Algorithmic work-life balance:

How algorithms influence gig-workers perceptions of work-life boundaries on platforms

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Abstract

With the rising trend of individuals embracing freelance work on online labor markets, it becomes crucial to comprehend how platforms and algorithms influence their experiences of well-being. This study employs a mixed methods approach to explore the effects of platforms and various algorithms, including matching, control, and rating algorithms, on freelancers' work-life balance. Drawing on preliminary data collected through surveys and interviews with freelancers on a major online labor market platform, our findings reveal that control and rating algorithms negatively impact work-life balance by amplifying feelings of insecurity among freelancers. However, we also discovered that freelancers who perceive the platform they work on as useful exhibit greater proficiency in navigating the boundaries between their work and family life. Our study sheds light on the intricate dynamics between platforms, algorithms, well-being, and work-life balance for freelancers and emphasizes the need for further exploration of algorithmic interventions that promote work-life balance in the online freelance context.

Keyword: work-life balance, platforms, algorithms, crowdworkers

1. Introduction

Digital platforms such as Upwork and Freelancer.com have become a popular mean to connect dispersed buyers and sellers of knowledge intensive services, and scholarly interest in the dynamics occurring in these digital workplaces is growing day by day (e.g. Cameron & Rahman, 2022; Elbanna & Idowu, 2022; Veen et al., 2020; Wood et al., 2019). Through these platforms, organizations and individuals can access a wide pool of talents (e.g., software development, web design, editing, design, etc.) and find the specific skills and competences they need to deliver tasks. On the other hand, freelancers, or crowdworkers (e.g. Elbanna & Idowu, 2022; Idowu & Elbanna, 2021), can access unprecedent work opportunities located worldwide by simply subscribing and filling an online profile with their educational background and skills.

Despite these positive aspects, online platforms are attracting scholarly attention because of their inherent algorithmic logics, which structure the way the freelancers who offer services are managed and evaluated (e.g. Bellesia et al., 2023; Bucher et al., 2021; Möhlmann et al., 2021; Rahman, 2021). For instance, algorithms calculate workers' performance from clients' feedback to reduce information asymmetries between parties. Algorithms are also responsible for matching clients and gig workers and define workers' rankings when clients search for an online freelancer. In addition, algorithms are used to monitor and surveil the work of freelancers during the delivery of their services, ensuring their active engagement in the assigned gigs. Algorithmic logics impact gig workers' job opportunities profoundly, and the risks of an 'algocracy' (Gandini, 2016) are being recently widely discussed in the management literature (Kellogg et al., 2020; Kuhn & Maleki, 2017; Newlands et al., 2018; Wood et al., 2019). As algorithms are opaque and increase control over workers (Kellogg et al., 2020; Rahman, 2021; Veen et al., 2020), they contribute to feelings of frustration, isolation, uncertainty, and even anger (e.g. Irani, 2015; Wood et al., 2019). However, algorithmic work can create new opportunities for some workers and can result in energizing their careers and lives (Bellesia et al., 2019; Idowu & Elbanna, 2021). Taken together, these findings suggest potentially negative, but also positive implications for the overall wellbeing of workers and, more specifically, their work life-balance, i.e. 'satisfaction and good functioning at work and at home' (Campbell Clark, 2000, p. 751).

While most of previous studies focus on how gig workers react to and circumvent algorithmic power (Bellesia et al., 2023; Bucher et al., 2021; Cameron, 2022; Cameron & Rahman, 2022; Curchod et al., 2020; Möhlmann et al., 2021), scholars have only recently started to question the way algorithmic management impacts on workers' well-being and, more specifically, work-life balance (Kellogg et al., 2020; Wood et al., 2019). Following scholars in the work-life balance research stream, who have recently started to account for the role played by technologies in contemporary flexible working arrangements (e.g. Choroszewicz & Kay, 2020; Derks & Bakker, 2014; Fonner & Stache, 2012; Gold & Mustafa, 2013), the aim of our study is to contribute to the emerging research field of worker's wellbeing on platforms by understanding how freelancers perceive and manage their work-life boundaries on platforms while being under algorithmic control. The aim of this study is therefore addressing the following research question: *How do algorithms and platforms influence crowdworkers' well-being, and more specifically their perception of work-life balance?* Indeed, despite work on platforms is, to some extent, flexible, flexibility seems to come with a (algorithmic) price, thus creating a theoretical puzzle. Addressing such a puzzle is important because new forms of work arrangements are becoming ubiquitous nowadays and, more generally, we live in times where maintaining a clear distinction between work and non-work domains has become increasingly challenging (MacCormick et al., 2012; Schieman & Glavin, 2015).

