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Algorithmic management of crowdworkers: Implications for workers' identity, belonging, and meaningfulness of work

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ABSTRACT

Online labor platforms function as meta-organizations, blending elements of an open market and hierarchical structure by algorithmically governing goals and objectives. This study investigates how this algorithmic management approach influences the perceived meaningfulness of work among crowdworkers, with a particular focus on its effects through identity and belonging. Drawing on survey data collected from 1291 crowdworkers, our findings highlight that algorithmic control and algorithmic matching are differently associated with the meaningfulness of work. Algorithmic control, characterized by directive oversight, exhibits a negative association with perceived meaningfulness. In contrast, algorithmic matching, which pairs workers with online tasks, fosters a positive perception of meaningfulness. We demonstrate that these associations are (partially) mediated by identity and belonging mechanisms. Specifically, we demonstrate that crowdworkers tend to self-organize support and social confirmation using online communities, which provides a sense of meaningfulness. This research advances our understanding of the experiences of crowdworkers within online labor platforms, shedding light on the multifaceted implications of algorithmic management. It emphasizes the importance of fostering supportive and communicative environments in work settings characterized by algorithmic governance mechanisms.

1. Introduction

Digitization in society has given rise to the creation of new ways of working and employment models, collectively known as the gig economy (Durward, Blohm, & Leimeister, 2020). Gig work refers to short-term tasks organized and mediated by digital labor platforms (Heeks, Graham, Mungai, Van Belle, & Woodcock, 2021). The gig economy presents a fundamentally new way of thinking about work and employment relationships by decoupling individuals from a distinct hierarchy or management structure (Duggan et al., 2019). Over the past two decades, platform work has evolved from a niche pursuit to an increasingly established phenomenon across the (European) labor market. There are many different forms of platform work, including app-work (e.g., Uber, Deliveroo), capital platform work (e.g., Etsy), and crowdwork (e.g., Amazon Mturk) (Duggan et al., 2019).

While many studies have articulated concerns over the precarity of working conditions in the gig economy more broadly (Berg, 2015; Duffy et al., 2017; Graham et al., 2020; Heeks et al., 2021; Vognoli et al., 2020; Wood, Graham, Lehdonvirta, & Hjorth, 2019; Woodcock & Graham, 2019), crowdwork is quickly becoming a widespread phenomenon, both in the number of platforms (e.g., Amazon Mturk, Appen, Clickworker, Figure Eight, Microworkers, Prolific, and Toloka) and the number of workers (Durward et al., 2020). The use of crowdworkers is rapidly expanding beyond small start-ups with large technology conglomerates like Google, LinkedIn, and Meta, and well-established firms in "traditional" sectors such as Unilever and Walmart are increasingly calling upon this workforce (Shestakofsky, 2017). If we are to take crowdwork seriously as a major transformation in the world of work, more empirical evidence of the experiences and outcomes of these workers is needed (Idowu & Elbanna, 2021).

We focus on a specific form of platform labor known as "crowdwork" because, even more so than other forms of labor in the gig economy – e.g., app-work, crowdwork remains largely hidden from the public eye and societal debate (Gray & Suri, 2019) and particularly susceptible to

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precarity (van Zoonen, ter Hoeven, & Morgan, 2023). The use of this type of hidden human labor is crucial to meet society's increasing demand for automation and artificially intelligent solutions (Roberts, 2019; Ross, Irani, Silberman, Zaldivar, & Tomlinson, 2010). We define crowdwork as encompassing 1) the completion of digital tasks which are 2) predefined by requesters and 3) distributed through an online platform 4) to a large number of workers 5) for some compensation (Bucher, Schou, & Waldkirch, 2021).

Academic and societal debates often chronicle the deplorable working conditions for platform workers, and discuss issues like wage theft, lack of (social) support, and unilateral algorithmic decision-making. As such, the labor conditions for crowdworkers often present a disenchanting everyday reality as crowdwork is enacted through a largely unseen and error-prone management system (Kost, Fieseler, & Wong, 2018; Vallas & Schor, 2020). This algorithmic management of workers impacts and shapes platform workers' behaviors and experiences. In particular, research has suggested that gig workers may experience tensions related to belongingness (Möhlmann, Zalmanson, Henfridsson, & Gregory, 2020) and professional identities (Caza, Reid, Ashford, & Granger, 2021). Identity challenges may become salient as gig workers lack clear anchors of identity-affirming communication for their sense of self in relation to their work (Bennett & Hennekam, 2018; Caza, Reid, Ashford, & Granger, 2021; Panteli, Rapti, & Scholarios, 2020). A particularly salient problem for online platform work, compared to platform-mediated work that is location-based (e.g., Uber, Taskrabbit), is that online crowdwork is almost exclusively individualistic. While Uber drivers may interact with other drivers and their passengers, the online crowdworker is algorithmically matched with a task and has limited to no opportunities to interact with the task provider (requester), the platform, or other workers (Gegenhuber, Ellmer, & Schüßler, 2021). Without access to an identity that is clearly defined or reinforced by an organizational setting and interactions with colleagues, clients, or customers, crowdworkers may face challenges developing a distinct identity as a worker (Caza, Reid, Ashford, & Granger, 2021). This is important because a clear and strong identity is important to one's sense of existence and purpose (Petriglieri, Ashford, & Wrzesniewski, 2019).

Hence, we examine how the algorithmic management of crowdworkers affects perceptions of identity and belonging and how these perceptions affect meaningfulness. In doing so, this study aims to make at least two important contributions. First, we focus specifically on crowdwork as an increasingly popular form of platform work that is largely overshadowed by academic and societal scrutiny of more visible and high-profile forms of platform work (for notable exceptions, see Gray & Suri, 2019; Roberts, 2019). In addition, we do this specifically in the context of European crowdwork, as the limited research on crowdwork is predominantly based on Amazon Mturk in the US or Indian labor market (i.e., Irani, 2015; Ross et al., 2010). Second, we move beyond the broad notion that crowdworkers face precarious work conditions by examining the implications of algorithmic management as a particularly distinguishing characteristic of platform work. Hence, this study contributes to the emerging literature on platform work by providing a quantitative account of some of the belonging and identity-related challenges crowdworkers experience. We provide a novel perspective by highlighting the implications of algorithmic management in shaping crowdworkers' identities and how these effects relate to perceptions of the meaningfulness of their crowdwork.

