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Creation of the algorithmic management questionnaire: A six-phase scale development process

Xavier Parent-Rocheleau[1] | **Sharon K. Parker**[2] | **Antoine Bujold**[1] | **Marie-Claude Gaudet**[1]

[1]HEC Montreal, Montreal, Quebec, Canada

[2]Centre for Transformative Work Design, Curtin University, Perth, Western Australia, Australia

Correspondence
Xavier Parent-Rocheleau, HEC Montreal, Montreal, QC, Canada.
Email: xavier.parent-rocheleau@hec.ca

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Abstract

There is an increasing body of research on algorithmic management (AM), but the field lacks measurement tools to capture workers' experiences of this phenomenon. Based on existing literature, we developed and validated the algorithmic management questionnaire (AMQ) to measure the perceptions of workers regarding their level of exposure to AM. Across three samples (overall $n = 1332$ gig workers), we show the content, factorial, discriminant, convergent, and predictive validity of the scale. The final 20-item scale assesses workers' perceived level of exposure to algorithmic: monitoring, goal setting, scheduling, performance rating, and compensation. These dimensions formed a higher order construct assessing overall exposure to algorithmic management, which was found to be, as expected, negatively related to the work characteristics of job autonomy and job complexity and, indirectly, to work engagement. Supplementary analyses revealed that perceptions of exposure to AM reflect the objective presence of AM dimensions beyond individual variations in exposure. Overall, the results suggest the suitability of the AMQ to assess workers' perceived exposure to algorithmic management, which paves the way for further research on the impacts of these rapidly accelerating systems.

KEYWORDS
algorithmic control, algorithmic decision-making, algorithmic management, gig work, measurement scale

1 | INTRODUCTION

The nature of work is rapidly changing, driven by increasingly advanced technological capabilities (Gagné, Parker, et al., 2022; Parker & Grote, 2022). The automation and augmentation of human work triggered by these technological developments have received a great deal of attention from researchers (Langer & Landers, 2021; Makarius et al., 2020; Raisch & Krakowski, 2021; Tschang & Alimrall, 2020). Besides the changes in workers' roles and tasks, advanced technological affordances also drive major changes in managerial roles (De Cremer, 2020; Wesche & Sonderegger, 2019). One of these changes is the increasing use of algorithms, often powered by artificial intelligence, to take over key activities previously accomplished by human managers. This phenomenon is referred to as algorithmic management (AM), defined as the use of programmed algorithms by an organization to partially or completely execute workforce management functions, such as monitoring the work; assigning tasks, targets or schedules; rating productivity and performance;

making pay-related decisions; and even sanctioning workers (Gagné, Parent-Rocheleau, et al., 2022; Lee et al., 2015; Rosenblat & Stark, 2016).

Algorithmic management has rapidly become a topic of much interest in the human resource management (HRM) literature. HRM scholars have been interested in how the introduction of autonomous decision-making algorithms impacts, augments, or disrupts the HR role, activities, and ecosystems (Cheng & Hackett, 2019; Keegan & Meijerink, 2023; Leicht-Deobald et al., 2019; Meijerink et al., 2021). Scholars have also examined how workers experience and react to this new way of organizing where HRM and management are mediated by autonomous technology (Bucher et al., 2021; Curchod et al., 2020; Myhill et al., 2021; Newman et al., 2020; Norlander et al., 2021). The rapid growth of research on AM has been described as the 'emergence of a new research field' (Jarrahi et al., 2021; Meijerink & Bondarouk, 2023).

However, there are important gaps that limit the gathering of new knowledge about AM. In particular, previous research has mostly been conducted at the firm or workplace level, considering the use of algorithms in the management of workers or in HRM as a contextual and dichotomous phenomenon (AM vs. not). In other words, most studies have been conducted in single work contexts in which AM is known to occur, with researchers investigating workers' reactions or consequences related to AM through case studies or in-depth qualitative studies (see Gagné, Parent-Rocheleau, et al. (2022) for a review). Other studies (e.g., Lee, 2018; Newman et al., 2020) have been conducted in research laboratories with simulated AM. This research has produced substantial knowledge on AM in a short period of time. Nevertheless, as the literature grows, there is a need to advance understanding of this concept, which we propose will be aided through a more nuanced approach to measurement. Specifically, we argue that researchers should approach the phenomenon beyond objective and/or dichotomous assessment, which considers that individuals are or are not managed by algorithms.

Two main reasons lead us to propose a measurement tool that would enable researchers to assess workers' perceptions of exposure to AM. First, we argue that the measurement of the perceived exposure is more representative of the growing complexity and entanglement of AM systems than objective assessments alone. With machine learning algorithms allowing "augmented management" or human–machine teaming, human and machine decisions are increasingly intertwined (Murray et al., 2021; Prikshat et al., 2023; Raisch & Krakowski, 2021). For example, metrics computed by an algorithmic system can be integrated into the overall assessment of workers' performance together with their manager's evaluation (Cameron & Rahman, 2022; Escolar-Jimenez et al., 2019; Palshikar et al., 2019; Wu et al., 2023), creating important variations in the degree of exposure to AM. In such context of hybrid (human–machine) management, where decisions are increasingly supported by automated recommendations, the exposure to AM may result less from the formal level of automation of decision-making than of the extent to which managers exert their autonomy, judgment, reflexivity, and responsibility in the application the system's recommendation (Einola & Khoreva, 2023).

Relatedly, the specificities of an AM system can thus vary within an organization, in terms of presence and scope, across branches, departments, or roles, generating different exposures to AM within a single workplace. For example, it is likely that individuals' exposure to AM may differ across job categories (e.g., blue collars vs. white collars) (Delfanti, 2021; Jarrahi et al., 2021). Even at the individual level, there can be objective variations among, say, team members within a team because AM systems actions and decisions (e.g., algorithmically assigned performance targets or schedules) are based on each workers' previous data (e.g., performance or customer ratings) (Duggan et al., 2020; Lee et al., 2021), thus further impacting the variations of individual perceptions. Going beyond a 'yes'/'no' assessment of AM allows these within-organization variations in AM scope and use to be captured. In contrast, considering AM as a uniform phenomenon within an organization or platform assumes that all workers within an entity are exposed to the same AM system, failing to capture how workers may experience AM to different degrees. Thus, given the complexity in the variation of AM use, measuring exposure at the micro level, the individuals, through their perceptions, is important.

Second, we argue that perceptions are more important than the objectivities in shaping workers' outcomes. We know from prior research that it is how individuals perceive and experience objective situations that most shapes their attitudes and reactions to those situations (Daniels, 2006; Spector, 1986). In HRM research specifically, employees' perceptions on practices are considered to inform employees' attitudinal and behavioral response far beyond the objective existence of the practice, such that perceptions have become a key linking pin between HRM and performance outcomes (Beijer et al., 2021; Nishii & Wright, 2008; Van Beurden et al., 2021). For similar reasons, technological features in the workplace have often been measured with self-reports of perceptions (Day et al., 2012; Wang et al., 2020). We thus believe that different workers exposed to some objective degree of AM are likely to perceive their degree of exposure differently. Individual variations occur regarding the perception of exposure to the system, and it is those perceptions that will impact one's attitudes and behaviors in the workplace. Therefore, a questionnaire measuring individual perceptions of AM exposure is of paramount importance to further our understanding of one's attitudes and behaviors in the context of AM.

Altogether, for these reasons, we developed and validated the AMQ to measure the perceptions of workers exposure to AM, or the extent to which they experience key elements of their work as managed through the use of AM. Our approach allows the examination of within- and between-context variations in AM systems, as well as the possibility to model more individual-level processes. Further, by systematically assessing workers' perceived exposure, there is a greater opportunity to investigate the repercussions of AM on them and to understand what factors shape these perceptions of exposure or mitigate these impacts. Previous research has mostly captured general impressions of AM, rather than examining the implication of AM systems in precise managerial activities as found in the literature (Kellogg et al., 2020; Meijerink & Bondarouk, 2023; Parent-Rocheleau & Parker, 2022). Previous approaches have also often failed to isolate the effect of the exposure to AM from other contextual variables in examining workers' experiences in these situations.

In what follows, we begin by defining the conceptual model underlying the proposed questionnaire, elaborating on the definition and dimensionality of AM. Next, we describe and detail the six phases through which we developed the scale and evaluated its content, factorial, discriminant, convergent, and predictive validity. Finally, we discuss the findings, contributions, guidelines for future research, and limitations of the study.

