model, using layman's terms. These informants validated our main findings and interpretations. This allowed us to finalize our grounded model (see Figure 2 for final version).

FINDINGS

Our grounded theory (see Figure 2) shows how freelancers perceive the specific affordances and constraints of algorithmic scores in two different phases: when they join the platform and need to build a score (phase 1), and once they have established their presence on the platform (phase 2). Using the grounded theory of Figure 2 as signposting, in the following sections we highlight how the perceived affordances in these two phases are associated with different behaviours and emotions.

Phase 1: Score Building

In a first phase, when they have just subscribed to the platform and are trying to catch their first jobs, freelancers perceive algorithmic scores as a constraint on their activities on the platform. Consequently, they comply with rules using different 'compromising' tactics to build a presence on the platform, but experience an initial fear of failure. Table I contains exemplary quotes about this phase.

Algorithmic scores as barrier. Many gig workers described their first job searches on GigStars as '*hard*', '*challenging*' and '*difficult*', and they blamed the lack of previous working experiences and clients' reviews for this hardship. Specifically, they described the 'without reviews period' as the time they were 'invisible' to matching and ranking algorithms and, as a consequence, not attractive to prospective clients. During this time, clients cannot rely on references and ratings of previous experiences to derive judgements. Jane's words show, for instance, that this information is extremely important for clients, who, through reviews, can get cues about what to expect from freelancers and whether to trust them to be able to deliver.

> 'When you subscribe to this platform, no one hires you if you don't have any review, if you hadn't worked on the platform before. [Clients] will clearly give more importance to someone who already has some experience, because they can see whether they can respect deadlines, deliver quality jobs'. [Jane, designer]

This field note, and many others, suggest that initial scores are perceived as a barrier to be overcome to be able to continue to work on GigStars. *Good* scores and reviews being absent, the algorithmic technology becomes a constraint on freelancers' activity and survival on the platform. Being considered from prospective clients is thus the first difficult task to be accomplished.

Consequently, in the first phase, we found freelancers focusing more on collecting reviews rather than gaining money or enhancing their skills (see Brad's quote in Table I).

As further underlined by Michael, starting out is a matter of catching projects to get reviews and acquire visibility.

> 'First, I took some really small jobs, a couple of dollars once, because there is a learning curve to get started on the platform. If you have no experience nobody will hire you for the project. So you need to make some compromises, where you invest your time for a future gain'. [Michael, designer]

Compliance. We noticed that freelancers' focus on catching good reviews influenced the way they engaged with their scores at the beginning of their career. Specifically, they seemed apt to comply to GigStars' rules. Michael's quote above hints to the need to *compromise* to catch reviews, and our analysis reveals freelancers used different tactics to adjust to platform rules.

First, freelancers enacted strategies to 'play' with algorithms and build an attractive online profile. For instance, we found informants playing with keywords and skills' descriptions to catch clients' attention and climb up the platform ranking. In this regard, Heather described the experience of her friend, Rita, who needed to improve her ranking. She

Table I. *Score building* exemplary quotes

Second order themes	*Representative quotes*
Barrier	Apparently, I have a really top-rated profile. This is the only thing that could help. If you have like zero experience people just do not answer, because they have 50 proposals, and they just skip yours. That's why at the very begging you need to work and maybe not gaining money, you need to work at a very low price. And you need to work that way until you have a top-rated profile. So now it helps me, but I have spent almost 2 years to get this advantage. [Henry, software developer]
	Clients will not hire you if you do not have experience they can use to judge you, and you cannot bid a project asking the same rate of a seasoned professional if you are new to the platform. [Charles, IT developer]
	Well, at the beginning I was basically capturing reviews, because I really wanted to bid some jobs that I could not get without reviews. So, at first, it wasn't really about money, it was about reviews. Now it's about money, because I can bid on better jobs than before. [Brad, designer]
Compliance	I think the first point is price and the second point is 'customer service', so you really need to read the job description, ask, tell them why you are the best candidate, why should they pick you, even if you do not seem to have experience. You really need to put efforts in it. [Michael, designer]
	The best for GigStars? Being inviting to clients, do not be boring, so investing a lot of time in building what you want a client to see, and then pursuing all types of projects that are on the four corners of the globe. [Harry, designer]
	At first, I put my work at a very low price. Well, I can say I was paying to get jobs, in a way I was doing that. I was more or less giving away work for free in order to get reviews with 5 stars. [Marcus, translator]
Fear of Failure	That episode was really frustrating, that was the moment I realized we do not have any kind of protection from that. […] I really felt like there is no protection against people not being honest. [Allison, IT developers]
	At the very beginning one client ended my contract because he wanted to work off of the platform. I reported him because I did not want to lose my place on the platform for having moving out with one client. I reported that client, but that was not enough. He did not pay me and he ended my contract. [Mary, virtual assistant]

played with the algorithm and discovered that the easiest way to climb the ranking was changing her job title to reflect hard-to-be-found competencies.

> 'So, basically we worked a lot with the title. […] In my title I state that I do several things, and she [Rita] is more specific. She started getting a lot of invitations on this particular field of work, and now we have found out that if you search on Google for an ASO [App Store Optimization] specialists, GigStars gives her one of the top ten ASO specialists, and she was on position 5. And then we changed the title and she went to position 3 like the next day'. [Heather, IT developer]

To build an attractive profile, freelancers relied on job application letters and the platform's certifications. A job application letter contained a general presentation of the freelancer and a detailed description of why he/she was supposed a good fit for a job. A platform's skills certifications (e.g., GigStars' Certification in Web, Mobile, and Software Development) were online trainings offered by GigStars on different topics. Job application letters and certifications were meant to be substitutive signals of quality in the initial stage, and they were used to make a good first impression and communicate not only capabilities, but also enthusiasm and willingness to enact helping behaviours.

> 'When you are a beginner, no one knows you. You have to show who you are. First, you have to take many tests on GigStars, like programming test, English test… just to prove that you know what you are talking about. Second, the difference stays in how you write your proposal. For example, when you want to do a job, you need to be really convincing with the client, you need to prove him precisely how you can help him. […] When you are a beginner that's what really helps, and also the price'. [Allison, IT developer]

Gig workers often decided to lower initial prices. This under-billing strategy was implemented to compete with other, more experienced freelancers, who usually set higher prices but could showcase larger buckets of reviews and higher scores to attract prospective clients. In more than one case, clients also asked to reduce payments in exchange for good reviews (see also Marcus' quote in Table I).

To speed up this first stage, many informants tactically applied to several small, easy jobs to increase the number of good reviews. In other words, gig workers at first tend to avoid applying for jobs perceived as demanding in terms of time and complexity, and thus compromise on the content of the first jobs. For instance, several IT developers told us that, to diversify themselves in the market and speed up the process of getting reviews against other freelancers' competition, instead of applying for software development jobs, they preferred to do some translations or database management. Benjamin, an IT developer, told us that he 'had some transcriptions jobs too at the beginning' and that he 'basically proposed [himself] for everything'. It was only after a few months on GigStars that he started to pick the jobs he really liked and was qualified for.