2. Literature review

2.1. Algorithmic management on online labor platforms

Online labor platforms exhibit control over work as meta-organizations by solving the problem of organizing without explicitly relying on formal authority as enshrined in an employment contract, and instead combining organizational and market mechanisms to govern work (Gawer, 2014; Möhlmann et al., 2020). Work in such arrangements takes place outside formal organizational environments and is performed remotely, anonymously, and largely without human oversight or interaction (Bucher et al., 2021). This means that key functions traditionally assigned to managers – e.g., monitoring, coordinating, evaluating – are now governed by algorithms (Duggan et al., 2020; Meijerink & Keegan, 2019; Wood et al., 2019). Therefore, a deeper understanding of the experiences of crowdworkers requires a closer look at the technologies that facilitate the organizational and market mechanisms that lie at the core of these online labor platforms (Constantiou, Marton, & Tuunainen, 2017). More specifically, there is a need to scrutinize the operation of algorithms used to manage labor exchanges.

Broadly, management is concerned with coordinating and controlling organizational resources such that goals and objectives can be achieved efficiently. In the control of online labor platforms, this function is allocated to an algorithm. Algorithmic management, therefore, can be defined as a platform's use of algorithms to carry out matching and control functions in a highly automated and data-driven fashion (Bucher et al., 2021; Galière, 2020; Helles & Flyverbom, 2019; Just & Latzer, 2017; Kellogg, Valentine, & Christin, 2020). Online labor platforms outsource managerial functions of control and coordination, traditionally performed by human managers, to learning algorithms (Möhlmann et al., 2020). Over time, algorithmic control reflects, and in some cases replaces, traditional notions of organizational control by reifying and enacting a market logic that seeks efficient matches between labor supply and demand.

Algorithmic control is a form of organizational control defined as the influence process that seeks to align the workers' actions with the desired platform objectives (Verelst, De Cooman, & Verbruggen, 2022). Put differently, organizations seek to encourage, facilitate, evaluate, track, and reward worker activities in ways that will support organizational goals – and these efforts are mediated through the presence, operation, and communication of algorithms. Through algorithmic control, an online labor platform can monitor and incentivize the behaviors of thousands of workers and ensure their alignment with the platform's goals – i.e., efficiently and effectively matching workers and requestors. These enactments of algorithmic control mean that online labor platforms can manage hundreds of thousands of global workers with little direct, ongoing human intervention (Roberts, 2019).

Moreover, online labor platforms often view themselves as a matchmaker between labor supply and demand, and algorithmically matching workers to tasks or requestors is a salient form of algorithmic management in online platform work (Möhlmann et al., 2020). Indeed, a hallmark of online labor platforms is that the coordination of work and matching of requesters and workers is efficiently offloaded to an algorithmic system (Jarrahi & Sutherland, 2019). This algorithmic matching mimics an open market mechanism inherent to platform labor and refers to the ways in which the coordination and interactions between labor demand and supply are algorithmically mediated.

Algorithmic control and algorithmic matching both impact and shape platform workers' experiences and behaviors (Möhlmann et al., 2020) and may relate to perceptions of meaningful work (Verelst et al., 2022). This may not be surprising as algorithmic management highlights a heavily transactional relationship that lies at the heart of crowdwork (Duggan et al., 2019). Such transactional ways of organizing require work to be parsed out into smaller tasks to be outsourced in branches to a geographically dispersed crowd. This may make it difficult for workers to have broader insights into how smaller tasks contribute to bigger projects or understand how they can make a meaningful contribution to a greater goal. Moreover, algorithmic management inherently requires an emphasis on quantification logics, which focuses on outputs, results, and metrics and is less concerned with affective aspects of work (e.g., Newman, Fast, & Harmon, 2020; Parent-Rocheleau & Parker, 2022; Schafheitle et al., 2020). There are at least three reasons to assume that algorithmic management reduces meaningful work experiences. Specifically, algorithmic management 1) limits human involvement and oversight (Duggan et al., 2019), 2) increases the risk of dehumanizing workers into numbers and means to an end (Lamers, Meijerink, Jansen, & Boon, 2022; Newman et al., 2020), and 3) limits workers opportunities to cultivate their virtue (i.e., fostering personal excellence to pursue a meaningful life; Gal, Jensen, & Stein, 2020). Hence, we hypothesize.

H1. (H1a) Algorithmic control and (H1b) algorithmic matching are negatively related to meaningfulness of crowdwork

2.2. Worker identity and belonging under the gaze of algorithms

A critical perspective on crowdwork argues that the nature of these arrangements may alienate workers by disconnecting them intellectually, socially, and physically from the larger product or organizational structures they help create (Aytes, 2012; Bucher et al., 2021; Glavin, Bierman, & Schieman, 2021; Gray & Suri, 2019; Roberts, 2019). Glavin et al. (2021) noted that "the organization of platform work fosters alienation through its tendency to challenge workers' autonomy, and their ability to maintain satisfactory work relationships" (p. 404). Broadly, alienation may refer to a disconnection of a person from oneself – i.e., worker identity – or from others – i.e., a social context. While crowdworkers may perceive themselves as micro-entrepreneurs who work independently, the reality is often bleaker with platforms exerting high levels of control that prioritize the efficient application of labor over opportunities to develop long-term work relationships or support worker growth and development (Bucher, Fieseler, & Lutz, 2019; Gegenhuber et al., 2021).