2 | THE CONCEPTUAL MODEL

2.1 | Definition and dimensionality of algorithmic management

Since its first apparition in the academic literature in 2015, the concept of AM has namely been defined as "algorithmic control over labor" (Griesbach et al., 2019, p. 2), as a "managerial practice whereby human managers are replaced by software algorithms that oversee, control, and optimize the performance of myriads of virtual workers at a large scale" (Jabagi et al., 2020, p. 4001), or as "a diverse set of technological tools and techniques to remotely manage workforces, relying on data collection and surveillance of workers to enable automated or semi-automated decision-making" (Mateescu & Nguyen, 2019, p. 1). Other authors describe AM as a system of control that directs, evaluates, and disciplines workers (Kellogg et al., 2020), "where self-learning algorithms are given the responsibility for making and executing decisions affecting labour, thereby limiting human involvement and oversight of the labour process" (Duggan et al., 2020, p. 119). Based on these definitions, and in line with our operationalization objective which requires a concrete representation and manifestation of AM, we refer to algorithmic management as the use of programmed algorithms, often powered by artificial intelligence, by an organization to partially or completely execute workforce management functions and control (Gagné, Parent-Rocheleau, et al., 2022, p. 248).[1] In this context, algorithms refer to "[…] computational procedures […] drawing on some type of digital data ("big" or not) that provide some kind of quantitative output (be it a single score or multiple metrics) through a software program" (Christin, 2017, p. 2). These algorithms are typically either descriptive (e.g., monitoring the work and assessing productivity), predictive (e.g., forecasting customer traffic in order to make on-demand schedules), or prescriptive (e.g., determining one's pay raise or bonus) (Leicht-Deobald et al., 2019).

As suggested by our chosen definition, AM is a multidimensional phenomenon involving several management functions that are partially or completely executed using algorithmic systems. Specifically, we draw on the AM functions identified by Parent-Rocheleau and Parker (2022). These authors conducted an extensive review of the literature on AM across sectors and, based on empirical evidence, classified the use and affordances of algorithms for HRM and management in six functions: monitoring, goal setting, scheduling, performance rating, compensation, and firing. Various authors have proposed typologies as to what algorithms can do in HRM, either in the gig economy, in traditional work settings, or both (Kellogg et al., 2020; Meijerink & Bondarouk, 2023; Parent-Rocheleau & Parker, 2022). Despite some nuanced differences, these typologies of AM functions generally converge and altogether comprehensively cover the affordances of algorithmic systems for workforce management. They draw on previous work addressing the algorithmic affordances for traditional management and HRM functions. For instance, Wesche and Sonderegger (2019) discuss technological affordance among a taxonomy of traditional leadership functions (Fleishman et al., 1991). Similarly, Tambe et al. (2019) elaborate on the algorithmic capabilities for each of the main HRM group of activities.

Among these typologies, we focus on management functions that can be executed by algorithms regardless of the sector, industry, or type of organization (i.e., gig work and traditional work). Also, like Kellogg et al. (2020), and because our definition of AM encompasses the notion of control, we retain the functions pertaining to the management of workers during their employment or collaboration with the company, thus excluding the hiring dimension. The functions of our model are as follows.

- *Algorithmic monitoring* refers to the use of algorithmic systems by organizations to collect, aggregate, and report data, usually in real time, on workers' behaviors and actions or on their work (Backhaus, 2019; Gandini, 2019; Leicht-Deobald et al., 2019; Moore & Hayes, 2017; Newlands, 2021; Schafheitle et al., 2020). Compared with other types of electronic monitoring (Ravid et al., 2020), algorithmic monitoring is (1) often connected to other AM functions, allowing the system to use the monitoring data in automated decision-making, and (2) capable of handling and processing more complex and heterogeneous data (Parent-Rocheleau & Parker, 2022).
- *Algorithmic goal setting* refers to the use of algorithmic systems to assign tasks, organize employees' work, or set performance or productivity targets (Parent-Rocheleau & Parker, 2022). The high responsiveness of these systems allows organizations to adjust, in real time, workers' goals to respond to various fluctuations in the work environment and customer demands (Delfanti & Frey, 2021; Holland et al., 2017; Lammi, 2021; Rani & Furrer, 2020).
- *Algorithmic scheduling* refers to the use of algorithmic systems to determine or influence employees' schedules or working times (Parent-Rocheleau & Parker, 2022). These systems determine the optimal trade-off between an organization's demand and supply of labor, integrating a variety of possible conditions such as the average performance and availability of workers, the average response time, their current location, their various individual preferences, and estimates of peak periods and customer demand (Costa et al., 2020; Heiland, 2022; Miao et al., 2022; Moore & Hayes, 2017; Quesnel et al., 2020; Van Oort, 2019; Vargas, 2021).
- *Algorithmic performance rating* refers to the use of algorithmic systems to appraise, rate or rank workers' performance or productivity, usually in real time, typically through the calculation of several metrics or quantified indicators (Duggan et al., 2020; Evans & Kitchin, 2018; Meijerink & Bondarouk, 2023; Parent-Rocheleau &

Parker, 2022). As a secondary use of algorithmic performance rating, AM systems may forecast future employee performance or guide talent management decisions such as training or promoting (Charlwood, 2021; Meijerink, 2021; Meijerink & Bondarouk, 2023; Wiblen & Marler, 2021)

- *Algorithmic compensation* refers to the use of algorithmic systems to calculate workers' pay, typically based on algorithmically managed conditions and metrics, and according to various indicators such as the number of tasks carried out, individual performance, customer satisfaction, or other data associated with, directly or indirectly, productivity (Griesbach et al., 2019; Kellogg et al., 2020; Meijerink & Bondarouk, 2023; Möhlmann et al., 2021; Mohlmann & Zalmanson, 2017; Parent-Rocheleau & Parker, 2022). In platform work specifically, algorithmic compensation mechanisms, such as surge pricing or dynamic pricing, are also used as a mechanism to regulate the match between labor demand and supply, generating demand-sensitive pay (Guda & Subramanian, 2019; Möhlmann et al., 2021; Rosenblat, 2018; Wood et al., 2019).
- *Algorithmic job termination* refers to the use of algorithmic systems to decide, implement, or facilitate job termination based on unsatisfying ratings. Algorithmic firing has been mostly observed in the gig economy, where workers get their account deactivated as an output of the algorithmic systems (Gerber & Krzywdzinski, 2019; Griesbach et al., 2019; Rosenblat & Stark, 2016).

We thus developed items to measure workers' perceptions regarding their exposure to those six functions of AM systems.

In most cases, AM acts as a system, meaning that more than one management action or function is executed by algorithm, and these functions are generally interconnected (Andersson et al., 2021; Gal et al., 2020; Meijerink & Bondarouk, 2023). Similar to other systems (i.e., high performance work systems), those practices interact with one another in shaping workers' perceptions and experiences. For example, in such systems, automated compensation decisions are often derived from performance ratings collected by algorithms. Similarly, an AM system often attributes tasks based on data monitored (e.g. geolocation) or previous performance on a similar task. Thus, as different management practices forming a system, we postulate that AM functions (exposure to) are distinct yet positively interrelated.

Furthermore, we argue that AM functions are manifestations of an AM system, leading to view the model as reflexive (rather than formative) (Diamantopoulos et al., 2008; MacKenzie et al., 2011). Because the focal AM construct is presumed to be reflected in six functions, all of them being measured by different set of items, we argue that the model will be best represented as a second order model, with exposure to AM as a second-order construct and the six functions as first-order dimensions. According to MacKenzie et al. (2011), "[…] a second-order measurement model with multiple first-order sub-dimensions as reflective indicators might be appropriate when a researcher (1) is interested in measuring a stable focal construct over time or across situations, or (2) has several randomly selected parcels of items each of which is reflective of a focal construct" (p. 301).

That said, albeit interconnected, each AM function is a sufficient but not necessary manifestation of exposure to the focal construct of AM. For instance, an individual could be highly exposed to algorithmic monitoring and performance rating, but less (or not) exposed to algorithmic compensation, goal setting, scheduling and job termination. This person would thus feel exposed to an AM system, but to a lower extent than if he/she felt exposed to all functions. The degree of overall AM exposure thus reflects the addition or the union of the degree to which they are exposed to each function (MacKenzie et al., 2011).