In this paper, we present preliminary results from an on-going study trying to unpack the effect of algorithms, and platforms in general, on crowdworkers' perception of work-life balance. This is a mixed-method study which gathers quantitative data from surveys and qualitative insights from semi-structured interviews. So far, our sample consists of 113 crowdworkers who completed the first of two surveys and 6 semi-structured interviews. The rest of the paper presents our theoretical background including a set of preliminary hypotheses. Then, we discuss how we are collecting data and present our preliminary results. We conclude this paper with expected contributions for theory and practice.

2. Theoretical Background

To achieve work-life balance, workers need to manage the relationship between their work and non-work domains (Sturges, 2012), so that the transition from one domain to the other requires to cross role boundaries (Ashforth et al., 2000). Workers need to cross boundaries daily, and this transition is said to be less or more difficult depending on the degree of boundary segmentation and integration (Ashforth et al., 2000; Campbell Clark, 2000). Over the years, scholars have been concerned with the antecedents and consequences of achieving a satisfying work-life balance (see Sirgy & Lee, 2018 for a review). To this regard, organizations play an important role in helping individuals minimizing conflict between family and work through a number of family policies or other forms of support (Batt & Valcour, 2003; Sirgy & Lee, 2018). However, this type of support is likely to be absent for workers in newer forms of work arrangements, and less is understood of how the relationship between work and life is negotiated by people with flexible working arrangements, like platform workers and employees of the gig economy (Kelliher et al., 2019).

Taking strides toward comprehending non-traditional forms of work and the dynamics of work-life balance, scholars have started to acknowledge the role played by technologies embedded in contemporary flexible working arrangements, such as telework, gig work, and online freelancers (e.g. Choroszewicz & Kay, 2020; Derks & Bakker, 2014; Fonner & Stache, 2012; Gold & Mustafa, 2013). For instance, Gold and Mustafa (2013) reveal that connected freelancers are likely to work irregular hours and that clients 'colonize' their life sphere. Relatedly, teleworkers prefer segmenting their work using rituals to manage work-life transitions, like purposefully using technology (e.g. smartphones, Choroszewicz and Kay, 2020) to disconnect from the organization's network, sticking to their work schedule, and separating the space for work and space for family in their houses (Fonner & Stache, 2012).

Platforms workers are likely to engage in similar struggles. For instance, workers in emerging and developing countries are said to work unsocial and irregular hours to deal with time-zones differences (Wood et al., 2019). Especially at the very beginning of their career on platforms, they are compelled to remain constantly connected online, as they need to monitor new job notifications and search for new job opportunities persistently (Bellesia et al., 2019). As a consequence, they deal with unpredictability and oscillations in the amount of work to be performed. Furthermore, to thrive and survive on platforms (Ashford et al., 2018), workers need to "deal with" algorithms. Algorithmically computed scores (i.e., a public 0-100 points evaluation on freelancers' profiles) keep track of workers' past performance and work with opaque rules. Sudden changes in scores are likely to occur, which push workers towards over-delivering and complying to algorithmic rules to avoid negative scores (e.g. Bucher et al., 2021). While most of previous studies focus on how gig workers react to and circumvent algorithmic power (Bellesia et al., 2023; Bucher et al., 2021; Cameron, 2022; Cameron & Rahman, 2022; Curchod et al., 2020; Möhlmann et al., 2021), there is a lack of empirical studies focusing on the specific link between algorithms and well-being.

3. Preliminary Hypotheses Development

To understand the effect of algorithms on work-life balance, we first need to underscore that different types of algorithms exist (e.g. Kellogg et al., 2020; Möhlmann et al., 2021). So far, most studies have focused on *rating algorithms* – i.e., algorithms that compute scores - (e.g. Bellesia et al., 2023; Cameron & Rahman, 2022; Rahman, 2021). In addition, *control algorithms* are responsible for reminding workers to use the platform's systems to communicate with clients or that they should run contracts and payments through Upwork. They sometime actively monitor that freelancers actually work on a project and remain engaged with a client, for example by using time trackers and taking screenshots. *Matching algorithms* propose new jobs to workers or suggest workers to clients. As these algorithms work differently to manage workers on platforms, they are also likely to have different – both positive and negative – impacts on people' work and, ultimately on their perception of well-being (Möhlmann et al., 2021). Moreover, following traditional studies on technology acceptance (Davis, 1989; Venkatesh & Goyal, 2010; Venkatesh & Davis, 2000), the platform itself can also be conceptualized as a technology artifact that is more or less "acceptable" to gig workers. As such, in this paper we study the effects of the underneath platform's technology by disentangling the effects of the different algorithms and of the platform's features.