Online labor platforms are said to view crowdworkers as "replaceable cogs in the machine," "anonymous numbers," or "artificial intelligence" (Salehi et al., 2015). This is important because these perceptions are rooted in the granular, modular, depersonalized, and decontextualized nature of online crowdwork. Specifically, workers affected by algorithmic decisions are likely to perceive that decisions reduce the qualitative aspects of their performance to quantifiable metrics and fail to adequately consider performance in a broader context (Newman et al., 2020). In addition, workers completing online tasks are often far removed not just from other workers, but also from the requesters and final products of their work (Bucher et al., 2019). This raises questions about crowdworkers' sense of belonging and identity. Möhlmann et al. (2020) describe how the algorithmic management of app-workers gives rise to belongingness tensions, as Uber drivers felt a strong sense of self-identity as independent workers while also feeling a need to be part of a larger community of drivers. In an autoethnographic field study, Anicich (2022) concluded that the sociotechnical context of app-work (food delivery) threatens workers' ability to constitute and animate their identities. Importantly, labor platforms, specifically the algorithmic governance structures these platforms utilize, create technological and social constraints and opportunities that affect identity dynamics.

This reliance on algorithmic management, which is both unseen and unknowable to individuals, facilitates both uncertainty and inconsistency for workers, which in turn makes it difficult to clearly define one's identity as a crowdworker. Furthermore, the absence of a formal organizational setting to provide guidance on roles or normative behaviors further complicates the reinforcement of worker identities (Caza, Reid, Ashford, & Granger, 2021). The algorithmic systems used to govern crowdworkers only present extremely limited identity-affirming contextual cues (e.g., personalized feedback, input from customers, peer interactions), if any (Newman et al., 2020). In addition, social isolation from other workers presents a barrier to constructing collective identities and an overall sense of belonging (Graham, Hjorth, & Lehdonvirta, 2017). Hence, we argue that the nature of algorithmic management is such that it may give rise to questions about crowdworkers' professional identity and belonging, which may, in turn, affect perceptions of meaningfulness (Petriglieri et al., 2019).

H2. (H2a) Algorithmic control and (H2b) algorithmic matching are negatively related to meaningfulness of crowdwork through increased identity challenges

H3. (H3a) Algorithmic control and (H3b) algorithmic matching are negatively related to meaningfulness of crowdwork through increased relational challenges

2.3. Self-organizing and the need for social recognition

As online crowdwork can be a lonely experience with limited social interactions with requesters, the platform, or other workers (Bajwa, Gastaldo, Di Ruggiero, & Knorr, 2018; Glavin et al., 2021; Graham et al., 2017), workers are found to self-organize virtual communities of reinforcement and care (Soriano & Cabañes, 2020). This interaction with others engaged in similar work can provide forms occupational learning, and facilitate identification with an occupational community, which crowdworkers may lack (Schwartz, 2018). This community support is particularly helpful for workers who may depend upon crowdwork for their current and future income, as it serves as a buffer against the perceived capriciousness of algorithmic management (Cameron & Rahman, 2022). Hence, solidarity and support generated through communication with other workers may become important social resources for workers (Wood, Martindale, & Lehdonvirta, 2021), enhancing the importance of being part of a larger community of workers to facilitate collective sensemaking.

Notably, research found that platform workers typically do not perceive adequate social support from platform operators (Myhill, Richards, & Sang, 2021). Instead, platforms facilitate a context where workers have a similar goal in trying to understand the algorithms used to govern them, yet these workers are also competing for the same gigs allocated and evaluated by the algorithms they seek to understand. Previous research suggested that workers may utilize technological platforms to seize opportunities to connect with other workers and derive social support from their peers (Kuhn & Maleki, 2017), "even though those workers are also their direct competitors" (Kuhn & Galloway, 2019, p. 188). In the context of ride-hailing, workers are found to use digital communication to search for help and provide support to peers in dealing with customers (Aslam & Woodcock, 2020; Maffie, 2020).

Hence, we propose the 'self-organizing hypothesis' reflecting the idea that crowdworkers under algorithmic management seek social recognition and support from other workers in online environments outside the platform. In the context of protest against poor labor conditions and resistance to ill-treatment, Wood et al. (2021) discuss mobilization theory to argue that workers may be inclined to engage in collective action (including solidarity and protesting). Mobilization theory highlights the importance of some collective interest in mobilizing action (Kelly, 1998). In the context of crowdwork, the collective interest may be reflected in the shared efforts to try and understand algorithmic decisions made by the platform. Again, in the context of Uber, Möhlmann et al. (2020) found that workers tried to compensate for the absence of membership to the company through engagement in informal communities. Specifically, algorithmic control and algorithmic matching highlighted both workers' independence and exacerbated their need to be part of a broader community. Hence, we hypothesize.

H4. (H4a) Algorithmic control and (H4b) algorithmic matching are positively related to the meaningfulness of crowdwork through the increased need for social recognition.

3. Methods

3.1. Procedure and sample

We collected 1291 responses from European crowdworkers on Clickworker. Clickworker is the largest digital labor platform for online crowdwork in Europe. This online labor platform was chosen because of its availability and popularity across Europe. The platform operates similarly to other crowdwork platforms, such as Amazon's Mechanical Turk, but this platform is not accessible to many European workers. Clickworker allows requesters to submit tasks and specify worker characteristics. Once submitted to the platform, Clickworker uses algorithms to distribute the tasks to workers who meet the criteria. Once a worker completes a task, the work is (automatically) rejected or accepted, after which workers receive their compensation through the platform.

To collect the data underlying this study, we created a requester account and posted a task in the form of a survey. In line with ethics recommendations, crowdworkers who participated in the survey were compensated for their time and effort (Gleibs, 2017; Silberman et al., 2018). Crowdworkers were instructed about the purpose of the study and informed about the presence of attention checks. We estimated the time needed to complete the survey generously. Based on the estimated 13 min to complete the survey workers were compensated €2,80 upon task completion, this is equivalent to an hourly wage of €12.92 ((slightly) above minimum wage in Europe).