3 | SCALE DEVELOPMENT

We followed recommended practices for scale development (Crocker & Algina, 1986; Hinkin, 1995, 1998; MacKenzie et al., 2011) to build and validate the AM questionnaire. We detail six phases of scale construction and validation.

3.1 | Phase 1: Item generation

A deductive approach (Hinkin, 1998) was used to generate a pool of items to capture the AM functions. The deductive approach is recommended when there is sufficient theory available to elaborate items from construct domains found in the literature. Our items are thus theoretically derived from the growing literature on AM. We were guided by several qualitative papers that provide an abundance of interview transcripts that illustrate "in users' words" the capabilities and usage of algorithms in each function. Specifically, as part of a larger literature review project, we found 105 qualitative papers on AM. Among them, 34 were selected on three criteria: (1) they were peer-reviewed; (2) they presented sufficient interview transcripts; and (3) these transcripts contained information about at least one of the AM functions of the model (e.g., Lehdonvirta, 2018; Möhlmann et al., 2021; Rahman, 2021; Wood et al., 2019). The papers were coded with six codes corresponding to each AM function and thematic analysis was performed (Robinson, 2022).

In this initial step, we generated a pool of 36 items, consisting of 6 items for each AM function. An example of this original set of items, assessing perceived task allocation, is "in my job, an algorithmic system determines what needs to be done".

3.2 | Phase 2: Item refinement and content validity

The refinement and content validity assessment of deductively generated items are essential (Hinkin, 1998). To assess content validity, we contacted 20 MTurkers and asked for their help as content experts, because their work is completely managed by an algorithmic system. They were 39 years old in average, 65% male, 65% American, and 40%

had a university degree. They were provided the list of all the items presented in a randomized order, along with the list and definition of constructs (AM functions). In exchange for a US$5 compensation, they were asked to sort the items and link them to what they considered as the corresponding dimension for each item. As recommended by Howard and Melloy (2016), we kept only the items for which the sorting success rate was higher than 80% (16 of 20 MTurkers). This led us to reject nine items from our pool. However, all the dimensions received sufficient correct sorting, such that the content validity of dimensions was deemed satisfactory.

As part of the same process, MTurkers were invited to give us their feedback regarding the items and dimensions. Two important comments were raised. First, most respondents mentioned not being aware of whether there were algorithmic job termination practices in their company or platform ("I guess you don't know until the system fires you"), such that they were unable to answer the questions related to this dimension. Taking this comment seriously, we examined carefully the literature and found indeed very little evidence for the prevalence of algorithmic job termination, and almost none in traditional work settings. MTurkers who were aware of firing cases in their platform mentioned that this practice was a part (or direct consequence) of the performance rating function. This suggests that these two functions might not be conceptually distinct. For these reasons, we decided to remove the job termination from the scale for the subsequent stages of validation.

Second, the respondents were quasi-unanimous about the unfamiliarity and complexity of the terms algorithm and algorithmic system. Hence, to make sure that the items would remain intelligible, and based on discussion with respondents, we opted for the terms "automated system" or "electronic system" and changed the items accordingly. We also formulated simple definition and example of each function to be displayed throughout the survey (see Appendix B). Besides those two points, the comments were encouraging for content validity, since they confirmed the meaningfulness and soundness of the questions for their daily work. We then moved on to exploratory factor analysis (EFA) with this pool of 21 items.

3.3 | Phase 3: EFA (factor structure)

3.3.1 | Method

To analyze the factor structure of the items, we collected data from the online crowdworking platform Mechanical Turk. Participants received US$5 for completing the 15-minute questionnaire. Again, MTurk was an appropriate setting to collect validation data because online platforms are, in most cases, extensively managed through algorithms. We ensured that the MTurkers who took part in phase 2 were not invited. After deleting survey responses with significant missing values ($n = 124$) and removing participants who failed attention checks ($n = 86$), the sample used for EFA was composed of $N = 481$ workers. The participants were 56% male, 71% were American residents, 21% were Indian, and 77% were below 45 years old. The job with the platform was the main income for 48% of them, and 41% had a university degree. Participants were asked to what degree they agreed with each item on a seven-point Likert scale (1 = completely disagree, 7 = strongly disagree). Besides the attention checks, we also ensured that participants could not complete the survey more than once.

3.3.2 | Results

The factors were extracted using principal axis factoring and promax rotation. Results are presented in Table 1. This EFA revealed five factors accounting for 77.04% of the total variance. The results led us to slightly refine the scale by deleting one item (PR4) due to low factor loading. The factor structure is consistent with our proposed five AM functions, leading us to conduct a confirmatory factor analysis (CFA). Cronbach alphas for the extracted factors were also satisfying (Monitoring (MON): $\alpha = 0.89$; Goal setting (GS): $\alpha = 0.92$; Scheduling (SCH): $\alpha = 0.94$; Performance rating (PR): $\alpha = 0.88$; Compensation (CMP): $\alpha = 0.92$).

As an ad hoc test, we wanted to examine the variance in responses on the seven points of the Likert scale. Specifically, we sought to assess whether the distribution of results shows variance between 1 and 7. Table 2 shows this distribution for each AM function (items averaged), and confirms the responses are well distributed across the seven response options. This reveals the existence of variation and confirms the relevance of examining AM as a perception rather than as a dichotomous phenomenon.

3.4 | Phase 4: CFA (factorial validity) and model specification

3.4.1 | Method

We conducted a CFA to assess the extent to which the hypothesized factorial structure of the 5 AM functions is well fitted to the pattern observed in the dataset. To collect data for this purpose, we recruited gig workers with the support of a research panel firm. Gig workers from different platforms (e.g., freelancing, ride hailing, delivery) were invited to take part in the study. We ensured that the MTurkers included in the sample used for phases 2 and 3 were not invited. Participants received US$6 for completing the survey. Five attention checks were included in the survey. After deleting the participants with excessive missing data ($n = 120$) and the ones who failed the attention checks ($n = 169$), the resulting sample contains 485 individuals. The participants were 58% male, 83% were American residents, and 76% were below 45 years old. The job with the platform was the main income for 64% of workers, and 43% had a university degree.

We tested the expected higher order (HO) model, and compared it with plausible alternatives. That is, our measurement items capture

TABLE 1 Exploratory factor analysis for the 5 AM functions ($N = 481$).

	SCH	CMP	GS	MON	PR
Factor characteristics					
Eigenvalue	9.72	2.56	1.60	1.24	1.06
% Variance extracted	46.30	12.18	7.60	5.91	5.06
Factor loadings					
MON1	−0.103	−0.020	0.265	**0.636**	0.058
MON2	0.014	−0.053	0.047	**0.855**	0.007
MON3	−0.001	0.073	−0.033	**0.758**	0.032
MON4	0.074	0.005	−0.089	**0.855**	−0.040
GS1	0.027	−0.081	**0.900**	−0.008	−0.009
GS2	0.051	−0.064	**0.883**	−0.060	0.045
GS3	−0.071	0.090	**0.821**	0.041	−0.042
GS4	0.053	0.035	**0.714**	−0.004	0.052
GS5	0.037	0.150	**0.647**	0.109	−0.070
SCH1	**0.838**	−0.028	0.075	−0.022	−0.031
SCH2	**0.909**	0.013	0.025	−0.025	−0.012
SCH3	**0.941**	−0.027	0.008	0.015	−0.006
SCH4	**0.924**	0.016	−0.058	0.065	−0.012
PR1	0.022	0.018	0.053	0.029	**0.721**
PR2	−0.036	0.032	0.031	−0.012	**0.830**
PR3	0.051	0.066	−0.040	−0.003	**0.875**
PR4*	−0.221	−0.123	−0.032	0.025	**0.343**
CMP1	−0.012	**0.820**	0.122	−0.044	0.006
CMP2	0.000	**0.913**	0.020	−0.048	−0.010
CMP3	−0.022	**0.869**	−0.041	0.049	−0.023
CMP4	0.025	**0.850**	−0.068	0.041	0.013

Note: Item marked with * was deleted. Bold values indicate the factor loading of selected items on their respective dimension.
Abbreviations: CMP, Algorithmic compensation; GS, Algorithmic goal setting; MON, Algorithmic monitoring; PR, Algorithmic performance rating; SCH, Algorithmic scheduling.

TABLE 2 Distribution of sample items across the points of the Likert agreement scale (% of responses).