Fear of failure. As freelancers under-bill and accept jobs that are not matched to their unique skills, they are exposed to frustrating working episodes when dealing with clients. The initial period on the platform was described as the most demanding in terms of satisfying clients' requests. The fear of getting negative scores pushed freelancers towards pleasing clients' whims and trying to avoid disputes, as Cameron clearly describes.

> 'If they're satisfied with the job, you get a qualification in stars. "Five stars" means that the job has gone nice. That's what I mean by getting the stars, drop prize, do a nice job, don't complain. So the client doesn't get upset, and luckily he will give you five stars. And so your competitiveness builds up'. [Cameron, designer]

Freelancers also lamented the lack of regulations against exploitation. Many informants complained about the dispute resolution system and reported that it tended to favour clients rather than workers. Others complained about being subscribed to something that, they felt, was not taking care of them and could drive them to fail, e.g., to get negative feedback from clients. Grace's experience provides an example.

> 'I can tell the client upfront: "This is what I'm willing to do for that price", but they can still ask me to do more and give a bad feedback if I don't do it, right? Like, I can go to GigStars and say: "Look, this is what I promised to do for this price and now they are asking me to do more". GigStars doesn't care'. [Grace, designer]

Phase 2: Score Management

In phase 2, freelancers reported how they increased their visibility once they caught some positive reviews and a good algorithmic score. In this second phase freelancers shifted the locus of their attention from catching reviews to building a career on GigStars. This happened because having a good score allowed receiving invitations from clients and increasing their pay rates and negotiating power. However, this also implied either maintaining their good scores or improving unsatisfying ones to continue and possibly expand their work on the platform.

In this second phase, we noticed a shift in the way freelancers engaged with algorithmic scores and saw technology affordances. Freelancers abandoned the perception of scores mainly as constraints and started to perceive specific affordances in the features of algorithmic scores. Specifically, we identified three different affordances and associated behaviours. First, we found some freelancers interpreting scores as instrumental to their *visibility* on the platform, i.e., as useful tools to showcase their abilities and intentions to behave as reliable professionals. Second, other freelancers developed the perception of scores as a *self-extension*, and, therefore, interpreted scores as an identity statement inextricably linked to their abilities and care for clients. Finally, we discovered a few freelancers looking at algorithmic scores as a *rule of the game*, focusing on accomplishing their tasks rather than being worried about them.

Very few gig workers described hybrid behavioural responses to scores. For example, in our interviews, only three informants talked about scores both as a self-extension requiring nurturing relationships and as a tool to increase individual visibility requiring moulding behaviours. In terms of emotional responses, our informants reported some recurrent emotions (e.g., mostly anxiety for those talking about scores as a self-extension), but we recognize that emotions oscillate over time. In the rest of our evidence, however, we will not focus on hybrid responses, as we will leave that to future research directions. We instead describe the different interpretations of scores and their consequences in terms of recurrent behaviours and emotions.

Phase 2: Instrumental Score Management

A few freelancers interpreted scores as a tool to enhance their individual visibility as professionals. Consequently, they enacted moulding behaviours, i.e., they actively reacted to negative feedback and 'gamed' algorithms to preserve their image on the platform, and used the score system at their advantage to set contract boundaries. These behaviours allowed them to control and reduce negative emotions related to bad experiences with clients. Table II contains examples of field notes.

Individual visibility. A first group of informants positively engaged with the opportunity of displaying their evaluations on the platform and interpreted this feature of algorithmic scores as useful to catch new clients. Specifically, algorithmic scores are here seen as tools enhancing individual visibility, i.e., as a legitimized proof of their value against those who do not deliver quality tasks. Visible scores are perceived as something improving freelancers' competitiveness in the market by signalling the intent of enacting positive behaviours, such as meeting deadlines, as recounted by Adams in the following field note.

> 'If I send clients an example of my work, that is not enough to make them understand that then I will respect deadlines, that I am someone who carefully reads the request, who tries to contribute with his own ideas, open to critiques. These are things clients are searching for. But you can't explain these things, they have all the rights to think you're lying, so I would prefer to use something other clients said when they worked with me. […] So, I've taken a pragmatic stance towards this rating system. I have asked myself: "What these reviews are useful for?". I think if someone delivers a good work, and thus deserves a high score, he has the right to show that to future clients. I personally believe this is a useful tool for both clients searching for freelancers in this jungle, among hundreds of proposals, and for freelancers trying to build their business'. [Adam, designer]

As suggested by Adam, algorithmic scores act as legitimized references, because they come from the words of previous clients. Thus, scores can strategically be used to present oneself to prospective clients and promote one's business 'in the jungle'. In other words, algorithmic scores are here seen as providing information to an external audience about an unobservable quality.

The individual visibility affordance emerged not only from interviews, but also from online profiles. Specifically, many informants decided to fill their personal description on profiles with past feedback and scores (see Figure 3 for an example).

Informants further described how they imagined clients reading their profiles. For instance, even if he had created multiple personal websites to showcase his work, Xavier told us he preferred to use GigStars' profile to present himself to clients, as GigStars' profile collects useful feedback describing his abilities (see the quote in Table II). Sean similarly underlined how he let his profile 'speak for itself'.

> 'I let my profile speak for itself, because I have a good score there, there is a lot of hours in there, and I have feedback from people who have worked with me. And this is kind of setting why people are willing to pay this $39 per hour'. [Sean, IT developer]

As we can see, scores and reviews are strategically used by freelancers to speak with prospective clients and communicate credibility, as well as promoting their work and

Table II. *Instrumental Score management* exemplary quotes

Second order themes	*Representative quotes*
Individual Visibility	About testimonials, I think it brings more trust to new clients when they visit your page. If previous clients thought that the freelancer is good, she/he is more likely to be hired. And including 4 testimonials in the overview allows clients to read what other clients think about me, my competences, my freelance work. [Neville, IT developer]
	When I write a proposal and I say I did this, and this, what is missing is what clients have seen in me. So, I feel like that label [i.e., Top Freelancer badge] gives me credibility with clients. It's a really good thing actually. [Allison, IT developer]
	I prefer my platform's profile to present myself to clients, because it's on GigStars and my feedback come from GigStars, and client can see what I have done and that I am a really good worker. [Xavier, IT developer]
Moulding	You have to also tell clients: 'Remember to leave the feedback'. I'm not sure if GigStars tells clients that they have to leave the feedback in 14 days, I'm not sure about that. But GigStars did tell me about this, that the client has to give you the feedback in 14 days. [Nancy, IT developer]
	If that happens [score drop] I say: 'Ok, what happened?'. I need to find jobs that help me having a good number again, that help me increasing it again for sure. Because clients are asking for at least 90%. [Helen, designer]
	We need to learn how to build a defensive weapon, an armour, to avoid scams. For instance, setting limits with clients. How many times they can change the output, for instance. […] I do not like dealing like this with clients, because there are clients that could potentially be your friends or siblings. But I have to do that. [Adam, designer]
Emotion Regulation	I like to establish my authority, so that way they know I'm not just playing around. This is a job to me, even if it's not to them, because sometimes some people are looking for something as a hobby. But first and foremost, I'm a worker on GigStars. Even if it's a hobby for them, it's a job for me. So, I always make sure that they know that I'm professional. [Victoria, designer]
	I know my profile is not outstanding. But I am a professional, and it communicates this. And I have good reviews. [Ken, translator]
	Sometimes is like: 'Okay, you finished the job'. And then the person takes forever answering you back. But you know she/he's a nice person. She/he's also just trying to work. Maybe she/he was busy that week, so you are not going to give her/him a true rating, but give her/him five stars because she/he's a good person, she/he was probably busy, it's okay. So I know people lie. Unless the person is a complete disappointment, people are not going to actually express their true opinion. [Kelly, designer]

capabilities. As technology is perceived to provide the affordance of individual visibility, i.e., of making freelancers' activity and positive evaluations visible, freelancers need to strategically think about how to maintain positive scores.