In total, 1526 crowdworkers started the survey task, but 235 crowdworkers did not complete the task because they failed at least one of the attention checks. Hence, the final sample includes 1291 crowdworkers. On average, these workers were 36.8 years old ($SD = 11.12$). The average experience with doing crowdwork was 4.2 years ($SD = 4.66$). Because crowdwork is often complementary to other sources of income, we asked about the number of hours and percentages of income derived from crowdwork. In our sample, the average number of work hours was 11.2 per week (SD = 10.54), and crowdworkers were able to generate an average of 18.3% of their personal income from this work. Most crowdworkers indicated that their employment status outside crowdwork included some form of full-time (40.3%) or part-time (11.9%) employment contract. In addition, 18.9% indicated being self-employed or freelancing, and about 27.2% of the crowdworkers did not engage in other employment arrangements (e.g., retired, unemployed, disabled, homemaker). For the educational degrees, 31.3% reported a graduate degree, 16.9% had an undergraduate degree, and 15.5% obtained a college degree. Finally, 54.1% of the respondents in our sample identified as male, while 43.9% identified as female. Others preferred not to self-describe their gender.

3.2. Measures

Table 1 reports all measurement items with corresponding factor loadings and descriptive statistics. All statements were measured on a seven-point Likert scale ranging from (1) strongly disagree to (7) strongly agree.

Algorithmic management. Following Möhlmann et al., (2020), we distinguish between algorithmic control and algorithmic matching. *Algorithmic control* was measured in three statements from Verelst et al. (2022) and three statements from Jabagi, Croteau, Audebrand, and Marsan (2021). Since the original statements refer to algorithmic control at Uber and a food delivery app, the statements were rephrased to fit the context of online crowdwork. Sample items include "I feel forced to follow instructions because I am afraid to be blocked from the platform" and "The platform rating systems (e.g., acceptance and rejection rates) prevent me from doing my job the way I want." *Algorithmic matching* refers to the algorithmically mediated coordination of labor demand and supply exchanges. Möhlmann et al. (2020) suggested that matching entails practices such as optimizing the matching of supply and demand and the use of input and output data in that process (e.g., worker ratings). The dynamic pricing strategies apps like Uber use to achieve economic efficiency in matching supply and demand are not common in online crowdwork, as requesters determine the compensation for their tasks. Hence, we generated three items reflecting the optimization of supply and demand and the use of data in doing so. Sample items include

Table 1
Measurement items and factor loadings.

Measurement items	Mean (SD)	R^2	St. Factor loading	Unst. Factor loading	Se
Algorithmic control					
I have the feeling of being under constant surveillance by the platform	3.43 (1.57)	.38	.615	1.000	
I feel under pressure to accept the tasks that are provided on the platform	2.95 (1.52)	.50	.708	0.985	05
I feel forced to follow instructions because I am afraid to be blocked from the platform	3.97 (1.76)	.36	.598	0.962	.05
The platform rating systems (e.g., acceptance and rejection rates) prevent me from doing my job the way I want	3.73 (1.53)	.45	.668	0.936	.05
When working on the platform, I feel forced to do things I do not want to do	2.74 (1.54)	.54	.736	1.040	.05
I feel penalized by the platform when ignoring a task	2.95 (1.58)	.48	.692	0.882	.05
Algorithmic matching					
The platform facilitates optimal matching of supply and demand	4.11 (1.30)	.57	.753	1.000	
The platform embeds logics to balance the interest of requesters and workers.	4.35 (1.26)	.72	.851	1.095	.05
The platform uses my ratings to determine what tasks will become available to me in the future[a]	4.56 (1.34)	.26	.507	0.694	.04
Identity Challenge					
I wear many hats as a gig worker that it is sometimes difficult to have a clear sense of who I am as a worker	3.51 (1.49)	.46	.681	1.000	
It is sometimes difficult to explain to others who I am as a worker	3.95 (1.62)	.73	.853	1.361	.05
It is difficult to develop a clear sense of who I am in the gig economy	3.88 (1.49)	.78	.880	1.298	.05
Relational Challenge					
Gig work is lonely	4.30 (1.57)	.46	.677	1.000	
I feel alone a lot of times in my gig work, separated from mentors and colleagues who might help me.	3.79 (1.62)	.83	.905	1.379	.06
Sometimes I miss being part of a team when doing my work	3.67 (1.71)	.47	.688	1.104	.05
Social Recognition					
I engage with other platform workers online	3.02 (1.66)	.58	.761	1.000	
I find that online forums are a good place to talk to other workers	4.18 (1.57)	.42	.644	0.800	.04
I offer advice and support to other workers	3.31 (1.68)	.75	.868	1.150	.04
I talk to others about my work on the platform	3.54 (1.72)	.47	.688	0.935	.04
Meaningfulness of work					
The crowdwork I do is meaningful.	4.67 (1.45)	.71	.844	1.000	
The crowdwork I do is very important to me.	4.52 (1.51)	.89	.945	1.167	.03
My crowdwork activities are personally meaningful to me.	4.62 (1.47)	.90	.948	1.145	.02

"the platform uses my ratings to determine what tasks will become available to me in the future" and "the platform facilitates the optimal matching of supply and demand."

Identity challenge refers to the development and maintenance of a coherent sense of work identity when work varies a lot from task to task and requester to requester (Caza, Reid, Ashford, & Granger, 2021). Three items are adopted from Caza, Reid, Ashford, & Granger, 2021 and include: "It is sometimes difficult to explain to others who I am as a crowdworker."

Relational challenge refers to how workers are coping with being alone most of their work time and the need to constantly sell to others – e.g., keep up individual ratings. Three items were adopted from Caza, Reid, Ashford, & Granger, 2021, including: "I feel alone a lot of times in my crowdwork, separated from mentors and colleagues who might help me".

Social recognition refers to the importance workers feel of being a part of a broader community of crowdworkers (Möhlmann et al., 2020). Bucher et al. (2019) note that social recognition reflects workers' perceptions of their role and voice vis-à-vis their peers. Importantly, social recognition is distinct from social support as social support pertains to a passive role of individuals (i.e., do I receive support in a social context?), while social recognition pertains to an active role of the individual (i.e., am I recognized for my role and actions in the social context?). Social recognition is measured by four items adopted from Bucher et al. (2019), including: "I engage with other crowdworkers online" and "I find that online forums are a good place to talk to other workers."