Figure 1 illustrates our initial hypotheses on how the three main types of algorithms, and the platform in general, may affect perceptions of work-life balance through different mechanisms, i.e.

feelings of techno-insecurity, perceived affordances, and perceived technology usefulness (see Figure 1 for a summary of our hypotheses and anticipation of main results).

------ Insert Figure 1 about here -----

3.1 Techno-insecurity, control algorithms, and WLB

When individuals have to deal with new technology, they are likely to experience *technostress,* which is stress experienced by individuals due to the use of ICTs (Ragu-Nathan et al., 2008). According to Ragu-Nathan and colleagues (2008), different are the factors triggering either high or low levels of technostress. Among the others, *techno-insecurity* captures how much individuals are afraid of losing their jobs because of the way technology works or because peers know more about how technology works. Techno-insecurity is listed among the factors that create technostress – i.e., technostress creators (Ragu-Nathan et al., 2008). On the other hand, previous literature has also shown that technology can provide users with action possibilities and opportunities that emerge when they engage with the technology itself – i.e., technology affordances (Faraj & Azad, 2012, p. 241; Nevo et al., 2021). As such, technology may also have positive effects when individuals engage with a focal technology.

Control algorithms limit what workers can do on a platform. They are responsible for suspending workers' accounts in case of suspicious behaviors, or taking screenshots of workers' activity during hourly contracts (Kellogg et al., 2020). These actions limit crowdworkers' autonomy on the platform. Thus, we hypothesize that dealing with control algorithms is likely to create stress related to technology, as crowdworkers may experience a constant sense of surveillance and fear of acting inappropriately, contrary to platform's expectations. To avoid suspensions or loss of job opportunities, crowdworkers invest time on keeping themselves informed about platform's rules, negotiating contracts' terms that align with the platform's expectations and, when in doubt, chatting with the platform's support system to gain clarity on appropriate conduct. This additional time devoted to handling control algorithms compounds the "paid" working time for crowdworkers. In addition to the time spent on delivering activities compensated by clients, they must allocate extra time to navigate control algorithms, potentially unbalancing the relation between time dedicate to work and time dedicate to personal life.

For all of the above, we thus hypothesize a negative effect of control algorithms on work-life balance. As they may make crowdworkers feel insecure about their job opportunities, control algorithms are likely to drive techno-insecurity, leading to a negative effect on work-life balance..

H1: Techno-insecurity related to control algorithms reduces crowdworkers' work-life balance.

3.2 Techno-insecurity, rating algorithms, and WLB

Recent literature on crowdwork and crowdworkers' reactions to rating algorithms suggests a similar, negative effect of rating algorithms on perception of work-life balance. First, this literature agrees that workers do not have full information about how rating algorithms work and algorithmic scores are computed – i.e., algorithmic opacity (e.g. Gandini et al., 2016; Rahman, 2021; Veen et al., 2020). If, on the one hand, algorithmic opacity levels the field for crowdworkers and protects them from other crowdworkers trying to game the system, on the other hand, opacity tends to make crowdworkers over-accountable for their behaviors (Jarrahi et al., 2020). For instance, on platforms like Upwork, crowdworkers are penalized when clients forget to close open contracts, as rating algorithms downgrade crowdworkers' score if contracts hold inactive for a long period of time. As negative algorithmic scores prevent workers from finding new job opportunities, rating algorithms might be responsible for techno-insecurity. As a consequence of rating algorithms' functioning, the literature has shown that crowdworkers are "forced" to adjust their behaviors to avoid negative evaluations and continue their work on platforms (e.g., Cameron & Rahman, 2022; Bucher et al., 2021; Curchod et al., 2020). This adjustment includes, for instance, delivering more, smaller jobs to increase their score or feeding rating algorithms with positive evaluations. Engaging in such adjustment behaviors can be time-consuming and emotionally draining, often encroaching into one's personal life. We thus hypothesize that:

H2: Techno-insecurity related to rating algorithms reduces crowdworkers' work-life balance.