To this regard, Nancy mentioned that, once being rated as a Top Freelancer, a freelancer needs to work to maintain the achieved status.

> 'It's competitive, it's very competitive, because I'm not the only top rated freelancer over there. It's like hundreds and thousands of freelancers. So, okay, it's a badge, you

(a) Exemplary personal description of freelancers interpreting algorithmic scores as *Individual Visibility*. Example from Nancy's profile description.

```
Looking for quality work with a little spark of experience and freshness,
here I am at your service! Myself Nancy. I am a web developer with 3 years
experience in web development.
[brief past experience]

Recent Testimonials: |
***************
Rating - 5.00 "Nancy was very prompt, professional & patient! Highly
recommended."
Rating - 5.00 "Extremely pleased with the job. Excellent communication.
Highly recommended."
Rating - 5.00 "Great communication, quick to begin work and easy to deal
with."
Rating -5.00 "She is a Wordpress expert. She solved an issue that I was
having. Thankyou!"
Rating - 5.00 "Nancy did amazing work!!! I will be hiring her again soon for
more projects :)"
***************
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(b) Exemplary personal description of freelancers interpreting algorithmic scores as *Self-Extension*. Example from Marcus' profile description.

```
Where did it all start you might wonder... Well.. It helps being told that
you can not do it. (Don't listen to that you parents out there. Acknowledge
the values of your children. Encourage them!) Apart from that, it does help
to be stubborn! and travel around a bit is not bad either. Being a software
developer is what I really want for my future. Challenges will come my way
and I will do whatever I can to meet those challenges in a professional
manner. Many old programmers or those taught a language at school see problems
and a box they are stuck in. In school, I was the one teaching my teachers.
I was the one thinking outside the box to get things done. I can be stubborn
sometimes, but in my mind, nothing is impossible. The impossible only takes
a little bit longer time. I wish to put my skills into good use and I hope
that will be something for you.
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Figure 3. Examples of different personal descriptions from online profiles. (a) Exemplary personal description of freelancers interpreting algorithmic scores as *Individual Visibility*. Example from Nancy's profile description. (b) Exemplary personal description of freelancers interpreting algorithmic scores as *Self-Extension*. Example from Marcus' profile description

> are a Top Freelancer. But you have to maintain it, you have to enhance it, you have to take care about it, time to time'. [Nancy, IT developer]

Moulding. Freelancers enacted *moulding* behaviours to take control over GigStars' algorithmic management. As negative feedback can lower their score and impact their image, freelancers applied specific strategies to actively avoid negative feedback. For example, they frequently reminded clients to evaluate their jobs, as explained by Victoria in the following field note.

> 'Then I became more conscious about what they [GigStars] were looking for. […] This is important because sometimes clients won't automatically leave feedback, you know, sometimes people forget… . So, at the end of every job, I usually ask them: "Can you please leave me feedback?"'. [Victoria, designer]

In addition, freelancers learned that GigStars' algorithms tend to lower scores when job contracts stay open for a long time or when profiles are identified as inactive. Thus, some freelancers tried to limit the time their contracts stayed open, as explained by Harry.

> 'There are clients out there that will talk with you for a while and then stop talking to you and keep your contract open and then 40 months later write: "Hey, I got more work for you!". Having that project open for so long does hurt the score, because every two weeks GigStars calculates your score and contracts that don't move. So, my score went from 96 down to 94 because of that one project. So, I closed that out, I just didn't want to waste my time worrying about a client that was not going to respond to me'. [Harry, designer]

Those willing to build more long-term relationships with clients must then regularly win random, smaller projects to prove they stay active. As explained by Helen (see Table II for a field note), this last strategy was also described as useful to work around negative feedback causing score drops. Informants further described how they tried to prevent score drops. For instance, some freelancers asked clients not to leave any feedback in case of unsatisfying working relationships.

> 'I even asked some clients not leaving a feedback when things didn't go well. My fault, his fault, it can happen. […] The relation with clients can't always resolve the best way possible and sometimes I happened to ask: "Please, do not leave a feedback". Because I noticed that, if clients left no feedback, then the work is listed as a completed job that doesn't count for the score mean'. [Adam, designer]

Other freelancers talked about clients who disappeared, kept contracts open, ignored freelancers and finally (indirectly) hurt their score. To avoid similar episodes, informants declared to take advantage of the rating system to gather information about clients and avoided those with bad reviews. They also decided to clearly define contracts' boundaries before delivery in order to avoid unpleasant surprises.

> 'First thing, when I see the client is new and that their payment method is unverified I just avoid him. And second thing, they might have a very long history. Then, I see if freelancers had left comments about their jobs. […] Third, I check their rating. So if I see the rating is less than four out of five, then I try to avoid him'. [Rudy, IT developer]

Emotion regulation. Taking control over algorithmic scores through moulding behaviours also helped freelancers to take control of their own emotions. We found freelancers focusing on their competences and qualities, reinforcing them 'against' clients, and being tolerant of low scores and bad experiences.

As we mentioned, individual visibility led freelancers to be particularly interested in communicating their qualities and their professional behaviours. In their storytelling, they often used words like *professional*, *serious*, *reliable* that we interpreted as a self-reinforcing coping strategy, and as a way of managing bad experiences. Informants seemed to use this strategy to keep their emotions under control against score drops. While talking about sudden changes in her score, for instance, Kirsten showed disappointment, but she explained that a score drop did not reflect her professionalism, as she was convinced about her own positive qualities.

> 'I'm at a loss for how they [GigStars] are figuring out that percentage, because it doesn't seem like that one worked. It doesn't seem like it's working for me. I'm a very hard worker, and I'm very talented, and with that calculation clients are missing that information'. [Kirsten, designer]

Along with keeping emotions under control, some freelancers also showed a higher tolerance for lower-than-100 per cent scores in the short term, because they perceived that they were able to influence these scores in the longer term. Although they recognized the need to stay on the market and to maintain the score over clients' bar to get jobs, they did not appear 'obsessed' by perfection. Rather, they designed corrective strategies to preserve the score against a market exit over time. This way, they were able to buffer negative feedback.