Meaningfulness of work was measured using three items developed by Spreitzer (1995). Meaningfulness refers to the fit between the needs of one's work role and one's beliefs, values, and behaviors (Hackman & Oldham, 1976). Spreitzer (1995) adds that meaningfulness taps the intrinsic motivation of workers manifested in intrapersonal empowerment. Sample items include: "The crowdwork I do is very important to me."

3.3. Analysis

The hypothesized model was tested in a two-step process. First, a confirmatory factor analysis (CFA) was conducted to examine the reliability and validity of the measurement model. Second, the hypothesized relationships were tested using structural equation modeling (SEM) in STATA. To inspect model fit several fit indices were examined. Comparative indices – i.e., Tucker-Lewis Index (TLI) and the Comparative Fit Index (CFI) – above .95 indicate excellent model fit. In addition, we examined absolute fit indices – i.e., the standardized root mean squared residual (SRMR) and the root mean square of approximation (RMSEA) – where values of $\leq$0.08 and $\leq$0.05, indicate excellent model fit. Furthermore, the χ2 statistic and the model's degrees of freedom are presented, and a χ^2/df of less than 5 is acceptable (Hu & Bentler, 1999). Finally, it should be noted that the models were estimated to obtain bias-corrected parameters using bootstrapping and a maximum likelihood estimator.

4. Results

4.1. Measurement model

The measurement model (CFA) estimating six latent constructs – i.e., algorithmic control, algorithmic matching, identity challenge, relational challenge, social recognition, and meaning – demonstrates excellent model fit: χ^2 (194) = 685.62; χ^2/df = 3.53; CFI = 0.96; TLI = 0.96; SRMR = 0.042; and RMSEA = 0.044 (CI: 0.041, 0.048); PClose = .995. First, the reliability of the constructs was examined. We report omega reliability (ω) coefficients as they are generally more accurate than alpha estimates of reliability and they do not require normally distributed items or equal factor loadings across items (Dann et al., 2013). In addition, we inspect the maximum reliability (MaxR(H)). The Omega reliabilities range between 0.75 and 0.94, while the maximum reliability (H) values range between 0.81 and 0.95, both indicating good reliability.

Second, we examined discriminant and convergent validity. Discriminant validity is established as no items demonstrate problematic cross-loadings. In addition, the Fornell and Larcker (1981) criterion is met, meaning that the square root of the average variance extracted for any construct is greater than its correlation with all other constructs (See Table 2). Convergent validity is also established as the mean of the squared loadings for each indicator associated with a construct is above 0.50. Notably, the average variance extracted for algorithmic control is just below that threshold at 0.45. However, following Fornell and Larcker (1981) convergent validity is considered adequate as both, omega reliabilities and maximum reliability (H) exceed 0.70. Hence, overall, the results do not indicate any reliability or validity concerns.

4.2. Structural model

The structural model indicated good model fit: χ^2 (197) = 861.28; χ^2/df = 4.37; CFI = 0.95; TLI = 0.94; SRMR = 0.048; and RMSEA = 0.051 (CI: 0.048, 0.055); PClose = .292. Table 3 presents a summary of the findings related to the hypothesized model. Fig. 1 presents a visual representation of the model with direct relationships.

The first hypothesis reflects the assumption that algorithmic management is negatively associated with the perceived meaningfulness of crowdwork. The results indicate that algorithmic control is significantly and negatively related to meaningfulness (B = −0.104 CI95% [-0.184; −0.033], p = .021). Algorithmic matching is also significantly related to meaningfulness, but contrary to our expectations, matching is positively correlated with meaningfulness (B = 0.380 CI95% [0.300; 0.462], p = .001). These results present support for H1a but do not support H1b.

Hypothesis 2 posits that algorithmic management is positively related to identity challenges, which in turn reduces meaningfulness. The findings demonstrate that algorithmic control is positively related to identity challenge (B = 0.438 CI95% [0.376; 0.507], p = .001) while algorithmic matching is not significantly related to identity challenge (B = −0.042 CI95% [-0.105; 0.020], p = .262). In turn, contrary to our expectations, identity challenge is positively related to meaningfulness (B = 0.108 CI95% [0.033; 0.189], p = .012). The indirect relationship between algorithmic control and meaningfulness through identity challenge is significant and positive (B = .047 CI95% [0.016; 0.085], p = .010), while there is no significant indirect relationship between algorithmic matching and meaningfulness through identity challenge (B = −.005 CI95% [-0.016; 0.001], p = .167). These results do not support hypotheses 2a and 2 b.

Hypothesis 3 focuses on the role of belongingness, specifically by suggesting that the relationship between algorithmic management and meaningfulness is mediated by relational challenges. Again, the results indicate that algorithmic control is significantly and positively associated with relational challenges (B = .393 CI95% [0.331; 0.466], p = .001), while the association between algorithmic matching and relational challenges is not significant (B = −0.064 CI95% [-0.130; 0.020], p = .093). Relational challenges experienced by crowdworkers are negatively associated with perceived meaningfulness (B = −0.150 CI95% [-0.221; −0.074], p = .001). Hence, the indirect relationship between algorithmic control and meaningfulness through relational challenges is negative and significant (B = −.059 CI95% [-0.092; −0.029], p = .001), while the indirect relationship between algorithmic matching and meaningfulness through relational challenges is not significant (B = .010 CI95% [-0.001; 0.023], p = .062). These findings support H3a but do not support H3b.

Finally, hypothesis 4 articulates that algorithmic management is positively associated with meaningfulness through social recognition. The results demonstrate that workers facing algorithmic control (B = 0.314 CI95% [0.248; 0.391], p = .001) and algorithmic matching (B = 0.389 CI95% [0.305; 0.489], p = .001) are more likely to seek social recognition from other workers online. In turn, crowdworkers who seek such recognition report higher levels of meaningfulness (B = 0.271 CI95% [0.210; 0.329], p = .001). As such, the indirect relationships between algorithmic control (B = 0.085 CI95% [0.063; 0.114], p = .001) and algorithmic matching (B = 0.105 CI95% [0.078; 0.139], p = .001)

Table 2
Validity and reliability statistics.

