Journal of Experimental Social Psychology 110 (2024) 104553

Contents lists available at ScienceDirect

Journal of Experimental Social Psychology

journal homepage: www.elsevier.com/locate/jesp

Algorithmic management diminishes status: An unintended consequence of using machines to perform social roles☆

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ARTICLE INFO

Keywords:
Algorithms
Algorithmic management
Automation
Status
Artificial intelligence
Social hierarchy
Psychology of technology

ABSTRACT

As artificial intelligence (AI) proliferates throughout society, it brings the potential to reshape how people perceive social roles and relationships. Across five preregistered studies, we investigated how AI-based algorithmic management influences perceptions and forecasts of social status. We found that people believe algorithmic management, compared to prototypical human management, leads to lower status in the eyes of others (Study 1). Moreover, forecasts of lower status mediated people's anticipated negative emotions when assessing remote jobs that were framed as primarily algorithmically managed (Study 2). Further, we found that people infer lower status given algorithmic management because they believe it signals that job tasks lack complexity, both when evaluating themselves or others (Studies 3 and 4). Finally, using OpenAI's natural language processing algorithm (GPT-3), we created an actual managerial algorithm and found that the lowered status inferences persist when people are managed by an algorithm that provides instructions, feedback, and monetary incentives (Study 5). We discuss theoretical implications for research on status, hierarchy, and the psychology of technology.

Throughout history, social hierarchies have been comprised of humans. As a result, people use their relationships with others as a way to assess their status. For example, when a superior treats a subordinate respectfully (versus with disdain), the subordinate may perceive high (versus low) personal status. Such attributions are important because status perceptions—both for self and others—shape key outcomes such as well-being, satisfaction, and motivation (Anderson, Kraus, Galinsky, & Keltner, 2012; Aquino & Douglas, 2003).

Interestingly, technological advancements are changing the nature of social hierarchy (Fast & Schroeder, 2020). Automated algorithms—defined as computerized processes designed to accomplish a specific goal or maximize a particular outcome—are becoming increasingly commonplace in both organizations and society (e.g., Brynjolfsson & McAfee, 2014; Logg, 2022; Raisch & Krakowski, 2021). Algorithms can increasingly make consequential judgments and decisions about people, including tracking work outcomes, predicting performance or "fit", and even autonomously managing human behaviors (Corritore, Goldberg, & Srivastava, 2020; Kosinski, Stillwell, & Graepel, 2013; Zhao, Hryniewicki, Cheng, Fu, & Zhu, 2018). In contrast to previous technological changes, AI-based algorithms additionally have such sophisticated interaction capabilities that they are fundamentally changing employees' perceptions of work, social relationships at work, and what a "coworker" truly is, often dramatically (Tang et al., 2023; Tang et al., 2023). This capacity to replace humans with machines, particularly in social roles, highlights a need for new theory regarding the psychology of status.

In the present research, we propose that an increased adoption of algorithmic systems to manage workers (Kellogg, Valentine, & Christin, 2020) could change how people infer social status in hierarchies. This is particularly relevant given recent advances in AI demonstrating that large language models (LLMs) are increasing machines' capacity to interact fluently across various domains (e.g., OpenAI, 2022). However, when AI algorithms perform traditional human roles or functions in social hierarchies, people may shift their evaluations of status away from

☆ This paper has been recommended for acceptance by Pranjal Mehta.

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https://doi.org/10.1016/j.jesp.2023.104553
Received 7 November 2022; Received in revised form 18 October 2023; Accepted 18 October 2023
Available online 2 November 2023
0022-1031/

how they interact with and are treated by others to who (or *what*) is overseeing them in the first place. Specifically, we explore the idea that algorithmic management may signal information about people's roles that lead them to attribute status loss, both in their own eyes as well as in others' perceptions.

1.1. Algorithms and status attributions

Status, defined as the extent to which an individual or group is respected or admired by others, is universally valued and desired because it leads to social and material rewards (Anderson, Hildreth, & Howland, 2015). Status is fundamentally rooted in how other humans see one in a specific context, and is distinguishable from power, or actual control over resources (e.g., Anicich, Fast, Halevy, & Galinsky, 2016; Blader & Chen, 2012; Fast, Halevy, & Galinsky, 2012; for a review, see Magee & Galinsky, 2008). That said, elevated status leads to social and economic resources (Anderson & Kilduff, 2009), and often creates self-reinforcing hierarchies in which higher-status individuals, groups, or organizations attract greater stakeholder support than lower-status actors (Bunderson & Reagans, 2011; Magee & Galinsky, 2008). Given the desirability of status, the prospect of losing it is also particularly threatening to both individuals and groups (e.g., Morrison, Fast, & Ybarra, 2009; Pettit, Yong, & Spataro, 2010; Scheepers, Ellemers, & Sintemaartensdijk, 2009).

Attributions of status emerge from a variety of sources. For example, individual factors have long served as signals of status in human groups and organizations, including physical characteristics and signals of competence, expertise, and performance (e.g., Fiske, Cuddy, & Glick, 2007; Nelissen & Meijers, 2011; Wagner & Berger, 1993). Beyond individual characteristics, research and theory concerning status has highlighted relational signals, such as the nature of one's relationships and how one's social interactions play out (e.g., Anderson & Kilduff, 2009; Benoit-Smullyan, 1944). However, in the present research, we are interested in how the insertion of AI-based autonomous decision-making systems into hierarchies (Cascio & Montealegre, 2016; Kellogg et al., 2020) might provide a new signal about one's status, holding constant individual factors and social interactions. Specifically, we focus on how algorithmic management might signal information about one's role which, in turn, influences perceptions of status.

The unique characteristics of autonomous algorithms make them good candidates to play social roles in hierarchies. Compared to traditional technologies, AI-powered algorithms have unique qualities in that they are "intelligent" such that they can autonomously collect, process, and interpret large quantities of data instantaneously (Kellogg et al., 2020; Tang et al., 2022; Tang, Koopman, Mai, et al., 2023; Tang, Koopman, Yam, et al., 2023). Indeed, algorithms' autonomy and ability to mimic human intelligence not only distinguish them from traditional augmentative technologies (e.g., a machine on an assembly line), but also facilitate their ability to manage human behaviors via judgments and decisions, often at scale (e.g., on gig economy platforms). Further, although autonomous machines may not appear to desire or achieve social status themselves, we argue that their introduction into hierarchies could reduce people's status in ways analogous humans do not: by signaling to others that a subordinate's tasks are simple and trivial.

1.2. Algorithmic competence and related perceptions

So far, research on attitudes about the use of algorithms in organizations has been mixed. For example, some studies have revealed opposition to algorithms (Bigman & Gray, 2018; Dietvorst, Simmons, & Massey, 2015; Newman, Fast, & Harmon, 2020), while others have found that people prefer algorithms for certain tasks where they may feel judged and negatively evaluated by humans, such as behavior tracking in the workplace (Raveendhran & Fast, 2021) or revealing personal information (Lucas, Gratch, King, & Morency, 2014). Indeed, many modern algorithms are increasingly sophisticated in their ability to both process large amounts of data as well as adapt given new or missing data (Cully, Clune, Tarapore, & Mouret, 2015; James, Witten, Hastie, & Tibshirani, 2013), and algorithms are increasingly deployed in numerous human resource and management contexts (e.g., managing the onboarding, consumer reviews, and payment for gig economy employees).

Algorithms' efficacy in performing human-like functions does not necessarily mean people will *perceive* these technologies positively, especially when they replace humans in social contexts (e.g., Newman et al., 2020). Although it has long been known that algorithms sometimes outperform human experts (Meehl, 1954), people tend to distrust these systems in domains that feel more subjective, including ones that involve making decisions about people, human behavior, or seemingly novel situations (Castelo, Bos, & Lehmann, 2019; Longoni, Bonezzi, & Morewedge, 2019; Newman et al., 2020; Yeomans, Shah, Mullainathan, & Kleinberg, 2019). Work in organizations can appear complex in that it reflects a variety of informal and formal social processes (Heaphy et al., 2018), often leading academics and practitioners to advocate for augmentative or collaborative processes, as opposed to the full automation of human jobs or roles (Wilson & Daugherty, 2018). Despite this criticism, many organizations are motivated to fully automate management functions due to algorithms' efficiency, perceived rationality, and low cost (e.g., Brynjolfsson & McAfee, 2014).

In the present research, we build on the discontinuity between algorithms' actual capabilities versus people's perceptions of algorithms' capabilities to explore a downstream consequence: that jobs appear simple and non-complex when managed by algorithms, compared to prototypical human management. While existing research focuses on how people interact with algorithms (e.g., recommender systems or other decision aids) in the course of work to accomplish tasks or make decisions (e.g., Castelo et al., 2019; Jago & Carroll, 2023; Logg, Minson, & Moore, 2019), we posit here that algorithms' ability to engage in prototypical management functions—and their subsequent insertion into social hierarchical positions previously occupied by humans—are changing the nature of the relational signals people parse from group memberships and arrangements in ways that lower status when algorithms are hierarchically superior to any target.