> 'Never mind, because it's going maybe to 98 or 97, maybe, it's not going to be down quickly. It's ok, never mind, I will increase after. It's still good so it never gets really low. […] I mean 90 per cent it's still good, it's still fine to find jobs'. [Helen, designer]

Phase 2: Affective Score Management

We found other freelancers engaging with algorithmic scores as if they were an authentic virtual embodiment of their work identity. In a search for authenticity on platforms, these freelancers focused on nurturing relationships with clients, i.e., they invested time in clients' selection and built long term relationships, but experienced high levels of anxiety and stress. Table III contains examples of field notes.

Self-extension. For some gig workers, algorithmic scores can act as an extension of their working self, or, as Mary says, a second identity.

> 'I have the advantage that I am top freelancer, and this means I have very good quotations, I'm treated like a very serious person, a very correct person. This is very important for me, it's somehow like my second identity, it's my proof that I'm a really honest person and a fair person'. [Mary, virtual assistant]

Specifically, we noticed freelancers highly identifying with what they do on the platform. The idea they have about themselves as workers was tightly connected with what they do on the platform, and what they do is corroborated by algorithmic scores and feedback. Putting it differently, algorithmic scores, way before telling something to prospective clients, speak directly to freelancers and are being used by freelancers themselves to make judgements about their own work identity. As Kate explains in the next excerpt, if freelancers are getting poor feedback, that is their responsibility, as the score is what they do on the platform.

> 'If you have a bad score, that is your responsibility. It is a matter of being fair with clients. The score shows what you do, shows what you are able to do, it is your responsibility, you own the responsibility of what you do and what you say on the platform. The profile, my profile, mirrors a lot what I am and what I do here'. [Kate, designer]

The way freelancers present themselves on their platform profiles corroborates this interpretation. Personal descriptions here identity statements where skills' presentations are enriched with historical nuances, personal values and distinctive traits, and affection. Figure 3 provides some relevant examples from profiles. Heather's quote in Table III also explains how freelancers searched for coherence between what they are and their online profiles.

Furthermore, informants used words like *pride*, *enjoy*, *love*, *passio*n in their profiles and during interviews. When talking about scores, they also often used the term 'personal', emphasizing being personally and emotionally concerned about algorithmic scores, and showing an emotional attachment to them. As Emily's quote shows, score drops do not necessarily negatively influence job opportunities. However, they personally impact freelancers, as they are material signals of something going wrong despite all their efforts, and they prove that they are not the 'perfect' professionals they think they are.

> 'It *disturbs* you, even though it doesn't dissuade people from using your services. It's still for you personally, it's not nice to see that for everything you do. You go through this extra mile and you try to do the best you can. And then you see this 4.6 rating on your page… It's more of a personal thing. I don't think people actually experience a drop in invitations or awarded projects because of a difference of like 2 per cent job success score. But it's more of like a personal thing for freelancers, because it's their business. And it hurts when you know that you did everything. And then there's this number, that's saying that you're not perfect'. [Emily, IT developer]

Due to the affective attachment to scores and the idea that they extend freelancers' working selves, informants cared about preserving the authenticity of that number, as suggested by Jake:

> 'When the job ends, a lot of freelancers ask clients to leave a… wonderful review. I have never asked for that, because I believe that should be an honest process, that the

Table III. *Affective Score management* exemplary quotes

Second order themes	*Representative quotes*
Self-extension	The score system is a bit tricky. I have always had 98% instead of 100%, and this is because of that negative experience. The client left a negative review, so the score dropped to 98%, and this creates problems. Yes, it is a problem. It is truly a personal problem. [Jake, designer] It's super difficult for me to say what I do, because I am constantly doing different things. Sometimes I am developing a game, right now I am developing a web site, sometimes I am doing keyword researches, and sometimes I am doing Facebook's adds. It keeps changing, and my cousin said something very interesting, she said that I am a 'Swiss knife'. I can do a lot of things, you know? And actually I found it very interesting and I place that on my profile. [Heather, IT developer] I'm very good in this kind of activity. It is very simple and I have experience from my office job, my job before platforms, and I wanted to use my experience. Actually, I don't want to be pride, but I am a Top rated freelancer. [Mary, virtual assistant]
Nurturing Relationships	I do video meetings, I accept any sort of offer where there is an interview period. I know they are interviewing me, but I am also interviewing them. [Tracy, designer] I am first of all honest with my contractors, I'm dedicated to my work and I'm in love with quality, because if you don't deliver quality, you can't receive quality. [Mary, virtual assistant] First thing is that, from the job post itself, I kind of try to read into what the client is like, and whether I'd be interested in working with him or not. And it's just like a sixth sense sort of thing where you're reading through how someone structured his words. […] And after all of that, if I feel comfortable proceeding with this client, I spend like three hours writing a proposal, specifically for him. [Emily, designer] I always try to keep the client updated. In every single activity, I always try to keep the client engaged. Every time I have a concern, even a small one, I contact the client, I ask his opinion, sometimes I even send two options and I ask him to choose. Clients like that. I guess this is one of the main reasons I have so many clients, because I keep them engaged. [Leo, IT developer]
Anxiety	That client […] was my first 4 stars rating, my only 4 instead of 5 stars rating, and up to today I am not really sure where things went wrong, that they stop working with me after that. For me this is very disconcerting, to not know what I did wrong. [Tracy, designer] It's completely uncertain, and the main objective is to get you into a point where is not uncertain anymore. [Heather, IT developer] I didn't know why I experienced that score drop. I literally had no idea. These things bother me. [Amelia, designer] Now, as far as the success score is concerned, it does seem really important. I would worry even if mine dropped to 99%. I don't know how that would affect things, but I have been 100% the whole time I have been on GigStars and it is really important to me to stay there. [Tracy, designer]

number they give should be honest. I think it is good to be judged for the work you have done'. [Jake, designer]

At the same time, they experienced a tension between being authentic and trying to avoid threats to their professional identity. To 'authentically' maintain a good score, they nurtured their relationships with clients.

Nurturing relationships. Freelancers who interpreted scores as a self-extension tried to manage working relationships instead of algorithms to prevent negative feedback. For instance, Marcus described how he wanted to avoid delivering bad work to preserve his professionalism and decided to be honest with clients and say no to jobs he could not or did not want to deliver.

> 'What clients do is they choose the first one and cheapest who is giving them an offer. […] I know my profession, I know that I don't want to deliver bad work, I don't want to read my name on a translation that is bad. So, that way I feel safer when actually I say no to a job, or I feel safer if some clients are saying that I don't have fit with that job'. [Marcus, translator]

A key aspect here is the need for being honest not only with clients, but also with themselves. As Marcus described, being honest with clients is a way to be true to himself and his professionalism. Similarly, when talking about freelancer-client relations, freelancers often used the word 'trust' and talked about the importance of trusting the other party in a contract. They described a two-way trust relationship, where not only clients need to trust them, but they also need to trust clients over time.

> 'It is really important to me since I started my business that my clients trust that I know what I am doing, because I have done it for a really long time. And so I do filter and I do not wanna work with people that seem like that they won't trust my experience and expertise. And that puts me in a position where I do feel to be taken care, they need to feel confident in me and in what I am doing, that I am gonna handle things for them'. [Tracy, designer]

Freelancers also needed to make sure to preserve a good working relationship over time. Informants told us they tried to keep open communications with clients and to continuously get feedback on their work. They described this practice as useful to 'pamper' clients and make them feel they are being taken care of.