Constructs	Mean (SD)	Ω	AVE	MSV	Max (H)	1	2	3	4	5	6	7	8	9	10	11
1. Algorithmic control	3.30 (1.16)	.83	.45	.19	.84	**.67**										
2. Algorithmic matching	4.34 (1.05)	.75	.52	.15	.81	−.02	**.72**									
3. Identity challenge	3.78 (1.34)	.85	.66	.27	.88	.44*	−.05	**.81**								
4. Relational challenge	3.92 (1.37)	.81	.59	.27	.87	.39*	−.06	.52*	**.77**							
5. Social recognition	3.51 (1.35)	.83	.56	.13	.86	.26*	.30	.18*	.02	**.75**						
6. Meaningfulness of work	4.60 (1.39)	.94	.84	.15	.95	−.03	.39*	.02	−.14*	.36*	**.91**					
7. Gender	0.55 (0.45)	–	–	–	–	.07*	−.07*	−.02	*.03*	−.01	−.11*	-				
8. Age	36.86 (11.12)	–	–	–	–	−.06*	*−.03*	−.06*	−.03	−.05	.05	.02	-			
9. Tenure	4.15 (4.67)	–	–	–	–	.04	.01	−.04	.00	.04	.01	−.04	.20*	-		
10. Work hours	11.21 (10.54)	–	–	–	–	.10*	.03	.06*	−.02	.21	.18	.00	.14*	.21*	-	
11. Income dependency	18%	–	–	–	–	.12*	−.03	.15*	.04	.14*	.18*	−.04	−.03	.06*	.50*	–
12. Other work	0.72 (0.45)	–	–	–	–	−.04	.03	−.10*	−.05	.02	−.06*	.10*	.15*	.10*	−.03	−.27*

Note: Ω = Omega Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance; the Square Root of the AVE is reported on the diagonal. Significant correlations are flagged *. Gender was coded 1 = male, 0 = female; Income dependency reports the mean percentage of personal income derived from platform work; Other work is a dichotomy reflecting whether workers have other vocational roles, 0 = only platform work, 1 = other forms of employment.

Table 3
Results for hypotheses.

			Bootstrapping		BC 95% CI		
		Result	Estimate	SE	Lower	Upper	P
Direct relationships x → y							
H1a	Algorithmic control → Meaningfulness of work	Supported	−.104	.044	−.184	−.033	.021
H1b	Algorithmic matching → Meaningfulness of work	Not Supported	.380	.049	.300	.462	.001
Indirect relationships x → m → y							
H2a	Algorithmic control → Identity challenge → Meaningfulness of work	Not Supported	.047	.021	.016	.085	.010
H2b	Algorithmic matching → Identity challenge → Meaningfulness of work	Not Supported	−.005	.005	−.016	.001	.167
H3a	Algorithmic control → Relational challenge → Meaningfulness of work	Supported	−.059	.019	−.092	−.029	.001
H3b	Algorithmic matching → Relational challenge → Meaningfulness of work	Not Supported	.010	.007	−.001	.023	.062
H4a	Algorithmic control → Social recognition → Meaningfulness of work	Supported	.085	.016	.063	.114	.001
H4b	Algorithmic matching → Social recognition → Meaningfulness of work	Supported	.105	.018	.078	.139	.001

Note: BC = bias corrected; CI = confidence interval. Entries represent unstandardized coefficients. N = 1291.

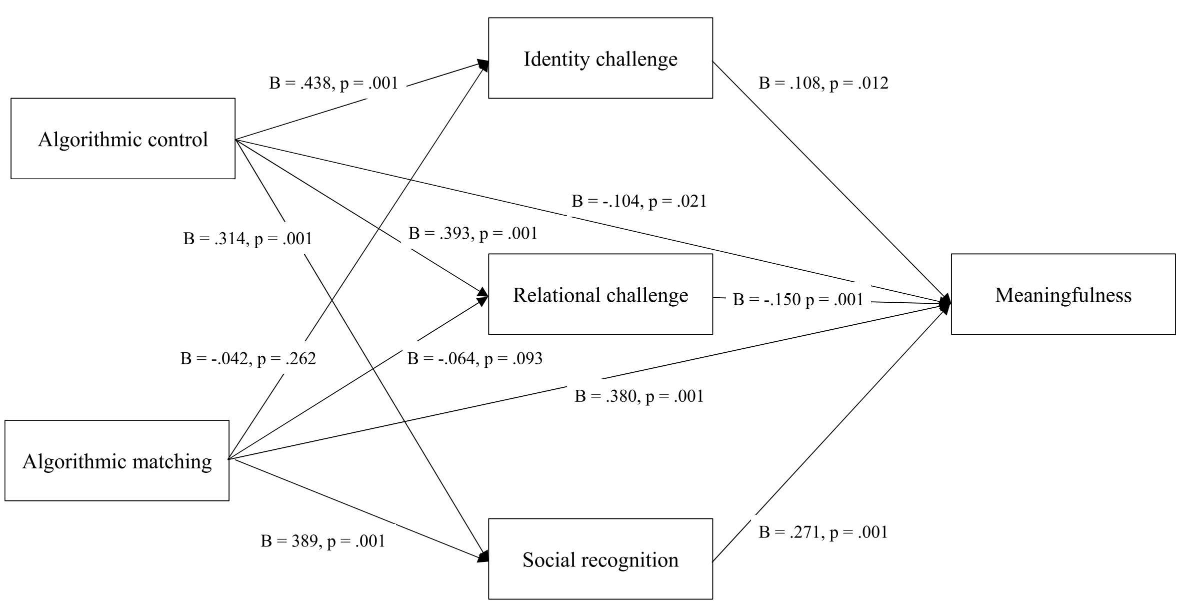

Fig. 1. Regression model with results for direct effects.

on meaningfulness through social recognition are positive and significant. These findings support H4a and H4b.