3.3 Affordances, rating algorithms, and WLB

Some studies have highlighted that rating algorithms can also have positive implications for workers. For instance, some literature shows that high scores on crowdworkers' profiles, as well as positive evaluations from clients, can be purposefully used by crowdworkers to market themselves on platforms, so that algorithmic scores provide the affordance of individual visibility (Bellesia et al., 2023) by communicating the reliability and ability of crowdworkers to deliver quality to potential clients. Consequently, algorithmic scores have the potential to assist workers in accessing unforeseen opportunities (Deng et al., 2016; Wood et al., 2019) and augment their earnings on platforms (Idowu and Elbanna, 2020; Möhlmann et al., 2021). Through rating algorithms, crowdworkers might then have the opportunity to choose the jobs which better suit their needs and schedule, thus helping them better balancing their work and non-work roles. As a consequence, algorithmic scores may increase workers' sense of autonomy in their personal and professional development (e.g. Bellesia et al., 2019; Idowu & Elbanna, 2021), and may thus improve their experiences of work-life balance.

H3: Rating algorithms' affordances positively affect crowdworkers' perception of work-life balance.

3.4 Affordances, matching algorithms, and WLB

Like the positive effect of rating algorithms, work-life balance is likely to be enhanced by the action of matching algorithms, too. Through keywords associated with jobs and crowdworkers' competences, and filtering criteria, matching algorithms facilitate crowdworkers' search for new jobs (Cameron & Rahman, 2022; Kellogg et al., 2020). In order to circumvent disputes, negative experiences with clients, and wasting time on endless job requests, crowdworkers often opt to select prospective clients based on factors such as location or payment method (e.g., Bucher et al., 2021; Bellesia et al., 2023). In a similar fashion, matching algorithms suggest workers' potential job opportunities, reducing the time they need to spend on platforms to find new jobs. When crowdworkers perceive that matching algorithms guarantee more autonomy in their everyday job decisions and enhance their decision-making power, they might also be able to better navigate between their work and non-work domains.

H4: Matching algorithms' affordances positively affect workers' perception of work-life balance

3.5 Usefulness, platforms, and WLB

Following traditional studies on technology acceptance (Davis, 1989; Venkatesh & Goyal, 2010; Venkatesh & Davis, 2000), the platform itself (e.g., Upwork) can be conceptualized as a technology artifact that is more or less "acceptable" to crowdworkers. According to these studies, perceived *platform usefulness* is the degree to which an individual thinks that using a particular platform will improve his or her job performance. For some workers, platforms represent a major source of income (e.g. Kuhn & Maleki, 2017), likely increasing their perception of usefulness of the platform. Similarly, some studies highlight how online platforms help workers meet unforeseen work opportunities and can result in energizing their careers and lives (Bellesia et al., 2019; Idowu & Elbanna, 2021). Moreover, platforms have been recently found to be useful for crowdworkers to significantly supplement their income (e.g. Ravenelle et al., 2021). As they also allow crowdworkers to choose the jobs they would like to deliver, and when to deliver them, platforms may support their attempt to better balance their work and personal life duties, thus increasing their perception of work-life balance. ~~Finally, the perception of platform usefulness can foster the capability of individuals to move between work and non-work demands effortlessly (e.g. Valcour, 2007).~~

H5: Perceived platform usefulness affect workers' perception of work-Life balance.

4. Data and Methods

To empirically test our hypotheses, we are reaching out to crowdworkers from a major knowledge intensive platform. We are conducting a mixed method study (Creswell & Clark, 2003) and triangulating quantitative data from surveys with semi-structured interviews with our participants. We chose this research design to complement quantitative data with qualitative insights from the field whose scope is to provide more details on hypothesized relationships and their underlying mechanisms.

4.1. Research Setting

We are recruiting participants from a major knowledge intensive platform which hosts both requests for short and more complex jobs, like graphic design, virtual assistance, software and mobile apps development, and translations. Client organizations can post their requests for tasks and then search for talents with required competences and abilities. This search is sustained by *matching algorithms*, which match keywords and characteristics of the job with workers' abilities and availability. In other words, matching algorithms help clients and workers filtering job opportunities and potential talents, suggesting potential workers to clients and potential job opportunities to workers.