> 'I think touching base is really important, but it's tricky because you can't touch base too often, because then you are annoying, and they do not want to deal with you. You have to write just the right amount, so that they feel that you haven't abandoned them, that you are still worried about their project'. [Tracy, designer]

To facilitate the process of maintaining good relationships with clients over time, informants declared they also invested a substantial amount of time at the beginning of each contract to investigate clients' intentions. This mainly meant trying to understand clients' reliability through the lines of job calls and setting up meetings where both clients and freelancers inquire about each other – called 'two-way interviews'. These latter are meant not only to allow freelancers to get cues on clients, but also to explain the way freelancers approach their work, eventually ruling out clients who do not seem to value or understand their work approach.

> 'I vet my clients carefully before I even start working with them. I usually have long conversations over Skype, like maybe half an hour or an hour conversation before I even accept the job. And if I'm sure that this sounds like a good relationship, only then I actually proceed with the contract'. [Emily, IT developer]

Anxiety. As freelancers interpreted algorithmic scores as a self-extension, they experienced high levels of anxiety. The absence of punctual information about computational mechanisms kept them stressed about obtaining positive scores. Eventually, this always drove the need to preserve the highest score possible. 'The reputation system is what [emotionally] grips freelancers the most', Kate, a designer, told us.

In turn, freelancers who strived to maintain good relationships with clients took it personally when something went wrong. For this reason, some informants harshly criticized the feedback system's structure and revealed being annoyed by potential asymmetries between the visible feedback and the private one, or by the serious consequences of a single negative review.

> 'The score is a bit tricky, also because clients do have reviews, but they do not have a score like the one we have. I always had 100% but that client, my negative experience, gave me like 0 or 1 stars, and then the score dropped to 98% and that is a problem and makes you feel anxious. It's also a personal thing, because then you say: "What went wrong? I could have done it better"'. [Jake, designer]

Not knowing what went wrong was also described as disconcerting (see also Tracy's quote in Table III). Moreover, freelancers described the way clients interpreted the rating system as idiosyncratic, creating rating fluctuations. Freelancers, despite all their effort to nurture relationships with clients, always run the risk of meeting dishonest clients who provide unrealistic feedback. These threats to freelancers' working life on GigStars were deemed as extremely stressful experiences.

> 'I was really upset about that negative feedback. It hurted my score. I was really upset because I always try to do the best I can in my job, and I couldn't get an explanation for that negative review. It is hard to have such explanations from clients and GigStars. I felt really bad'. [Olivia, designer]

Emotional attachment to scores and feedback, and uncertainty when dealing with clients, led freelancers to feel anxious about potential score drops in their attempt to be 'perfect' on GigStars. As Emily described, lower scores say that '*you are not perfect*', and a lack of rating perfection '*hurts*'.

Phase 2: Reactive Score Management

In this final path, we found freelancers adopting an agnostic stance, which means they did not see either affordances or constraints when engaging with algorithmic scores. As a consequence, they conformed to algorithmic management and focused on living with it, i.e., on doing their best work. Interestingly, these behaviours did not dissolve the sense of uncertainty and actually contributed to a sense of frustration. Table IV contains examples of field notes.

Rule of the game. A few informants talked about algorithmic scores as 'simple rules' needed to make GigStars work. Thus, they described scores as a peculiar aspect of their work that they needed to accept, not understand. In this regard, Cameron told us:

> 'They [algorithms] count the number of successful jobs that you have in the past, in the last three months, over the last 12 months, the earnings. But GigStars really doesn't tell you exactly how it works. So, in a way, that's the way it goes. It's not a matter of trust, you have to work with it. It's how the platform works'. [Cameron, designer]

Our analysis reveals informants perceive the algorithmic score as something out of their control, coming from aspects of their work they can hardly influence, and thus not worthy to be considered or not important, as Mia declares.

> 'You know, reputation is really based on how many jobs you have done, how your clients rated you. I basically just really try to do my best. The reputation isn't that important'. [Mia, designer]

Although no one had perfect information on how algorithms work, freelancers knew scores and ratings were based on clients' reviews. As reviews come from experiences with clients, they were understood as a consequence of freelancers' good behaviour on GigStars.

> 'It's really not that hard if you want to work and you basically give good work to the client, it's really easy to gain the good grades and the work'. [Brad, designer]

Therefore, freelancers seemed not be worried about scores and did not seem interested either in finding how these scores can be leveraged at their own advantage, or in what these scores told them about themselves. Informants did not seem to engage with algorithms here, but rather, they seemed to focus more on performing their work and on grasping what needed to be done to accomplish tasks.

Table IV. *Instrumental Score management* exemplary quotes

Second order themes	*Representative quotes*
Rule of the Game	So, I have quite high ratings, this 100%. It wasn't my goal at the beginning, it has just happened this way. I'm telling you that I'm not like a mature poker, as I do not have this clear understanding of how it influences my work. [Norman, IT developer]
	From my personal point of view, GigStars is focused on money, on getting clients for cheap and fast projects, and I am not quite into this concept as I prefer having longer projects focused on quality and not on offering the client the cheapest possible option. [Scott, IT developer]
Living with it	This score system is something out of your control. You cannot influence it. So you should just find your way to work with this, to work in this environment successfully. [Norman, IT developer]
	I have started working on GigStars and I am learning and growing through GigStars. I think there are other more experienced people, more capable than me, and I have 97% score … I don't know, maybe I am lucky, but I do not think it is hard to keep a high score when you do a good job. [Amanda, designer]
	It is like relations with people. If you spend the whole time thinking: 'Would he like me?', then everything goes wrong. So you just need to stop overthinking and try to do the best at that very moment. [Jane, designer]
Frustration	I am always not frightened but concerned that my work won't be good enough for my clients. I am always concerned about this stuff. […] I am really concerned about whether it is really good or it is not, and the other thing that is really concerning is the payment. Sometimes it takes a while and sometimes I get the contracts on GigStars and they offer me to pay outside, I agree with that and I have to wait like three months to get paid. [Rachel, virtual assistant]
	I never did ask for additional money for those things because I know the client would not be happy and I would probably get a bad grade, if you understand. [Brad, designer]
	What happened is that I lost a lot of time. It happened also other times, but with that client in particular I lost a lot of time. It took forever, he gave a job to do, I did it, then he wanted some changes, I did them, and then again and again … I lost a lot of time, and then … well, he didn't pay me. But that's another story. [Jane, designer]

Living with it. According to some informants, high scores simply happen while delivering good results. In other words, freelancers here did not seem to actively search for high scores (see also Table IV for more examples).

> 'And for the top rated, it's also something that I basically didn't… I mean of course is really good to have it, but I didn't really go for it, in terms of searching for the client and asking for the grade or something like that, it basically came along as an additional thing while I was working on the other part of it'. [Brad, designer]

As scores are understood to be the result of good work on projects, the locus of freelancers' attention seems to be more on doing the best they can and trying to deliver excellent work for clients. As Jane told us, instead of devoting her attention to score signals, she preferred to focus on being professional and distinguishing herself from other designers. Similarly, Norman acknowledged the freelancer's inability to influence the score and, therefore, the need to simply find a personal, satisfying way of working (see Table IV).