5. Discussion

This study explored how algorithmic management influences the meaningfulness of crowdwork, with a specific focus on identity and belonging. The findings suggest that algorithmic control is negatively associated with the perceived meaningfulness of crowdwork. This implies that when crowdworkers experience stringent oversight, their sense of meaningfulness diminishes. Algorithmic matching, which pairs workers with tasks, showed a positive correlation with meaningfulness. This unexpected finding suggests that efficient task assignment processes may be positively related to crowdworkers' perceived meaningfulness.

Additionally, algorithmic control was positively linked to identity challenges, indicating that greater control can lead to identity struggles among workers. However, algorithmic matching did not significantly impact identity challenges. Interestingly, identity challenges were positively associated with meaningfulness, implying that crowdworkers grappling with identity issues tend to find more meaning in their work. This suggests that defining one's work identity in the complex world of crowdwork might contribute to a greater perceived meaningfulness. Regarding belongingness, algorithmic control was significantly and positively associated with relational challenges. This suggests that increased algorithmic control often leads to more difficulties in forming social connections for crowdworkers. However, the relationship between algorithmic matching and relational challenges was not significant. Crowdworkers facing issues related to social connections and interactions tended to perceive their work as less meaningful. Finally, algorithmic control and algorithmic matching were positively linked to crowdworkers seeking social recognition from their online peers. Importantly, those actively seeking social recognition reported higher levels of meaningfulness in their work. These findings provide valuable insights into the dynamics of algorithmic management in platform work and its effects on the work experiences of crowdworkers in Europe.

5.1. Theoretical implications

This study makes at least three contributions to our understanding of how communicative processes operate in the distinct organizing contexts of crowdwork. First, we examined how an online labor platform's use of algorithmic management relates to individual workers' experiences. We started from the premise that for organizations operating and utilizing online labor platforms, algorithmic management solves problems (organizing labor supply and demand) by combining organizational and market mechanisms (Constantiou et al., 2017). Specifically, in the context of platform work, algorithmic management entails algorithmic control, the providing and assessment of roles and responsibilities, and algorithmic matching, the pairing of humans with online tasks (Möhlmann et al., 2020). Our findings demonstrate that algorithmic matching has a positive relationship with the perceived meaningfulness of work, while algorithmic control is negatively associated with meaningfulness. The notion that different aspects of algorithmic decision-making have different implications for workers aligns with previous investigations of algorithmic management and decision-making in traditional organizational contexts. For instance, Lee (2018) demonstrated that employees considered algorithmic decisions as equally fair as human decisions when these decisions required mechanical skills (e.g., coordination and scheduling). However, when decisions required human skills and capabilities (e.g., performance evaluations), human decision-makers were preferred over algorithmic decision-makers.

We suggest that algorithmic control may limit perceived meaningfulness and value by instilling control mechanisms that direct, surveil, and discipline workers to extract as much (economic) value from workers as possible (Meijerink & Bondarouk, 2023). This may limit the meaning and value workers themselves derive from work as it reduces personal growth, a sense of accomplishment, and the ability to develop a desired work identity (Goods, Veen, & Barratt, 2019; Wood et al., 2019). Algorithmic matching, on the other hand, was positively related to meaningfulness. One explanation for this finding is that algorithms effective coordinate and match with tasks. Bai and colleagues (2021) noted that algorithmic (vs. human-based) work assignment increased perceptions of fairness and worker productivity. These findings are attributed to the impression of efficiency of algorithmic work assignment. For crowdworkers, this notion of efficiency is important as this will enable them to take on more work and facilitate individual growth and accomplishment. When workers can more easily find jobs, and jobs they like or want, they are more likely to find work meaningful.

Hence, to understand algorithmic management as a new form of organizational control (Duggan et al., 2020; Kellogg et al., 2020; Möhlmann & Zalmanson, 2017), we argue that the implications of algorithmic management depend largely on what managerial functions and decision-making authority is offloaded to an algorithm (Parent-Rocheleau & Parker, 2022). Algorithmic management does not operate in a uniform singular way to shape workers worker experiences, and therefore we must examine different ways algorithmic management may support or constrain worker practices (Cameron & Rahman, 2022). For example algorithmic management asserts control over workers through surveillance and tracking of activity, but offers some agency back to workers by allowing them control over when to engage in labor. Future research needs to explore the 'duality of algorithmic management' in greater depth (Meijerink & Bondarouk, 2023).

Second, we explored the impact of algorithmic management on identity and belonging (Caza, Reid, Ashford, & Granger, 2021). We extend research on challenges associated with crowdwork by demonstrating the mediating role of identity and relational challenges in the relationship between algorithmic management and meaning. Research has highlighted that crowdworkers experience difficulties in forming and maintaining a coherent work identity, as they lack many self-affirming cues and organizational structures to define the contours of their vocational roles (Caza, Reid, Ashford, & Granger, 2021; Idowu & Elbanna, 2021). Möhlmann et al. (2020) suggest algorithmic management may create a tension of belonging highlighting the entrepreneurial and independent aspects of work while also increasing the need for community to make sense of a complex work environment and opaque algorithmic decisions. Our findings confirm the positive relationship between algorithmic control and identity and relational challenges, but do not confirm this relationship for algorithmic matching. In addition, it is noteworthy that the identity challenge is positively related to meaningfulness, while the relational challenge is negatively related to meaningfulness. This suggests that crowdworkers who struggle with defining their work identities may report higher levels of meaningfulness. The dynamic between identity challenges, flexibility, or fluidity and meaningfulness may be particularly pronounced in crowdwork and merits further attention. Given the perceived liminal professional role of crowdworkers, this type of work may be well-suited for individuals who do not easily align with a singular vocational pursuit. It may be the case that crowdworkers need to develop their own work identities and ensure that their image is flexible and fluid enough to meet the different roles and tasks they occupy. Arguably, being faced with the challenge of defining one's work identity forces workers to think about their existence and position as a worker in a much larger crowd (Caza, Reid, Ashford, & Granger, 2021), which may trigger a sense of meaning or purpose (Petriglieri et al., 2019). In contrast, relational challenges reduce perceived meaningfulness. This finding is in line with Spreitzer (1995) who suggested that the social structural context of work presents important antecedents to an intra-individual sense of empowerment, including meaningfulness. Crowdworkers that experience greater relational challenges – e.g., feel lonely or isolated – may be deprived of important social-structural antecedents of meaningfulness such as access to resources, support, or information.