1.3. Algorithmic management and perceived job complexity

The fact that algorithms can operate effectively in relatively complex situations does not necessarily mean that people will perceive them as capable of doing so. Indeed, people's assumptions about algorithms—-which may guide their subsequent behavior—can deviate from algorithms' actual capabilities. For example, people might trust algorithms more or less depending on the context in which algorithms are operating, regardless of their actual efficacy in that context (Castelo et al., 2019; Dietvorst et al., 2015; Dietvorst, Simmons, & Massey, 2018; Logg et al., 2019). People also assume algorithms neglect unique or context-dependent qualities when making decisions, again regardless of their actual capabilities in this space (Longoni et al., 2019; Newman et al., 2020).

Because people believe algorithms neglect both unique (Longoni et al., 2019) and context-sensitive (Newman et al., 2020) information, we argue that people will further assume that algorithms that dictate work and/or behaviors can only "manage" tasks that lack complexity. This lay belief is likely reinforced by narratives whereby organizations justify automation along the lines of reducing the burden of simple, "… repetitive work" (Ackerman & Kanfer, 2020). This prediction contrasts with how people will likely evaluate prototypical human management, where supervisors can rely on their creativity, knowledge, or decision-making abilities to manage new or difficult situations (i.e., skills that are required for helping employees navigate complex work).

We further posit that people's assumptions about task complexity will shape their perceptions of social status. In social hierarchies, status is typically conferred on those who are perceived to have competencies that are valuable to the group (Blader & Yu, 2017; Kellett, Humphrey, & Sleeth, 2002). Engaging in complex tasks and performing them well may signal—both to others and oneself—that one is competent and may possess skills that are valuable; conversely, having non-complex tasks may signal that one has less-valuable skills and is relatively replaceable.

Putting these theoretical pieces together, introducing algorithms into managerial roles brings implications for people's status. If people perceive algorithms as only capable of managing simple and trivial tasks, they may also perceive others managed by these algorithms as doing work that is similarly simple and rote, implying the expertise and/or competence necessary for elevated status is lacking (Magee & Galinsky, 2008). Indeed, research indicates that when individuals believe that others see them as having lower competence or as less capable of making valuable contributions to the group, they have lower self-perceived status (Anderson et al., 2012). Based on this theorizing, we posit the following hypotheses:

Hypothesis 1. People attribute lower status to those managed by algorithms as compared to those managed by humans.

Hypothesis 2. Algorithmic management diminishes status by producing the perception that the job responsibilities are less complex.

It is important to note that, even if people believe algorithms cannot adequately manage "complex" situations, this lay belief is not necessarily true. Given proper training data, algorithms can form recommendations in extremely complex decision-making environments (though it should be noted that close and ongoing attention to the quality of the training data and decision outcomes is necessary; e.g., Obermeyer, Powers, Vogeli, & Mullainathan, 2019). For example, modern algorithms can form sophisticated psychometric profiles of people based on their online activity (Kosinski, Matz, Gosling, Popov, & Stillwell, 2015), manage complex business operations and supply chains (Aytug, Khouja, & Vergara, 2003), and outperform humans making complex human resources decisions (e.g., predicting whether or not a potential hire will be a high-performing employee; Chalfin et al., 2016). People perceive modern algorithms as increasingly autonomous and intelligent, which prevails psychological consequences when working with them (Tang et al., 2022; Tang, Koopman, Mai, et al., 2023; Tang, Koopman, Yam, et al., 2023). Indeed, much recent research has focused on algorithms' potential sophistication and usefulness in numerous classically "complex" work domains, such as medicine (e.g., Rajkumar & Reena, 2010) and law (e.g., Scholz, 2017), a stark contrast to these hypotheses regarding how people *perceive* these technologies.

The present research broadly contributes to literature concerning human-AI interaction and management, as well as status and status signaling processes in modern work environments. First and foremost, a great deal of recent research investigates the unique relationship people have with AI-based algorithms and technologies, as well as what factors influence how people interact with these technologies (e.g., Yam et al., 2022). Here, we argue that there are social implications stemming from algorithmic management that echo beyond manager-subordinate interactions, specifically by shaping people's perceptions of their positions in broader social and organizational hierarchies. We also explore a novel mechanism for how algorithmic management and status interrelate. In particular, as AI-based management processes become more common, the concomitant signals of low job complexity will ultimately shape status attributions and correspondingly, commercial decisions (e.g., a person deciding whether or not they are interested in a lucrative job that employs algorithmic management; see Study 2). Finally, as algorithms and other AI-based technologies engage in more and more traditional management work in organizations, we argue here that the nature of social status is fundamentally changing: *what* you are working with—or what is above you in an organizational hierarchy—can be an important signal of status above and beyond agents' capabilities or actual control over resources, simply based on people's stereotypes and assumptions about machines.

1.4. Overview of studies

Across five pre-registered studies, we investigated our hypotheses. These studies employed both within-subjects (Study 1) and between-subjects (Studies 2–5) designs to compare how people assigned status to both themselves and others under conditions of algorithmic (vs. human) management. We designed the first two studies to investigate perceptions of status in algorithm vs. human-based managerial arrangements (Studies 1–2), and the next studies to investigate the potential mechanism of signaled job complexity as an explanation for why people might infer lower status given algorithmic management (Studies 3–4). Finally, in Study 5, we developed an application using OpenAI's GPT-3 large language model to manage and evaluate participants engaging in a creative brainstorming task (OpenAI, 2022). This design allowed us to investigate whether participants' lower status attributions given algorithmic management would emerge when managed by a sophisticated algorithm.

Consistent with our pre-registrations, we report parametric tests for all results and the significance thresholds for all reported results remained the same when conducting analogous nonparametric tests. We report all manipulations, measures, and exclusions for all studies and determined all sample sizes prior to data collection and analysis. In all studies, we pre-registered the number of participants we planned to recruit using the heuristic of recruiting $N = 100$ participants per experimental cell for a two-cell between-subjects design. There were two exceptions: In Study 1 (the first study we conducted), we recruited $N =$ 200 participants in a repeated-measures design to ensure adequate power to detect any effects given its somewhat more exploratory nature. In Study 4, given that we employed an interactive design across four experimental conditions, we chose to double this heuristic to $N = 200$ participants per experimental cell, to increase power to detect any interactive effects (in addition to main effects). Pre-registration links are available in the introduction to each study, and all data and materials are available via the Open ScienceFrameworkat: https://osf.io/fet7u/.

2. Study 1

In Study 1, we examined whether working adults would infer lower status at their current jobs if an algorithm—compared to a human—took over the role of managing them. To this end, we worked with Qualtrics to curate a sample of full-time working adults to complete a survey. We asked participants to describe their status in their current position, and then instructed them to consider the possible automation of their management—in other words, a scenario where their human boss was replaced with an "AI based algorithm". After this, we asked them to indicate the degree to which others would attribute them with status under such conditions. We predicted that people would perceive lower status when subjected to algorithm-driven management. We also included an exploratory measure investigating the degree to which participants naturally anthropomorphized algorithms to see whether or not participants inferred different levels of status depending on their natural anthropomorphic tendencies. We preregistered this study at: https://aspredicted.org/r9fb7.pdf.

2.1. Method

2.1.1. Participants

We preregistered recruiting 200 participants via Qualtrics panel. After working with a recruiter at this service, two hundred and thirty-two American working adults (full-time) ultimately completed the study. Of these, three participants indicated that their current manager ("e.g. the one who gives you management instructions") was "an algorithm" and not "a human" at the beginning of the survey; we excluded these participants, yielding a final sample of 229 (86 Male, 144 Female; $M_{age} = 41.07$). On a nine-point scale ranging from "1–4" to "1000 or more", the modal participant (41) worked in a large organization with

1000 or more employees, although participants reported working in a diverse array of organizational sizes (at least 16 participants in each row, the lowest (16) being an organization of "5–9" employees). The vast majority of participants (66.8%) worked in private for-profit companies, although we again observed a diverse array of industries and self-reported job titles (see supplemental data on OSF). This analysis had 80% power to detect an effect size of $d = 0.18$.

2.1.2. Procedure

In addition to targeting adults who were working full-time, we also verified that participants worked full-time via an employment status question at the beginning of the survey. Participants provided their current job title via an open-ended text box and also indicated whether their current manager was "a human" or an "algorithm". Next, participants answered the degree to which their positions provided status using four items (adapted from Anicich et al., 2016) along a 1 (Not at All) to 7 (Very Much) scale: "To what extent does your position at work give you high status in the eyes of others?", "To what extent does your position at work make people look down on you?" (reverse scored), "To what extent do people admire you because of your position at work?", and "To what extent do you have a low-status position at work?" (reverse scored). While the reliability for these items was lower than we expected ($\alpha = 0.55$), we aggregated these items into a composite of current status.[1]

Next, we told participants that many organizations are "…replacing managers and managerial functions with AI-based algorithms" and that we were interested in how they would feel if their organization replaced their (human) boss with an AI-based algorithm using the same four status items. Specifically: "Given this change, would you change your opinion? Please answer the following items about your current job given this new AI-based algorithm boss." Participants next responded to the same four status items, but adapted to reflect a forecast about the future: "e.g. To what extent will your position at work give you high status in the eyes of others?". These items again exhibited lower reliability than we expected ($\alpha = 0.57$), but consistent with our pre-registration, we proceeded to aggregate a composite of anticipated status.