> 'You must be professional, not only professional, but even more, you have to be available, and you must deliver your work even before the deadline. You must work better, in other words. […] So what I did, I invested in being professional and, even more, on being available'. [Jane, designer]

Frustration. Although mainly focused on the quality of their work, informants told us they still needed to react in case of scores' decreases or negative feedback from clients. Interestingly, we found that the absence of explicit score management strategies made them perceive those situations as frustrating because it forced them to deliver more than promised to preserve over-the-bar scores or simply even be paid. As Jane expressed in her previous quote, freelancers need to '*work better*', but this could turn into an unexpected and unbeneficial situation where freelancers deliver more than was promised, and where they do not know exactly whether this strategy would pay or not.

In other words, informants live within a paradoxical experience. On the one hand, they seem to be focused on their job, while on the other they look very client-oriented and afraid of disappointing their expectations. As Brad told us while talking about his working practices, '*if the client says something you should really listen to what he said and try to basically not making any mistake, so he has to pay you*'. Similarly, Cameron talked about the necessity to go on with over-demanding clients to avoid fights.

> 'Well, sometimes you agree on the work, but then they kind of start to ask more and more things, which were not previously really agreed, and they do not want to pay more for it. So it gets to a point where it would be better to just jump on and find someone else. […] And that's really hard to do. That depends on the clients. And sometimes I have done that. But with a client that I see it's nice and respectful. But sometimes it doesn't work, you fear that they won't understand that'. [Cameron, designer]

Despite their indifference towards algorithms, because of their strong client-orientation and the need to maintain a good score, freelancers did not seem to 'protect' themselves enough from potential bad experiences. Even though freelancers' experience looks positive and less stressful at first, the lack of perceived technology affordances reveals instead frustrating consequences in terms of day-by-day activities and working practices.

DISCUSSION

The purpose of this research was to investigate how freelancers interpret algorithmic scores in the attempt to understand how and why behavioural and emotional responses to algorithmic scores differ. Results allow us to contribute to the literature on algorithmic management and workers' responses, an emergent stream of studies in the future of work area.

An Affordance Perspective on How Workers Interpret Algorithmic Scores

Our study speaks to the conversation about workers' experience with algorithms and, particularly, to other recent works explaining workers' reactions to algorithmic scores (i.e., Bucher et al., 2021; Cameron and Rahman, 2022; Cheng and Foley, 2019; Rahman, 2021). This current debate is evolving around the idea that algorithms are opaque (e.g., Kellogg et al., 2020; Wood et al., 2019). Scholars investigated how workers deal with such opaqueness (Bucher et al., 2021; Rahman, 2021) and how, through invisible mechanisms, workers' activity is being controlled (Cameron and Rahman, 2022). Rather than focusing on what workers *cannot* see of algorithms, our paper is concerned with what they *can* see, that is, the output of algorithmic computations (algorithmic scores) and its performative aspect (Scott and Orlikowski, 2012). In other words, we wondered how workers perceive and how they can use what they see of algorithms for their own advantage, rather than trying to understand how they can resist algorithms and elude control. This approach allowed us to disentangle a key mechanism explaining the variety of workers' responses, that is, workers' perceptions of technology affordances (Leonardi, 2011; Leonardi and Vaast, 2017).

So far, the affordance perspective has been proposed to analyse how algorithms can help *employers* in various organizational contexts (Kellogg et al., 2020). By being the first to apply the affordance perspective to the experience of gig workers, our findings underline opportunities for action fostered by algorithms, i.e., individual visibility and self-extension. Importantly, the affordances we discovered can be used to interpret the behavioural responses to algorithms described in previous studies. For instance, Bucher et al. (2021) found that Upwork freelancers engage in direct – i.e., aimed at directly game algorithmic computations – and indirect – i.e., aimed at influencing clients' behaviour – compliance practices to 'pacify' algorithms, even if they did not explain why these different behaviours occur. Cameron (2022) found that Uber drivers engage in 'relational' or 'efficiency' games to play with algorithms, even if she acknowledges she cannot tell why drivers play algorithmic games differently. Individual visibility and self-extension affordances are likely to be an explanation of why gig workers engage in the different behaviours. Indeed, based on our findings, we propose that when workers see algorithmic scores as tools enhancing their individual visibility, they engage in behavioural responses aimed at *directly* influencing algorithms and algorithmic computations. On the other hand, when informants perceive algorithmic scores as extensions of their self, they *indirectly* influence algorithms by working on their relations with clients.

Our empirical results also confirm that 'people may perceive that a technology offers no affordances for action, perceiving instead that it constrains their ability to carry out their goals' (Leonardi, 2011, p. 153). At the beginning of freelancers' careers on a platform (phase 1), algorithms are perceived mainly as constraints, because freelancers need to comply to algorithmic mechanisms to survive in the market. Under-billing and downsizing are the behaviours needed to catch reviews, while experimenting with how algorithms work. Some of our informants continue not to perceive algorithmic affordances even in phase 2, when scores are visible. When algorithms are just perceived as a rule of the game, freelancers simply focus on their work and on delivering the best work they can. Interestingly, in both cases (under score building and under reactive score management), freelancers negatively experience their permanence on GigStars.

Workers' Reactions to Algorithms over Time

As far as the broad workers' experience on platforms is concerned, our study shows workers' perception of technology affordances as a key mechanism explaining how freelancers differently respond to algorithms over time. Although other very recent studies describe freelancers' strategies of dealing with algorithmic scores (Bucher et al., 2021; Cameron and Rahman, 2022; Cheng and Foley, 2019; Rahman, 2021), only one study focuses on the *mechanisms* that make freelancers' responses different (i.e., Rahman, 2021). The author shows that freelancers either employ constrained or experimental reactivity to the evaluation short term setbacks depending on whether they are high or low performers, and whether the platform is their main source of income ('platform dependence', see also Kuhn and Maleki, 2017). Rather than focusing on how freelancers experience specific instances of evaluations' setbacks, in our study we focus on how freelancers holistically engage with algorithmic scores depending on perceived technology affordances. In other words, the strategies to deal with algorithmic scores are, in our study, more similar to a long term and systematic approach to algorithmic scores – interpreted as an enduring characteristic of freelancers' job – rather than a reaction to something that potentially harms their presence on the platform in the short term. We found pure reactivity only when freelancers could not see affordances provided by algorithmic scores and interpreted scores as a rule of the game. Thus, we more generally argue that a relevant mechanism shaping freelancers' behaviour towards algorithmic scores is their perception of technology affordances when they look at what is visible of algorithms, that is, algorithmic scores. Indeed, as we outlined before, we focus on the visible part of algorithms rather than on their opacity, as other scholars have done (Bucher et al., 2021; Cheng and Foley, 2019; Rahman, 2021).