After a match occurs, clients and crowdworkers typically agree on the tasks to be performed and start their collaboration by signing a contract through the platform. Then, interactions take place entirely at a distance and are fostered and constrained by other types of algorithms. For instance, the platform uses *rating algorithms* to compute algorithmic scores. These are 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 signaling 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 crowdworkers. Crowdworkers are also subject to *control algorithms*. These algorithms are responsible for suspending crowdworkers' account, taking screenshots when they perform hourly jobs, reminding parties to use the platform to communicate. Both clients and crowdworkers do not have perfect information on how all these types of algorithms work.

4.2. Data collection and Sample

We are recruiting participants by posting the request for participation directly on the platform and offering 20$ as a reward for completing two surveys. We are interested in crowdworkers who have at least 10 completed jobs on the platform aand that belong to either the IT developers, designers, and translators' categories. We are interested in crowdworkers from different regions of the world (e.g., Europe, US, and Asia).

Crowdworkers are asked to complete two surveys at a one-month time distance to avoid common method bias. As such, the first survey gathers respondents' demographic information (e.g., gender, years spent on the platform, number of children) and measure our independent variables. In the second survey, crowdworkers are asked to fill measures related to work-life balance.

So far, we have collected data from 113 participants in the first survey. Therefore, this paper discusses preliminary insights and relations that we are finding in this subsample. The sample is quite balanced in terms of gender (51.3% are males, 48.7 are females) and regions of the world (60% of the sample is from Europe and Northern America, 40% from Asia, Africa, and Oceania). In terms of job category, 34.5% of respondents are writers and translators, 25.7% are designers, 26.5% are developers and 13.3% fall into the 'Others' category. 73.2% of respondents holds either a bachelor's or master's degree. Almost half of the sample has less than 3 years of experience on the platform (42.5%).

4.3. Measures

All measures in this study used a five-point Likert scale where 1 = strongly disagree and 5 = strongly agree, unless otherwise indicated. Items were averaged within the scales to create composite measures for each variable. Items were coded such that higher scores equate to higher levels of the construct of interest. All scales' Cronbach alphas are greater than 0.75.

4.3.1. Dependent variable

To measure crowdworkers' perception of *work-life balance (WLB)*, we used the 5-item, newly developed scale of global work-nonwork balance (Wayne et al., 2021). We used this measure as it allows, first, to assess a global perception of balance between work and non-work roles, including roles that are not limited to the family sphere. Second, compared to other measures of balance (e.g. Carlson et al., 2009), it does not take into account expectations from employing organizations or family members. This suits well with the purpose of our study, as we are studying work-life balance of self-employed workers without a referent employing organization.

4.3.2. Independent variables

Control algorithms' techno-insecurity (ContIns). We measure crowdworkers' perception of insecurity related to control algorithms through one of the dimensions of technostress, that is techno-insecurity (Ragu-Nathan et al., 2008). We took the 5-item scale and slightly adapt the items to fit the platform's context.

Rating algorithms' techno-insecurity (RatIns). Similarly, we measure crowdworkers' perception of insecurity related to rating algorithms through one of the dimensions of technostress, that is techno-insecurity (Ragu-Nathan et al., 2008). We took the 5-item scale and slightly adapt the items to fit the platform's context.

Matching algorithms' Affordances (MatchAff). In our HP4 we hypothesized a positive impact of matching algorithms on work-life balance. In order to capture the positive aspects related to algorithms, we leveraged the concept of *technology affordances*. Technology affordances are "action possibilities and opportunities that emerge from actors engaging with a focal technology" (Faraj & Azad, 2012, p. 241). Through the concept of affordances, we aimed to capture crowdworkers' perceptions that algorithms could create (job) opportunities for them. To do that, we used the measure of in-role affordances developed by Nevo and colleagues (Nevo et al., 2021).

Rating algorithms' Affordances (RatAff). Similar to what we did for matching algorithms, we measured rating algorithms' in-role affordances through the measure developed by Nevo and colleagues (Nevo et al., 2021).

Platform's Usefulness (Usefulness). To measure crowdworkers' perceptions of platform's usefulness, which is a very well-established concept in the literature, we used the shortest version of the traditional scale developed by Chin and colleagues (Chin et al., 2008).