At the end of the survey, we administered an exploratory adapted version of the IDAQ anthropomorphism questionnaire designed to assess participants natural anthropomorphic tendencies (Waytz, Cacioppo, & Epley, 2010). Each item utilized a 1 ("Strongly Disagree") to 7 ("Strongly Agree") scale, and each began with "To what extent do you think AI algorithms…": "Have free will?", "Experience emotions?", "Have consciousness?", "Have minds of their own?", and "Have intentions?". These items exhibited high reliability ($\alpha = 0.93$); overall, participants' levels of natural algorithm anthropomorphism fell slightly below the scale midpoint ($M = 3.18$), but exhibited relatively high variance ($SD = 1.79$; aggregate responses ranging from 1 to 7).

2.2. Results

Consistent with our hypothesis, a paired-samples *t*-test indicated that participants anticipated lower status following a change to algorithmic management ($M = 4.67$, $SD = 1.39$) compared to what they perceived given their current human manager ($M = 5.14$, $SD = 1.27$; $t(228) = 5.65$, $p < .001$, $d = 0.35$). This result indicated that a sample of full-time working adults believed they would experience a decrease in status if their organizations implemented algorithmic management processes in place of their human managers.[2]

2.3. Discussion

Using a panel of working adults within a variety of organizations alongside a relatively simple within-subjects paradigm, Study 1 provided evidence that people believed they would experience a loss of status if their organization switched them from working for human management to algorithmic management. As such, although algorithms can indeed offer efficient and/or useful management given their capacity to process large amounts of personalized data and make effective recommendations (which can sometimes outperform human recommendations), this possible benefit could come with a potential cost to morale: participants in Study 1 believed that the implementation of such a technology would lead them to have lower status. Interestingly, this forecasted loss in status appeared to be somewhat smaller among participants who naturally anthropomorphized these algorithms and saw them as more capable of mental states (e.g., thinking and feeling; see General Discussion).

3. Study 2

In Study 2, we primarily wanted to conceptually replicate the status effect we observed in Study 1 in a different context. Given that having low status predicts experiencing negative emotions (Anderson et al., 2012) and employee emotions are central to job satisfaction and turnover decisions (e.g., Cote & Morgan, 2002; Fisher, 2000), we also wanted to investigate if participants' assumptions about the status they would derive from algorithmically-managed work arrangements would impact their forecasted feelings towards those jobs. We finally wanted to explore participants' real interest in different jobs given both algorithmically- and human-managed remote work arrangements. To this end, in Study 2, we utilized a within-subjects design during the COVID-19 pandemic to explore participants' attitudes towards real remote data management work. Specifically, we characterized some remote data jobs as primarily managed by algorithms and others as primarily managed by humans. We then assessed participants' willingness to view and explore jobs managed by both agents. In addition, we asked participants to—using natural language—express how they would feel working under both a human and algorithm given such work arrangements. In addition, whereas studying a change in management from an old system to a new system (e.g., Study 1) could introduce some confounds, Study 2 more directly compared human and algorithmic

[1] Given this lower-than-expected reliability, we conducted separate analyses creating two separate status scales: one consisting of the two "regularly" scored (e.g., non-reverse scored) items, and one consisting of the two reverse-scored items, which exhibited higher reliability than the full four item composite (*rs* > 0.70, *ps* < 0.001 and *rs* > 0.87, *ps* < 0.001, respectively). As a robustness check, the significance thresholds for all results were the same when conducting identical analyses using the full status composite, a composite consisting of the two regularly-scored status items, or a composite consisting of the two-reverse-scored status items, save for their interaction with anthropomorphism (see Footnote 2).

[2] A generalized repeated-measures linear model including participants' natural anthropomorphism as an interactive effect alongside the within-subjects status composites indicated main effects of this within-subjects factor for status ($F(1, 227) = 32.25$, $p < .001$, $\eta_p^2 = 0.12$) and anthropomorphism ($F(1, 227) = 11.98$, $p = .001$, $\eta_p^2 = 0.05$), along with a marginally-significant interaction between the two, $F(1, 227) = 3.29$, $p = .071$, $\eta_p^2 = 0.01$. Simple effects analyses revealed that the status "penalty" people anticipated given algorithmic management was somewhat smaller among participants who naturally anthropomorphized algorithms to a greater extent (1 *SD* above the mean, $F(1, 227) = 7.43$, $p = .007$, $\eta_p^2 = 0.03$) compared to participants who naturally anthropomorphized algorithms to a lesser extent (1 *SD* below the mean, $F(1, 227) = 28.05$, $p < .001$, $\eta_p^2 = 0.11$). When examining the status composite as two separate composites (i.e., grouping the two regularly-scored items into one composite and the reverse scored items into another), this interaction was significant when operationalizing status using the two regularly scored items ($F(1,230) = 7.21$, $p = .008$, $\eta_p^2 = 0.03$), but not significant when operationalizing status using the reverse-scored items ($F(1, 230) = 0.09$, $p = .767$; $\eta_p^2 = 0.000$). In addition to the marginally significant interaction, given these inconsistent results, we hesitate to draw very strong conclusions regarding the intersection of anthropomorphism and status.

management in the context of an entirely new position. We preregistered this study using AsPredicted.org: https://aspredicted.org/pv3qr.pdf. .

3.1. Method

3.1.1. Participants

Two hundred and three American adults (129 Male, 71 Female, 1 Nonbinary, 1 Agender; $M_{age} = 25.55$) who reported that they were not currently working full-time completed the survey via Prolific. Participants had an average of 3.12 years of work experience ($SD = 3.25$), 30.8% were actively looking for work, while 24.9% were currently doing some paid work for an organization (22.9% were not working for "other" reasons, e.g., they were full-time students). As in Study 1, participants reported having worked in variety of different industries, the most common being "Arts, entertainment, or recreation" (15.3%). These analyses had 80% power to detect an effect size of $d = 0.20$.

3.1.2. Procedure

We designed and advertised the survey as being about remote work during the COVID-19 pandemic. Participants read that "data management professionals" often manage data-oriented projects remotely, and often work with coworkers at a parent company (e.g., "marketing" and "human resources"). We provided this information to make salient the fact that, even during remote work, others' impressions of the status of these kinds of positions could matter. Participants next read that: "Data management professionals are generally managed by one of two kinds of managers: people or algorithms driven by artificial intelligence." Participants continued to read that, if they worked in data management, either a person or algorithm would "…assign you tasks, manage your work, and make 'promotion' and 'raise' recommendations given your performance." This added specificity offered a slightly more precise description regarding the management functions this new technology would take compared to Study 1. We chose this context, in part, because both a human and algorithm could reasonably quantify and evaluate different performance indicators.

After reading about this remote work context, we administered the same status scale used in Study 1 twice to all participants: they indicated how much status they anticipated given a "person" as their manager, as well as how much status they anticipated given an "algorithm" as their manager. We aggregated these responses into two composites of status ($\alpha s = 0.60$ and 0.76). We additionally included two exploratory measures following these status composites. Next, participants read the following: "At the end of this survey, we will provide you with actual (remote) data management job postings. Would you like to see postings where a person is your manager, or an algorithm is your manager?" and allowed them to select one of the two options. Finally, we asked participants to indicate, using open-ended text boxes, how they would feel given both human and algorithmic management: "How would you personally feel about working in a remote data management job with [a person / an algorithm] as your manager? Please tell us in 1-2 sentences." At the end of the survey, following the demographic questions, we provided a link to open remote jobs in data management, given the nature of the survey and that we conducted it during a pandemic where many were losing their jobs.

3.2. Results

Consistent with the results from Study 1, a paired-samples t-test indicated that participants indicated they would have significantly lower status under conditions of algorithmic management ($M = 4.21$, $SD = 1.19$) compared to human management ($M = 4.69$, $SD = 0.92$; $t(201) = 5.00$, $p < .001$, $d = 0.45$).[3]

Interestingly, we observed a relatively even split in terms of participants' desire to see job postings with human managers ($N = 99$, 49%; $CI_{95} = [41.6, 55.9]$) compared to algorithmic managers ($N = 103$, 51%; $CI_{95} = [44.1, 58.4]$). We hesitate to draw strong conclusions from this null result given that the study was conducted during a pandemic which brought about considerable work insecurity as well as technological change to facilitate remote work arrangements. These factors could have increased interest in perusing fully remote job opportunities to learn what they entail. Furthermore, participants may have just been curious about what an algorithm-managed job looks like, despite the lower status perceptions.