	MON	GS	SCH	PR	CMP
1 (Totally disagree) to 2	15.2	27	38.7	7.4	22.8
2. 01 to 3	10.4	6.7	6.5	4.5	7.8
3. 01 to 4	10.1	11.5	8.6	10.7	12.4
4. 01 to 5	17	17.6	17.9	28.9	19.0
5. 01 to 6	28.7	23.8	20.5	33.1	27.5
6. 01 to 7 (Totally agree)	18.6	13.4	7.8	15.4	10.5

manifestations of the 5 AM functions, considered as first-level latent constructs. According to our conceptual framework, these five latent dimensions in turn reflect the general construct of AM, which is considered as a second-order latent construct (Jarvis et al., 2003; MacKenzie et al., 2011). We propose a HO model because, as described, the 5 AM functions operate mostly as a system and are likely to co-occur with each other, just as in traditional management, where data from one function (e.g., PR) are often linked to other management decisions (e.g., GS or compensation). These interrelationships are reflected in the moderate to high correlations between AM functions found in the combined sample (Table 5) and in the phase 6 sample (Table 6).

3.4.2 | Results

Results of the CFA performed using the lavaan package with R 4.1 and maximum likelihood estimations are presented in Table 3. The goodness of fit was assessed using six indicators (Hu & Bentler, 1999): (a) chi-square (χ^2 = significant values: $p < 0.01$), (b) chi square over degrees of freedom (df; target: $\chi^2/\text{df} = < 3$), (c) comparative fit index (CFI; target: >0.90), (d) Tucker–Lewis index (TLI; target = > 0.90), (e) root mean square error of approximation (RMSEA <0.08), and (f) Standardized root mean square residual (SRMR; target = < 0.08) (Kline, 2015). Our hypothesized model (model 1) shows excellent fit (Model 1: $\chi^2 = 346.8$, df = 162, χ2 / df = 2, CFI = 0.975, TLI = 0.971, RMSEA = 0.048, SRMR = 0.044). Results indicate that, compared with other higher

TABLE 3 CFA results ($n = 485$).

Model		χ^2	Df	CFI	TLI	RMSEA	SRMR
(1)	One HO construct and 5 dimensions (first order)	346.76	162	0.975	0.971	0.048	0.044
(2)	Model 1 combining GS and SCH	814.18	190	0.912	0.897	0.091	0.058
(3)	Model 1 combining GS and MON	754.40	190	0.920	0.906	0.086	0.054
(4)	Model 1 combining CMP and PR	554.55	163	0.948	0.939	0.070	0.066
(5)	Two HO constructs and 5 dimensions (first order): C1: MON-PR. C2: GS. SCH. CMP.	339.89	161	0.977	0.973	0.047	0.040
(6)	Two HO constructs and 5 dimensions (first order): C1: MON-PR-CMP. C2: GS-SCH.	342.92	161	0.976	0.971	0.048	0.042

Note: For acronyms on the factors of the model, refer to the Appendix.
Abbreviations: CFI, Confirmatory Factor Index; df, degrees of freedom; RMSEA, Root Mean Square Error of Approximation; SRMR, Standardized Root Mean Square Residual; TLI, Tucker–Lewis Index.

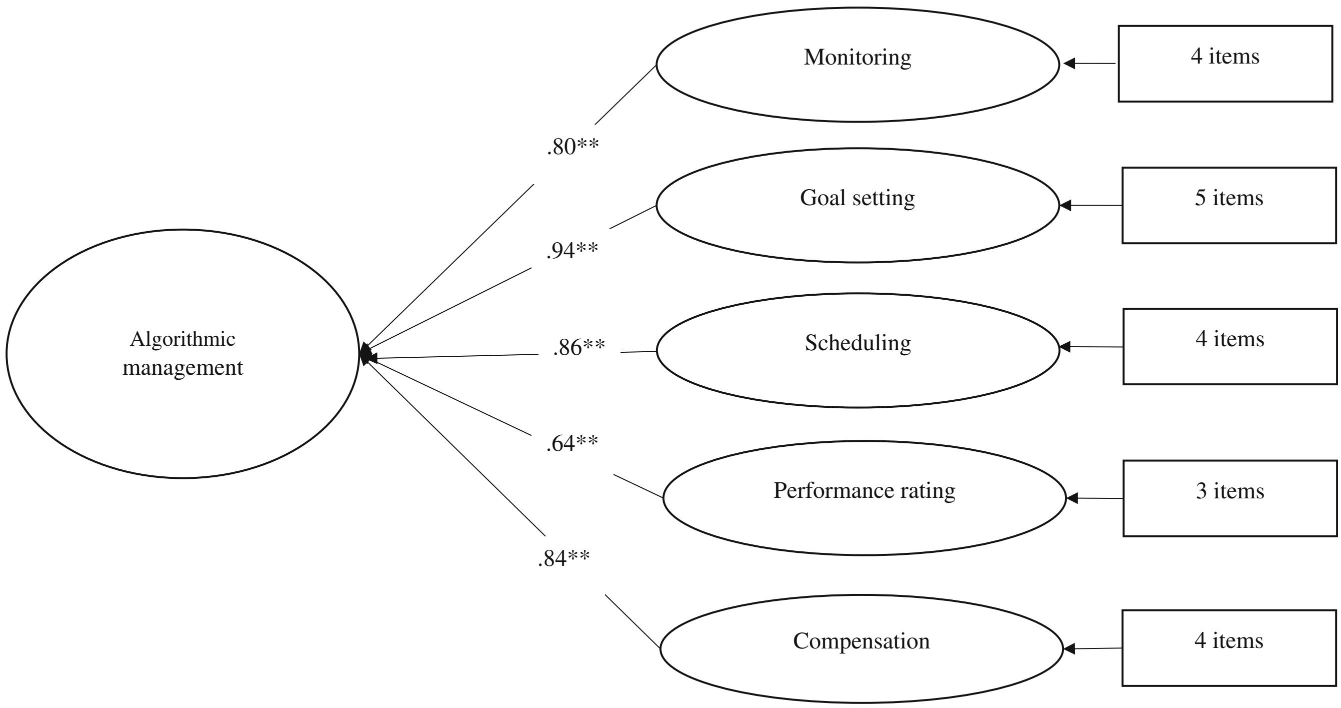

FIGURE 1 Final measurement model.

order configurations, the model consisting of one HO construct represents the best balance between the goodness of fit, parsimony, and simplicity of operationalization. Models 5 and 6 in Table 3 proposing the same five dimensions reflected in two (rather than one) HO constructs showed comparable fit to model 1, but (1) we could not find conceptual support for the presence of two HO constructs and (2) the two higher order dimensions were highly correlated (0.81 and 0.83, respectively), creating collinearity issues and other statistical problems (MacKenzie et al., 2011). In sum, none of the alternative models emerge as a better solution than the current model specification.

The list of items (measured on a seven-point Likert scale ranging from 1 (totally disagree) to 7 (totally agree)) and their confirmatory factor loadings is presented in the Appendix A. All items were kept because their factor loading are above the recommended threshold of 0.40 (Raykov & Marcoulides, 2011) or 0.50 (Hair et al., 2014). The overall measurement model is presented in Figure 1. The internal reliability statistics and average variance explained for each dimension are shown in Table 4.

TABLE 4 First-order dimensions statistics using the CFA subsample ($N = 485$).

	Cronbach α	AVE
MON	0.896	0.539
GS	0.891	0.776
SCH	0.907	0.673
PR	0.810	0.368
CMP	0.885	0.508

TABLE 5 Descriptive statistics and correlations for phase 5 ($N = 966$).

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1. Platform type	0.45	0.50	–											
2. Main income	0.63	0.48	0.12**	–										
3. Age	3.7	1.1	−0.11**	−0.22**	–									
4. System usefulness	4.91	1.43	0.14**	0.08*	−0.05	(0.93)								
5. System ease of use	5.10	1.23	0.07*	0.06	−0.07*	0.67**	(0.85)							
6. POT	5.51	1.13	−0.12**	−0.04	0.06	0.42**	0.40**	(0.85)						
7. AM	4.30	1.42	0.38**	0.30**	−0.10**	0.54**	0.40**	0.16**	(0.86)					
8. Monitoring	4.62	1.70	0.33**	0.22**	−0.06	0.47**	0.43**	0.18**	0.79**	(0.91)				
9. Goal setting	4.26	1.82	0.40**	0.23**	−0.07*	0.53**	0.36**	0.14**	0.78**	0.68**	(0.93)			
10. Scheduling	3.44	2.02	0.30**	0.31**	−0.19**	0.43**	0.35**	0.03	0.75**	0.52**	0.66**	(0.95)		
11. PR	4.91	1.47	0.11**	0.16**	0.03	0.42**	0.37**	0.22**	0.78**	0.51**	0.48**	0.32**	(0.89)	
12. Compensation	4.26	1.82	0.35**	0.25**	−0.07*	0.43**	0.31**	0.11**	0.69**	0.56**	0.68**	0.54**	0.51**	(0.93)

Note: Platform type: 1 = Appwork. 0 = Crowdwork. Main income: 1 = Yes. Age was coded in categories (1 to 7). Cronbach's alpha in parentheses along the diagonal.
Abbreviations: AM, Second order construct of algorithmic management; PR, performance rating; POT, positive orientation to technology.
$^{**}p < 0.01$; $^{*}p < 0.05$.