4.3.3. Control variables

Our hypothesized relations might be affected by a range of individual variables we controlled for.

Gender. We controlled for gender, which we measured as a categorical variable (0=male, 1=female, 2=non-binary, 3=others).

Age. This is a continuous variables meant to gather participant's age.

MainSource. The crowdwork literature suggests that the crowdworkers' perceived platform dependance is likely to affect how much they feel controlled by algorithms (Kuhn & Maleki, 2017; Rahman, 2021). We asked participants how much (in percentage) they would consider the platform as their main source of income and include this variable in our models.

YearsPlatform. As the more experienced crowdworkers may have found ways to circumvent algorithmic actions (e.g. Bellesia et al., 2023), we controlled for participants' tenure on the platform. This was a categorical variable with four different options.

Score. Because crowdworkers' success on the platform may be related to their perception of the platform's usefulness, we also controlled for their computed score on the platform.

JobCategory. As we are interested in the effect of algorithms, we suspected that crowdworkers holding a background in IT might have more knowledge on algorithmic functioning, and therefore perceive to be less affected by their actions. As such, we controlled for participants' job category in our models. This dummy variable is 1 when the freelancer has a background in IT, 0 otherwise.

Region. Finally, we controlled for participants' living country in order to exclude some location-based effects.

To test our preliminary hypotheses, we run a series of linear regressions models whose results are presented in Table 2.

4.4. Semi-structured Interviews

At the end of the surveys, respondents are invited to participate in a follow-up semi-structured interview. Interviews last about one hour and are concerned with how workers balance their work-family duties, which strategies they have developed to manage boundaries, what is their perception of the boundary given platform's use of algorithms, how and how much platforms' rules (i.e., the feedback system, matching algorithms) contribute to shape their work-life balance strategies. We have conducted 6 interviews so far.

Following a mixed-method triangulation design (Creswell & Clark, 2003), we plan to compare and contrast qualitative findings from the interviews with quantitative results from the surveys.

5. Preliminary Results

In this section, we provide preliminary results of our study. Table 1 provides correlations between our variables. Table 2 provides instead results from our preliminary linear regressions.

------ Insert Table 1 about here -----

------ Insert Table 2 about here -----

Specifically, in Model 1 we tested for the effects of our control variables. The model does not prove itself significant in explaining variance in the level of the dependent variable (F=0.384, *p=0.888*), and the coefficients are not significant. This means that work-life balance is not a consequence of gender, age, country of origin, dependance on the platform, type of job, and platform's tenure.

As far as algorithms are concerned, we tested for their effects in models 2 to 5. This means that, along with control variables, each model tests an effect of algorithms on crowdworkers' work-life balance. In models 2 and 3, we found support for H1 and H2 respectively. Both rating and control algorithms' insecurity hold indeed a significant negative effect on work-life balance. The more individuals feel insecure about how control and rating algorithms work, the lower their perceived work-life balance.

Model 4 provides results for the relation between rating algorithms' affordances and work-life balance (H3), that is, it tests for the positive effect of rating algorithms on work-life balance. We did not found support for H3 (p=0.240). We obtained a similar result when we tested for H4 in Model 5.

Specifically, we tested for the positive effect of the affordances provided by matching algorithms on work-life balance. Again, contrary to our expectations, this effect is not significant (p=0.233). We conclude that, based on our preliminary analysis, the affordances of algorithms do not drive any increase or decrease in our respondents' perceptions of work-life balance.

Finally, in model 6, we tested for the effect of platform's usefulness on work-life balance (HP5). Our results show a positive, significant effect, which means that the more crowdworkers perceive the platform as useful to their work, the higher their perception of work-life balance.

In sum, as represented in Figure 1, our preliminary results support our HPs 1, 2, and 5. We did not find support for HPs 3 and 4.

6. Discussion

Our preliminary results seem to corroborate the negative effect of algorithms on crowdworkers' well-being, which we capture here through the concept of work-life balance. Specifically, we measured techno-insecurity related to control and rating algorithms and found that this reduces crowdworkers' work-life balance. We claim that, as control and rating algorithms trigger reactions to algorithmic opacity, adjusting behaviors exceed the regular time devoted to job delivery, and thus may steal time to crowdworkers' personal life. This interpretation resonates with previous studies in the crowdwork literature (Bellesia et al., 2023; Bucher et al., 2021; Möhlmann et al., 2021; Rahman, 2021).