To analyze participants open-ended responses, we used LIWC text analysis software (Tausczik & Pennebaker, 2010). Specifically, we used LIWC to code the open-ended responses for language indicating both positive and negative affect. Overall, whereas algorithmic (vs. human) management did not influence participants' forecasted positive emotions ($M = 7.28$, $SD = 9.45$; $M = 6.82$, $SD = 13.81$; $t(202) = 0.46$, $p = .646$, $d = 0.04$), participants naturally generated more negative emotional language given algorithmic management ($M = 3.36$, $SD = 5.67$), compared to human management ($M = 2.17$, $SD = 5.51$; $t(202) = -2.15$, $p = .033$, $d = 0.21$). We next utilized the MEMORE within-subjects mediation macro (Montoya & Hayes, 2017) to investigate if participants' lower anticipated status given algorithmic management mediated their increased negative emotionality given algorithmic management. Results indicated that participants' lower anticipated status given algorithmic management significantly mediated their more negative expressed emotionality given this work arrangement ($b = -0.44$, $CI_{95} = [-1.03, -0.007]$). One limitation of this particular analysis is that we did not measure other potential mediators beyond status in Study 2, limiting our ability to test other potential mechanisms for this effect. In addition, we did specify these models using our own theoretical framework; it was possible to additionally specify other models using these data (such as affect mediating status).

3.3. Discussion

Overall, Study 2 demonstrated that participants anticipated lower status under conditions of algorithmic management using a real job context: remote data management during the COVID-19 pandemic. When we framed these positions as managed by both humans and algorithms, participants believed that they would have lower status given algorithmic management relative to human management. Interestingly, participants did not express greater interest in seeing real job postings managed by humans; we observed a roughly equal split in terms of interest in both human- and algorithm-managed jobs. Although people may generally want to avoid low-status positions, participants in this study may have been curious as to what algorithm-managed jobs are posted as in job boards and/or otherwise characterized. Using text

[3] Although we did not pre-register this analysis, given the somewhat lower status scale reliability in the "person" condition ($\alpha = 0.60$), significance thresholds for these results were identical ($ps < 0.001$) when—like in Study 1—we conducted analyses treating the two regularly scored status items as one status composite ($rs > 0.77$, $ps < 0.001$), and the reverse-scored status items as a separate status composite ($rs > 0.61$, $ps < 0.001$); here, the two reverse-scored items appeared to contribute to lower scale reliability. However, results were similar using the full status composite or either of these two regularly-scored or reverse-scored scale subsets.

analysis, we also observed evidence that participants expected to feel more negative emotions given algorithmic management, compared to traditional human management. Lower status anticipations additionally mediated this effect. Although algorithms may be capable and/or useful in management functions, this particular result insinuates that people may be averse to such options by virtue of anticipating they will feel low-status and experience negative emotions as a result (Wilson & Gilbert, 2005). As such, organizations wishing to employ AI-based management technologies would likely benefit from accounting for the negative emotions job seekers, or even current employees, might experience as a function of this implementation.

4. Study 3

In Study 3, our goal was to use a between-subjects design to investigate our first hypothesis indicating that people will anticipate lower status when subjected to algorithmic (vs. human) management. In addition, we wanted to investigate our second hypothesis regarding signaled job complexity. Specifically, our theorizing suggests that people assume lower status given algorithmic management because their job will both appear and be relatively simple and rote, compared to human management. To this end, we created a vignette where online contract-worker participants pictured themselves as having a job analyzing social media text, and their organization was replacing their boss with either a new "person" or a new "AI-based algorithm". We predicted that when participants believed their new manager would be an algorithm, they would anticipate lower status than participants who believed their new manager would be a person, and that perceptions that others will see their job as non-complex would mediate this effect. Wepre-registeredthisstudyusing AsPredicted.org: https://aspredicted.org/5jd6b.pdf.

4.1. Method

4.1.1. Participants

Two hundred and three American adults (106 Male, 91 Female, 3 Nonbinary, 1 Gender-Neutral; $M_{age} = 34.11$) completed the experiment via Prolific. These analyses had 80% power to detect an effect size of $d = 0.40$.

4.1.2. Procedure

Participants pictured themselves as an employee at a "large consulting" firm that works with social media companies to provide feedback about the value of different posts on social media feeds. Participants read that their role was to do "systematic analysis" on social media feeds, including "…reading, evaluating, and rating user posts (both words and images) along a variety of dimensions…" (e.g., emotional content, valence, appropriateness, etc.; see supplemental materials on OSF for full stimulus materials). Participants read that their boss oversaw their work and identified "…what specific social media types and topics you should focus on each day. In addition, this person assesses your efficiency and gives you instruction about how to improve." We chose this domain, in part, because it is one where elements of performance (e.g., number of posts processed and/or interrater reliability with other workers) as well as workflow could be reasonably assessed and administered, respectively, by both a human and an algorithm.

Next, we randomly assigned participants to receive either a new "person" or "AI-based algorithm" boss: "Recently, it was announced that your boss will be replaced by [a new person / a new AI-based algorithm]". Immediately after learning about this change, we presented our two main dependent variable composites on separate pages in counterbalanced order. First, participants indicated their status given this new change using the same items employed in Study 2 (after imagining a similar change). These items exhibited adequate reliability ($\alpha = 0.71$). Next, participants indicated how complex they believed others would see their position using items adapted from Zacher and Frese (2011) along a 1 (Not at All) to 7 (Very Much) scale: "To what extent will people think that you can learn new things in your work?", "To what extent will people think that you often have to make very complicated decisions in your work?", "To what extent will people think your job tasks are extraordinary and particularly difficult?", and "To what extent will people think that you can use all your knowledge and skills in your work?". These items formed a reliable composite of forecasted job complexity ($\alpha = 0.87$). These status and complexity composites significantly correlated, $r = 0.62$, $p < .001$.

4.2. Results & discussion

Overall, participants anticipated marginally less status given new algorithm-driven management ($M = 3.92$, $SD = 1.08$) compared to a human replacement ($M = 4.21$, $SD = 1.05$; $t(198) = 1.95$, $p = .053$, $d = 0.28$). In addition, participants assumed that others would see their job as less complex given algorithmic management ($M = 3.84$, $SD = 1.31$) compared to human management ($M = 4.37$, $SD = 1.12$; $t(199) = 3.09$, $p = .002$, $d = 0.43$). Despite observing a marginal effect predicting status, we followed our pre-registration plan and created a 5000-iteration bootstrapped mediation model using agent (0 = human, 1 = algorithm) as the independent variable, anticipated status as the dependent variable, and signaled complexity as the mediator (PROCESS Model 4). Results indicated a significant indirect effect, $b = -0.28$, $CI_{95} = [-0.48, -0.11]$: given algorithmic management, participants assumed others would see their role as less complex, which mediated lower anticipated status in their organization (see Fig. 1). This aligned with our theoretical model concerning the role of signaled complexity (Hypothesis 2), although this approach did have limitations in that other potential mediators were not measured. In addition, as with Study 2, we specified this particular model in line with our own theoretical framework; it was also possible to create models reversing this pathway (i.e., with anticipated status mediating signaled complexity).

In sum, Study 3 provided support for both Hypothesis 1 and Hypothesis 2. In a situation where participants pictured themselves having an algorithmic boss, they (marginally) assumed they would be lower status in the organization. In addition, participants assumed that others would see their job as less complex given algorithmic management, which mediated their diminished anticipated status. As such, using a between-subjects design, Study 3 offered evidence that people spontaneously infer lower status given algorithmic management, compared to analogous human management, and this effect was driven by perceptions of lower job complexity.

5. Study 4

We had two primary goals for Study 4. First, we wanted to investigate whether people's association between algorithmic management and lower job complexity—and subsequently lower status—persist not only for themselves (as in Studies 1–3), but also when evaluating other people assigned to algorithm-based managers. While research on status suggests that people are generally accurate when perceiving their own (versus others') status, given how costly errors can be when perceiving

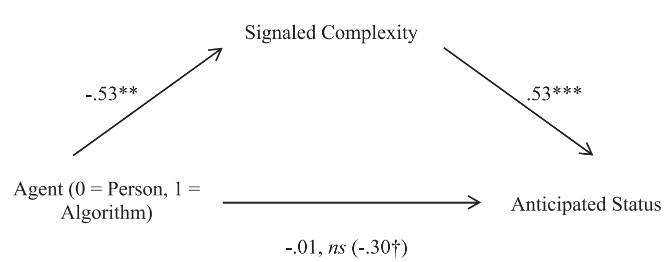

Fig. 1. Anticipated status as a function of agent and signaled complexity (Study 3). †$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$.

one's own status (Anderson, Srivastava, Beer, Spataro, & Chatman, 2006), we wanted to empirically investigate this potential boundary condition. Second, our measures thus far investigated meta-perceptions of both status and complexity (e.g., whether one believes others will think one has high or low status) as opposed to direct perceptions of this construct, or how one personally sees themselves or others (e.g., as having high or low status; see Carlson, Vazire, & Oltmanns, 2011). In Study 4, we investigated whether the algorithmic management ➔ lower job complexity ➔ lower status mediation pattern we observed in Study 3 would emerge when assessing direct perceptions of these constructs. We pre-registered this study using AsPredicted.org: https://aspredicted.org/hr9hh.pdf.

5.1. Method

5.1.1. Participants

Eight hundred and two (424 Male, 367 Female, 11 Other, M_{age} = 36.77) American adults completed the experiment online using Prolific Academic. These analyses had 80% power to detect an effect size of f = 0.10.