3.5 | Phase 5: Discriminant and convergent validity

3.5.1 | Method

In the fifth stage, we sought to assess the discriminant and convergent validity of the scale. We used data resulting from the combination of the two previous datasets ($n = 966$). The individuals in this sample were 61% male, 74% were American residents, 79% were below 45 years old, and 42% had a university degree. The job with the platform was the main income for 63% of them, and 49% worked more than 20 hours per week for the platform. Regarding the type of platform, 54% of participants worked for a crowdworking platform (like MTurk, Prolific, or Upwork), while the remaining 46% worked for appwork platforms (ride-hailing like Uber and Lyft or delivery like Postmates, Uber Eats, or Instacart). A significant proportion (40%) of them worked for more than one platform on a regular basis, but all were asked to fill the survey referring to the one for which they worked most often. Descriptive and reliability statistics for AM functions, higher order AM, and other variables included in the study are presented in Table 5.

Because all variables were measured at the same occasion in both cases, we used the CFA marker (Williams et al., 2010) technique to detect common method bias (CMB). This technique assesses CMB through the calculation of shared variance between a marker variable and substantive constructs. We used a theoretically unrelated four-item measure of time pressure as a marker (e.g., "There is just not enough time to do my work"; Kinicki & Vecchio, 1994). We followed the four-step CFA procedure consisting of comparing a method-R model (more constrained) to a method-C or method-U model. The results do not indicate superiority of method-R model over method-U model ($\Delta\chi 2$ [10; $N = 966$] = 11.09, ns), suggesting that CMB was not problematic.

3.5.2 | Discriminant validity results

Discriminant validity refers to the degree to which the construct measured is not similar to (diverges from) other constructs from which it should theoretically differ. We verified the correlations between AM functions and positive orientation toward technological change (Fugate et al., 2012), defined as "a constellation of malleable individual characteristics that affect how individuals perceive and respond to [technological] change" (p. 894). We specifically used the self-efficacy dimension (e.g., "Wherever technological changes take me, I am sure I can handle it") and the positive appraisal dimension (e.g., "I consider myself to be 'open' to technological changes in general"). We expected these variables to show low to moderate correlations with AM, mostly because they represent general attitudes (not directed to a system in particular), whereas AM refers explicitly to the perception of a system in particular. Results presented in Table 5 are in line with these expectations, with a correlation of 0.16 between exposure to AM (second order) and the criterion variable, and correlations ranging from 0.03 to 0.22 (mean = 0.14) between specific AM functions and the criterion variable.

3.5.3 | Convergent validity results

Convergent validity refers to the degree to which the construct is similar to (converges on) other constructs to which it should be theoretically similar. We chose to correlate exposure to AM with perceived usefulness and ease of use of the system, as part of the well-established Technological Acceptance Model (TAM: Davis, 1989). Ease of use refers to how much end users believe that the information system usage in his work will be difficult free or effortless (Davis, 1989). Usefulness refers to the degree to which a person believes that using a particular system would enhance their job performance (Davis, 1989). We expected to find moderate to high correlations because both constructs refer to perceptions of a specific system (technological acceptance questions focused on the platform's algorithmic system). As shown in Table 5, usefulness of the system presents moderate to high correlations with the exposure to AM functions (ranging from 0.43 to 0.53, mean = 0.46) and with AM (0.54). Likewise, ease of use presents moderate to high correlations with AM functions (ranging from 0.35 to 0.43, mean = 0.37) and with AM (0.40). These results suggest that our measure presents satisfactory convergent validity while also being clearly distinct from those two well-established constructs.

3.6 | Phase 6: Predictive validity

This sixth and final stage of validation sought to assess the predictive validity of the AMQ, which refers to the ability of the measured construct to predict something it should theoretically be able to predict.

3.6.1 | Expected consequences

As explained, our AM model is rooted in a work design approach. That is, its elaboration was guided by the literature focusing on how AM influences the key characteristics of meaningful and decent work (Hackman & Oldham, 1976). There are several important work design variables but that we chose to be selective in this early stage of development. Hence, to assess the predictive validity of the AMQ, we focus on job autonomy and job complexity because they cover the vertical division (e.g. the extent to which decision-making is shared across different vertical levels of an organization) and the horizontal division of labor (e.g. the degree to which work is broken down into narrow and simple sets of tasks) (Parker & Wall, 1998). In the work design framework, job autonomy is viewed as a task-related characteristic (i.e., concerned with how the work itself is accomplished and the range and nature of tasks associated with a particular job) referring to "the extent to which a job allows freedom, independence, and discretion to schedule work, make decisions, and choose the methods used to perform tasks" (Morgeson & Humphrey, 2006, p. 1323). Although gig workers in theory can choose to work when they want, this expected freedom has been contradicted by many studies (Goods et al., 2019; Heiland, 2021, 2022; Lehdonvirta, 2018; Veen et al., 2020). The literature shows how AM systems reduce workers' control over their work, and how this control is reinforced but the difficulty or impossibility to question the system and their decisions (Rani & Furrer, 2020; Rosenblat, 2018; Rosenblat & Stark, 2016; Stark & Pais, 2020). Also, because AM implies data-driven control of the workers' goals, tasks, schedules, and compensation, it has been found to lead workers to "work for data" rather than for more intrinsic reasons (Gagné, Parent-Rocheleau, et al., 2022; Gagné, Parker, et al., 2022; Parent-Rocheleau et al., 2021), thereby altering perceptions of autonomy (Möhlmann et al., 2021; Shapiro, 2018; Vargas, 2021).

Job complexity is viewed as a knowledge characteristic (i.e., reflects the kinds of knowledge, skill, and ability demands that are placed on an individual as a function of what is done on the job) and refers to "the extent to which the tasks on a job are complex and difficult to perform, focusing on the "positive" aspect of complexity; the opposite is task simplicity" (Morgeson & Humphrey, 2006, p. 1323). Job complexity is usually preferred to be moderately high (challenging and stimulating work). AM often implies task decomposition for better datafication and monitoring (Kellogg et al., 2020; Meijerink et al., 2021), which can make human tasks simpler and more repetitive, reducing job complexity (Bhardwaj et al., 2019; Rani & Furrer, 2020; Schörpf et al., 2017). It allows for a fine-grained analysis of work processes, for the identification of best sequences or routines, and for the optimal pairing between demand and supply. For this reason, AM is typically associated with a repetition or routinization of the optimized tasks rather than with problem-solving or non-routine work (Parent-Rocheleau & Parker, 2022; Rani & Furrer, 2020; Wood, 2021). We thus formulate the following hypotheses:

> **Hypothesis 1.** The perceived degree of exposure to AM will lead to lower job autonomy.

> **Hypothesis 2.** The perceived degree of exposure to AM will lead to lower job complexity.

Job engagement

Moreover, we expect exposure to AM to indirectly predict individuals' level of engagement in their work for the platform through its influence on job autonomy and complexity. Work engagement is a construct composed of three dimensions: physical (vigor), emotional (dedication), and cognitive (absorption). Vigor refers to the level of energy, will of effort, perseverance, and mental resilience that a person has in work, even when facing some difficulty. Dedication refers to how involved a person is with work at the level of enthusiasm, inspiration, pride, and challenge. Finally, absorption refers to the degree of concentration and abstraction that a person has when working (Demerouti et al., 2001; Schaufeli & Bakker, 2004). While early evidence on work engagement among gig workers is still ambiguous (Pereira et al., 2022; Roberts & Douglas, 2022; Wang et al., 2022), the literature on AM and motivation tends to suggest that exposure to AM would contribute to deplete vigor, absorption, and dedication in work (Gagné, Parent-Rocheleau, et al., 2022; Gagné, Parker, et al., 2022). A key explanation for reduced engagement is that we expect that key work design characteristics, namely job autonomy and complexity, will be negatively impacted by exposure to AM, and yet these have been largely viewed as key elements leveraging work engagement (for a review: Parker, Morgeson, & Johns, 2017). Hence, we formulate the following hypothesis.