Though we hypothesized also a positive effect of algorithms on work-life balance via the concept of affordances (Faraj & Azad, 2012), so far, our analyses do not seem to support our claims. Our preliminary evidence supports a negative, rather than positive impact of rating algorithms on work-life balance. Surprisingly, the hypothesized positive effect of matching algorithms is also not significant. One plausible explanation for the lack of observed positive impact is that, while matching algorithms bring to the fore a greater number of work opportunities, the time required to review and assess the suggested opportunities may offset the potential positive effect. When busy with ongoing projects, crowdworkers often make the decision to skip new opportunities. This selective behavior can introduce bias in their perception of the affordances of matching algorithms.

In terms of positive effects on work-life balance, our results support the idea that the platform, as a working environment and as an overarching technology with specific features, might be perceived as a useful vehicle of positive spillovers between professional and personal lives, for example in relation to autonomy and flexibility, thus enhancing their perception of work-life balance. Interestingly, our results suggest that although algorithms tend to have negative implications for individual wellbeing, the contextual environment provided by the platform is positively interpreted by crowdworkers.

This study is meant to assess how gig workers perceive work-life balance, given the high degree of uncertainty embedded in their work (Ashford et al., 2018). The goal is to disentangle the technological dimension represented by platforms and algorithms to further theorize experiences of work-life balance. Our findings are also expected to illuminate the different strategies used by gig workers to manage their work-family boundaries, contributing to previous findings on work-life balance in the digital age (e.g. Fonner & Stache, 2012; Gold & Mustafa, 2013; Kossek, 2016).

This research has prominent importance as more and more people will become workers of the so called ‘gig economy’ (Kessler, 2018), especially in the post-pandemic world (Ozimek, 2020). There seems to be poor understanding about how workers in flexible, non-standard working arrangements achieve a satisfying work-life balance (e.g. Kelliher et al., 2019). Given the precarious conditions of the gig economy’s workforce, new reflections are needed on the meaning of work-life balance (Ashford et al., 2018). By building on employees’ strategies to manage and cross work-life boundaries (Ashforth et al., 2000; Campbell Clark, 2000; Choroszewicz & Kay, 2020; Sturges, 2012) and on previous findings on work-life balance in the digital age (Fonner & Stache, 2012; Gold & Mustafa, 2013; Hilbrecht et al., 2013; Hilbrecht & Lero, 2014; Kossek, 2016), we plan to extend theories of work life balance of gig workers. Simultaneously, we join the emerging conversation on algorithmic work, by assessing the impact of algorithms on how gig workers manage their work-life boundary. So far, the identified negative implications of control and rating algorithms on work-life balance underscore the importance of designing algorithms that consider the well-being of freelancers. Moreover, the positive association between platform usefulness and work life balance highlights the potential for platforms to foster healthier boundaries between work and life experiences..

References

Figure 1. Hypothesized relations (green arrows represents supported hypotheses).