5.1.2. Procedure

This study used materials adapted from Study 2, where participants responded to questions about remote data management jobs. After reading a short description about remote work opportunities in data management, we randomly assigned participants to answer either questions about themselves or a colleague of theirs starting a new job in remote data management. Specifically, we instructed participants to respond to a situation in which either: "…you recently accepted a remote data management job" or "…a colleague of yours accepted a remote data management job", both with a large organization. After this, we randomly assigned participants to read that this remote data management position would be managed by either a "person" or an "algorithm" that would: "…assign [your / your colleague] tasks, manage [your / their] work, and make 'promotion' and 'raise' recommendations given [your / your colleague's] performance". This yielded a 2 (target agent: self vs. other) X 2 (managing agent: person vs. algorithm) design.

After these materials, we administered an adapted version of the complexity items used in previous studies under the header "At this job…": "To what extent do you think that [you/your colleague] can learn new things in [your/their] work?", "To what extent do you think that [you/your colleague] will often have to make very complicated decisions in [your/their] work?", "To what extent do you think that [your/your colleague's] job tasks are extraordinary and particularly difficult?", and "To what extent do you think that [you/your colleague] can use all [your/their] knowledge and skills in [your/their] work?" using the same 1 ("Not At All") to 7 ("Very Much") Likert scale as previous studies. These items formed a reliable composite of job complexity ($\alpha = 0.80$). Instead of the four-item status scale used in previous studies, we administered a single item reflective of direct (i.e., one's own opinion, not a "meta" assessment of others' opinions) perceptions of status adapted from Anderson et al. (2006): "I have a lot of status within this organization" in the "self" condition, and "My colleague has a lot of status within this organization" in the "other" condition. We administered both single items along a 1 ("Strongly Disagree") to 7 ("Strongly Agree") scale.

5.2. Results and discussion

5.2.1. Job complexity

We first created a 2 (target agent: self vs. other) X 2 (managing agent: person vs. algorithm) ANOVA predicting job complexity. Results indicated a main effect of managing agent ($F(1, 798) = 41.58, p < .001; \eta_p^2 = 0.05$), no main effect of target agent ($F(1, 798) = 1.85, p = .174; \eta_p^2 = 0.002$), and a marginally significant interaction between the two, $F(1, 798) = 3.81, p = .051; \eta_p^2 = 0.005$. Despite only observing a marginally significant interaction, we proceeded to analyze simple effects breaking down this interaction. When participants evaluated themselves, consistent with previous studies, simple effects analyses indicated that participants perceived significantly lower job complexity given an algorithmic manager ($M = 4.46, SD = 1.07$) compared to a human manager ($M = 4.78, SD = 0.97; F(1, 798) = 10.15, p = .001, \eta_p^2 = 0.01$). When participants evaluated "a colleague", they displayed a similar pattern: they attributed lower job complexity to another person given algorithmic management ($M = 4.42, SD = 1.07$), compared to human management ($M = 5.01, SD = 0.89$). Simple effects analyses indicated that, reflecting the marginally significant interaction, the human-algorithm difference was actually stronger when participants evaluated another person in a similar job arrangement, $F(1, 798) = 35.14, p < .001, \eta_p^2 = 0.04$. This was driven by the fact that participants attributed significantly greater job complexity to another person with a human manager compared to themselves ($F(1, 798) = 5.46, p = .020; \eta_p^2 = 0.007$); they did not distinguish between themselves or "a colleague" when both agents were managed by algorithms ($F(1, 798) = 0.18, p = .675; \eta_p^2 = 0.000$). In other words, the tendency to attribute more job complexity to another person under conditions of human management vanished under conditions of algorithm-based management.

5.2.2. Status

We next constructed an identical 2 (target agent: self vs. other) X 2 (managing agent: person vs. algorithm) ANOVA predicting perceptions of status. Consistent with previous studies, results revealed a significant main effect of managing agent $F(1, 798) = 17.53, p < .001; \eta_p^2 = 0.02$. Participants believed, regardless of target agent, that the algorithm-managed work arrangement reflected lower status ($M = 3.69, SD = 1.27$) compared to the human-managed work arrangement ($M = 4.09, SD = 1.15$). Results also revealed a significant main effect of target agent, such that participants more readily conferred status to another person ("a colleague"; $M = 4.11, SD = 1.18$) compared to themselves ($M = 3.68, SD = 1.24; F(1, 798) = 20.97, p < .001; \eta_p^2 = 0.03$). In contrast to the marginally significant interaction when we used these two manipulations to predict job complexity, there was no significant interaction when predicting status, $F(1, 798) = 1.96, p = .162; \eta_p^2 = 0.002$ (algorithm condition: $M_{self} = 3.57, SD_{self} = 1.27; M_{other} = 3.84, SD_{other} = 1.25$; human condition: $M_{self} = 3.81, SD_{self} = 1.18; M_{other} = 4.32, SD_{other} = 1.08$). Status and job complexity correlated significantly, $r = 0.49, p < .001$.

5.2.3. Moderated mediation by self-versus-other target agent

Consistent with our pre-registration, we proceeded to create a 5000-iteration bootstrapped moderated mediation model using managing agent (0 = person, 1 = algorithm) as the independent variable, status as the dependent variable, job complexity as the mediator, and target agent (0 = self, 1 = other) as the moderator. We first allowed target agent (self vs. other) to moderate the managing agent (person vs. algorithm) ➔ job complexity link (PROCESS Model 7). Results revealed significant moderated mediation, $b = -0.16, CI_{95} = [-0.32, -0.001]$, indicating that the strength of the indirect effect differed as a function of target agent (self vs. other). Although job complexity mediated perceptions of status in both the "self" condition ($b = -0.18, CI_{95} = [-0.30, -0.06]$) as well as the "other" condition ($b = -0.34, CI_{95} = -0.47, -0.22$), this indirect effect was significantly stronger when participants were evaluating a colleague (i.e., someone who they attributed significantly higher status than themselves given traditional human management), compared to their own work arrangement. This moderated mediation remained statistically significant when allowing target agent (self vs. other) to also moderate the managing agent ➔ status link, in addition to the managing agent ➔ complexity link (PROCESS Model 8; $b = -0.16, CI_{95} = [-0.32, -0.001]$. We did not observe moderated mediation allowing target agent (self vs. other) to moderate the job complexity ➔ status link (PROCESS Model 14; $b = -0.01, CI_{95} = [-0.09, 0.06]$). Notably, perceptions of job complexity mediated attributions of status, regardless of evaluation target. These results thus reinforce the theoretical relationship between job complexity and status, and also offer evidence that algorithmic management signals relatively low job complexity among subordinates, regardless of if people are evaluating themselves or another person.

However, although we observed consistent mediation through complexity to status regardless of evaluation target, these moderated mediation results additionally indicated that this mediating process was stronger when participants evaluated other people, compared to themselves (see Muller, Judd, & Yzerbyt, 2005). People generally prefer to be humble when self-assessing status and status-relevant characteristics (Anderson et al., 2006). These results were consistent with Anderson et al., 2006 in that people may be more conservative when self-assessing the relationship between job complexity and status. Finally, in Study 4, we also measured direct perceptions of status and job complexity, compared to meta-perceptions of these constructs (e.g., Study 3); we observed similar results across studies using both operationalizations of these social perceptions. Thus, these findings allowed us to shed light on two important potential boundary conditions (self vs. other ratings and direct vs. meta-perceptions) for our hypothesized relationships between algorithmic management, job complexity, and status.

6. Study 5

In Study 5, our primary goal was to investigate participants' status inferences both before and after actual interactions with a managerial algorithm. Using Amazon Web Services (AWS) and OpenAI's GPT-3 natural language processing architecture, we created an integrated AI tool that could provide task instructions and performance evaluations to participants. Importantly, this study was conducted prior to the release of OpenAI's ChatGPT and the general public was not yet aware of large language models. This allowed us to create a controlled experience that was believably human or algorithmic. Over the course of the task—-brainstorming names for a small business—the algorithm provided participants with real-time feedback about their name submissions and ultimately provided participants with a quantitative score tied to a financial bonus. Although all participants were actually managed by an algorithm, we randomly assigned participants to believe that this managing agent was either a person or an algorithm, allowing us to confirm that any differences across conditions were due solely to participants' own pre-experience beliefs and not due to differences in managerial style. This experiment allowed us to compare both forecasted and actual experiences with a real algorithm engaging in traditional management functions (e.g., providing feedback and rewards). We pre-registered this study using AsPredicted.org: https://aspredicted.org/4286p.pdf.

6.1. Method

6.1.1. Participants

Two hundred and two American adults (90 Male, 108 Female, 4 Other; $M_{age} = 35.13$) completed the experiment online via Prolific Academic. These analyses had 80% power to detect an effect size of $d = 0.40$.

6.1.2. Procedure

We told all participants that they would be engaging in a writing and brainstorming exercise. Specifically, we told participants that we were working with a consulting company ("Epicher") to come up with small business names. Throughout the experiment, we modeled this exercise to mirror brainstorming and idea generation tasks that businesses routinely post on contract labor websites such as Upwork. Creative tasks are increasingly algorithmically managed, and reflect algorithms' sophistication to manage relatively sophisticated business decisions and processes, making a brainstorming task such as this a relevant context to study human-algorithm work interaction (Tang et al., 2022b). Next, we randomly assigned participants to either a human or algorithmic manager: Participants read that a(n) [person / algorithm] employed by this consulting company would be managing them for the duration of the work task, and that this agent would "…provide you with instructions and evaluate your work output."