Our grounded theory further explains the reasons for different reactions to algorithmic control and suggests that temporality matters. Other scholars took a micro perspective and revealed that tactics to deal with algorithms change during a single task's lifecycle (Cameron and Rahman, 2022). We adopted a macro perspective and further claim that behaviours are likely to change according to each freelancer's tenure on the platform. To our best knowledge, we are the first suggesting that there is an initial stage and a 'mature' stage for workers on these platforms, and that their behaviours to deal with algorithms change accordingly. When they are new to the platform and they do not have enough good reviews to have their score visible, freelancers perceive algorithms as constraints and react by complying to the platform's rules to obtain good reviews, e.g., underbilling. Similar practices were described in Bucher and colleagues' work (i.e., workers 'undervaluing their work', (Bucher et al., 2021, p. 56)), but we claim this strategy to be particularly relevant to freelancers' first phase on the platform. Our data suggest that downsizing strategies tend to disappear gradually the longer freelancers stay on platforms and gain positive scores.

Emotions and Algorithmic Scores

Our results allow us to join the current conversation on positive and negative experiences on platforms by focusing on the emotions associated to different algorithmic affordances and behaviours. Although a negative view of algorithms and platforms' mechanisms prevails (e.g., Curchod et al., 2020; Irani, 2015; Rahman, 2021), some scholars have started to acknowledge positive experiences (Bellesia et al., 2019; Deng et al., 2016; Elbanna and Idowu, 2022; Idowu and Elbanna, 2021; Kellogg et al., 2020; Wood et al., 2019). On the one hand, as algorithms increase control over workers, they contribute to workers' feelings of frustration, isolation, uncertainty, and even anger (e.g., Cameron and Rahman, 2022; Wood et al., 2019). On the other hand, algorithmic work can create new, unprecedented opportunities for some workers and can result in energizing their careers (Bellesia et al., 2019; Elbanna and Idowu, 2022; Idowu and Elbanna, 2021).

We believe our findings contribute to a better understanding of *when* negative feelings, such as frustration or anxiety, are likely to arise, and when, instead, freelancers' experience becomes bearable, even exciting. First, we claim that, at the beginning, freelancers are vulnerable, and algorithms strongly constrain their agency (see also Curchod et al., 2020). Thus, at the beginning, freelancers' experience is largely perceived as negative. We further explain that, when freelancers, over time, decide to ignore scores and try to do their best with clients, they face a paradoxical situation in which they feel frustrated, as they have not developed specific behaviours to deal with algorithmic scores. We further show that, when freelancers perceive algorithmic scores as self-extension, they are likely to experience feelings of anxiety and suffer for negative feedback and score drops, even if the negative feelings are here more nuanced than in the previous two circumstances. However, we also show that some freelancers engage positively with algorithms and see them as an opportunity to increase their individual visibility. This way, they also keep emotions under control. In sum, although we acknowledge and confirm that negative feelings are present under certain conditions, our affordance perspective allowed us to investigate when technology is instead likely to turn into a positive experience for freelancers.

However, as a final remark, our results further confirm that the way algorithmic scores are designed create trade-offs in terms of consequences for individuals and platforms (Orlikowski and Scott, 2014). For example, emotion regulation occurs when freelancers interpret algorithmic scores as tools increasing their individual visibility and enact moulding behaviours. However, moulding behaviours potentially lead to negative consequences for the platform itself. Through moulding behaviours, scores are likely to be inflated (Gandini, 2016b; Gandini et al., 2016; Horton et al., 2015). Overall, although algorithmic scores can be useful to reduce information asymmetries, our results show they become costly, either in terms of stressful experiences for freelancers or risks of system manipulations for the platform. This may hamper the claim that algorithmic scores can engender system trust in the platform itself (Jeacle and Carter, 2011).

Limitations, Future Research Directions, and Practical Implications

Our grounded theory suggests that algorithmic scores can provide different affordances or constraints to freelancers. We wondered whether there are possible explanations for freelancers perceiving the technology differently. We searched for this piece of information in our data and found the initial motivation to join the platform as a possible reason. Most of informants perceiving the affordance of individual visibility said they joined GigStars because of specific needs. For instance, most of them simply needed a job to earn money. In contrast, we found that most of informants interpreting scores as self-expansions decided to join to make new experiences, expand their pool of clients, or search for alternative working arrangements, such as more flexibility in working hours or working from home. We further checked for other possible explanations for the different paths, such as profession – i.e., IT developer or designer –, years of experience on the platform, or country, but our profiles appear to be heterogeneous along these dimensions. We still miss a proper explanation for the diversity in affordance perceptions, which would be an important integration to our grounded model. We believe that alternative explanations for the different paths might be hidden in freelancers' experience during the first stage – e.g., mostly negative or positive experiences with clients – or personal traits and attitudes, and thus we encourage future studies to investigate these aspects to extended our grounded theory.

Furthermore, our grounded theory implicitly assumes that, in the second stage, freelancers' tactics and engagement with the technology remain stable over time. The shift in informants' perceptions that we observed is related to algorithmic scores becoming visible on freelancers' profiles. Our theorization would benefit from a longitudinal research design. Such an approach would also contribute to explaining why we also observed a few hybrid responses in our data. For example, three freelancers interpreted scores both as a self-extension and as a tool to increase individual visibility. How the two perceptions interplay over time and affect behavioural and emotional responses can represent an intriguing avenue for future research.

Our evidence comes from a single online platform, and therefore the way GigStars is structured and designed could possibly have influenced our results. We thus encourage further investigation of different platforms to compare new and different strategies. Moreover, the way we chose to reach respondents did not allow us to identify freelancers who did not continue to work for GigStars. To extend and further refine our grounded model, future studies should also include unsuccessful examples to understand whether other, unsuccessful strategies exist. Future studies should then try to consider alternative data collection techniques or alternative sources of data to include these missed informants, such as asking for informants' participation on online forums (e.g., Reddit, Glassdoor).

Although our theory is grounded in the specific setting of online labour markets and we cannot claim generalizability to other contexts, we suspect that the mechanisms described in our model are likely to arise in other settings adopting algorithmically computed scores, for example other gig economy's platforms (e.g., Uber or Lyft, or AirBnb and Tripadvisor) and traditional organizations that increasingly use algorithms to control employees through surveillance systems or eHRM platforms. For example, we can imagine that in a traditional organizational setting adopting algorithmic scores for performance evaluations, affective versus instrumental responses may be influenced by different levels of organizational identification, with affective responses from high identifiers and instrumental responses from low identifiers. We invite future research to explore how workers interpret algorithms in other contemporary work settings.

In terms of practical implications, this study shows that the way algorithmic scores and algorithmic rules are currently designed is very likely to produce deviant behaviours hampering either workers or the score system itself, leading freelancers and clients to distrust it. Although scores on these platforms can be useful tools, they tend to be ambiguous and subjective, despite being designed to be objective and meritocratic. Our practical implications address platform providers, then, and our suggestions are twofold. We first suggest sensitizing clients to how the score system can profoundly impact workers' experience and encouraging a fair use. For instance, our informants revealed they accepted lower payments in exchange for good reviews, which contributes to making their online experience unfair and hampering the platform's reputation. Second, we suggest deemphasizing the importance of scores on freelancers' profiles and allowing workers to attain a better personalization and design of their CV or other quality signals.