Hypothesis 3. The perceived degree of exposure to AM will indirectly lead to a lower level of work engagement through its negative effect on (a) job autonomy and (b) job complexity.

3.6.2 | Method

Procedure

We collected data in two time-separated waves to assess predictive validity. Two data points are necessary to reduce the risk of common method bias and better demonstrate causality (MacKenzie et al., 2011). We measured perceived AM exposure and control variables at T1. We measured again AM exposure at T2 (2 weeks later) along with the three expected outcome variables. We used the platform Prolific to invite 650 pre-screened individuals who worked for a gig work platform at least 20 hours per week, among which 515 completed the T1 survey. We excluded 41 of them for missing data or attention check failure. Two weeks later, the remaining 474 were invited to the second survey, which was returned by 391. We had to reject 25 of them for missing values or attention check failure, for a final sample of 366 who successfully completed the two surveys. The relatively low attrition rate between T1 and T2 may be explained by the conditional payment (USD 11$) contingent upon completion of both surveys.

Sample

The individuals in this sample were 56% male, 87% were below 45 years old, and 64.5% had a university degree. The job with the platform was the main income for 41% of them. Regarding the type of platform, 68% of participants worked for a crowdworking platform (like MTurk, Prolific, or Upwork). A significant proportion (79%) of them worked for more than one platform on a regular basis, but all were asked to fill the survey referring to the one for which they worked most often.

Measures

Job autonomy was measured by nine items from Morgeson and Humphrey (2006); for example, "The job allows me to decide on my own how to go about doing my work". Job complexity was measured by four items from Morgeson and Humphrey (2006); for example, "The job comprises relatively uncomplicated tasks" (reverse scored). Work engagement was measured by the nine items (three per dimension) of the UWES-9 questionnaire (Schaufeli et al., 2006). Sample items are "At my work, I feel that I am bursting with energy" (vigor); "I am proud of the work that I do here" (dedication); and "I am immersed in my work." (absorption). As for control variables, age, centrality of income, the platform for which the respondent was working (we created dummy variables for each platform ($n = 4$) with 10 workers or more represented in our sample), TAM variables (usefulness and ease of use of the system), and positive orientation to technology were included in the models with the intent of testing the predictive validity of the exposure to AM beyond these variables, for the same reasons than their inclusion in the convergent validity test.

3.6.3 | Results

We first performed a CFA to assess the fit of our measurement model, which showed a good fit ($\chi^2 = 300.29$, df $= 161$, CFI $= 0.968$, TLI $= 0.962$, RMSEA $= 0.049$, SRMR $= 0.052$). The structural model (measurement model + outcomes) also showed a good fit ($\chi^2 = 383.73$, df $= 218$, CFI $= 0.964$, TLI $= 0.958$, RMSEA $= 0.048$, SRMR $= 0.052$). Correlations and descriptive statistics are presented in Table 6.

Results of the structural equations models tested with R 4.1 are presented in Table 7. Exposure to AM at T1 significantly and negatively predicted job autonomy at T2 (est. $= -0.24$, $p < 0.01$) and job complexity at T2 (est. $= -0.26$, $p < 0.01$), beyond the effect of control variables. This shows full support to H1 and H2. We tested the mediation effect expected by H3 using a bootsrapping approach with the lavaan package of R 4.1 (5000 bootstrapped sample and a 95% confidence interval). Results in Table 7 indicate that the confidence intervals of the indirect effect of AM on work engagement through autonomy (est. $= -0.05$) and through complexity (est. $= -0.03$) did not include zero, and their path were both negative as expected. Moreover, the total indirect effect was also significant (confidence interval does not include zero) and negative (est. $= -0.09$). Overall, this brings full support to H3a and H3b. Based on this, we conclude good predictive validity of the AMQ scale.

3.7 | Supplementary analyses: AM perceptions relative to objective representation

The scale measures the individual perceptions of exposure to AM. In order to evaluate how these perceptions relate to a more objective representation of AM exposure, we explored to what extent they were shared among workers of the same platform, as well as divergent across different platforms. For instance, some platforms algorithmically assign schedules while others incentivize work times or do not exert any control. The idea is that, since one platform often has a relatively uniform AM system across workers, and consistent with the platform having particular objective degree or scope of AM, there should be strength of the consensus regarding the presence of an AM function. We thus calculated the aggregation indices of each AM function, and the portion of variance in the perceptions of AM exposure that occurs between and within platform. The within-platform variance corresponds to the differences in exposure perceptions in the same platform, while the between-platform variance relates to the shared perceptions as a representation of the objective exposure.

TABLE 6 Descriptive statistics and correlations for phase 6 ($N = 366$).

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Prolific	0.55	0.50	–																	
2. Uber	0.08	0.27	−0.32	–																
3. Fiverr	0.08	0.27	−0.32	−0.08	–															
4. UberEats	0.03	0.18	−0.20	−0.05	−0.05	–														
5. Main income (= no)	0.59	0.50	0.28	−0.10	−0.08	0.03	–													
6. Age	3.28	0.99	−0.05	−0.06	0.00	−0.07	0.14	–												
7. Usefulness	4.90	1.36	−0.10	0.20	0.01	0.10	−0.10	−0.17	(0.94)											
8. Ease of use	5.21	1.13	−0.02	0.15	−0.01	0.08	−0.03	−0.13	0.53	(0.81)										
9. POT	5.77	0.93	0.07	0.11	−0.01	0.02	0.04	−0.18	0.34	0.40	(0.86)									
10. AM	4.03	1.18	−0.09	0.20	−0.10	0.04	−0.16	−0.01	0.49	0.33	0.17	(0.77)								
11. MON	4.4	1.59	−0.16	0.23	−0.10	0.06	−0.14	0.02	0.39	0.29	0.12	0.77	(0.87)							
12. GS	4.2	1.8	−0.10	0.13	−0.13	0.11	−0.16	−0.01	0.40	0.29	0.14	0.77	0.58	(0.86)						
13. SCH	3.50	1.69	0.21	0.02	−0.09	−0.11	−0.05	−0.06	0.24	0.12	0.12	0.62	0.29	0.44	(0.90)					
14. PR	4.45	1.05	−0.08	0.15	0.02	0.04	−0.16	−0.11	0.41	0.33	0.17	0.66	0.47	0.40	0.26	(0.87)				
15. CMP	3.93	1.78	−0.16	0.21	−0.04	0.04	−0.09	0.04	0.31	0.24	0.08	0.67	0.40	0.39	0.22	0.31	(0.91)			
16. Autonomy (T2)	5.03	1.20	0.04	−0.08	0.13	−0.05	−0.04	−0.12	0.02	0.13	0.16	−0.15	−0.09	−0.20	−0.10	−0.02	−0.07	(0.93)		
17. Job Complexity (T2)	4.25	1.53	0.03	0.16	−0.07	0.07	0.02	−0.09	0.23	0.20	0.04	−0.27	−0.21	−0.26	−0.14	−0.17	−0.20	0.06	(0.89)	
18. Work Engagement (T2)	4.48	1.35	0.06	0.01	−0.00	−0.03	−0.03	−0.08	0.33	0.23	0.19	0.11	0.14	0.07	0.18	0.15	0.01	0.24	−0.05	(0.95)

Note: Variables 1 to 15 were measured at T1. Results higher than 0.11: $p = <0.05$. Results higher than 0.14: $p = <0.01$. Control variable 1 to 4 are dummy coded (1 = yes).

TABLE 7 Predictive validity results ($N = 366$).