We told participants that, before they engaged in this brainstorming task, we wanted them to predict how they would feel in this situation: doing work for a consulting company (Epicher), that would be employing either human or algorithmic management over the course of the exercise. In addition to measuring status, we opted to measure three additional relevant forecasts and experiences that could be influenced by algorithmic management: interactional justice, trust in the organization employing this agent, and trust in the managing agent itself. All items were rated along 1 ("Extremely Unlikely") to 7 ("Extremely Likely") scales unless otherwise specified.

Forecasted Status. We measured status using the same four items from Anicich et al. (2016) used in previous studies, but adapted to this situation and reversing the directionality of the two reverse-scored items. Given this remote context, we also adapted the items to reflect forecasted status in the eyes of the company employing the managing agent. All items began with "Based on this description, to what extent does (or will) Epicher…": "See you as high status?", "Look up to you?", "Admire you?", and "Think you have a high status job?". These items formed a reliable composite of forecasted status, $\alpha = 0.95$. Given this novel design, in addition to status, which was our main interest with this particular research project, we opted to include three additional measures.

Forecasted Interactional Justice. Firstly, previous research indicates that people perceive often algorithmic management as unfair (Lee, 2018; Newman et al., 2020). Although status was our main theoretical interest, given that we evaluated both forecasts and experiences with a real algorithm in this study, we included an exploratory measure of interactional justice, or perceptions that one is respected by one's company, to conceptually replicate these effects alongside investigating our main research question. We adapted three items from Colquitt's (2001) interactional justice scale, removing one item ("Has (he/she) refrained from improper remarks or comments?"), which was not relevant to this particular remote situation. This resulted in three items, all beginning with "Based on this description, to what extent does (or will) Epicher…": "Treat you in a polite manner?", "Treat you with dignity?", and "Treat you with respect?". These items formed a reliable composite of forecasted interactional justice, $\alpha = 0.96$.

Forecasted Organizational Trust. Second, we also included exploratory measures of participants' trust in both the organization employing the managing agent, as well as the managing agent itself. People often trust algorithmic systems less than humans, particularly in more "subjective" feeling domains, potentially including management (Castelo et al., 2019; Lee, 2018). Like described above, given that this design included both forecasts and interactions with a real algorithm, we decided to conceptually replicate this effect—for both the organization employing these different agents as well as the agent (i.e., person vs. algorithm) itself—alongside investigating our (more central) status research questions. We measured the degree to which participants trusted the organization employing the human or algorithmic managing agent using three ad-hoc items along a 1 ("Strongly Disagree") to 7 ("Strongly Agree") scale: "I trust Epicher", "I have confidence in Epicher", and "I feel like I can rely on Epicher". These items formed a reliable composite of forecasted organizational trust, $\alpha = 0.95$.

Forecasted Agent Trust. We finally measured participants' estimates of how much they would trust the person (vs. algorithm) that would manage them using the same three organizational trust items, but referring to the organization's agent as opposed to the organization itself: "I trust this [person / algorithm]", "I have confidence in this [person / algorithm]", and "I feel like I can rely on this [person / algorithm]. These items formed a reliable composite of forecasted agent trust, $\alpha = 0.98$.

After indicating their forecasts, participants engaged in the brainstorming task. We redirected participants to a new webpage where we told them that they would see instructions the [person / algorithm] prepared for them, and also that they would interact with this [person / algorithm] for the duration of the task. Regardless of which agent we randomly assigned participants to believe their remote manager would be, all participants next engaged in a brainstorming task where they were evaluated twice by an algorithm we created employing GPT-3's natural language processing capabilities (OpenAI, 2022). Specifically, participants read the following instructions:

> For this exercise, you will be brainstorming small business names and slogans for a coffee shop that will be opening up in Los Angeles, California in Autumn 2023. This coffee shop will serve standard espresso fare in a relaxing, comfortable setting. The furniture will be high end, and the shop will have numerous artworks and books for sale in addition to coffee drinks and teas. Jazz and lounge music will be playing when the coffee shop is open.

Next, the tool prompted participants to generate a name for this coffee shop that reflected the culture and "feel" of this business plan. Importantly, all participants read a message from the managing agent that: "I will evaluate your name, and then provide you with feedback". At this point, participants generated an initial name for this coffee shop and input it into the tool using a text box. After submitting the name, to mimic a human manager taking time to read and evaluate the idea, all participants viewed a twenty-second loading screen indicating "Please wait a moment...", which we designed to mirror the amount of time it would take for an attentive manager to type two to three sentences.

During this period, the interactive tool queried GPT-3's natural language processing algorithm to "Evaluate the following coffee shop name: '[name]'. Describe the name's strengths and weaknesses, but do not provide other name options". We otherwise used the default natural language processing settings embedded in GPT-3. After the twenty-second timer had elapsed, all participants received customized feedback from the algorithm evaluating their particular name (see Fig. 2 for examples; also see data posted via the Open Science Framework for all participant interactions with this algorithm and its responses). The algorithm customized these evaluations to provide unique feedback to each participant, depending on their user-submitted input.

After receiving this initial managerial feedback, all participants read a second communication from this manager indicating that, now that they had received preliminary feedback, "…I want to give you another opportunity to generate a name for this small business. Please improve the name as much as possible and type it below." Participants also read that the manager would assign this new name a rating from 0 to 50—with 50 being the best—and that the highest scoring 20% of names in the task would receive a $1.00 bonus. We designed this task to incentivize participants to generate the best name possible for this coffee shop (however, after all data had been collected, we awarded the bonus to all participants). After providing their second and final small business name, participants again waited for twenty seconds prior to receiving feedback, which the tool again queried via GPT-3's natural language processing algorithm: "Evaluate the following coffee shop name: [name]. Describe the name's strengths and weaknesses, and assign it a rating from 0 to 50, with 50 being the best". After the timer elapsed, the

Query A ("Space Age Coffee"): *The name "Space Age Coffee" is eye-catching and unique. It implies a modern, futuristic atmosphere which could be appealing to some customers. However, it might also turn some customers away if they are not interested in that type of environment.*

Query B ("Wormhole Coffee"): *The name Wormhole Coffee is unique and suggestive of a strange, otherworldly experience. It could be seen as off-putting to some customers, however, who might not be interested in a coffee shop with such a surreal name. Overall, the name gets a rating of 35.*

Query A ("Brew Time"): *The name "Brew Time" is short and easy to remember. It is also descriptive, as it tells customers what they can expect to find at the coffee shop. However, the name is not very unique, and there are already many coffee shops with similar names.*

Query B ("The Gather"): *The name "The Gather" is short, simple, and easy to remember. It is also evocative of the warm, social atmosphere of a coffee shop. However, the name is somewhat generic and does not convey any information about the shop's unique offerings. Overall, I would rate the name "The Gather" a 40.*

Query A ("Jazzy Java"): *The name "Jazzy Java" is a good coffee shop name because it is short, easy to remember, and has a positive connotation. The name is also unique and can help the coffee shop to stand out from its competitors. However, the name is not very descriptive, so potential customers may not know what to expect from the coffee shop.*

Query B ("Jazzy Java Joint"): *The name "Jazzy Java Joint" is fun and unique. It has a great rhythm and is easy to remember. However, it is a bit long and may be difficult for some people to pronounce. I would give it a rating of 45.*

Fig. 2. Example algorithm interactions.

algorithm again provided participants with managerial feedback regarding their submitted name idea, including a final score out of 50 ($M = 37.38$, $SD = 5.77$).

After engaging in this brainstorming task and receiving feedback from the algorithm framed as the consulting firm's managerial agent, we redirected participants from the interactive tool to answer questions about their experience. Prior to answering any questions, we reminded them that "For this task, Epicher employed a[n] [person / algorithm] to manage you in the form of providing instructions and evaluating your work output." Next, all participants responded to the same status, interactional justice, organizational trust, and agent trust questions as they did earlier, but referring to the experience they just had with the managerial agent, as opposed to indicating their forecasts. All items were accompanied with the header "Based on your experience…" as opposed to "Based on this description…", and formed extremely reliable composites of status in the eyes of the organization ($\alpha = 0.97$), interactional justice ($\alpha = 0.97$), trust in the organization itself ($\alpha = 0.97$), and trust in the managing agent ($\alpha = 0.98$).

6.2. Results

Consistent with our pre-registration, we first conducted independent-samples *t*-tests investigating whether the agent condition (person vs. algorithm) influenced participants' forecasts about—or experiences with—the consulting organization's managerial agent. Time 1 (pre-algorithm interaction) and Time 2 (post-algorithm interaction) means, standard deviations, test statistics, and effect sizes for all dependent variable composites are summarized in Table 1. Additionally, we constructed a series of 2 (agent: person vs. algorithm, between-subjects) X 2 (timing: before vs. after algorithm interaction, within-subjects) repeated-measures ANOVAs.