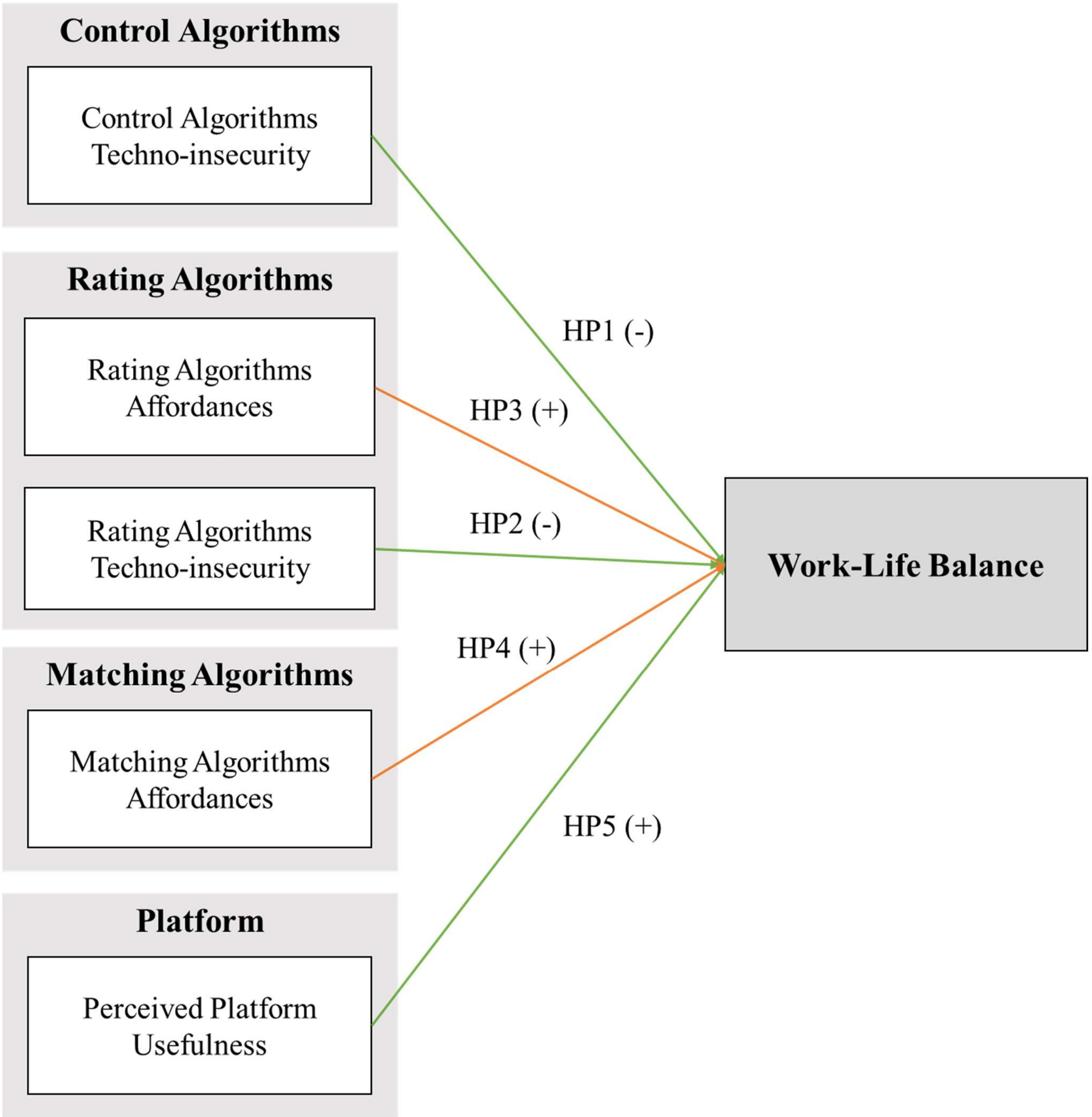

Table 1. Correlations.

	1	2	3	4	5	6	7	8	9	10	11	12
Control variables												
1. Gender	1											
2. Age	,105	1										
3. Region	-,105	-,286**	1									
4. MainSource	-,163	,156	,065	1								
5. YearsPlatform	,065	,287**	-,258**	,047	1							
6. JobCategory	,055	,015	-,276**	,104	,107	1						
Independent variables												
7. Usefulness	,022	-,095	,167	,323**	-,054	-,003	1					
8. RatIns	-,016	-,092	,066	-,228*	,048	-,071	-,293**	1				
9. ContIns	-,001	-,066	-,023	-,228*	,149	-,057	-,241*	,871**	1			
10. MatchAff	,097	,062	,057	,241*	,116	,019	,476**	-,053	-,139	1		
11. RatAff	,171	-,076	,050	,139	-,109	,051	,274**	-,001	-,080	,735**	1	
Dependent variable												
12. WLB	-,106	-,061	,047	,025	-,101	-,031	,266**	-,342**	-,364**	,100	,107	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 2. Results of linear models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
1. Gender	-0.093	-0.114	-0.103	0.084	-0.112	-0.054
2. Age	-0.029	-0.037	-0.032	-0.015	-0.002	-0.043
3. Region	,000	0.021	0.040	0.012	0.007	-0.086
4. MainSource	0.020	-0.079	-0.079	-0.013	-0.010	-0.103
5. YearsPlatform	-0.085	-0.017	-0.048	-0.106	-0.076	-0.098
6. JobCategory	-0.019	-0.040	-0.038	-0.023	-0.034	-0.010
Independent variables						
7. Usefulness						0.305**
8. RatIns			-0.368**			
9. ContIns		-0.383**				
10. MatchAff					0.120	
11. RatAff				0.124		

** p < 0.01, * p < 0.05