	Autonomy (T2)		Complexity (T2)		Work engagement (T2)		
Controls	Est.	SE	Est.	SE	Est.	SE	95% CI
Prolific (=yes)	0.02	*0.07*	−0.12*	*0.06*	0.06	*0.05*	
Uber (=yes)	−0.07	*0.06*	−0.15*	*0.06*	0.03	*0.03*	
Fiverr (=yes)	0.10*	*0.04*	−0.02	*0.05*	−0.01	*0.05*	
UberEats (=yes)	−0.04	*0.04*	−0.07	*0.06*	−0.03	*0.05*	
Main income (= yes)	−0.07	*0.05*	−0.06	*0.05*	0.01	*0.05*	
Age	−0.07	*0.06*	0.08	*0.05*	−0.01	*0.05*	
System usefulness	−0.01	*0.05*	−0.06	*0.07*	0.30**	*0.06*	
System ease of use	0.16*	*0.06*	−0.10	*0.07*	0.03	*0.06*	
Positive orientation to technology	0.13*	*0.06*	0.10	*0.06*	0.03	*0.06*	
AM (T1)	−0.24**	0.07	−0.26**	0.07	0.05	*0.07*	
Job autonomy (T2)—direct					0.23**	*0.06*	
Job complexity (T2)—direct					0.13*	*0.05*	
AM—Job autonomy (T2)—indirect					−0.05**	*0.02*	[−0.09; −0.01]
AM—Job complexity (T2)—indirect					−0.03*	*0.01*	[−0.07; −0.001]
Total indirect effect					−0.09**	*0.03*	[−0.14; −0.04]
R^2	0.14		0.13		0.19		

Note: All controls were measured at T1.
Abbreviations: CI, Confidence interval [lower bound; upper bound]; SE, Standard error.
**$p < 0.01$; *$p < 0.05$.

TABLE 8 Shared perceptions of exposure to AM ($n = 1303$).

	Sum of squares				Aggregation indices		
	Between platform	Within platform	Total variance	F coefficient	ICC1	ICC2	Rwg
Monitoring	488.7 (14.4%)	2898.9 (86%)	3387.6	10.15**	0.26	0.89	0.41
Scheduling	583.9 (12.5%)	4076.2 (87.5%)	4660.1	8.62**	0.21	0.87	0.20
Goal setting	686.4 (18%)	3142.4 (82%)	3828.8	13.15**	0.22	0.87	0.20
Performance rating	114.7 (4.3%)	2549.1 (95.7%)	2663.8	2.71**	0.14	0.80	0.44
Compensation	589.8 (14.7%)	3413.1 (85.3%)	4002.9	10.39**	0.27	0.90	0.28
AM (overall)	435.9 (17.4%)	2065.0 (82.6%)	2500.9	9.45**			

Data used for this analysis were a combination of the three datasets respectively used for EFA, CFA, and predictive validity assessment. This sample consists of 1303 individuals working for 20 different platforms (we included only the platforms represented by at least three individuals, leading us to reject 29 individuals). The results reported in Table 8 show, for all AM functions, moderate intraclass correlation (ICC), high inter-rater consistency (rWG(J)), and significant between-platform variance and high within-platform variance, indicating moderate to high consensus. Taken together, these results suggest that our perceptual measure is, to a significant extent, shared across workers exposed to the same AM system. This means that our measurement of individual perceptions reflects objective aspects of an AM system, while also taking into account differences in perception that occur between individuals facing the same reality. It also suggests that, on the contrary, a purely objective assessment of AM would fail to consider the perceptual differences between workers of a same platform. Using Daniels' (2006) classification of job characteristics, our measure captures perceived job characteristics which, when to some extent shared by workers exposed to this characteristic, reflect what this author calls latent job characteristic.

4 | DISCUSSION

The aim of this paper was to develop and validate a new measure to assess individuals' perceived exposure to AM. We created the algorithmic management questionnaire (AMQ) drawing on evidence as to which management functions are increasingly executed by algorithmic systems. We developed items to measure the degree to which workers perceived the involvement of such systems in monitoring, GS, scheduling, PR, and compensation. We collected data across three samples ($n = 1332$) in order to assess the content, factorial, discriminant, convergent, and predictive validity of the scale. Analyses revealed that our measurement items successfully and distinctively capture these five functions of AM, reflective of a higher order construct of exposure to AM. The results lead us to conclude that the scale presents good validity.

4.1 | Contributions

The elaboration and validation of the AMQ substantially contribute to the development of the knowledge in this new but rapidly growing field of research. First, a valid measurement tool of the exposure to AM that reflects the objective exposure to AM systems while also capturing individual variations allows vast possibilities for empirical investigation of AM. Namely, expanding the knowledge on the nomological network of the phenomenon, conducting cross-context investigation, or using longitudinal or mixed-method designs are new research possibilities emanating for the development of the AMQ. The scale will allow future research to draw comparisons across platforms, work roles, teams, units, and organizations in order to better understand how different scopes and types of AM influence workers. The development of the scale will also augment researchers' capacity to establish the nomological network of AM, to observe how it relates to a variety of relevant attitudinal, behavioral, or emotional constructs. The validation study reported in this paper provides a glimpse of the potential relationships to be explored in order to better understand the AM phenomenon.

Second, we believe that the development of the AMQ will help researchers to look at AM in a more nuanced manner, with individual reports augmenting the ability to shed light on potential benefits of AM. As mentioned, previous literature has mostly focused on and observed negative outcomes for employees. With a more diverse measurement toolkit and by measuring perceptions, it becomes possible to investigate more in depth the plausible positive effects of AM at different levels (individual, teams, organizations). For example, it might be that individuals who experience high levels of AM perceive less gender or racial bias in how their performance is rated. Similarly, by expanding the research to consider moderators of the relationships between exposure to AM and outcomes, it allows the identification of what might help to promote more positive outcomes. For example, it might be that particular individual factors (e.g., seniority, familiarity with AM, managerial experience) or contextual factors (domain of application of AM) shape the impact of exposure on different outcomes. This sort of research will generate impactful knowledge for the development of best practices.

Third, through the measurement of workers' perceptions, the questionnaire overcomes the limitations to current research associated with considering AM as a dichotomous phenomenon (present vs. absent, or automated vs. not). The increasing complexity of algorithmic systems, with human and machine-made decisions intertwined, highlights the necessity of a more nuanced level of examination and analysis.

Fourth, the scale helps researchers to observe how workers' exposure to AM can shape their reactions. This approach dovetails with the literature on IT experiences (Wang et al., 2020) and technological control perceptions (Ravid et al., 2020), which shows that individuals differ in their way of perceiving features of technology such as invasiveness or usefulness. In other words, while the perceptions we measured are likely to reflect the objective presence of an AM system in an organization, as has mostly been examined by previous research, we reiterate the importance of measuring perceptions related to AM. Prior research shows that worker outcomes (emotions, attitudes, and behaviors) are generally shaped by the conjugation of objective manifestations of a phenomenon and how they perceive this phenomenon. In that sense, the scale will contribute to consolidating existing knowledge and increasing the capacity of researchers to capture the complexity of the AM phenomenon at the individual level, leading to generalizable and replicable research.

Fifth, the development and validation of the AMQ contributes to the work design literature. Technology has been identified as an antecedent of work design, as has management and leadership characteristics (Parker, Van den Broeck, & Holman, 2017), but the scale enables researchers to investigate work design when management is embedded in technology. Consistent with early literature on AM, our results show the higher is the perceived exposure to AM, the lower workers perceive autonomy and complexity in their work, and the lower they are engaged. On the other hand, work design literature is also rich on ways and interventions aiming to redesign jobs in order to improve their quality (Knight & Parker, 2021). The AMQ will be useful in building the knowledge on how redesigning AM systems can improve work design characteristics and consequently create higher quality of algorithmically managed work.

Also, we believe that the AMQ represents a milestone in the development of the knowledge on algorithmic HRM. Researchers of the field unanimously call for more responsible use of algorithmic systems in AM and for greater implication of HRM professionals in systems' design, implementation, and impacts' evaluation (Cheng & Hackett, 2019; Gal et al., 2020; Leicht-Deobald et al., 2019; Meijerink et al., 2021; Rodgers et al., 2023; Tambe et al., 2019; Vrontis et al., 2021). However, to do so, HRM researchers and practitioners first need tools to evaluate how these systems are used and perceived. HRM actors in organizations have a key and strategic role regarding the deployment of these sorts of technologies but lacked evaluation tools. The AMQ can now be used to evaluate how AM is affecting workers.

4.2 | Limitations and future research

This article provides initial validation of the AMQ. More research is necessary to uncover new aspects and address plausible limitations. It is important to shed light on the potential impact of the sample bias or limitation. For instance, our sample was mainly composed of US residents. As the literature emerges on racial and cultural considerations in the AM phenomenon (Jarrahi et al., 2021; Rani & Furrer, 2020; Wood et al., 2019), a validation of the scale in different countries is necessary.