Status. Prior to interacting with the agent (Time 1), participants assumed that they had lower status in the eyes of the consulting organization given an algorithmic manager, compared to a human manager. Furthermore, after interacting with the algorithm (Time 2), participants still indicated that they were lower status in the eyes of the company given an algorithmic manager. A repeated-measures ANOVA indicated no interaction between the agent manipulation and timing ($F(1,200) = 0.05$, $p = .823$, $\eta_p^2 = 0.000$), suggesting that participants' actual experiences of being managed by an algorithm did not mitigate their original forecasts of low status. However, this ANOVA did indicate a main effect of agent indicative of lower perceived status broadly given algorithmic management ($F(1, 200) = 6.50$, $p = .012$, $\eta_p^2 = 0.03$). This model indicated no significant effect of timing ($F(1, 200) = 2.16$, $p = .144$, $\eta_p^2 = 0.01$).

Interactional Justice. At Time 1, participants forecasted lower levels of interactional justice from the organization given algorithmic management, compared to human management. Similarly, at Time 2, participants still felt they were treated with relatively less politeness, dignity, and respect after the interaction with the algorithm. An ANOVA identical to the one constructed above—but predicting interactional justice instead of status—indicated a main effect of agent type, broadly indicating lower perceived interactional justice given algorithmic management, $F(1, 199) = 9.17$, $p = .003$, $\eta_p^2 = 0.04$. This model also yielded a main effect of timing, indicating that participants felt they were treated *more* positively following the interaction with the agent, compared to their forecasts, $F(1, 199) = 6.89$, $p = .009$, $\eta_p^2 = 0.03$. This likely reflects the sophistication of the GPT-3 algorithm and its ability to provide customized and detailed feedback in a relatively short period of time. We did not observe an interaction between these two predictors, $F(1, 199) = 2.09$, $p = .150$, $\eta_p^2 = 0.01$.

Organizational Trust. After learning they would have an algorithmic manager, participants forecasted less trust in the consulting organization employing this agent, compared to when we told them their manager would be human. While directionally similar, this effect was no longer significant after actually interacting with the algorithmic manager, compared to a simulated-human. A repeated-measures ANOVA did not indicate a significant interaction, conveying that these two effects did not differ significantly, $F(1, 200) = 1.96$, $p = .163$, $\eta_p^2 = 0.01$. However, this ANOVA did indicate a marginally-significant main effect of agent broadly reflective of less organizational trust given algorithmic management ($F(1, 200) = 3.63$, $p = .058$, $\eta_p^2 = 0.02$), as well as a main effect of timing conveying greater trust in the organization after actually interacting with the manager, regardless of how it was framed ($F(1, 200) = 8.98$, $p = .003$, $\eta_p^2 = 0.04$).

Agent Trust. As with their trust in the organization itself, participants forecasted less trust in the managing agent when it was introduced as an algorithm, compared to a human. At Time 2, this difference was no longer significant; participants trusted the algorithm to a similar extent as the ostensible person, although the directionality of the difference between these conditions was the same as Time 1. Similarly to organizational trust, the interaction between agent type and timing was not statistically significant predicting agent trust, although these results suggested that participants' experiences with the agent boosted their trust in the algorithm more than the ostensible person, $F(1, 200) = 2.52$, $p = .114$, $\eta_p^2 = 0.01$. This model also yielded main effects indicating that participants trusted humans more than algorithms ($F(1, 200) = 5.57$, $p = .019$, $\eta_p^2 = 0.03$), and also that their trust in the agent increased after actually interacting with [them / it], compared to forecasting this interaction ($F(1, 200) = 8.58$, $p = .004$, $\eta_p^2 = 0.04$).

Models Accounting for Managerial Ratings. Although we did not pre-register these analyses ex-ante, we did observe some variance in terms of the ratings the algorithm gave participants' second coffee shop names (out of 50). This led us to question whether participants who received particularly high (or low) ratings from an algorithm might change their reactions to the situation and/or attitudes towards this agent on account of the evaluation. To examine this possibility, we created a series of general linear models using agent type, the rating participants received, and their interaction predicting each of the four outcome composites at Time 2, which was after participants interacted with the agent and received a rating. These models did not indicate any significant interactions ($Fs < 1.98$, $ps > 0.160$, $\eta s_p^2 < 0.02$), and the significance thresholds for the agent manipulation remained the same for all four composites when accounting for the actual managerial rating participants received, suggesting that participants' experiences and subsequent attitudes were relatively robust to different actual outcomes stemming from the evaluation (see Supplemental Materials for test statistics controlling for agent rating).

6.3. Discussion

Using a real managerial natural language processing algorithm

Table 1
Pre- and post-agent interaction means, standard deviations, and test statistics (Study 5).

	Time 1 (Pre-Agent Interaction)				Time 2 (Post-Agent Interaction)			
	Human *M* (*SD*)	AI *M* (*SD*)	*t*-statistic	Cohen's *d*	Human *M* (*SD*)	AI *M* (*SD*)	*t*-statistic	Cohen's *d*
Status	3.50 (1.32)	3.08 (1.29)	$t(200) = 2.31$, $p = .022$	0.32	3.63 (1.37)	3.17 (1.39)	$t(200) = 2.36$, $p = .019$	0.33
Justice	5.21 (0.94)	4.86 (1.09)	$t(199) = 2.41$, $p = .017$	0.34	5.49 (1.04)	4.95 (1.45)	$t(200) = 3.09$, $p = .002$	0.43
Org. Trust	4.52 (1.07)	4.13 (1.09)	$t(200) = 2.57$, $p = .011$	0.36	4.64 (1.17)	4.44 (1.43)	$t(200) = 1.05$, $p = .296$	0.15
Agent Trust	4.52 (1.15)	3.99 (1.39)	$t(200) = 2.97$, $p = .003$	0.42	4.62 (1.29)	4.33 (1.57)	$t(200) = 1.46$, $p = .145$	0.20

administering feedback and financial rewards for performance, Study 5 indicated that participants both forecasted and experienced lower status given algorithmic (versus human) management, even when their actual experience with this agent was otherwise identically administered. We additionally found evidence that algorithmic management—conceptually replicating previous research (Lee, 2018; Newman et al., 2020) using a real human-algorithm interaction—decreases perceptions of interactional justice, lowers trust in an organization employing this kind of managing agent, and lowers trust in the agent itself. Interestingly, participants reported feeling more respected and trusting of both the agent and organization employing it following the interaction with the managing agent, although these positive experiences were not able to overcome the perceived status difference between the human and algorithm frames. While people's forecasts about algorithmic management will likely drive many important career decisions (e.g., whether or not to pursue an opportunity or accept a job employing these processes), this study suggests that status-based inferences will also manifest in actual experiences and attitudes given algorithmic management.

7. General discussion

Across five preregistered studies, we found evidence that algorithmic management—specifically, working for an algorithmic manager as opposed to a human manager—leads people to assume lower social status in an organization (Study 1). Using a real remote-work context where both human and algorithmic management processes exist, we found that the lower anticipated status mediated more negative emotions towards algorithmic management work arrangements (Study 2). Moreover, this perception of lower status was driven by the assumption one's role will be rote and non-complex when overseen by algorithms (Studies 3 & 4). Finally, an incentivized behavioral study—in which people were managed by a real algorithm that provided feedback and offered rewards—showed that people's forecasts of lower status when managed by an algorithm management is not mitigated by actually being managed by an algorithm, in spite of the fact that participants seemed to experience the interaction relatively positively (Study 5): People perceived having lower status after actually being managed by an algorithm (compared to when the experience was framed as involving a human manager), and also had lower perceptions of interactional justice, lower trust in the organization, and lower trust in the algorithm.

In sum, across five studies using different measures of status and social perception (including direct vs. meta-perceptions, forecasted vs. actual, and self vs. others), we observed consistent results that algorithmic management reduced perceived status across a variety of organizational contexts and different forms of algorithmic management. These studies broadly suggest that, as algorithms become more common in social and business environments, leaders of organizations, systems, or governments interested in implementing these technologies should be wary of the inferences people will make about their social standing when managed by algorithms, as well as how automation is changing the nature of relational status in hierarchies previously only occupied by humans.

7.1. Contributions to theory and practice

Overall, these findings demonstrate the potential for technological change—and the potential replacement of humans in social hierarchies by algorithms—to produce changes in status. Status is, in part, a relational construct, often positioned within human hierarchical systems (Anderson et al., 2012). Although some may naturally anthropomorphize algorithmic systems (e.g., Waytz et al., 2010; Yam et al., 2022), the increasing, and sometimes autonomous, use of algorithmic systems threatens the removal of humans within such status hierarchies, possibly changing their structure and subsequent perceptions. As these technologies become more and more commonplace, the social contexts in which status hierarchies emerge or dictate personal and professional outcomes will likely also change. In particular, our findings suggest that when algorithms replace humans in social hierarchies, people's perceptions of relational attributions of status change, leading to perceived status loss and related consequences.