CONCLUSION

As online labour markets and other platforms become established workspaces for knowledge intensive freelancers, understanding experiences of algorithmic control and algorithmic management has become centerstage in the debate on the future of work. Our paper extends previous research by underscoring the mechanisms driving different gig workers' behaviours on a major platform. While previous research on algorithms has emphasized issues of control and opacity, we adopted an affordance perspective and proposed that the way gig workers respond to algorithmic management depends on the *possibilities* and *constraints* they *see* in algorithmic scores. We invite future research to further disentangle the trade-off between control and agency in contemporary online work.

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NOTE

[1] Though they had a mixed profile in terms of jobs delivered, these informants fell into the platform's 'IT developer' and 'designer' categories. For instance, they are translators who also perform design tasks, or they are content writers or database administrators who also work on websites. We decided to include them into the 'virtual assistant and translator' broad category as those were the terms they used to describe themselves.

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APPENDIX A
Details on informant

#	*Fictitious Name*	*Job Category*	*Country*	*Sex*	*Education*	*Experience [Years]*	*Hourly Rate*	*Score*
1	Mary	Virtual Assistant	Romania	F	HS Diploma	6	11.25	98%
2	Scott	IT developer	UK/ Romania	M	HS Diploma	3	68.00	89%
3	Ronald	Virtual Assistant	Burkina Faso	M	Master Degree	2	5.00	Building phase
4	Alec	Virtual Assistant	Pakistan	M	Degree	8	5.00	80%
5	Faith	IT developer	Pakistan	F	Bachelor Degree	0.5	5.00	Building phase
6	Rachel	Virtual Assistant	Indonesia	F	Bachelor Degree	1	5.00	100%
7	Ken	Translator	Indonesia	M	Bachelor Degree	3	12.50	100%
8	Paul	IT developer	Slovenia	M	HS Diploma	5	5.00	97%
9	Trevor	IT developer	Croatia	M	Bachelor Degree	1.5	10.00	Building phase
10	Sean	IT developer	Portugal	M	Diploma	7	39.00	100%
11	Robert	IT developer	Italy	M	Getting a PhD	2	20.00	86%
12	August	IT developer	Greece	M	Bachelor Degree	0.8	40.00	Building phase
13	Benjamin	IT developer	Hungary	M	Bachelor Degree	2	25.00	100%
14	Henry	IT developer	Russia	M	Master Degree	2	30.00	100%
15	Xavier	IT developer	UK	M	Degree	2	30.00	100%
16	Allison	IT developer	France	F	Bachelor Degree	1	40.00	100%

(Continues)

APPENDIX A (Continued)

#	*Fictitious Name*	*Job Category*	*Country*	*Sex*	*Education*	*Experience [Years]*	*Hourly Rate*	*Score*
17	Neville	IT developer	Russia	M	Bachelor Degree	3	30.00	100%
18	Jordan	IT developer	Italy	M	HS Diploma	1	10.00	Building phase
19	Justin	IT developer	Spain	M	Bachelor Degree	2	25.00	Building phase
20	Heather	IT developer	Portugal	F	Bachelor Degree	2	24.44	100%
21	Liam	IT developer	Pakistan	M	Master Degree	5	16.50	99%
22	Charles	IT developer	India	M	Bachelor Degree	4	40.00	100%
23	Nancy	IT developer	India	F	Bachelor Degree	3	10.00	97%
24	Mark	IT developer	Bangladesh	M	Degree	3.5	20.00	91%
25	Tommy	IT developer	India	M	Bachelor Degree	7.5	33.33	100%
26	Celia	IT developer	India	F	Degree	3	22.22	100%
27	Brian	IT developer	India	M	Degree	1.5	27.78	Building phase
28	Jamey	IT developer	Pakistan	M	Bachelor Degree	2	30.00	100%
29	Marcus	Translator	Norway	M	Bachelor Degree	6	44.44	96%
30	Brad	Designer	Serbia	M	Bachelor Degree	2	15.00	100%
31	Kate	Designer	Italy	F	Bachelor Degree	2	16.67	98%
32	Megan	Designer	Spain	F	Bachelor Degree	1	10.00	82%
33	Lily	Designer	Spain	F	Degree	1.5	9.00	100%
34	Joe	Designer	Spain	M	HS Diploma	4	39.00	100%
35	Reece	Designer	Ukraine	M	Bachelor Degree	3	10.00	99%
36	Susan	Designer	Ireland	F	Master Degree	2	40.00	100%
37	Malcom	Designer	Serbia	M	Degree	4.5	24.00	95%
38	Adam	Designer	Spain/Italy	M	Professional Specialization	5	45.00	100%
39	Jane	Designer	US	F	Degree	4	30.00	100%
40	Victoria	Designer	US	F	Bachelor Degree	2	25.00	100%

APPENDIX A (Continued)

#	*Fictitious Name*	*Job Category*	*Country*	*Sex*	*Education*	*Experience [Years]*	*Hourly Rate*	*Score*
41	Mia	Designer	US	F	Bachelor Degree	3	15.00	94%
42	Grace	Designer	US	F	Professional Specialization	2	45.00	95%
43	Harry	Designer	US	M	First degree	0.5	50.00	90%
44	Roy	Designer	US	M	Bachelor Degree	1	30.00	98%
45	Sophia	Designer	US	F	Bachelor Degree	5	60.00	100%
46	Tracy	Designer	US	F	First Degree	2	110.00	100%
47	Daniel	Designer	UK	M	Bachelor Degree	2.5	50.00	92%
48	Kelly	Designer	Portugal	F	Bachelor Degree	1	20.00	100%
49	Michael	Designer	Hungary	M	First degree	9	28.00	92%
50	Helen	Designer	France	F	First degree	4	30.00	100%
51	Cameron	Designer	Spain	M	Bachelor Degree	3	35.00	100%
52	Jake	Designer	Italy	M	Bachelor Degree	3	30.00	89%
53	Olivia	Designer	Italy	F	Master Degree	3	78.00	100%
54	Kirsten	Designer	UK	F	Master Degree	3	27.00	87%
55	Amanda	Designer	Italy	F	Bachelor Degree	2	20.00	97%
56	Brittany	Designer	Italy	F	HS Diploma	2	30.00	100%
57	Norman	IT developer	Ukraine	M	Online specialization	1	25.00	100%
58	William	IT developer	India	M	Bachelor Degree	3	26.00	94%
59	Christopher	IT developer	Germany	M	Getting a PhD	2	70.00	100%
60	Ethan	IT developer	India	F	Online specialization	1	10.00	100%
61	Amelia	Designer	Germany	F	HS Diploma	8	25.00	89%
62	Emily	IT developer	Netherlands	M	Bachelor Degree	7	50.00	100%
63	Oliver	IT developer	Philippines	M	HS Diploma	3	6.50	86%
64	Kyle	IT developer	Netherlands	M	HS Diploma	3	30.00	98%
65	Rudy	IT developer	UK	M	HS Diploma	3	50.00	75%
66	Neville	IT developer	Italy	M	HS Diploma	2	25.00	83%