Another potential limitation pertains to our empirical focus on gig workers, who are presumably more used to algorithmic systems because most have worked with platforms extensively. In contrast to traditional work settings where AM is used to progressively automate management activities that have been historically carried out by people, AM has been the key reality in most platform-based organizations. This distinction could generate a difference in workers' perceptions of exposure to AM systems. Although a recently published study among traditional truck drivers reports high perception of exposure to algorithmic monitoring and PR (Bujold et al., 2022), more research is needed to assess the validity and applicability of the AMQ across a broad range context beyond gig work.

On that note, although beyond the scope of this article, we believe that the AMQ could be a suitable instrument to measure exposure to AM in traditional, or non-gig, work contexts. Despite the existing differences between gig work and these more traditional contexts, the frontiers between these two forms of employments are expected to progressively blur. With the massive Uberization of work in traditional sectors like care (Glaser, 2021), public corporations (Davis, 2015), police (Sandhu & Fussey, 2021), translation (Firat, 2021) and many others (Edward, 2020), and with new forms of digital nomadism exacerbated by virtual and globalized work (Aroles et al., 2022), much future work is likely to be increasingly characterized by a mix of employed, hybrid and self-employed workers, and by technology-mediated management (Duggan et al., 2020; Keegan & Meijerink, 2023). In this context of increasing and widespread presence and exposure to AM, we believe our instrument will be applicable across sectors. Moreover, based on conceptual comparisons of AM forms and features between gig and non-gig work (Baiocco et al., 2022; Lippert et al., 2023; Wood, 2021), the five management dimensions measured by the AMQ can be found in both types of settings. We strongly invite researcher to examine empirically these suppositions.

Furthermore, our scale measures exposure to AM. This assessment of the perceived presence of AM is necessary, but, in the aim of guiding the understanding and development of responsible AM, should be accompanied by valid measurement tools to assess other individual experiences related to AM. These experiences could include, for instance, the perceived transparency or fairness of an AM system, or the perceived control or agency in the face of the system (Parent-Rocheleau & Parker, 2022). Lastly, we encourage researchers further explore the respective effects of the AM dimensions, and even their potential interactions.

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CONFLICT OF INTEREST STATEMENT

The authors declare having no conflict of interest in this research.

DATA AVAILABILITY STATEMENT

Data available on request from the authors.

ORCID

Xavier Parent-Rocheleau https://orcid.org/0000-0001-5015-3214
Sharon K. Parker https://orcid.org/0000-0002-0978-1873

ENDNOTE

[1] This definition is not restricted to a specific type of algorithm and can be equally applied to machine-learning or more standard algorithms.

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AUTHOR BIOGRAPHIES

Xavier Parent-Rocheleau is an Assistant Professor of human resource management at HEC Montreal. His research is focused on the human aspects of digitalization work, algorithmic management of the workforce, workplace surveillance, quantification and datafication of work, and artificial intelligence. His work has been published in influential journals such as *Human Resource Management Review*, *Nature Reviews Psychology*, *Journal of Business Research*, European Journal of Work & Organizational Psychology, *Public Administration Review*, *Journal of Leadership & Organizational Studies*, *Journal of Business & Psychology*, and *Surveillance & Society*.

Sharon K. Parker (ARC Laureate Fellow) is a John Curtin Distinguished Professor at Curtin University, Director of the Centre for Transformative Work Design at Curtin University, and a Fellow of the Australian Academy of Social Science. She has published over 200 research articles, and in 2019, she was named among the world's most influential scientists in the Web of Science Highly Cited Researchers list. Her research is concerned with topics such as work design, job performance, proactivity, organizational change, and work stress.

Antoine Bujold is a PhD student in organizational behavior and human resources management at HEC Montreal. Interested in the future of work, his research focuses on the relationship between digital technologies (e.g., algorithmic management) and human behavior in organizational environments, as well as the impact of these technologies on human resources practices. His work was published in academic journal and presented in several conferences.

Marie-Claude Gaudet is an associate professor of human resource management at HEC Montreal. Her expertise and research

interests include leadership, performance, organizational justice and the impact of algorithmic management on attitudes and behaviors in organizations. Her research has been published in a variety of journals, including *European Journal of Work and Organizational Psychology*, *Journal of Leadership and Organizational Studies* and *Personnel Review*.

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APPENDIX A: LIST OF ITEMS AND LOADINGS ON THEIR RESPECTIVE DIMENSION

Items		Loading	Error
MON1	An automated system tracks me carefully to ensure I am completing my tasks.	0.865	0.020
MON2	An automated system closely monitors me while I am doing my work.	0.905	0.028
MON3	An automated system inspects my work closely.	0.834	0.039
MON4	I am constantly being watched by an automated system to see that I obey the rules pertaining to my job.	0.871	0.032
GS1	My daily tasks are assigned by an automated system.	0.914	0.017
GS2	An automated system decides what tasks I will be doing.	0.922	0.019
GS3	In my job, an automated system determines what needs to be done.	0.912	0.021
GS4	An automated system determines the targets I must attain at work (productivity targets, time targets, sales target, etc.).	0.802	0.033
GS5	The targets I have to reach are set by the automated system.	0.790	0.033
SCH1	An automated system decides when I work and when I do not.	0.871	0.029
SCH2	My work schedule is made by an automated system.	0.939	0.030
SCH3	An automated system is responsible for determining my working hours.	0.944	0.035
SCH4	My working hours are determined automatically by an electronic system.	0.937	0.037
PM1	The evaluation of my work performance is handled by an electronic system.	0.875	0.048
PM2	An automated system generates the metrics used to assess my performance.	0.800	0.057
PM3	My performance evaluation is based on metrics computed by an automated system.	0.831	0.057
CMP1	A large part of my compensation is determined by an automated system.	0.864	0.024
CMP2	The decisions related to my earnings are mostly made by the automated system.	0.884	0.020
CMP3	An automated system is responsible for calculating my pay, with no human intervention.	0.888	0.034
CMP4	What I earn is the result of an automated system calculation only.	0.901	0.035

APPENDIX B: INTRODUCTION AND DEFINITIONS INCLUDED IN THE SURVEY

B.1 | Introduction

Some of the activities that are carried out by managers are now sometimes performed by 'automatic' systems, with little human input.

For example, assigning rides to an Uber driver is not usually done by a human manager. Rather, the electronic system automatically assigns rides to a driver based on 'algorithms', or rules built into the system. Likewise, in some retail stores, an application automatically prepares the employees' schedule based on expected occupancy, weather forecasts and other data.

This new role of automated systems has been called "algorithmic management". The actual study aims to examine the effects of this phenomenon for employees.

B.2 | Algorithmic monitoring

These next questions are about whether an automated system monitors what you are doing. As an example, the route that an Uber driver or a *delivery* truck driver takes, and the time he or she takes for each drive or delivery, is monitored by the app.

Please indicate to what extent do you agree with the following statements, using a scale ranging from 1 (completely disagree) to 7 (completely agree).

B.3 | Algorithmic goal setting

These next questions are about whether an automated system is used to set your goals, such as allocating your tasks or setting the targets that you have to reach (productivity targets, pace, time targets, sales targets, etc.). As an example, the rides assigned to an Uber driver are decided by the automated system. Likewise, the number of packages per hour that warehouse workers are asked to handle is usually determined by algorithms.

Please indicate to what extent do you agree with the following statements, using a scale ranging from 1 (completely disagree) to 7 (completely agree).

B.4 | Algorithmic scheduling

These next questions are about whether an automated system is used to determine your schedule or to provide recommendations and incentives to influence your working hours. As an example, the app of some delivery platforms creates and assigns timetables for workers. Likewise, when drivers log out, the Uber app often shows messages saying how much they could earn if they keep driving for another hour or two.

Please indicate to what extent do you agree with the following statements, using a scale ranging from 1 (completely disagree) to 7 (completely agree).

B.5 | Algorithmic performance rating

These next questions are about whether an automated system is used to process your performance ratings. As an example, most platforms use quantified performance metrics to rate the performance of workers, like the Uber "stars" system.

Please indicate to what extent do you agree with the following statements, using a scale ranging from 1 (completely disagree) to 7 (completely agree).

B.6 | Algorithmic compensation

These next questions are about whether an automated system is used to process your compensation (or your pay). As an example, some food delivery apps automatically calculate workers pay based on information like customer satisfaction, the number of deliveries, the distance traveled, tips, etc.

Please indicate to what extent do you agree with the following statements, using a scale ranging from 1 (completely disagree) to 7 (completely agree).