Although algorithms are increasingly trained to augment and/or substitute for human work, people's impressions of their relationships to these technologies are often fundamentally different than similar impressions of their relationships with humans. This work additionally highlights how and why being managed by algorithms can influence perceptions of low status among different social targets, for example, if people are initially motivated to feel positive and optimistic about a colleagues' job, but later learn it involves algorithmic management (Study 4).

These results also speak to the emerging literature on how people respond to algorithmic implementation at work and in society. While this research often focuses on how and why people accept algorithmic decisions (e.g., Castelo et al., 2019) as well as downstream consequences such as trust and fairness, the present studies showcase how algorithms' implementation may also influence important social perceptions above and beyond decision making. As such, future research on algorithmic processes in organizations may benefit from exploring other characteristically social processes and/or relationships with technology, particularly given people's natural anthropomorphic tendencies. Similarly, the present studies speak to literature related to person perception, algorithm perception, and social cognition by showcasing how social judgments about technology can influence important interpersonal and work-related forecasts. Given the proliferation of autonomous algorithms, recent research on "person" vs. "algorithm" perception often compares analogous human and algorithmic decisions, identifying how and why they differ (e.g., Jago & Laurin, 2022; Newman et al., 2020; Raveendhran & Fast, 2021). These discontinuities additionally contribute to emerging theories of how people assess algorithmic processes in light of its substitutability with humans (e.g., "theory of machine"; Logg, 2022).

From a practical standpoint, as organizations continue to integrate novel technologies to perform various functions, including prototypical management functions, it is important to consider these unintended social consequences such as perceived status losses. This research indicates that by appropriately framing why these technologies are integrated, organizations, governments, and/or other social systems may be able to preemptively address some of these inherent challenges with adopting autonomous technologies such as algorithms. However, as people's assessments of status given an actual experience with algorithmic management remained relatively lower than their assessments of status given ostensible human management, the (negative) social information people derive or assume from such systems being hierarchically superior to oneself may be relatively stable. People are additionally motivated to be relatively conservative when self-assessing positive job-related qualities relating to status (Anderson et al., 2006). In Study 4, while we observed moderation evidence that people assigned greater job complexity to others (vs. oneself) given identical job descriptions, algorithmic management equalized low predicted complexity among both the self and other. This particular result adds to existing literature indicating that people have very strong assumptions about algorithmic—compared to human—decision processes and what they mean for people inside social systems (Logg, 2022). While people may be somewhat more hesitant to self-assign positive attributes like job complexity in prototypical management systems, this result suggests that people have stronger assumptions about algorithmic management and will generate more consistent attributions about people's social roles and relationships vis-à-vis intelligent machines, compared to other humans.

7.2. Limitations and future directions

The present research carries both limitations as well as guidance for future research broadly related to literatures on the psychology of technology, status, and algorithmic decision making. Firstly, the present studies contained relatively unambiguous information regarding algorithmic management and their role vis-à-vis a person. In reality, many organizations will not publicize their use of algorithmic management processes to this explicit extent, instead making decision processes more opaque and less transparent. While somewhat dystopian to imagine, it is not impossible that work arrangements will emerge where algorithms take on increasing management responsibilities for people without those people necessarily being aware. Organizations can also frame algorithmic management as something else entirely. For example, rideshare companies utilizing algorithmically managed dispatch and human resources processes might choose to "hide" these algorithms and frame contract work arrangements as lacking management at all, despite such systems profoundly influencing worker behavior in an often-reciprocal fashion. It will be important for future research to examine employee responses to the use of algorithmic management when it is done so covertly, rather than overtly, as this is likely an important boundary condition. Similarly, our theorizing suggests that situations involving extremely complex job tasks—e.g., aerospace engineering or medicine—might retain relatively high status even given algorithmic management, as people's assumptions about different managing agents might serve as a less important signal of job complexity given overt and explicit information regarding a job's *actual* complexity. Algorithms that are justified and/or described as being extremely sophisticated might also attenuate this status "penalty".

We studied a variety of different job tasks and roles across these five studies and found relatively consistent evidence that algorithmic management lowers status perceptions given moderate levels of ambiguity in describing job tasks. However, many of these contexts were relatively "technology facing" contexts where people might expect to interact with algorithms more, and other humans less, which may or may not be ecologically valid depending on the speed at which different industries transition to algorithm-based management. Future research could explore whether these effects would be amplified or reduced in contexts where people interact frequently with other humans, which could potentially restore perceptions of relational status in other ways, or also potentially highlight one's hierarchical inferiority to a machine.

Across these studies, we found generally consistent results regardless of if we operationalized status as "meta" perceptions (e.g., if one believes others will see their job as low status) as well as more direct perceptions of status (e.g., if one sees their or another's job as low status; Study 4). However, it is important to note that different audiences might make different assumptions and/or attributions in different situations. For example, people are likely more comfortable with status signals stemming from algorithmic management in an explicitly automation-embracing organization, compared to an organization more reticent to enact—or openly hostile towards—such technological change. In addition to situational boundary conditions like these, future research can more thoroughly investigate how people's personality traits and/or personal attitudes towards—or relationships with—technology might influence their responses to algorithmic management.

It is also worth noting that, while we used OpenAI's GPT-3 algorithm to facilitate Study 5, the rapid proliferation and consumer and organizational use of this exact technology in the months afterward might have changed how people think about and respond to natural language processing algorithms in a significant way. Indeed, one key limitation of this study was that we used an algorithm to emulate human decision-making (e.g., by framing it as a person and instituting a 20-s delay for both agents, regardless of their actual decision and typing speed), which—particularly today, given people's experiences with consumer-facing natural language processors like ChatGPT—may not be fully persuasive. Across these studies, we surveyed a variety of different participant populations that differed along key demographic characteristics (e.g., job status in Study 1 vs. Study 2), which also generated some variability in age, although we did observe evidence that people's status attributions given algorithmic management were relatively consistent across a variety of different populations. Particularly as algorithms that can manage human behaviors become more commonplace, future research can more thoroughly examine how demographic differences shape attributions regarding algorithmic management and work.

Additionally, while these studies focused on complete automation (i.e., algorithms independently performing management functions), a variety of technological changes in business and society will produce augmentation (e.g., algorithms assisting human workers and/or taking low-level decision responsibilities), compared to complete automation (Kellogg et al., 2020). These "hybrid" management processes—or even management processes framed as reflecting more human involvement—could capitalize on the benefits of human management, such as perceptions of care or voice, while also simultaneously capitalizing on the benefits of algorithmic management, such as cost efficiency or accuracy. In addition, there are a variety of potential automated technological agents beyond algorithms that may engage in management functions in the near future. For example, anthropomorphized, physical robots with corporeal form (e.g. Tang et al., 2022) could utilize algorithmic processes to simulate a social interaction with a subordinate that feels more similar to an actual human-human conversation. Future research broadly concerning automation will likely benefit from considering the different manifestations of technological changes.

The present studies also did not present much information in terms of what algorithms in the studies were using as training data, inferring and/or predicting. While somewhat limited information regarding technological processes might be ecologically valid for many digital transformation efforts, people may be more comfortable with algorithmic management processes, and anticipate greater status as a result, given more information regarding their decision process and/or accuracy. For example, someone who truly believes they will receive more personalized or useful management from a technological system may feel more comfortable with its implementation, although our theorizing suggests they still may infer low status given lower (at least initial) signaled job complexity. Although we made an effort in conducing these studies to use a variety of operationalizations of algorithmic management across different work industries (e.g., establishing a training dataset for a company or creative brainstorming), there are necessarily many different implementations of managerial algorithms. Differences between systems will intuitively influence the magnitude of social effects and inferences such as the ones documented here. Similarly, longitudinal research could better investigate whether people's social inferences about themselves given algorithmic management change across time or persist.

8. Conclusion

As new technologies proliferate, a variety of different organizations are increasingly implementing algorithmic systems to communicate with, make decisions about, and even manage people. The present studies showcase one important psychological consequence of such a change: lower status perceptions. Although many algorithmic systems inspire much optimism given their accuracy, efficiency, and low cost of maintenance after being initially implemented, the present studies suggest that technological change also heralds lower perceived hierarchical positions relative to one's peers. In turn, the present research echoes much other recent research in suggesting that organizations and other social systems may benefit from understanding the psychological consequences stemming from technological change.

Open practices

We report all manipulations, measures, and exclusions for all studies and determined all sample sizes prior to data collection and analysis; all data and materials are additionally available via the Open

ScienceFrameworkat: https://osf.io/fet7u/.. We additionally preregistered all studies using AsPredicted.org: Study 1 (https://aspredicted.org/r9fb7.pdf), Study 2 (https://aspredicted.org/pv3qr.pdf),Study3 (https://aspredicted.org/5jd6b.pdf),Study4 (https://aspredicted.org/hr9hh.pdf),andStudy5 (https://aspredicted.org/4286p.pdf).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data are posted online via the Open Science Framework.

Acknowledgements

We would like to thank members of the Hierarchy, Networks, and Technology Lab at USC for their helpful comments on early versions of this research as well as Eli Fast for programming and hosting the algorithmic management application designed for Study 5. This project was supported through the Minerva Research Initiative, in partnership with the Air Force Office of Scientific Research, under grant FA9550-18-1-018

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jesp.2023.104553.

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