Finally, the findings indicate that crowdworkers subject to algorithmic control and matching report higher self-organizing practices, which in turn increase perceived meaningfulness of crowdwork. Self-organizing reinforcement and social interaction with workers is a crucial way for crowdworkers to fill the gap the absence of social and organizational structures leaves in crowdwork (Soriano & Cabañes, 2020). This is in line with findings that suggest that independent workers in the gig economy seek to fulfil social and informational needs by engaging in informal online communities for instance on Reddit or social media networks (Möhlmann et al., 2020). Workers use these communities to exchange information and experiences with other workers, in part to make sense of algorithmic management and to find ways to optimize their algorithm-controlled behavior (*ibid*). We add that engaging in such communal activities outside the labor platform environment contributes to a sense of meaningfulness of work.

The type of communities developed by crowdworkers resemble networks of practices (Vaast, 2004; Wasko & Faraj, 2005) in which individuals engaged in similar tasks can share knowledge related to work experiences, and members of the network can learn from each other. However, scholars have questioned the value of such communities in contexts where individuals may lack a shared space, engage in disparate practices, and have little to no established relationship (Amin & Roberts, 2008). Though this study focused primarily on social recognition within and among workers, the results confirm that crowdworkers actively seek other crowdworkers and that their interactions have implications for workers' experiences. Future work should explore these communities of crowdworkers in more detail to examine the nature of communication and knowledge exchange that occurs.

5.2. Practical implications

The findings have several practical implications for online labor platforms, requesters, workers, and policymakers. Many studies and labor organizations such as the International Labor Organization (ILO) have articulated concerns about the labor conditions of crowdworkers (Borghi, Murgia, Mondon-Navazo, & Mezihorak, 2021; European Commission, 2021; Garben, 2021; Graham et al., 2020; Heeks et al., 2021). Crowdwork suffers from unclarity about workers' legal status highlighting broader concerns about, for instance, fair pay, fair work conditions, fair management, and fair representation (Graham et al., 2020). Organizing collectively when work is digital, dispersed, and sporadic presents unique challenges to building collective agency and voice (Howcroft & Bergvall-Kåreborn, 2019). The findings demonstrate that crowdworkers subjected to algorithmic management practices of online labor platforms experience greater identity and relational challenges and seek ways to self-organize social belonging. While a hallmark of online labor platforms is to organize the exchange of labor supply and demand effectively and efficiently, most of these platforms do not utilize their organizing potential to facilitate social exchanges between and within stakeholder groups. An important step for labor platforms to help workers establish stronger worker identities and develop a sense of belonging is to allow them to collectively make sense of their work environments and voice their opinions and concerns to requesters and the platforms.

Second, the rise of platform work has not gone unnoticed among legislators. While platform work is already a widespread phenomenon in the labor market, regulations prove to be complicated as the legal status of this vastly heterogenous group of workers in the gig economy is yet to be established. While ongoing initiatives to improve the working conditions of people working in the gig economy are urgently needed so is information about the experiences of crowdworkers. This group is particularly invisible and hard to reach as their online labor 'does not hit the ground.' This also complicates mapping the concerns of workers. However, our findings indicate that workers may benefit from engaging in social interactions (i.e., overcoming relational challenges) and self-organizing support networks in online communities (Soriano & Cabañes, 2020). This can be an important source of information for labor organizations. Conversely, worker representation initiatives can support workers by helping them to build communities of workers that facilitate collective agency and voice (Howcroft & Bergvall-Kåreborn, 2019).

5.3. Limitations and future research directions

Our study comes with several limitations. First, the study relies on self-reported cross-sectional data, which may be prone to bias typical in self-reported data (e.g., social desirability, incorrect attribution, selective memory) and prevents any causal inferences. Future research may consider drawing from multiple data sources and utilizing longitudinal research designs to test mediation hypotheses more adequately. Second, we have focused on one specific online labor platform, Clickworker. While this is a prominent labor platform for crowdwork in Europe and workers typically operate on multiple platforms, it is difficult to generalize our findings to other online labor platforms that facilitate crowdwork. Future studies may adopt a multiple-platform strategy comparing worker experience across different online labor platforms. Research has demonstrated that work conditions and experiences may vastly differ across platforms (Graham et al., 2020; Heeks et al., 2021).

Third, we have focused on the impact of algorithmic management on perceptions of meaningful crowdwork through identity and belonging mechanisms. In doing so, we have only scratched the surface of the ways in which algorithmic management of crowdworkers may affect their experiences. For instance, research has noted tensions related to work execution and work compensation (Möhlmann et al., 2020) as well as variety of other challenges including viability challenges, career-path uncertainty challenges, and emotional challenges (Caza, Reid, Ashford, & Granger, 2021). In addition, research on algorithmic management is burgeoning, and with come a variety of different ways in which algorithmic management may be operationalized. We acknowledge that there is a wide array of management functions that may be offloaded to an algorithm. Asa case-in-point, Parent-Rocheleau and Parker (2022) discuss six different functions of algorithmic management – i.e., monitoring, goal setting, performance management, scheduling, compensation, and job termination. The argument here is not to suggest that this conceptualization is better, or worse, but that future research may explore algorithmic management functions at various levels of granularity.

Despite these limitations, this study offers valuable insights into the world of crowdwork and the experiences of its participants. Our research relies on robust empirical analysis of data from 1291 crowdworkers and underscores the nuanced implications of various dimensions of algorithmic management, shedding light on how these dimensions simultaneously facilitate and restrict identity development and a sense of belonging among crowdworkers, with consequential implications for their perception of meaningful work.

CRediT author statement

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Declaration of competing interest

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Data availability

Data will be made available on request.

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